D-Jogger: An interactive music system for gait synchronisation
With applications for sports and rehabilitation

Bart Moens
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Proefschrift voorgelegd tot het behalen van de graad van Doctor in de kunstwetenschappen en in de ingenieurswetenschappen: computerwetenschappen
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Seven years ago, prof. Marc Leman asked if I was interested in continuing my masters’ thesis research as a PhD student. After some thought I realised this would be my dream job: combining my interest for computers, music and automation (i.e. make something else do the work for you) in a social context. So I rushed back to Ghent, ran to the second floor of the Blandijn and, of course out of breath, announced in all seriousness in the middle of the hallway that I would like to continue at IPEM.

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Finally, I am very grateful for my parents’ continuous support and love throughout this work. And the Friday night crew - evolving to after work more recently - thank you for the fun, laughs and jokes or serious questions about the timing or content of my dissertation - it is always good to get a completely different perspective and some grasp of the real life.

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Finally, I would like to thank all participants and patients who took part in our experiments, in particular the Parkinson Disease patients. I know the effort and tasks to participate in the experiments were often hard, and I hope that one day, some part of this research can be used to make your walks more comfortable. Thank you!

Ghent, December 2017

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Nederlandse samenvatting

D-Jogger: een interactieve muziekspeler voor stapsynchronisatie
Met toepassingen voor sport en revalidatie

In deze thesis ontwikkelden we D-Jogger, een interactieve muziekspeler die het muziektempo automatisch aangepast aan het stap- of looptempo van de gebruiker. De muziekspeler past de muziek zodanig aan dat elke muzikale beat samenvalt met het neerkomen van de voet. Het onderzoek spitst zich toe op de gevolgen van dergelijke muzikale stimulatie: zijn er effecten op prestatie, plezierbeleving en energieverbruik? Heeft dit voordelen bij muziektherapie en Parkinson revalidatie?


De koppeling tussen muziektempo en looptempo kan op verschillende wijzen gebeuren, genaamd 'music alignment strategieën'. Een strategie beschrijft hoe en wanneer de muziek zich moet aanpassen aan de gebruiker alsook wanneer beter passende muziek dient gekozen te worden. Dit is het onderwerp van het derde hoofdstuk.

In de eerste fase van dit onderzoek starten we van een heel intuïtieve strategie: het muziektempo wordt elke stap gelijkgesteld aan het gemiddelde recente tempo van de gebruiker. Er werden bij deze strategie inderdaad meer stappen in synchronie met de beat genomen, maar we constateerden dat de interactie tussen mens en machine oscilleerde. Niet enkel het systeem paste zich aan de gebruiker, maar ook omgekeerd: de gebruiker paste zich eveneens aan de muziek. Dit algoritme leidde uiteindelijk niet tot gewenste resultaten.
Uit verdere experimenten bleek dat het startmoment van de muziek belangrijk is. Als er enkele stappen goed samenvallen met de beat, een tijdelijke 'phase lock', bleef de gebruiker vaak gesynchroniseerd voor de rest van het nummer. Door het nummer reeds in de maat te starten, behaalden we betere resultaten. Hierbij moest de gebruiker zich nog steeds aanpassen aan de muziek, maar dit gebeurde vaak spontaan onder invloed van een effect dat men entrainment noemt. Entrainment is het spontaan synchroniseren van twee dynamische systemen. In dit geval betreft het de gebruiker die zich aangetrokken voelt tot de beat en hierdoor geregeld zijn eigen tempo aanpast. Niet iedereen kan dit of deed het spontaan. Deze bevinding gaf aanleiding tot nieuwe strategieën.


D-Jogger en de bijhorende music alignment strategieën zijn vervolgens in meer empirische experimenten gebruikt voor het toetsen van verschillende onderzoeks vragen in vakgebieden zoals sportwetenschap en revalidatietherapie.

Uit het experiment in hoofdstuk 4.3 blijkt dat Parkinson patiënten geholpen kunnen worden door correct aangepaste muziek. De literatuur wees reeds uit dat tempo-aangepaste metronomen en andere ritmische stimuli een positieve invloed hebben op het gangpatroon van een patiënt. Door gebruik van gesynchroniseerde muziek aan de hand van D-Jogger hebben we soortgelijke, doch minder uitgesproken verbeteringen opgemerkt binnen het gangpatroon: er werden grotere stappen genomen en het staptempo lag hoger dan zonder muziek. Het merkwaardigste resultaat was echter dat muziek ook positieve invloed had op de voorspelbaarheid van het gangpatroon, terwijl een metronoom een negatieve invloed had. Negatieve voorspelbaarheid wordt gelinkt aan valrisico, waardoor patiënten bij het stappen op muziek potentieel een lager valrisco hebben dan bij het stappen met een metronoom. Bovendien werd muziek ook motiverender en stimulerender bevonden dan metronomen. Het onderzoek concludeert dus dat synchrone muziek heel nuttig kan zijn voor Parkinson revalidatie.

Een tweede vakgebied was de sportwetenschap. Een eerste experiment, beschreven in hoofdstuk 4.4, ging na of synchrone muziek een positief effect kan hebben op de prestatie van de loper, dit zowel qua energieverbruik als subjectieve uitputting. Proefpersonen liepen op
een loopband tegen constante snelheid gedurende 30 minuten. Muziek werd aangeboden volgens verschillende muziekstrategieën. Hierbij werd hun zuurstofverbruik, verzuring, hartslag en subjectieve uitputting gemeten. In tegenstelling tot andere studies merkten we weinig significante verbeteringen. Wat echter opviel was dat er 2 groepen waren: de helft van de personen reageerden duidelijk positief (minder energieverbruik); de andere helft niet. Het is tot op heden niet duidelijk waarom sommige personen al dan niet positief reageerden op de synchrone muziek.

De volgende experimenten hadden als doel om het looptempo van de gebruiker onbewust te beïnvloeden: de personen sneller of trager laten lopen op muziek. Deze experimenten werden uitgevoerd op een atletiekpiste met mobiele apparatuur, om een zo een natuurlijk mogelijke setting te creëren waarbij de persoon vrij was zowel paslengte als looptempo aan te passen. Beide experimenten zijn gebaseerd op entrainment of de aantrekkingskracht van de beat van de muziek: de tendens om eigen bewegingstempo aan te passen aan muziekaal tempo indien beide voldoende dicht bij elkaar liggen.

Het experiment, beschreven in hoofdstuk 4.5, versnelde het tempo van de muziek lichtjes ten overstaan van het spontane looptempo (van 5% vertraging tot 5% versnelling in kleine intervallen). Hieruit blijkt dat lopers zich inderdaad aanpassen aan de muziek, zij het in beperkte mate: aanpassingen van -2.5% tot +2.0% worden gevolgd. Het is dus mogelijk lopers onbewust te vertragen. Vertragen bleek ook iets makkelijker te zijn dan versnellen. Door het staptempo aan te passen, werd men dus beloond met synchrone muziek. Dit had echter ook tot gevolg dat er geen synchroniciteit was indien mensen zich niet aanpasten, wat weer een negatieve impact zou kunnen hebben op onder andere de motivatie.

Om deze impact te voorkomen, is een tweede variant van het experiment bedacht. Deze wordt beschreven in hoofdstuk 4.6. Hierbij werd het looptempo exact gevolgd, maar werd de timing lichtjes opgeschoven waardoor de beat consequent net voor of net na de stap gehoord werd. De hypothese was dat lopers zich opnieuw aangetrokken gingen voelen tot de beat wanneer dit na de stap ge- hoord werd. De resultaten toonden aan dat dit ook het geval was: opnieuw pasten lopers zich aan maar in mindere mate dan het eerdere experiment (-2.0% tot +1.0%). De aanpassingen waren wel consequenter: het resultaat had betrekking op een grotere populatie. Opmerkelijk was ook dat deze strategie resulteerde in kleine invloed op de loopsnelheid, in tegenstelling tot eerdere strategieën. De resultaten en gevolgen hiervan kunnen leiden tot verschillende toepassingen binnen sport maar ook binnen revalidatie en trainingsprogramma’s.

D-Jogger en het concept van music alignment strategieën hebben de laatste jaren ook bijgedragen aan andere experimenten. De technologie wordt nu gebruikt bij tests ten behoeve van impactreductie bij lopers om zo blessures te verminderen, bij multiple sclerosis revalidatie en bij onderzoeken betreffende muzikale expressie. Deze worden beschreven in
hoofdstuk 5. De technologie heeft eveneens een grote bijdrage geleverd aan het Europese project BeatHealth, een samenwerking tussen vijf universiteiten. Het consortium paste synchrone muziek toe bij lopers en Parkinson patiënten, waarbij onderzoek gedaan werd naar onder andere synchroniciteit, energieverbruik en koppeling met de ademhaling. Het finale BeatHealth experiment was een uniek en grootschalig experiment, waarbij 32 proefpersonen een mobiele versie mee naar huis kregen met een bijhorend trainingsschema. Door het gebruik van een nieuwe alignment strategie kon men het looptempo van de gebruiker beïnvloeden naar het optimale tempo, bepaald aan de hand van een blootsvoetse looptest. Dit optimale tempo zou aanleiding kunnen geven tot minder blessures. De resultaten tonen aan dat het looptempo inderdaad werd aangepast na een viertal weken, en dat dit optimale tempo ook wordt aangehouden bij lopen zonder muziek. Het concrete algoritme is aanleiding geweest tot een patentaanvraag.

Het laatste hoofdstuk vat het werk en de resultaten kort samen. We lichten ook enkele beperkingen van onze onderzoeken toe. Vooral het beperkte gebruik van het theoretische kader en enkele vragen waarop we doorheen dit werk geen antwoord hebben gevonden komen aan bod. Verder lichten we ook onze valorisatie of commercialisatie-pogingen toe, alvorens af te sluiten met een globale conclusie over synchrone muziek en D-Jogger.
The dissertation describes the development of D-Jogger, an interactive music player that aligns music to the gait of the user. D-Jogger adjusts the tempo of a song so each beat coincides with a footfall. This research focuses on the effects of the resulting synchronous musical stimulation: are there effects on motivation, performance or energy consumption? Are there advantages in music therapy such as Parkinson Disease rehabilitation?

The first chapter summarises the theoretical background, methodological choices and circular statistics. The second chapter describes the development of D-Jogger by explaining the software architecture and its individual components. The cadence of the user, expressed in steps per minute, is determined in realtime using sensors. D-Jogger then chooses a song with a tempo close to that cadence. The music tempo is further adjusted to continuously match the cadence, without changing the pitch. The auditory effect of this tempo variation is therefore often inaudible to the user.

The method how music is matched to the cadence is called a 'music alignment strategy'. Such a strategy describes how and when the music should adapt to the user and when more appropriate music should be chosen. This is the subject of the third chapter.

In the first phase, we started experimenting with an intuitive and simple form of alignment: matching the musical tempo to the average recent cadence of the user. While we noticed more synchronisation (footfalls coinciding with a beat), the system was highly unstable due to an effect called mutual synchronisation: the user automatically adjusting to the music and the system adapting to that change. This is also called entrainment: the spontaneous synchronisation of 2 dynamical systems. In this case it is the user that is attracted to the beat and therefore slightly adjusts cadence. This algorithm was not designed to cope with entrainment and ultimately did not lead to optimal results.

Further experiments showed that, when a few consecutive steps coincided with a beat (a temporary phase lock), the user often synchronised for the remainder of the song. This lead to the next strategy, where music was started on the exact moment of a footfall - thereby stimulating synchronisation and using the entrainment effect to remain in a phase lock.
This approach was successful for most participants, leading to a majority of steps taken in synchrony with a beat. However, not everyone did so spontaneously, or could do this even if requested.

This led to new alignment strategies. Using phase alignment on top of tempo adjustments, each beat can be matched automatically to a footfall. One approach uses adaptive oscillators: a mathematical model that also adjusts the tempo between steps. This model is loosely based on synchronisation of chemical and biological processes, and thus finds its origins in nature. With this strategy, almost all steps were in taken in synchrony. Additionally, surveys indicated that it felt less mechanical than previous ones and resulted in a higher motivation during exercises.

D-Jogger has also been used in empirical research to test several different research questions in disciplines such as sport science and rehabilitation therapy.

The experiment described in chapter 4.3 shows that Parkinson Disease patients can benefit from correctly adjusted music. Literature already indicated that cadence-adjusted metronomes and other rhythmical auditory stimuli have a positive influence on the gait pattern of the patient. We got similar but less pronounced results using D-Jogger for synchronous music. Gait improvements include larger steps and increased cadence. The most remarkable result was that music also had a positive impact on the predictability of the gait pattern, whereas a metronome had a negative impact. Negative predictability is linked to fall risk, therefore music could be used to reduce falling risks compared to metronomes. Moreover, music was found to be more motivating and stimulating than metronomes. The research thus concludes that synchronous music can be very useful for Parkinson Rehabilitation.

A second research domain was sport science. A first experiment, described in chapter 4.4, examined whether synchronous music has a positive effect on the performance of the runner, both in terms of energy consumption and perceived exhaustion. Participants ran on a treadmill with constant speed for 30 minutes. Music was synchronised using different alignment strategies. Dependant variables included oxygen consumption, blood lactate, heart rate and perceived rate of exhaustion. In contrast to the literature, we noticed no statistically significant differences. Data did however show that there were 2 groups: half of the participants clearly reacted positively (less energy consumption); the other half did not. As of yet it is still unclear why some people react positively, and others do not.

The last experiments tried to influence the cadence of the runner using music. These experiments were performed on an indoor athletic track using a mobile version of D-Jogger. Therefore participants could adjust both their stride length and cadence. The experiments attempted to use entrainment or the attraction of the beat of music to manipulate cadence.
The experiment, described in chapter 4.5, adjusted the tempo of the music slightly compared to the spontaneous cadence (from 5% slower to 5% faster using small increments). Results show that runners indeed adapt to the music, albeit to a limited extent: adjustments from -2.5% to +2.0% are followed. It is therefore possible to slow down or speed up runners without explicit instruction and without the participant realising it. Slowing down was slightly easier than accelerating. By adjusting their cadence to match the music, they became rewarded with synchronous music. However, this also meant that non-followers were mostly out of phase with the music, which could have a negative impact on motivation.

To prevent this, a second experiment was executed (chapter 4.6). In this case, the running cadence was matched exactly, but there was a slight timing shift so that the musical beat occurred consistently right before or right after the footfall. The hypothesis was that runners would be attracted to the beat (e.g. to ‘catch up’ with the beat and thus accelerate). The results show that this was indeed correct: runners again adapted their cadence, but to a lesser extent than the previous experiment (-2.0% to +1.0%). However, the behaviour of the participants was more consistent; and the result could be related to a larger population. Remarkable was also that there was a small influence on the velocity, in contrast until the previous experiment. These results can be applied within sports (e.g. to create coaching apps that influence your tempo) but also within rehabilitation contexts and training programmes.

D-Jogger and the concept of music alignment strategies have also contributed significantly to other experiments. The technology is now used studies, for example to reduce foot-strike impact, multiple sclerosis rehabilitation and studies concerning musical expression (chapter 5). The technology also made a major contribution to the European project BeatHealth; a collaboration between five universities. The consortium used synchronous music for runners and Parkinson Disease patients. Topics of interest were synchronicity, energy consumption and coupling with breathing. The final BeatHealth experiment was a unique and large-scale experiment, involving 32 participants subjects who received a mobile BeatHealth version with a personalised training schedule. The goal was to influence the spontaneous cadence of runners towards optimal levels as determined in a barefoot pre-test. This optimal pace could result in fewer injuries. The results show an adjusted cadence after four weeks of trailing. This optimal tempo is also maintained when running without music in the post-test. The experiment resulted in a patent application for the specific alignment strategy.

Finally, the last chapter briefly summarises the work and the results. We highlight some limitations from our studies, such as the limited theoretical framework and some open questions. Furthermore, we also explain our valorisation or commercialization attempts; before ending with a global conclusion about synchronous music and D-Jogger.
List of publications and patents

**Peer reviewed journal publications included in SCI**


**Submitted SCI Publications**

- Beat synchronized running and motivation: an investigation of different music-to-movement alignment strategies. Buhmann, J., Moens, B., Van Dyck, E., et al. *Inter-
List of Publications


Book Chapters


Conference proceedings


Miscellaneous


Patents

- Provisional patent application: *Mobile system allowing adaptation of the runner’s cadence*, co-inventor (first inventor Benoît Bardy), filed on July 27 2017, EFS ID 29906030
Introduction

Moving along with music is a widespread phenomenon. When listening to music, some people will spontaneously nod their head, tap their feet, or dance along with music. Some people use music to guide their jogging activities. Music thereby affords movement, and much music is indeed made for stimulating people to move. During movement, music also affects human motivation, and music may therefore be associated with phenomena such as euphoria and attention distraction, which has as an effect that music-assisted movement overcomes physical effort, fatigue, and pain (Fritz et al., 2013). Overall, moving along with music is particular, engaging, and empowering.

This power of music merits further research for two reasons. The first reason is that the mechanisms behind this power are still badly understood. The second reason is that this power can be used for building devices that engage people in moving along with music. Both questions form the backbone of our research.

To better understand our proper contribution to this research, it should be mentioned here that we gained the capability to use music in this individual context quite recently, thanks to rapid advances in technologies. Portable music players, for example, have made an immense evolution the last 50 years. We mention them here because they play a key role in our research. Before 1980, only portable radio’s were available, not allowing for individual playlists. From 1980; walkmans, discmans and later MP3 players (see figure 1.1) became available and they could store a personalized music selection. These devices were merely playback devices. However, their development went fast and the latest generation
Figure 1.1: Visual overview of music playback device evolutions

of music playback devices is now embedded on smartphones. Currently, smartphones are not only capable to playback music individually, but they also have a lot of processing power and sensors which can be used to intelligently select or personalize music, possibly enhancing the effects of music even further.

Starting from this state of the art, our goal was to add a next stage in the development of mobile music players, which is based on the idea that people can interact with their mobile music player. We mean by this that based on human actions, mobile music players should be able to select (context aware) and adapt (interactive) the music to what is happening at the current time. The development of such a tool for use in walking and running scenario’s was a main topic of this thesis. In addition, we believe that by developing such a tool, we would be able to set up experiments that give insight into the mechanisms behind the motivational power. By this, our answer to the main research questions was based on a double basis. First, the development of a proper interactive tool where motivational power could be manipulated. Second, the execution of empirical tests that use these manipulations in order to get more insight into the mechanisms behind the motivational power. In both cases, interaction with music was the major point of departure.

Research tracks and questions. The work in this thesis can be described in terms of two parallel research tracks that continuously influenced each other.

The first research track focussed on the development of D-Jogger, a tool to provide individualized and contextualized auditory feedback during walking, such as music feedback
that matches the tempo of walking. We quickly noticed that this simple notion of the machine adapting to the human was inadequate and insufficient; mainly because the human also adapts to the machine. The real situation is indeed a situation in which mutual interaction occurs. This observations led to the initial research question, detailed in chapter 3: what is the most efficient way to synchronise music to the gait? To explore and possibly exploit this mutual interaction, we developed D-Jogger as a complete music playback system capable of synchronising music to human movement in several different ways. While these different methods of aligning music playback with human movement may vary only slightly, at first sight, it turned out that small details may have a big impact on the way in which humans respond. Therefore, the mutual interaction cannot be underestimated and needed our full research attention.

The second research track explored the effects of synchronous music playback in different fields such as entrainment theory, sports and rehabilitation. These scenario’s or research questions can be seen as 'practical usecases' for D-Jogger or even more specific music alignment strategies.

The first question related to the sports domain: does synchronous music influence runners' motivation, cadence or velocity? Does running on synchronous music reduce energy consumption? Chapter 4.2 describes an experiment comparing synchronous and asynchronus music during running exercises.

Another practical use-case of synchronous music is to asses potential positive effects during rehabilitation therapy. Music is often used as a means to distract or reduce effort, but could it also have other benefits? A typical example for this can be found in Parkinson Disease rehabilitation. Patients benefit from synchronous metronomes, showing a positive effect on their gait patterns and stability. We therefore formulated our second research question as follows: is synchronous music useful for Parkinson’s disease rehabilitation? Chapter 4.3 describes an experiment with patients, using synchronous music as stimulus instead of metronomes.

During the experiments, we often saw participants being attracted to the either the beat (phase) or tempo of the music, i.e. the entrainment effect. Our last research questions were therefore inspired by the subtle power of music: can we influence our walking and running cadence with music? Chapter 4.4 describes the first experiment manipulating the music’s tempo; while the follow-up experiment shown in chapter 4.5 attempted a more subtle approach by shifting the beat forward or backward compared to the step?

To answer the research questions, we build upon the theoretical interdisciplinary framework of professor Leman (2008). In his works, he couples several aspects of movement with music using embodied music cognition. We use it as the theoretical foundation for our thesis. We also used his recent work (Leman, 2016) as a source of inspiration, while this work itself has been partly based on our research outcomes (e.g. those on entrainment).
In this chapter, we briefly summarize the embodied music cognition theory and introduce concepts such as entrainment, human computer interaction, and music information retrieval. Next, we introduce our main methodology, the problem specification, the state of the art, and an outline of the dissertation structure. In the next chapter we then describe our main application, D-Jogger. Both this chapter and the next chapter provide the theoretical and practical framework for the empirical studies that are presented in the chapters that follow.

1.1 Theoretical framework

The theoretical framework needed for understanding how people interact with music traditionally draws upon cognitive science approaches to music. Systematic musicology can be seen as that branch of cognitive science that is devoted to understanding how humans interact with music, in particular, how they perceive music, and how they perform music. The main research paradigm is currently called Embodied Music Cognition (EMC), and it is built upon a former research paradigm in music cognition in which the embodied aspect was less developed (Leman, 2008). A main focus of the older paradigm was on perception, whereas in the new (embodied) paradigm, it is on performance. The EMC also holds that corporeal interaction with the environment imposes constraints on perception. In other words, that moving determines aspects of our perception of music (Leman and Maes, 2014). Throughout this dissertation, EMC is used both as the theoretical foundation but also as an empirical guide into musicology research, offering an empirical approach to the field of human-computer interaction (HCI). This chapter introduces some of the main theoretical foundations and concepts of EMC that we needed for our research.

1.1.1 Fundamentals of embodied music cognition

Embodied music cognition (EMC) approaches the study of human interaction with music from a viewpoint where the coupling between mind, body and environment plays a central role (Leman, 2008; Godoy and Leman, 2010). This viewpoint is dynamic and it puts interaction at the centre. Moreover, in embodied music cognition, the human body is considered as a major constituent of this interaction. In particular, the human body has been conceived as 'a mediator between the physical environment (matter) and the subjective experience (mind)' (Leman and Lesaffre, 2013). This viewpoint considers how the biomechanics of the human body contributes to cognition, and it provides a new way of addressing emotions, through movement, and through embodiment of music. This viewpoint also allows the development of models of social cognition, which link with neuroscience work, using concepts of emotion synchronicity, social entrainment, and empathy (Davis et al., 2012).
According to Leman (2016), interaction with music is embodied (i.e. mediated by the body), situated (i.e. embedded in an environment), and enacted (i.e. put into practice through action and gestures) (Gover, 1996; Barsalou, 2008). The latter notion of enactment is of particular interest in our understanding of why interactions between humans and machines can be appealing. It is because enactment engages a sensorimotor prediction process through which musical patterns get related to human actions and intentions. As a result, human realize an intentionality-induction process, through which music is experienced in terms of actions. Furthermore, enactment is a key process for getting stable music interaction situations, that is, situations where humans, through moving along with music, can establish and maintain a high-level stable interaction dynamic, called homeostasis (Leman, 2016).

![Embodied music cognition framework](image)

**Figure 1.2: Embodied music cognition framework**

Figure 1.2 shows the basic sensorimotor scheme of the embodied music cognition theory. Amelynck (2014) used this figure and he summarized the EMC theory as follows: "The figure represents an agent that acts in the environment and that receives information from that environment. When the agent decides to perform an action (e.g. the intended playing of a note on a music instrument) it will rely on the action repertoire (1) to launch an action pattern that gets executed (2). Along that pathway, a copy of the action pattern and its predicted outcome (3) is made and compared (4) with the actual action execution and the
sensed outcome of the action (the instruments sound) (5) and (6). Based on the perceived outcome of the action the motor pattern can be adjusted. Leman makes a distinction between two mechanisms for adjustment of body movements, called the sensor-motor loop and the action-perception loop. The sensor-motor loop (7) is a low-level circuit where the motor activity is basically driven by sensory input from the environment. In contrast, the action-perception loop (8) is responsible for prediction and for issues that involve musical intentions. It is the circular flow of information that takes place between the subject and the real world in the course of a sensory-guided sequence of behaviour towards a goal. Each action causes changes in the environment that are perceived and that lead to the processing of further actions. The latter cause new changes that are analysed and lead to new actions, and so the cycle continues (Leman, 2008, pg. 26).

The theory is discussed in detail in the books 'Embodied music cognition and mediation technology’ and 'The power of music - researching musical experiences’ (Leman, 2008; Leman and Lesaffre, 2013). Interestingly, both books offer theoretical as well as practical viewpoints. With mediation technology, various technologies for capturing, storing, transmitting, and generating music come into the focus of attention in musicology. The book, therefore, denoted a shift of paradigm for musicology, from mind-centred perception studies, towards more ecological, body-centred performance studies. One of the main challenges here was the idea to develop technology in line with the embodied music cognition view. Such technologies should be ecological and useful in natural settings. This was a real challenge for our research, as Leman (2008) stated that 'adopting this empirical approach, the research field suddenly becomes extremely interdisciplinary and rich in the sense that questions get answered in collaboration with other scientists who introduce different know-how and perspectives, such as biomechanics, brain science, and engineering’.

The embodied music cognition paradigm suggested that scientific progress in the domain of music interaction would draw upon a strong connection with technology development. The idea was that mediation technology could give the human body, and the human mind, an extension in the digital musical domain (Davis et al., 2012). An example is the 'Sync-in-team’ game (Leman et al., 2009), which applies synchronisation and entrainment in a social music interaction game. The extension of the human body with technology offers possibilities to synchronisation that are otherwise not possible.

In short, embodied music cognition is a strong theory that could serve as a guideline for our practical applications (as put forward in Leman (2008)). Meanwhile, the embodied music cognition approach started getting a tremendous impact in the field, as well as in related fields such as sonification, music education, and even interactive multimedia (Correia Da Silva Diniz et al., 2010), where natural (embodied) mappings between human gestures and control parameters of the system (Maes et al., 2010) are essential for the experience of presence and flow (Nijs et al., 2010). Due to the interdisciplinary basis of embodied music
cognition research, knowledge of several domains is required to develop applications. And as a consequence, the research requires new hard- and software solutions from an engineering perspective. New solutions are needed to measure and provide stimuli, test musicological knowledge about the music, and use theory for assessing the limits or constraints of the human system.

1.1.2 Entrainment

While the concept of embodiment refers to the overall role of the body in music cognition, we focus here on a particular concept that fits within that overall concept of embodiment. Entrainment thereby refers to a situation in which two or more independent entities get synchronised to each other. More particularly, entrainment can be defined as an adaptation of synchronisation behaviour (Leman, 2016, see also chapter 5). This definition captures the idea that when independent entities get synchronised, they entrain each other using push and pull forces that may affect the state of the synchronisation.

Entrainment occurs in different fields, such as in engineering, musicology, physics, and cognitive sciences. There are typical examples in nature, such as a swarm of fireflies blinking in harmony at nights’ end (Buck and Buck, 1967), synchronised frog calls (Patel et al., 2009), human individuals adjusting their speech rhythms to match each other in conversation (Cappella and Planalp, 1981), sleep-wake cycles synchronising to the 24-hour cycle of light and dark (Pittendrigh and Minis, 1964), and other remarkable phenomena. Figure 1.3 illustrates the concept of entrainment using an example of synchronous metronomes (Pantaleone, 2002). This example was initially introduced by Christiaan Huyghens and it is therefore known as Huygens’s Clocks (1665). Kelso (1997) points to the importance of coupling and entrainment as the basis for dynamic interactions among humans.

In a more musicological context, Clayton et al. (2005) define entrainment as ‘a phenomenon in which two or more independent but interacting rhythmic processes synchronise with each other’. This can be applied in the embodied music cognition paradigm, and is summarized as ‘the natural tendency to be attracted to, move along with, or imitate a given pattern in music’ (Leman, 2008). A typical example is tapping to the beat, which is also a form of coordinated rhythmic movement. The coordination of rhythmic movement with rhythmic sensory stimuli is defined as sensorimotor synchronisation (SMS) (Repp, 2006a).

In our studies, we differentiate two forms of entrainment: intentional or instructed entrainment and spontaneous/unintentional/uninstructed entrainment, similar to Repp and Su (2013). Intentional entrainment requires a conscious effort or request to synchronise, such as dancing to music or tapping in synchrony with a metronome during a SMS experiment. Unintentional entrainment is entrainment which occurs naturally - or more specifically, without request during an experiment. For example, when a human subject is asked to
Figure 1.3: Set the five metronomes to the same frequency and place them on the foam core base. They will be out of phase. Rest the base on the two pop cans and the now weakly-coupled metronomes will become synchronised within a minute. Place the base back on the table and the metronomes will fall out of sync again. Image and example from Pantaleone (2002)

walk to the beat in a synchronous way, he or she will try to be in sync with the beat and therefore he or she will adapt, and thus entrain, to the music in order to become and remain in synchrony. Spontaneous entrainment, on the other hand, might only occur in some circumstances. A typical example of spontaneous interpersonal entrainment happens when a walking pattern gets synchronised unintentionally and often without knowing (see figure 1.4), which may occur when walk and talk together (Zivotofsky and Hausdorff, 2007).

In unintentional or spontaneous entrainment, studies often focus on sensorimotor synchronisation activities linked with walking or running. For example, unintentional tempo and phase-locking occurs in pairs of people walking side-by-side on different treadmills such as in Nessler and Gilliland (2009), or for interlimb coordination when only visual coupling is available (Schmidt et al., 1990). However, between a person and a machine, a stable system in both phase and frequency of tapping was more easily formed when the
virtual partner’s adaptation rate was slow (Fairhurst et al., 2013a,b). Miyake (2009a) also showed that two walking systems (one human and the other a robot) can adapt mutually, and that stable synchronisation can be achieved automatically on the basis of metronome cues.

Modelling approaches (Haken et al., 1985a; Kelso et al., 1990) show that spontaneous entrainment emerges from dynamical laws that operate via mediators on interactions, whereby entrainment is facilitated if certain conditions are fulfilled (Schmidt and Richardson, 2008). These conditions can also occur with visual and even tactile stimuli, but it was shown that auditory stimuli is a common and universal phenomenon, whereas entrainment with purely visual rhythms is a rare sensation (Repp and Penel, 2004).

Synchronisation and entrainment also often occurs in groups. Wiltermuth and Heath (2009) provide some examples where synchronicity could lead to a higher motivation and 'contribute toward the collective good'. Armies (see figure 1.5), churches, organizations, and communities often engage in activities, for example, marching, singing, and dancing, lead group members to act in synchrony with each other. This movement synchrony could lead to attributions of rapport and entitativity (Lakens and Stel, 2011). The concept of how a steady beat or stimulus can facilitate inter-person synchrony is further explored by Ikeda et al. (2017).

In this dissertation we are interested in the requirements, effects and applicability of the spontaneous entrainment that can occur when walking or running on music. When something happens 'automatic', it might have a different effect than when something happens
on demand. Therefore, this is an intriguing phenomenon that needs more study. In rehabilitation research, for example, a given task to synchronise to music or metronomes can lead to an increased cognitive load, which might actually hinder further development of the rehabilitation. A similar situation occurs when using music in sport: the task to synchronise might change the participant’s cadence or gait pattern resulting in unnatural gait or unwanted behaviour. However, the same tasks done with spontaneous entrainment may suddenly become more efficient and beneficial.

1.1.3 Sensory and auditory-motor synchronisation

Having defined the notion of synchronisation and entrainment, we can now be more specific about the type of synchronisation that we focus upon in this thesis. The coordination of rhythmic bodily movement with rhythmic sensory stimuli is defined as sensorimotor synchronisation (SMS) (Repp, 2006a). When coupled with external acoustic stimuli, such as acoustic metronomes and music, it is called auditory-motor synchronisation (Miura et al., 2011; Large, 2000; Repp, 2005). Dancing to music, for example, involves the synchronisation of whole-body movements to the beat (Miura et al., 2011). Another example is our natural tendency to tap our fingers, hands, or feet along to a beat when listening to music (Large, 2000; Repp, 2005; Wilson and Davey, 2002). Research demonstrates that even young infants spontaneously sway and wiggle around with rhythmic acoustic stimuli (Zentner and Eerola, 2010), which supports the notion that humans have a predisposition for auditory-motor synchronisation (Zentner and Eerola, 2010; Patel, 2010; Zatorre et al., 2007).

SMS requires us to ‘feel’ the musical beat, and requires musical beat perception and synchronisation (BPS). BPS is a fundamental aspect of music cognition that develops without special training, in young children (Van Noorden, 2014; Bregman et al., 2013) and is
observed in every human culture (e.g. dance) (Brown and Jordania, 2013; Nettl, 2000). Bregman et al. (2013) summarized: ‘Synchronisation to a musical beat in humans has several important features that distinguish it from other examples of rhythmic entrainment in nature (Patel et al., 2009). First, BPS involves the extraction of a beat from a complex acoustic stimulus (i.e., music vs. from simple pulse trains). Second, BPS involves substantial flexibility in movement tempo: humans can easily synchronise their movements to a musical beat across a fairly wide range of tempi. Third, BPS is cross-modal, with rhythmic sound driving movement that is not necessarily aimed at sound production. In addition, an important feature of BPS is phase matching: people spontaneously align their taps and other rhythmic movements with a beat. That is, people tap slightly before the beat or on the beat. Stated more formally, the average temporal asynchrony between taps and beats is slightly negative or around zero (Patel et al., 2005; Rankin et al., 2009). This indicates accurate temporal prediction of beats.’

Repp recently did four extensive literature reviews (Repp, 2005, 2006a,b; Repp and Su, 2013), which summarize the field of SMS. The reviews focused on traditional tapping studies, music performance, rate limits of SMS, other forms of moving in synchrony with external rhythms (including dance and non-human animals’ synchronisation abilities), interpersonal synchronisation (including musical ensemble performance), and the neuroscience of SMS. However, the majority of the research done is into the classical tapping/SMS field using metronomes which lack information between beats.

1.1.4 Human-computer interaction and interactivity

Our study of interaction focusses on human interaction with music, or better, with devices that play back music. Therefore, it is useful to introduce here the concept of human-computer interaction and its particular focus on interactive technologies and devices. Overall, Human-Computer Interaction (HCI) is the study of the way people use, and interact with, computer technology (Dix, 2009). The focus is often mainly on the interfaces that stand between people (users) and computers. However, HCI can be broadly applied. While it may be applied to computers with screens and keyboards, it may also be applied to mobile phones, sensors and all kinds of computational units. Currently, the field is rapidly expanding towards devices that allow human interaction. In our thesis, HCI applies to the interfaces that ensure the alignment between human movement and music playback.

Important for our study is that new sensing capabilities became available that enabled explicit movement-based HCI. Gaming devices such as the Nintento Wii (Schlömer, Poppinga, Henze, and Boll, 2008) use accelerometers and gyroscopes to identify gestures and react accordingly; the Microsoft Kinect for XBox uses body postures to interact or play (Zhang, 2012). These devices have been quickly adapted to other purposes, including ways
in which these devices became available for experimental and artistic research.

Note that HCI is not limited to explicit interaction with a device. Recently, a more implicit HCI emerged, not requiring direct interaction from the user with the application. Typical examples can be found in domotica systems: embedded sensors and actuators such as automatic lighting or thermostats. Due to the use of sensors, applications become context-aware (they know what is happening around them, i.e., a user enters the room). Schmidt (2000) notes how ‘the availability of processing power and advanced sensing technology enabled a shift in HCI from explicit interaction, such as direct manipulation GUI’s, towards a more implicit interaction based on situational context’. In other words, computational systems are getting smarter and more context-aware, and can thus provide better, smarter or personalized content for the user. This context-awareness of technology is an important aspect of our work, especially when the goal is to engage people in spontaneous entrainment situations controlled by music.

1.1.5 Music information retrieval

Context aware HCI and personalization are two very interesting aspects which can be applied in music playback applications. Intuitively, we know that the use of context can automate or enhance music experience in some ways. But in order to automate music selection or playback, the system needs to have more information about the music. The computational method that extracts high level information, or simply ‘interpret music’, is called music information retrieval (MIR): the interdisciplinary science of retrieving information from music.

MIR attempts to reduce the semantic gap between low-level audio data (typically how the computer sees music) and high-level musical information (how humans experience and feel the music, i.e., tempo, key, timbre, chords, genre, song structure, arousal, etc.) (Downie, 2003). MIR systems and algorithms attempt to extract this information, enabling systems to perform extensive sorting, searching, music recommendation, metadata generation, transcription, and even aiding/generating real-time performances.

MIR and HCI combined allow for intelligent context-aware personalized music recommendation systems: automatically providing optimal music - whatever or however that is defined - for the current situation (Schedl, Flexer, and Urbano, 2013).

One specific example of MIR is beat and tempo extraction from the music. For most humans, beat tracking or tapping is a relatively simple and intuitive task (Repp and Su, 2013; Drake, Penel, and Bigand, 2000), the ability to engage in dancing being an obvious example. For computers however determining the main beat is less trivial. The task becomes even more difficult when the music is less common, for example when musical tempo is ambiguous (Moelants and McKinney, 2004) or has a very low tempo (Bååth and Madison,
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In 2006, several tempo and beat extraction algorithms were compared at the Music Information Retrieval Evaluation eXchange (MIREX) (McKinney et al., 2007). The goal of this particular study was to evaluate algorithms 'in terms of their accuracy in predicting beat locations annotated by a group of listeners’ (Brossier, Brossier). Results showed that beat tracking was still a technical challenge, but most algorithms successfully tracked 4/4 music with reasonable tempo's around 120 BPM (general pop music).

To sum up, the basis of our study is grounded in some of the major research fields that cover the disciplines of musicology and engineering: embodied music cognition (EMC), human computer interaction (HCI) and music information retrieval (MIR). Given these research fields as background, our goal is to develop an interactive music device (D-Jogger) that exploits entrainment and auditory-motor synchronisation. At the same time, D-Jogger will be a tool that offers measurement and further exploration of the principles behind entrainment and auditory-motor synchronisation.

1.2 Methodology

In this section, we introduce D-Jogger; a multimodal music player which allows us to walk on contextualised music. We describe the general methodology used in the experiments with D-Jogger, including qualitative and quantitative data capture and analysis. The last section introduces the concept of the relative phase, a quantitative measure for synchronicity or timing offsets between two repetitive processes. Using circular statistics we can test our assumptions and hypothesis on such data.

1.2.1 Initial research questions

The idea to develop a 'smart' music player arose in 2005. It was based on the personal experience of walking to music with a slightly faster tempi. That tempo unintentionally entrained us to walk in synchrony with the the music’s tempo. This situation was similar to a DJ who tries to match the tempo of two songs. We quickly noticed that the situation of synchronised walking gave a sort of extra motivation during the walk, once synchronisation was obtained. For example, our arm swings were more expressive. However, there was also a downside because at this tempo, the walking did not feel as the most optimal or natural walking tempo as we were forced to take smaller but more steps. But why did we synchronise to the music? Couldn’t, or shouldn’t the music synchronise to us?

At the time, there were no smartphones or easily accessible mobile platforms that could handle this type of interaction. Gesture control was uncommon, but Nintendo did just release their Wii device and wireless controller - and that device contained an easily hackable accelerometer. If it could detect arm swings to play a game, we reasoned that it should also
be able to detect steps - and thus the idea of an adaptive music player became a topic of interest.

A first working prototype was made which showed interesting results: the prototype worked to some degree given the technical challenges, but it was unclear who did eventually synchronise to who when a stable interaction was formed. Did the music system synchronise to the human or did the human synchronise to the music system? Much more questions arose and it was quickly understood that we were confronted with a complex dynamical interaction. A refinement of the theoretical background was needed and possible applications other than a pure form of subjective enjoyment had to be explored in order to better understand how this interaction worked. These questions became central topics in this dissertation.

In line with the concept of embodied music cognition, we believed that empirical research had to be conducted in natural or ecological settings. However, this confronted us with a huge technical challenge. If mobile apps and smartphones are not available (because they need to be developed), how do we manage to do experiments with walking and running outside a lab on a large scale? The solution was more difficult then anticipated, so the first iterations were semi-ecological using a treadmill in combination with unobtrusive sensors. This treadmill, however, was put at different public events that gave access to the ecological setting.

A functional prototype of our interactive device on the treadmill solved some technical issues, but other questions arose:

- Can the observed adaptation also be found in larger populations? Why are humans attracted to music?

- Who synchronises to who in this human-machine interaction? Can we manipulate the algorithms in such a way that this relationship becomes one-sided or mutual?

- What about the user’s experience? Does synchronised music interaction alters subjective enjoyment of music interaction?

- What about people who cannot synchronise or lack a rhythmical feel? Why is that, or how can we explain it?

Our two main fields of interest became the sports science (the most obvious question being 'does synchronised music have an effect on performance?') and health sciences ('can synchronous music have a positive effect on rehabilitation?'). Later in this chapter, we introduce these research fields and subsequent research questions.
1.2.2 D-Jogger

To answer the questions above, we developed D-Jogger. It is an interactive, contextualized music player (Moens, Van Noorden, and Leman, 2010) that extracts the tempo of a person’s walking and provides music synchronised to the gait (see figure 1.6). D-Jogger makes it possible to manipulate the timing differences between salient moments of the rhythms (beats and footfalls) through the manipulation of the musical tempo and phase, which affect the condition in which entrainment functions. By doing these manipulations, D-Jogger can facilitate the emergence of spontaneous entrainment.

D-Jogger is built from several individual components, including sensor input, step detection, annotated playlists, audio tempo manipulation and algorithms to align music to the gait (see figure 1.6). These components are discussed in detail in the following chapter. At this moment it suffices to say that the core concept behind D-Jogger is a music alignment strategy. Such a strategy can be a very simple matching strategy (e.g. match musical tempo to gait), but it can also be a strategy to control complex dynamical systems (adaptive oscillators). Our music alignment strategies were developed over several years in an iterative development scheme: new versions and ideas are build upon results from previous experiments that revealed new insights about the entrainment mechanisms. Chapter three describes this development and experiments in detail.

Specific versions of D-Jogger were build to answer more practical research questions
above. User preference, enjoyment and spontaneous tempo adjustments were compared in
an experiment aptly called Stratego (chapter 4.2). A clinical prototype was made to test the
influence of alignment strategies for Parkinson Patients (chapter 4.3). Several experiments
were performed to influence performance of runners (chapters 4.4 to 4.6).

1.2.3 Experimental and empirical approach

In our research approach, each new iteration of D-Jogger was followed by an experiment.
Key features in such an experiment are control over variables, measurement, data analy-
sis and interpretation, as we want our results to be based on verifiable observations rather
than theory or pure logic. Given our primary focus on ecological experimental settings, we
wanted to perform our experiments in a natural environment. But this ecological require-
ment had a significant effect on the methodological design of our experiments.

Each experiment was an investigation in which we wanted to test a hypothesis (McLeod,
2012). In an experiment, an independent variable (the cause, in our case timing between
footfalls and beats) is manipulated and the dependent variable (the effect, e.g. running ve-
locity, enjoyment or spontaneous entrainment) is measured; any extraneous variables should
then be controlled (location, music, etc.).

Experiment types

In our study we used three types of experiments (McLeod, 2012). Each of them has advan-
tages and disadvantages:

• Controlled Experiments are conducted in a well-controlled environment, often a lab-
  oratory, and therefore accurate measurements are possible. The researcher decides
  where the experiment will take place, at what time, with which participants, in what
  circumstances and using a standardized procedure. A general disadvantage is that
  such an approach does not necessarily reflect natural behaviour and thus makes it
difficult to generalise findings.

  In chapter 4.4 we present a controlled study to measure energy consumption during
  running on music. The equipment for the energy measurements was not portable, thus
  the experiment was performed on a treadmill which implied a fixed running velocity
  (see figure 1.7) - which might not be the optimal or natural one. Also, running with
  the equipment and an oxygen mask does not reflect real-life running; thus results
  could not be generalised to general running without further testing.

• Field Experiments are done in more general or everyday environments of the partici-
  pants. For runners, this might be a sport centre or running track instead of a labora-
  tory. The experimenter still manipulates the independent variable, but it is difficult to
control all external extraneous variables (e.g. indoor temperature and humidity on a running track changes every day). This approach results in a higher ecological validity because of its natural settings. However, the design also makes it somewhat more difficult to interpret results from repeated measurement experiments and reduces the repeatability of the experiment. Rigorous data analysis and higher number of participants can negate these effects.

In chapter 4.2, we present a study comparing several music alignment strategies. Participants ran on an indoor track (see figure 1.8) with lightweight equipment in order to replicate ecological settings that reflect real-life running. Many basic variables could be measured; but much less than controlled experiments (no energy consumption etc.).

- **Natural Experiments** are conducted in the everyday life of the participants, but here
the experimenter has even less to no control over the independent variables. This results in the highest ecological validity, but such experiments are very difficult to setup.

*Figure 1.9: Example of the equipment for a natural experiment: a set of equipment for each participant to take home and train over the course of several months.*

For example, in the European project BeatHealth we participated in such a natural experiment by letting people run in their own spare time in their own preferred locations with a portable device based on D-Jogger. The goal of the experiment was to optimize gait cadence (slowing down or speeding up the cadence). Results of this experiment will reflect actual and practical behaviour, but the effort required was much greater than the pilot studies (controlled & field experiments). Figure 1.9 illustrates the equipment needed for this test.

**Ethics**

The university follows strict rules about the ethics of our experiments. All ethical standards and guidelines have been followed in our experiments. During each experiment, the rights of the participants were protected by a system of ethical protection.

*For small experiments,* the subjects signed a consent declaration which states that they are freely participating in the experiment, have been informed in advance about the task, the procedure and the technology used. They were given the opportunity to ask questions and agreed that anonymous recordings of their actions would be made for scientific purposes, only. In accordance with the general standards set by our university and our faculty, security was guaranteed (the indoor task carries no risk), and privacy is respected. According to
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Belgian law for experiments aimed at research performed to further the development of biological or medical knowledge (cf. 7 May 2004 Law concerning experiments on the human person (Ch.II, Art.2, Par.11)), means our research is exempt from the requirement to obtain ethical approval because the study only involves behavioural knowledge.

For larger experiments, involving patients and moderate or high intensity exercises, we got the approval from the Ethics Committee of either the Faculty of Arts and Philosophy, the Faculty of Sport Science or the University Hospital.

For physically intensive experiments, participants were fully informed of any risk associated with the experiments and each underwent a medical check-up ahead of any testing, and before giving their written consent for participation. The study was approved by the ethics committee at the University of Ghent Hospital. Procedures were followed in accordance with the Helsinki Declaration recommendations.

Stimuli

Selecting the optimal stimuli to use in controlled, field our natural experiments is a challenging task due to humans individual preference towards music. The major questions that turned up in our research were: do we personalise music selection, thus different songs for all participants? And: do we use the same songs in all different conditions or trials? If all songs are different, how can we compare the results over trials or participants? We want to compare the results of different trials with each other, which presents us with several options.

The naive music selection would be to use the same song for all conditions and participants. This makes it easy to compare between conditions and participants, thus the song can be factored out (it is a controlled variable). However, this is not a good approach for most experiments because it induces boredom and most likely frustration when hearing the same song multiple times. This can result in different reactions in the experimental conditions, invalidating the experiment and not mimicking ecological conditions.

Therefore, it is recommended to use different songs in the experiments. However, people react differently to songs, based on their own preference, familiarity with songs, etc. In order to compare conditions with different songs, the selected songs should have the same individual familiarity factor, motivational quality, preference, etc. For example, an ideal experiment would have an individual database for each participant only containing well known and preferred songs which are perceived as motivational by the participant.

In addition to the personal aspects, music selection criteria also include tempo aspects: we want to use music which is musically unambiguous (Moelants and McKinney, 2004) and has a tempo which is close to the running or walking frequency of the participant. Music can also influence participants into walking faster or slower, e.g. in Leman et al.
(2013) it is shown that musical features such as the meter can have an activating or relaxing effect. Buhmann et al. (2016a) found that some music has an activating influence, increasing velocity and motivation, while other music has a relaxing influence, decreasing velocity and motivation.

It is clear that controlling the music in terms of experimental validity is a difficult challenge and a balance has to be found between practicality, ecological validity and methodological validity. The approach differs for each experiment and is documented in the methodology section for each experiment.

Qualitative data: surveys

Another essential tool for our experiments were questionnaires and surveys. The questions asked can be open ended, allowing flexibility in the respondent’s answers, or they can be more tightly structured, requiring short answers or a choice of answers from given alternatives (McLeod, 2012). In this section, we list our most used questionnaires:

- Personal details: demographic information regarding the participants age, gender, education, music interest, etc.
- The Brunel Music Rating Inventory 2 (BMRI2) test (Karageorghis et al., 1999, 2006). In order to have an idea about the motivational qualities of the music, participants were asked to rate all items of the music database by answering six questions about the motivational aspects of each song. Each item referred to an action, a time, a context, and a target (e.g., 'The rhythm of this song would motivate me during a running exercise') (Ajzen and Fishbein, 1977). Participants responded on a 7-point Likert scale anchored by 1 (strongly disagree) and 7 (strongly agree) (see figure 1.10).
- PACES: Physical Activity Enjoyment Scale (Kendzierski and DeCarlo, 1991a; Mullen et al., 2011; Motl et al., 2001). This is a questionnaire of 17 questions to be answered on a 7-point Likert scale. Respondents were asked to rate 'how you feel at the moment about the physical activity you have been doing'. Higher PACES scores reflected greater levels of enjoyment.
- Rating of Perceived Exertion (RPE) Scale, often referred as the BORG scale (Borg, 1998), ranges from 6 (no exertion at all) to 20 (maximal exertion), indicating how heavy the effort has been during the exercise.
- Open-ended interviews after experiments to obtain feedback and opinions for further evaluation. A typical open ended question could be: 'did you notice anything about the music?'. This could learn us if the participant noticed the tempo adaptation of the music.
Quantitative data: data capture

During experiments we gather a lot of data. This includes motion data, sensor signals, music playback information, synchronisation data, gait data, and audio recordings. Most of this data was captured and logged using our own software (D-Jogger). However, in several experiments multiple data sources were captured for two reasons: they provide unique data for our experiment (e.g. the GaitRite system (Bilney et al., 2003) provides detailed clinical gait data, Mobility Lab (Mancini et al., 2012) provides step length estimations, XSens provides high quality kinematic data (Roetenberg et al., 2009), ...) or they can be used to compare with the D-Jogger system for validation.

Multiple systems tend to complicate ecological experiments. They often include additional wired hardware or sensors to be worn by the participant (using body cabling), and the software is generally ‘closed’. Furthermore, this proprietary software often not build for real-time data retrieval. This makes it impossible to use them as a primary data source for real-time feedback. Multiple systems also need to be synchronised which is generally tricky as in different data formats a particular event (‘start’) has to be found. Finally, these professional systems are often having a significant price tag which is a considerable risk factor when used outside laboratory environments - it would not be the first sensor to fall off during an experiment or gets soaked in sweat. For these reasons, we mainly use the external measurement systems for pilot or validation studies.
1.2.4 Quantifying synchronisation: data and interpretation

Our data capture systems provide timing information in real-time about footfalls (the moment a step is detected) and beats (the moment when a musical beat is detected). These data can be easily converted to standard tempo units such as steps per minute (SPM) or beats per minute (BPM); either by counting the steps or beats in one minute or based on the inter-beat intervals (IBI) or inter-step intervals (ISI).

Synchronisation is the timing relationship between beats and steps. This section introduces the quantifiable concept of synchronisation as relative phase as well as the statistical tests that can be applied on distributions to differentiate between chance and actual synchronisation or entrainment.

Relative phase: tempo-independent timings

Timing differences can be easily expressed as absolute milliseconds. For example, when the beat occurs at \( t = 1000 \text{ ms} \) and the step at \( t = 1100 \text{ ms} \), the difference is \( \Delta t = 100\text{ ms} \). This 100ms however does not include any tempo information. When a slow song is playing at 60 BPM, meaning the interbeat interval is 1 second, this 100ms equals 10% of the interval. When a fast song is playing at 200 BPM; the interbeat interval matches 300ms and this 100ms timing difference becomes 33% of the interbeat interval. The lack of a ’tempo reference frame’ makes absolute timing data difficult to use and interpret, and therefore generally a tempo-independent measurement is preferred: the relative phase. The relative phase \( \phi \) denotes the timing difference between footfall and musical beat in relation to the tempo or period, specifically as a value bounded by the preceding and succeeding musical beats.

This difference can be expressed in degrees (from \(-180^\circ\) to \(+180^\circ\), or from \(0^\circ\) to \(360^\circ\)). \( \phi = 0^\circ \) means that the footfall occurred simultaneously with the beat. This is called in-phase or in-sync. \( \phi = -or + 180^\circ \) means that the footfall occurred exactly between two consecutive beats; in anti-phase or offbeat. Figure 1.11 shows part of a gait cycle that starts near anti-phase and moves towards the in-phase. Left and right footsteps are regarded as equal in terms of relative phase: the phase is calculated for each individual step and is, thus, not based on one complete walking cycle (a stride, one left step and one right step). \( \phi \) is calculated in real-time using the timing information of two beats and one footfall. Taking \( f \) as the moment in time of the footfall for which we want to calculate \( \phi \); \( b_1 \) as the time of the onset of the preceding musical beat and \( b_2 \) as the time of the succeeding musical beat, then the relative phase is calculated as follows for each footfall: \( \phi = 360 \ast (f - b_1)/(b_2 - b_1) \). This results in relative phases between \(0^\circ\) and \(360^\circ\). For visualisation \( \phi \) is represented on the \(-180^\circ\) to \(+180^\circ\) scale (i.e. figure 1.11), so that a negative phase angle indicates that the footfall preceded the musical beat (the footfall is followed by a beat, see Figure 1.11 for an
Figure 1.11: Relative phase of walking on music. Figure A shows the visual gait cycle for left and right steps, figure B shows the waveform of the music with annotated beats. Finally, figure C shows the resulting relative phase which expresses the timing difference between footfalls (A) and musical beat (B).

example) and vice versa: a positive phase angle indicates the footfall succeeded the musical beat (the footfall occurred right after the beat). When the phase equals $-180^\circ$ or $+180^\circ$, the footfall occurred exactly between the beats.

Figure 1.12 shows an example of a series of relative phases while walking on music as a discrete time series. A part where the participant synchronised is clearly visible, using purely visual inspection.

The figure also illustrates the circular or warping aspect of the relative phase: when the relative phase becomes 'larger' than 180 degrees, the step will occur closer to the next beat than the current beat. In this case, a beat is skipped and the relative phase warps to $-180^\circ$.

**Circular statistics**

Given that phase angles represent directional or circular data, we cannot use standard tests to compare the resulting phase distributions. Consider the following example: the arithmetic mean angle of $-179^\circ$ and $+179^\circ$ is $0^\circ$, in the framework of our data, the circular mean is $180^\circ$ (either seen as $-180^\circ$ or $+180^\circ$). Conventional statistics and tests hence do not work well on this circular data; therefore synchronisation data were analysed with circular statistics (Fisher, 1995) using the Circular statistics Toolbox for Matlab (Berens, 2009).

A set of relative phases (for a trial or experiment) results in a distribution of relative phase angles. Figure 1.13 shows such a distribution of 8 phases. Such a distribution can
Figure 1.12: Time series of relative phase values. Relative phase (in degrees) is plotted on the vertical axis with zero indicating perfect alignment of footfalls and musical beats. Negative values indicate footfalls that occur before the nearest beat, positive values indicate footfalls that occur after the nearest beat, and values of +/-180 indicate footfalls that are midway between beats (i.e., in antiphase with the beat). The black box shows synchronisation: a series of steps relative phase close to 0. Example from Bregman et al. (2013).

Figure 1.13: Illustration of 8 relative phases represented on a circle. The numbers around the circle are degrees (0 represents perfect alignment of footfall and musical beat; negative numbers indicate footfalls preceding the nearest musical beat; positive numbers indicate footfalls following the nearest beat). Note that two vectors have a very similar value (near 3 degrees) and hence overlap in this image. The dark red arrow is the mean or resultant vector of these eight phase vectors, and the black arrow is a projection of the mean phase vector onto the zero phase axis. Example from Bregman et al. (2013)
be described using the following parameters: the mean angle $\phi$ and its confidence interval representing the mean direction, the resultant vector length $R$ and the circular variance $CV$, angular deviation $s$ (dispersion around the mean), circular skewness $b$ (asymmetry) and the circular kurtosis $k$ (‘peakiness’).

For each distribution, the mean resultant vector $R$ can be calculated (Berens, 2009; Fisher, 1995). On figure 1.13, the dark red arrow is the resultant vector. The vector $R$ has a phase angle $\phi$ and a length $|R|$. The angle $\phi$ corresponds to the mean relative phase or music synchronisation accuracy and can be interpreted if the distribution of relative phase angles is neither random nor uniform; this is tested with the Rayleigh or Omnibus test. The length $|R|$ is a measure for synchronicity, which is the mean phase coherence of an angular distribution. $|R|$ values can range from 0 to 1, $|R|$ reaches the value 1 if, and only if, the condition of strict phase locking is adhered to, i.e. all steps were taken in perfect synchrony, whereas $|R| = 0$ for a uniform distribution of phases, i.e. random phase angles. The circular variance $CV$ represents the amount of variation in the relative phase angles and is the inverse of the resultant vector length. $|R|$ is calculated by $|R| = \frac{1}{N} \sum_{j=0}^{N-1} e^{i\phi_j} = 1 - CV$, where $N$ is the number of samples and $\phi$ is the relative phase angle for step $j$.

How to determine if there was synchronisation?

An angular histogram is used to visually assess the distribution: is it unimodal (single cluster) or multimodal (two or more clusters)? To assess whether participants performed above chance, i.e. whether the our music manipulation has an influence on the participants behaviour, the Rayleigh test (Wilkie, 1983) can be used (for unimodal distributions) while the Omnibus or Hodges-Ajne test (Ajne, 1968) can be used for multimodal distributions. Intuitively, the test examines whether the relative phases tend to cluster around a mean phase, as would be expected if footfalls and beats were in synchrony and phase-matched.

The null hypotheses for these tests is circular uniformity (random distribution). The alternative hypothesis is a unimodal or multimodal distribution of circular data points centred on a given phase angle. The Rayleigh test additionally tests the significance of the directional mean value, which is not applicable to multimodal distributions (tested with the Omnibus test).

Finally, we can analyse the synchronisation stability of individual participants by calculating the resultant vector length and performing a Rayleigh test per participant. When the Rayleigh test reports a significant result ($p < 0.001$), the participant synchronised. We then report the percentage of synchronised participants per experiment.

Optionally, a dataset can be split up in several individual parts so the Rayleigh test can determine temporary synchronisation during a temporal window (e.g. 30 seconds), a specific event (a song) or a trial.
1.3 Problem Specification

Up until quite recently, beat-synchronised walking or running was only possible when the person was explicitly instructed to adapt to the fixed beat played by the music player. However, it was shown in Mendonça et al. (2014a) that without instruction to synchronise, spontaneous gait synchronisation did not always occur. Even when explicitly instructed, not all participants managed to synchronise to the beat (Styns et al., 2007).

The D-Jogger system provides synchronised music and is applicable in several different domains. In this section, we briefly describe the state of the art of the sports, rehabilitation and entrainment research fields and show how synchronised music can help further this research.

1.3.1 Walking on music

Styns et al. (2007) present an experiment where participants were explicitly instructed to synchronise their footsteps to metronomes or music while walking on an outdoor athletic track. The stimuli tempo varied between 50 and 190 beats per minute. It was found that people can synchronise walking movements with music over a broad spectrum of tempi, but this synchronisation is optimal in a narrow range around 120 BPM. Results thus indicated that not all participants were able to synchronise. Participants also walked on half or double tempo when stimuli tempi was low or high. Results also indicated a correlation between stimuli tempo and walking velocity, but only up to 2 Hz. From 2 Hz, walking speed did not increase with walking tempo but resulted in smaller steps. The 2 Hz also seems to be the preferred locomotor frequency for humans (MacDougall and Moore, 2005b; Van Noorden and Moelants, 1999) due to a possible resonance curve. Interestingly, most popular music is also centred around the 2 Hz or 120 BPM tempo.

In Van Noorden and Franek (2012), researchers found little spontaneous entrainment of long-distance walking to music, even when the musical beat was close to participants’ preferred stride frequency. However, faster music nevertheless accelerated walking. Another study (Sejadić, Jeffery, Kroonenberg, and Chau, 2012) which included walking on random varied music showed ‘intermittent synchronisation’ leading to prolonged periods of stable gait; most likely due to with the musical beat.

Not only the tempo of the music, but also some sonic features seem to influence performance of walking. In Leman et al. (2013), music stimuli was played at a fixed 130 BPM tempo with instructed synchronisation. Results show participants changed step length and speed when music of different character was played. In particular; four musical features had the greatest effect on velocity, most notably the meter: ternary tempo music seemed to have an relaxing effect while binary music had a speedup effect. Similar results were found in a more recent study (Buhmann et al., 2016a), attempting the same experiment but
with uninstructed synchronisation and music played back at the spontaneous gait cadence to encourage entrainment.

To summarize, synchronous music seems to positively influence performance of walking in certain conditions; but these do not occur often when not explicitly instructed to synchronise.

1.3.2 Synchronised music in sports

On February 18th, 1998, Haile Gebrselassie ran a new 2000m world record on the beats of the ‘Scatman’ song. Gebrselassie indicated that he had coupled his running cadence with the beat of the pop song Scatman by the late Scatman John, which was played throughout his race at Birmingham’s National Indoor Arena, UK. New research questions arose about the possible influence of music on sports performance. In a literature review in 2012, Karageorghis reported (Karageorghis and Priest, 2012b) that 24 of the 32 studies found ergogenic effects of asynchronous and synchronous music on different sports performances (rowing, running, cycling,...). A clear distinction was made between asynchronous and synchronous music; however most of the synchronous experiments were instructed synchronisation.

Terry and Karageorghis (2006) summarised the influence of synchronous music in their paper as follows: 'Synchronous music has been reliably shown to produce an ergogenic effect. Therefore, if athletes or exercisers work in time to music, they will likely work harder for longer. Responses to asynchronous, or background, music are less predictable and beneficial effects are less reliable, although considerable potential remains if certain principles are followed.'

However, not all results have been so straightforward as indicated by the 2012 review. Specifically towards ergogenic effects no definite answers are found. For example, in the study about synchronous music with cycling (Lim, Karageorghis, Romer, and Bishop, 2014), it was found that synchronising movement to a rhythmic stimulus did not reduce metabolic cost. However, using synchronous music while walking resulted in an 15% increase in endurance as well as a strong positive influence on post exercise mood scales (Karageorghis et al., 2009). These two results are seemingly contradictory, but it is clear that several important criteria need to be considered in the approach of musical influence on sports performance: the type of music, personal preference, exercise intensity, synchronous or asynchronous music, foreground or background, etc.

There is however consensus about the motivational aspects of music during sports; which might also explain why a great deal of runners exercises while listening to music. Van Dyck, Moens, Buhmann, Demey, Coorevits, Dalla Bella, and Leman (2015a) highlights some effects: 'Music listening during sport activities is believed to capture attention (Priest and Karageorghis, 2008), distract from fatigue and discomfort (Yamashita et al.,
2006), prompt and alter mood states (Edworthy and Waring, 2006; Shaulov and Lufi, 2009),

enhance work output (Rendi et al., 2008; Priest et al., 2004), increase arousal (Lim et al.,

2014), relieve stress (Särkämö et al., 2008), stimulate rhythmic movement (Atkinson et al.,

2004), and evoke a sense of power and produce power-related cognition and behaviour (Hsu et al.,

2015).

The effects have not gone unnoticed for competitive running, in some cases leading to

a ban on music playing equipment for contests or even disqualifications (Van Dyck and

Leman, 2016). It is however still unclear whether regulations are required given some con-

tradictory results; but it is reasonable to avoid these devices and headphones in case of

championships for professional athletes.

The D-Jogger system can be used as a training tool or to facilitate experiments to com-

pare synchronous and asynchronous music conditions; which is nothing new in itself. How-

ever, synchronous music can be provided without instruction or conscious synchronisation

effort (which might alter preferred frequency) from the participant. Adaptive music can

also change with changing pace of the participant, while the synchronised requirement for

a condition is still retained. The D-Jogger system will allow experiments to thoroughly

compare asynchronous and synchronous music in ecological settings.

1.3.3 Rhythmic Auditory Stimuli in rehabilitation

Rhythmic Auditory Stimuli (RAS) has been used extensively in rehabilitation contexts, with

generally positive and often remarkable results. A specific population of interest is Parkin-

son Patients. Parkinson Disease (PD) is a progressive degenerative disease (it generally

only gets worse) of central nervous system (see 1.14). Symptoms include movement disor-

ders (Knutsson, 1972), tremors at rest (Geraghty et al., 1985) and low dopamine production

(Remy et al., 2005). Furthermore, there is currently no cure, but only ‘management’ of the
disease using medication.

Specific changes in Parkinson’s Disease (PD) gait include a shuffling gait pattern, de-

creased walking speed, shortened stride length, insufficient heel strike and toe clearance,

inadequate flexion about the hip, ankle, and knee and asymmetric stride times for both

lower limbs (McIntosh et al., 1997). Often, during walking, patients can start to shuffle (decreasing step length) which can induce freezing (the inability to move further) or falling of the patient.

Parkinson’s Disease (PD) is related to dopamine, a hormone that functions as a neuro-
transmitter in our brain and nerve cells. Dopamine plays an important role in our reward-
motivation behaviour; it could be characterised as essential in our ‘happy hormone’. PD

patients however suffer from low dopamine production, potentially leading to depression

but generally suppressing a form of being pleased or rewarded with exercise or therapy. In
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These aspects combined make the disease especially difficult to treat using classic movement therapy as the patient does not feel comfortable to walk (given the gait deficiencies and potential falling risks involved) nor are they easy to motivate to walk. However, frequent movement and walking has been shown to slow down the progression of the disease. Only for this last aspect, music is an interesting motivator; because for the healthy population music has been show to have a motivational effect during walking and thus it might motivate PD patients to walk more. However, repetitive stimuli (i.e. music and metronomes) also have a positive effect on the gait.

McIntosh et al. (1997) pioneered in early PD rehabilitation research using auditory metronome stimuli. In his studies metronomes were played at different tempi (baseline cadence and baseline plus ten percent), resulting in significantly positive effects on the gait. These included increased velocity, cadence and stride length. Freezers generally seem to have better results with faster rhythmical auditory stimuli (RAS) tempi. These results are in line with previous and prior research using RAS, e.g. as indicated in several literature reviews (Thaut and Abiru, 2010; Lim et al., 2005). It was also noted that comparative studies have shown RAS to be more effective than other sensory cues and other techniques in physical rehabilitation.

Not only metronomes, but also music can also used as RAS. However, as noted earlier, music selection can be difficult, especially for a specific target population. Li et al. (2010) developed a music information retrieval search engine, to select optimal music to use in PD rehabilitation. In 2012, experiments started with interactive stimuli or stimuli using adaptive tempo (Hove et al., 2012), a system similar to the proposed D-Jogger system. Hove found that interactive rhythmic auditory stimulation reinstates natural 1/f timing in
gait of Parkinson’s patients which might in turn reduce the risk of falling.

Most RAS studies incorporating music in rehabilitation training programs (de Bruin et al., 2010; Hove et al., 2012; Willems et al., 2006; Chaiwanichsiri, 2011) use a baseline measure to determine the preferred locomotor frequency. Next, specific stimuli are selected or generated by manually adjusting the tempo of a click track or a song; to match this frequency. This is a cumbersome and time consuming procedure, which D-Jogger can facilitate in real-time.

Recently, Alter et al. (2015) showed a semi-automated approach of providing RAS to cardiac rehabilitation patients. They used ‘tempo-pace synchronised preference-based audio-playlists, which was feasibly implemented into a structured exercise program. It was show to be efficacious in improving adherence to physical activity beyond the evidence-based non-music usual standard of care.’

We apply the D-Jogger system in two studies on Parkinson’s disease. The reason why D-Jogger may be of interest to Parkinson’s disease is that D-Jogger can automatically adjust the phase of the music so that the music coincides with the steps (i.e. forced synchronisation). When synchronisation happens ‘automatic’, it might have a different effect than when synchronisation is the result of an intentional act. In the intentional case, the task to synchronise to music or metronomes can lead to an increased cognitive load, which might actually obstruct further development of the rehabilitation. The goal of using D-Jogger in the context of Parkinson’s disease was to figure out whether a smart walkman would be useful.

1.3.4 Music alignment strategies

Synchronised music has many application domains. We briefly discussed the entrainment research, sports (walking and running) and rehabilitation. However, it is clear that there are many ways to synchronise music to gait; and some domains may require other strategies for optimal results. The concept of how music is synchronised to gait in real-time, is introduced as a music alignment strategy. A strategy describes in detail how beat timings are influenced in order to obtain the goal.

A very simple and intuitive example is matching the tempi of the music to the gait tempo. This is a tempo-based approach. More complex would be a phase-aware strategy: adjusting each beat interval so the next beat coincides with a step (a resulting relative phase of 0°), which would require a loosely matched tempo and phase adjustment approach. Figure 1.15 illustrates the concept. Another idea could be based on empirical results from rehabilitation: a strategy adjusting the tempo 10% upwards, or linearly increasing difference from 0% to 10%.

Other than tempo offsets, a set of rules is included in a strategy to define what happens
in special cases, for example a sudden increase or decrease in walking tempo. A strategy also sets limits for adjustments as to avoid noticeable degradation in audio quality. These limits are generally imposed by the quality of audio components in the D-Jogger software.

In this dissertation, we develop and explore several strategies to answer our research questions. What strategies induce spontaneous entrainment and stable synchronisation behaviour between a person and an adaptive music player? In addition, can these strategies be optimised and used in practice?

### 1.3.5 The BeatHealth Project

The BeatHealth project was a ECT project co-funded by the European Union under the Seventh Framework Programme (FP7). The project was one of the winners of the ICT 2013 Call 10 in the Challenge 5.1 (Personalised health, active ageing, and independent living) and it spanned three years, until 2016. The BeatHealth project capitalizes on the expertise and technology of five laboratories: Motor control and neuroscience at Montpellier 1 University (France), Musicology at Ghent University (Belgium), Bioengineering at the National University of Ireland, Maynooth (Ireland), e-Health at the Tecnalia foundation (Spain), and Movement disorders at the Montpellier Academic Hospital (France).

The purpose of BeatHealth was to exploit the link between rhythm and movement for boosting motor performance, enhancing health and wellness using a personalised approach (Timoney et al., 2015a, 15 b,c). BeatHealth thereby draws upon the achievements of the work on D-Jogger. The project focussed on two groups: healthy runners (called BeatRun) and Parkinson Disease Patients (called BeatPark). The D-Jogger technology was used as a basis for providing synchronous music feedback in running and rehabilitation experiments. However, new music alignment strategies were developed and tested in fundamental research using laboratory experiments.

The resulting architecture and know-how was then ported to a mobile platform (An-
droid device and custom sensors) to allow large scale natural experiments with both target populations. The novelty about the BeatHealth project, compared to our state of the art of our D-Jogger system before BeatHealth started, has been the ecological aspect of the experiments and the focus on practical results. The BeatHealth project offered a welcome addition to our research results with D-Jogger and some of the results from this project have been beneficial for our thesis.

1.3.6 Delta of the PhD

The idea of synchronised music is not new. Before the start of our research, several conceptually similar devices or components were already documented. A first generation of gait-enabled personalised sound devices were presented in 2006 to 2008 (Biehl et al., 2006; Elliott and Tomlinson, 2006; Masahiro and Takaesu, 2008). These devices aimed at providing music around the same tempo as the gait frequency in order to increase motivation. These systems analysed the mean walking frequency and provided music selection and limited adaptation based on that. Audio quality was greatly improved in later research adding high quality digital sound processing (DSP) algorithms so that audio tempo could be changed without modifying the pitch. In Hockman (2009), a phase vocoder was used instead of typical resampling which resulted in better audio quality. This, in turn, allowed more tempo adaptations without the user noticing. This lead to the development of the first prototype (Moens et al., 2010), which focussed on the aspect of synchronisation rather than performance or enjoyment.

Recently, several applications on mobile platforms have emerged that support synchronised music. Most of these works target mobile music consumption, typically matching music with the current pace of the user while doing sports, incorporating idea’s put forth in these publications.

In sports, research with synchronised music (Simpson and Karageorghis, 2006; Bacon et al., 2012; Terry and Karageorghis, 2012) was mostly done with manually selected or
adapted music (with tempo’s determined in pretests rather than real-time) pioneered but not automated. In rehabilitation, the concept of synchronised music was already used in state of the art non-intrusive research such as rehabilitation training programs incorporating using music in rhythmical auditory stimuli (RAS) (de Bruin et al., 2010; Hove et al., 2012; Willems et al., 2006; Chaiwanichsiri, 2011) but again, automation and music selection were mostly done manually and in laboratory settings.

In contrast with this state of the art, the D-Jogger system presented in this dissertation is rather unique because of its focus on supporting music alignment strategies, entrainment research and its use in different application domains with an ecological setting in mind. In our research activities, we could improve the state of the art in mobile contextualised music players; and this has resulted in several advances in technology:

- Synchronised music in all use cases; even when participants are unable to synchronise
- Performance of manipulative music alignment strategies: subtle influence on cadence by manipulating the music
- Obtain perfect synchronisation in uninstructed synchronisation scenario’s for entrainment research
- A device capable to study entrainment and spontaneous synchronisation
- Synchronised music for Parkinson patients, resulting in a portable clinically validated device from the BeatHealth consortium
- The focus on ecological, uninstructed and self-selected or self paced music interaction (synchronisation) is in essence why this research is novel.

1.4 Outline

This dissertation comprises three main topics:

1. Chapter two: The development and validation of our soft- and hardware platform D-Jogger

2. Chapter three: The iterative development of alignment strategies. Each strategy is build on knowledge gained in with previous experiments; and thus describes the iterative design process.

3. Chapter four and five: the use of these developments in real world applications. Several of the problems and research questions described earlier in this chapter are summarised here.
Chapter four forms the main body of this dissertation. We look explore the use of alignment strategies in both the health and sports domains. We can sum up our research questions:

- Does synchronous music influence runners’ motivation, cadence or velocity?
- Is synchronous music useful for Parkinson’s disease rehabilitation?
- Does running on synchronous music reduce energy consumption?
- Can we manipulate runners’ cadence by changing only the music tempo?
- Can we manipulate runners’ cadence by shifting the beat forward or backward?

Chapter six concludes this thesis.
2.1 Introduction

D-Jogger is a multimodal software and hardware framework that allows the manipulation of the tempo and phase of a song played based on sensory input. The technology was developed first and foremost for walking and running applications, adapting music to the gait of the user. The goal of D-Jogger is to be able to perform research into the phenomenon and applications of entrainment; therefore flexibility and modularity of the system were key aspects in its design.

This chapter introduces the resulting D-Jogger system. We introduce the hardware platforms and software architecture, including the main components. These include the music playlist, music time stretcher, step detection, music alignments and beat trackers (see fig. 1.6). Music alignment strategies - algorithms describing how music is synchronised to the gait - are only described briefly as this is the main topic of interest of chapter three. Finally, this chapter concludes with a series of experiments to validate the D-Jogger.

2.2 Supported hardware

Our primary hardware environment is a simple computer running a Windows operating system. This was our primary choice due to available software and frameworks, resulting in faster development of the software.
2.2.1 Fixed setup: 2008 - 2012

The initial versions of D-Jogger have been developed on a Macbook Pro 2009 with limited processing power and memory (Core2 duo, 4GB ram), whilst Bootcamp 2.0 was used to run Windows XP in dual boot mode with OSX 10.6. During experiments, a dedicated Dell Latitude Laptop with an Intel i7 processor and 8GB RAM was used. Connections with the sensors were typically managed by the internal bluetooth radio, USB connection or an external WiFi router. An external WiFi router was used for the sensor connections (see later), specifically a TPLink AC750 router with extended omnidirectional antennas providing an 8 dBi gain over the default setup.

This hardware was typically used for fixed setups when the walking or running was limited to a restricted space (eg laboratory, treadmill, small sports hall). Often, wireless headphones were used in this setup so the participant could run ‘completely wireless’ in order to achieve our focus on ecological settings. The wireless headphones were ‘analog’ 800 MHz transmitters, no digital recoding took place resulting in no measurable delay. Detailed examples of this setup can be found in chapter 3 (strategy 1 to 4). Figure 2.1 shows such a setup.

The downside of this setup was that in some situations; the wireless signal (for both sensors and audio) was jittery and resulted in deteriorated results. This was due to larger distances between sender-receivers and occlusions of the direct line of sight. Therefore the practical range where the participant was allowed to walk-run was limited to 20m around...
the equipment. When the phase of the gait was not used for real-time auditory feedback, the range was increased to 50 metres.

Some unforeseen situations occurred with this setup due to WiFi interference. A simple but striking example was a laboratory, where sensor signal drop-outs and jitter occurred only around midday - between 11:30AM and 1:00PM. Such signal losses were fatal to real-time auditory feedback because the signal to synchronise audio to is delayed or lost, resulting in unusable trials and lost data. The cause turned out to be the location of the laboratory: beneath the kitchen, where the microwave oven was used by students at noon. Microwaves use the same frequency (2.4 GHz) as the WiFi band and are known to cause issues with wireless equipment.

### 2.2.2 Transportable setup: 2013 - 2016

However, with our focus on natural or ecological settings, a more mobile solution was needed to allow phase-accurate audio manipulation with a less restricted range (i.e. outdoors, indoor or outdoor athletic tracks, etc). A new iteration was needed to move out of the laboratory or small spaces and into an ecologically valid setting. Therefore, the new hardware had to be portable (to be transported in a backpack) and it had to be rugged (i.e. could withstand a fall, high temperatures due to restricted airflow, high humidity, waterproof, salt-proof (sweat), etc.). No typical laptop was sufficient for our goals. After a search, the Panasonic Tablet (FZ-G1) was chosen as our future computing platform. There are two versions: the 7" tablet (smallest) and 10" tablet. The 7" version was more challenging to develop due to weaker hardware and passive heating system - resulting in a throttling CPU when stressed, reducing performance and inducing stutter in the audio. Initial development thus occurred on the larger tablet, but this was not as lightweight or mobile as anticipated. The 10" tablet was therefore jokingly called ‘transportable’ as it was not truly mobile but it could be transported during the experiment in the backpack. Later, software updates and optimisation resulted in optimal performance on the 7" tablet. See figure 2.2 for a visual comparison.

Additionally, a new portable WiFi router (TP-Link M5360) was used as a hotspot to connect sensors to the tablets. The router allows a lot of configuration parameters such as the channel and WiFi standard (IEEE 802.11 b/g/n). In addition, the fixed short distance between router (on the back) and the sensors (at the ankles) resulted in more stable connections and less to none jitter from the sensors. Finally, additional sensors such as sonar devices could be added using the USB connection.

Figure 2.3 shows a typical mobile setup. These setups are used in experiments shown in chapter 4 and later.
Figure 2.2: Hardware comparison of the rugged tablets

Figure 2.3: Mobile setup of D-Jogger with a 7" tablet
2.2.3 Mobile application setup: BeatHealth 2016

The D-Jogger concept inspired the European project BeatHealth (see chapter 5.3 - 5.5). This project aimed to provide auditory stimuli in ecological settings for extended tests and trials for both healthy runners and Parkinson Patients. This implied that the setup should not include laboratory setups or involve difficult to operate equipment.

As such, a true mobile solution was created by the university of Maynooth (Timoney et al., 2015b). Several Android applications were developed, which included the D-Jogger core concepts, new alignment strategies and support for a cloud architecture. In addition, they developed a set of sensors (gyroscopes and accelerometers) which can be connected to an Android phone using bluetooth. The system also supports a commercial heartrate sensor for additional data during experiments. Figure 2.4 shows the components.

![Components for the mobile app setup of BeatHealth (based on D-Jogger)](#)

The main advantage of this setup is scalability: during the project, a total of 64 sets were created and handed out to participants in Belgium and France. The disadvantage was increased complexity in terms of development and end-user support. Because this is a completely distinct setup, it is only provided here to show the evolution of D-Jogger. As D-Jogger formed a basis for the project, both conceptually and architecturally, the setup and results are briefly described in chapter 5.

2.3 Components

Our primary software environment included Windows 7 as operating system, Max/MSP 5.0.7 as graphical prototyping environment and Java as programming language using Eclipse as IDE. Max/MSP is a graphical programming environment for music, audio and multimedia developed and maintained by San Francisco-based software company Cycling’74. It has been used since 1990 by composers, performers, software designers, researchers and artists...
interested in creating interactive software.

The Max/MSP program itself is highly modular, with most routines existing in the form of shared libraries. An API allows third-party development of new routines (called external objects). As a result, Max/MSP has a large userbase of programmers not affiliated with Cycling’74 who enhance the software with commercial and non-commercial extensions to the program.

One of the most notorious aspects of Max/MSP is its extensible design and graphical interface (which in a novel way represents the program structure and the GUI as presented to the user simultaneously). Its distinguished and sometimes demanding interface also provides a great example of how to work with a network of interdependencies and can certainly be a source of inspiration for interactive models of this kind.

Additional externals were programmed in Java SDK 1.6 update 45.

2.3.1 General components and architecture

Figure 2.5 gives a general overview of the required components and system architecture. We can identify hardware (such as typical input-output, i.e. sensors and speakers) and several different software components such as the music synchronisation framework, music alignment strategies and the music database. Each of these components is comprised of several different smaller interconnected objects, which are discussed in detail in this chapter.

2.3.2 Movement sensors and step detection

Different step detection approaches D-Jogger was programmed to support a wide range of sensors, capable of measuring the users’ movements. We are interested in two aspects of the gait: the stride or step frequency, i.e. the amount of steps per minute (SPM) and the actual impact timing of a footfall (phase). We tried various sensors to gather this information; but the challenge was to be able to determine these in real-time, using limited computing power and filtering; and preferably using easily-accessible and user-friendly sensor devices.

Our first attempts used an accelerometer attached to the ankle to detect footfall impacts. Figure 2.6 A and C show such a sensor signal of the highest-impact axis. Based on earlier research, eg (Ying et al., 2007; Jang et al., 2007; Marschollek et al., 2008), it was clear that using accelerometers, a ‘one solution fits all’ would not be easy to develop. Indeed, after evaluating, combining and creating several different approaches and algorithms (onset detection (Bello et al., 2005), Fourier analysis (Antonsson and Mann, 1985), autocorrelation (Bollens et al., 2010), ...) we could not find a solution that worked sufficiently well in real-time over a wide population and in different conditions. We noted two main problems: different running styles (eg low impact foot rolls vs heel impact style, see figure 2.6 A and C) and different environments or surfaces (eg impact on grass looks different and less
pronounced than impacts on asphalt or concrete pavements). For our envisioned goals of large-scale ecological experiments, this approach was not developed further.

Our second attempt used in-sole pressure sensors (Morris and Paradiso, 2002; Bamberg et al., 2008), because it seemed the most trivial place to detect footfalls. However; while they detected steps and cadence were indeed correct; the sensors (Round Force-Sensitive Resistor (FSR) and Arduino ADC’s) have proven cumbersome to use in practice due to the wired setup and the fragility of the equipment. This made the ecological goal unobtainable. We did use the setup for validation purposes as they provided a reliable ‘ground truth’.

Our last approach uses a gyroscope to detect the lower leg rotation. A gyroscope measures the angular rotation, meaning the change in pitch, jaw and roll of the sensor. When attached to the lower leg, the signal shows the rotation of the leg which is directly linked to the footfall (using the assumption that one moves forward). Figure 2.6 shows two participants’ synchronous recordings of accelerometer and gyroscope signals. While accelerometer signals differ significantly between participants, the gyroscope signals are remarkably similar. This is the main reason to further focus our efforts on gyroscope sensors; while using FSR pressure sensors as ground truth during development.

The efforts of developing, testing and comparing step detection algorithms and sensors are documented in (Moens, 2010), a COST/SID project performed at McGill University (IDMIL, McGill University, Montreal, Canada).
Figure 2.6: Example of gait signals: highest-impact acceleration (fig. A & C) and angular rotation (fig. B & D). Figure A represents a clear acceleration impact or footfalls (* marks). Another participants’ signal was less clear (figure C). Differences between these participants are due to different walking styles (e.g. heel-runner or toe-runner). Figure B and D show the same time periods of the participants, but we see that the signal is remarkably similar in pattern - even with completely different running styles. This lead us to focus primary on gyroscope signals for step detection as this approach had the best potential for a ‘one solution fits all’ algorithm.
Gyroscope sensors and step detection  A basic algorithm for detecting gait events was described in (Fraccaro et al., 2014). The core idea of the algorithm is based on the trivial observation that the angle of the lower leg changes from negative to positive when swinging the leg forward. If this were not the case, the person would not move forward.

Given our ecological goals and non-intrusive nor wired setup; we opted to use common commercial devices. The Wii-Motion plus was the first easily hackable gyroscope; but using the bluetooth protocol several timing issues arose leading to jitter and clustering. Fourth generation iPods and later also featured a gyroscope, which could stream its data to the computer using a Wifi connection. When properly configured, no jitter or other issues arose with these devices. Figure 2.7 shows both devices and the rotational axis.

The gyroscope sensor signal contains clearly identifiable points that indicate gait events such as mid-swing, initial contact, full contact and terminal contact points (see figure 2.8). An adjustment to the algorithm was made to predict the initial contact moment, making the Matlab algorithm usable in real-time. Steps are detected using a zero-crossing detection; cadence is determined using an average of the peak-to-peak time or inter-step-interval.

The forward-backward swing (with resulting angular rotation) occurs for all steps, independent of the terrain or gait pattern and even subject; so it should provide a stable signal for real-time analysis. The following picture shows the gyro signal of the same participants and moment of the examples above. While the acceleration signals differed significantly (see figure 2.6 A and C); the gyro signals recorded at the same time are remarkably similar (see figure 2.6 B and D).

The algorithm has proven to work on different people and terrains; plus also on treadmills. Furthermore, no complicated processing or calculations are needed so it is very good to be implemented on CPU-constrained systems such as mobile devices and the 7” tablet.
One downside of this approach was that the algorithm was very sensitive to the orientation of the sensor; and different pre-processing was needed on left and right signal streams of sensors were placed outward at the lower ankles. The algorithm has also been tested on a small Parkinson Disease population with promising results.

**Smoothing algorithm: trade-off between accuracy and responsiveness of a real-time systems** It takes at least two steps to estimate the current cadence or SPM, by converting the inter-step interval (in milliseconds) to the ‘per minute’ measurement \( SPM = \frac{60000}{\text{step interval}} \). However, human gait shows considerable variability (Winter, 1984) at the kinetic level, while there is also intra-person variation. It is, in essence, an unstable process. We can obtain more stable measurements by applying a smoothing algorithm (moving average of the last \( x \) steps); this however reduces responsiveness of the music to sudden gait changes while stabilising smaller gait changes (eg due to an obstacle). We found empirically that by averaging the cadence measurement over the last 5 steps (for walking) or 9 steps (for running) results in a responsive system that is more stable than when no smoothing is applied.

**Step detection remarks** During our research, we have been criticised often by the use of ‘gaming’ devices instead of using professional inertial measurement systems. However,
these devices provide several advantages, especially with our ecological focus in mind. They are easily replaceable (if one breaks during running, we can just buy a new one behind the corner). They are cheap (in contrast to e.g. a professional X-Sens system). They run on simple batteries or are easily rechargeable, and lastly, they are not 'scary looking': people are familiar with these devices and generally do not distrust them. We noticed for example with the FSR sensors, participants were not keen on moving in crowded places because of external wires and visible control boards.

The step detection components were developed as 'black box' externals for Max/MSP, providing only the gait frequency and phase information using the sensor data as input.

### 2.3.3 Velocity sensors

With step detection, we can measure cadence and phase. However, this does not indicate any performance-related information: how fast are we running (velocity, km/h)? While there is a connection between steps per minute and velocity, without accurate step length, one cannot be calculated from the other.

Therefore we needed additional sensors for measuring velocity. Outdoor velocity measurements are typically done with a GPS and relatively accurate when averaged over a larger distance. Together with cadence measurements the data can be used to calculate step length and other standardized gait characteristics.

However, our experiments are often conducted on indoor athletic tracks making GPS measurements unusable. Measuring velocity in indoor locations has proven to be very difficult (eg. (Dedes and Dempster, 2005)); however a solution was found for our indoor running track.

A sonar sensor was added to our transportable setup (see section 2.2.2 and figure 2.3). The sonar sensor measures the distance between the sensor and any object in front of it. Figure 2.9 illustrates the principle. The range is limited to 8 metres to sustain a reasonable samplerate (22 Hz) based on the speed of sound. Objects were placed around the athletic at fixed distances, eg 10 metres. When a runner passes by such an object ('pole'), the sonar detected the distance decreased from 5 metres to 1 metre. This resulted in a peak in the sensor signal stream. By measuring the time between peaks, we can calculate the time needed for each 10 metres interval, and hence the velocity (km/h) and step length for that interval.

The sonar continuously measured absolute distance and provided an analogue signal representing the measured distance. During most of the experiment, the sonar did not receive an echo and returned its maximum distance. Only when the sonar (thus, the participant) passed by a marker rod, which were placed 1 m from the participants’ running track, there was an easily detectable drop in the sonar signal. By placing the marker rods at a
regular interval and measuring the time it takes to cover this interval, absolute speed was
determined. During the experiment, a MaxBotix LV-MaxSonar-EZ sonar (MB1010) was
connected to a Teensy 3.1 micro-controller which, in turn, was connected via USB to the
tablet. The analogue signal was sampled at 60Hz and digitized using the Teensy. To prevent
interference it extended from the participants body. The rods had a height of 1,90 m and a
diameter of 0,02 m and were placed 10 m apart.

This sensor setup was used in some experiments described in chapter 4 and 5.

2.3.4 Annotated music library

Playlist component. A general component in all D-Jogger iterations is the music library, a
Max/MSP external Java object developed between 2009 and 2013. The library is a database
with a simplified interface which could be queried in real-time to find the most fitting song
for specific usecases (e.g. close to a specific tempo, least recently played, based on inter-beat
parameters such as variability, highest-rated song, BMRI-Rating, etc). All needed metadata
was saved as a serialized java object in a text file. The component was developed as a black
box external for Max/MSP, and shown in figure 2.10. The database contained a selection of
annotated and preprocessed audiofiles; created on-experiment basis.

Database construction. The database had to be populated with a sufficiently large set of
music. We based an initial selection on a set of intuitive requirements:

• Familiarity: should be familiar to most participants (also based on age). We often
  referred to pop-radio hit-lists for initial inspiration.
• Tempo: in the ranges of 70-130 for walking experiments and 130-200 BPM for run-
  ning experiments.
• Language: should be in the local or English language for recognisability.

Once a general music database is constructed, MIR tools were used to annotate the
songs in terms of tempo using Mixmeister BPM analyser, BeatRoot (Dixon, 2007) (see
Figure 2.10: Playlist demo
figure 2.11) and Essentia Beat Tracker (Bogdanov et al., 2013). Only when multiple trackers agreed, the song was allowed in the database. Using Audacity software (SourceForge, 2016a), intros without clear beats were cut from the stimuli. The ReplayGain algorithm implemented in MP3Gain (SourceForge, 2016b) was used to normalize perceived loudness and minimize possible imbalances in sound pressure level.

**Personalised music selection** For most experiments, the general database was queried to generate a personalised music selection for experiments. Criteria for playlist generation mostly included music tempo and personal music surveys (e.g. a motivational questionnaire such as the BMRI2 test (Karageorghis et al., 1999, 2006)). Figure 1.10 shows a developed program to automate the process of personalisation based on motivation.

**2.3.5 Real-time beat tracking in Max/MSP**

To calculate the relative phase, we not only need the step information but also the beat information. While there are several real-time beat tracking solutions, we have the knowledge of the beat positions after pre-processing a song for our database. Therefore, a new external was created that signals the exact moment when the user hears a beat: the beat-tracker.

An algorithm was created to compare the current playhead position (which is updated every 256 samples or 6 milliseconds at 44.4 kHz) to the list of beat positions provided by the music library. However, the reported playhead position does not correspond exactly to the position the user is currently hearing: there is a latency chain in the computers hard- and software. We manually correct this by applying an offset which is determined
Figure 2.12: Typical computer hardware latency. This differs based on hardware and driver settings; and therefore requires calibration on each new platform.

by the computer, soundcard settings, software version and playback speed. Factors include the Digital-To-Analogue conversion (DAC, typically .5ms), Driver scheduler (DSP settings, ASIO driver, low latency, 1 to 6 ms), operating system (± 1ms), BUS (PCI, USB) buffer (± 1ms) and some unaccounted delays. The typical latency chain is visualised in figure 2.12.

The algorithm finds the time to the closest beat given current position, the list of beat timestamps and the current playback tempo. The searching algorithm is a naive implementation: the list is sorted once ($O(n \times \log(n))$); followed by a check every millisecond (in a different thread) by iterating over the array of beats and comparing it the actual position. If the list is sorted, the time to the playhead position decreases and then increases - at which point we return the first beat after the playhead position (thus the rest of the array is neglected). This results in an algorithmic complexity of $O(\log(n))$; with $n$ being the total number of beats.

We note that this algorithm can be further optimised because time generally evolves linear - but, these would prevent jumping to different positions in the song later on and was therefore not implemented.

2.3.6 Music alignments

This component defines the machine’s response to the sensor input and the music phase (beats), according to the defined alignment strategies. It is a set of rules or algorithms that define how the music will be aligned to the gait signal.

The strategies are based on different elements that are, in a specific way, combined with each other. The basic concepts are period and phase measured at footfall and musical beat. Several alignment situations are shown in Figure 2.13.

Ultimately, the goal is to achieve a period and in-phase alignment. To that aim, the
period of the music can be manipulated to match the person’s gait period. The period of the music can be set at the start of a song, using the observed gait period of a person. The phase of the music can be neglected, or manipulated into a certain position with the gait phase. Finally, the start of a song can be delayed so that it begins automatically in phase synchrony with the user. However, once started, the relative phase can be fixed. Based on these elements, period and phase manipulations can be used in conjunction with each other. It is the development of these experiments that has led to these four alignment strategies based on discrete timing information.

A fifth approach aligns individual adaptive oscillators to both the music and the gait. These two oscillators can be coupled using specific formula’s. This approach therefore uses continuous data.

More details about the specifics of the strategies can be found in the subsequent chapter.

2.3.7 Music processing

This component alters the timing of the music without disturbing the pitch. We use a phase vocoder, which is a real-time music time stretcher (a combination of frequency and time-domain methods) based on the technology Elastique Pitch of ZPlane (Zplane.de, 2017). It alters the tempo of a song without changing the pitch of the music, making small tempi changes barely audible to the users.

The ‘Elastique Efficient’ implementation gives good time-stretching quality at a moderate workload; so it is also applicable on tablet implementations. The algorithm is targeted at complex polyphonic signals like complete music. Efficient uses specifically developed technologies to efficiently detect tonal and transient components with high accuracy in the frequency and time domain at a low latency.

We empirically determined that tempo changes of up to +10% and -10% were accept-
able in terms of sound quality, resulting in a 20% tempo adjustment range. The tempo adjustment is controlled by the alignment strategies.

Image 2.14 shows how the components’ options. It allows adjustment of the playback speed, pitch and loop points for any given song or input. It features a phase output which we use to determine the exact playhead position (as it is difficult to calculate with variable tempos). Using this playhead position and metadata of the playing song, real-time accurate beat-tracking was implemented by comparing the current position with all known beats. This way, we know when a beat is played back. Together with step detection, we can calculate in real time the relative phase: the time-difference between a beat and a step.

2.3.8 Calibration

Delays are inherent to digital computing systems. In practice for D-Jogger, this means that it takes some time between detecting a step and providing the correct feedback (i.e. a beat or metronome).

This delay or offset is taken into account as a fixed integer (generally ± 100 ms); which is the latency chain (see above), step detection latency, and some Max/MSP processing time combined. This integer is deemed ‘the magic number’ or optimal delay compensation: it
Figure 2.15: Calibration procedure of D-Jogger. By recording audio and footsteps of an uncalibrated or default setup, the required delay compensation can be calculated.

is required for everything to work correctly and can be determined by experimentation. It is dependant on the software and hardware configuration, so a calibration was performed prior to each experiment.

The calibration procedure is the method to find this magic number. The procedure is relatively straightforward: we configure D-Jogger to provide a metronome track for which the ticks synchronise to each footfall (phase synchronisation). Next, a simple test is done to record (externally) the output of the phase synchronised metronome and the auditory sound of the steps (using a two channel microphone, eg Zoom H1) at different cadences. The resulting audio file can then be used to calculate the time between step onset and beat onset. This is the new delay compensation. Afterwards, it is verified that footfall & metro tick indeed occur simultaneous. Figure 2.15 shows such an audio recording (merged to mono).

2.4 Validation

Validation of the prototype documents a series of smaller tests and experiments to verify if the system functions correctly and as expected. The core components (sensors, step detection and music manipulation) are tested individually, in addition to general prototype or device tests.
2.4.1 Sensor (iPod) validation

Initially, we used more professional data capture systems; such as the Xsens (9DOF sensors, wired to central hub on body, wireless transfer to PC), mobility lab, and the Delsys wireless accelerometer/gyroscope system. However, they all are expensive, cumbersome to setup (especially in ecological settings - one of our main aims), and required larger hardware to be attached to the participant. After looking for alternatives, we decided to go for iPods because they have some great usability features; long battery life, integrated sensors, cheap, easy to replace (it would not be the first one to fall/break/get moist due to sweat), and comfortably attachable using specifically designed third party pockets for runners (albeit for use on their upper arm).

To validate the use of the iPods, Maynooth University compared them in a synchronous data capture experiment to the Delsys IMU (inertial measurement unit) capture system. The Delsys system also featured extra analog input signals to measure additional synchronisation or audio data. The sensor comparison was made in the context of the BeatHealth project. Figure 2.16 shows a comparison between Delsys systems (IM2&4) and the iPod systems for both gyroscope and accelerometer. The key results were:

- Signals from all sensors agree well.
- Delay between sensors’ arrival time on the receiving windows platform is minor (10ms max) in optimal conditions (the Wi-Fi hotspot uses a free Wi-Fi channel, no 2.4 ghz interference nearby and distance smaller than 10m).
- Up to 60m no samples were lost but jitter increased (inter-sample time variation increased, deviating from the reference clock signal, resulting in the use of a receiving buffer).
- A direct line of sight between sender (iPod)/receiver (hotspot) at distances greater than 10m is required to minimize jitter.

Given these results, we deemed that the embedded gyroscopes in the iPod were sufficient for use in real-time step detection algorithms.

2.4.2 Step Detection Validation

This section describes some tests of the algorithm described in section 2.3.2 for step detection, for both a healthy and Parkinson Disease population.

Comparison with Mobility Lab For verifying the step detection algorithm, the University of Montpellier (Euromov) compared the D-Jogger step detection subsystem with Mobility Lab; a specialized software and hardware suite for wireless gait analysis focused on
rehabilitation. The system is verified and frequently used in scientific experiments (Mancini et al., 2011).

Figure 2.17 shows a phase histogram of the timings differences of detected steps in both applications. Steps are detected at approximately the same time, with a mean phase angle difference of $10^\circ$ (about 14 ms at 120 steps per minute). The limited results were considered good and stable for use in real-time auditory feedback systems.

**In-depth data look for healthy participants** After calibration we performed additional step detection verifications. The complete D-Jogger system was configured so that an auditory stimulus would be produced when a step was detected. This auditory pulse was logged with a Delsys capture system, to indicate when the system detects a step. Additionally, for comparing with a ground truth, a pressure sensor (FSR) was embedded in the shoe-sole of the participant, which was logged simultaneously with the auditory feedback. Both signals can be compared to verify the step detection.

*Protocol:* The participant was equipped with the 7" tablet, iPod sensors and the pressure sensor in the shoe sole. Synchronous data logging was done on the Delsys capture system of the pressure sensor (ground truth) and the auditory feedback. The participant completed a 3-minute walk at 4 km/h, a 3-minute walk at 5 km/h, a 3-minute run at 8 km/h, and a 2-minute run at 10 km/h on the treadmill.

*Data analysis:* Ground truth was extracted from the FSR’s to calculate the amount of steps. This was compared with the amount of detected steps (audio pulses detected). As a
The second test, the delay between both pulses (heel strike and audio feedback) was calculated to see if the system reacts in real time to footsteps.

**Example:** Figure 2.18 shows the data from both pressure sensors (FSRs) and the detected steps by D-Jogger. A sharp increase of the FSR signal indicates a heel strike and is easily detectable in offline-analysis using peak-picking algorithms. The third signal shown is the audio feedback as received by the Delsys system. The plot is an excerpt from the test during the walking part. It is clear that with each step, a sound pulse was produced which mostly coincided with the actual footfall.

**Results** In total, 1367 steps were detected from the pressure sensor. 1365 steps were correctly detected by the system, thus less than 0.15% of the total steps were not detected. The average offset between step and auditory feedback was 13ms (+- 21ms); very similar to the results compared to Mobility Lab. Given that the iPod sensors function at 100Hz (1 sample each 10ms), this was deemed a very good result. As a comparison, the natural sound of the heel strike reaches one’s ear around 5 ms (1.8m at 343m/s). For the participant, the auditory feedback seemed simultaneous with the actual footfall. Both results indicate that the real-time footstep detection works very well, especially for real-time feedback.
In-depth data look for Parkinson Disease Patients (PD)  

PD patients have a different gait signal compared to healthy participants (see chapter 4.3 for more details about gait deficiencies of PD patients). Therefore, it was necessary to validate the step detection algorithms with PD patients. The setup and data analysis was similar to the test with healthy participants, but the protocol was focussed on walking.

**Protocol:** The two patients each completed three walks: one at low speed, one at medium speed, and one at high speed. The patients were asked to walk around four cones in the lab while taking wide turns so not to change the velocity/gait frequency during turns.

**Example:** figure 2.19 shows the data from both pressure sensors (FSRs). A sharp increase indicates a heel strike and is easily detectable in the signal. The third signal shown is the audio feedback as received by the Delsys system. The plot is an excerpt from the test of the first patient. It is clear that with each step, a sound pulse was produced which coincided within a certain margin with the actual footfall.

**Results** The data shows that 683 of the 689 steps were correctly detected. We can estimate that for PD patients, there are generally about 1% incorrectly detected steps. The delay between footfall and the auditory feedback (after calibration) was about 50 to 60 ms. The offsets are consistent per patient and independent of step frequency (fast/medium/slow walks), but differ up to 20 ms for both participants. While the total delay is still acceptable for walking, it should be taken into account with the calibration to correct the delay per patient. Generally, we were very pleased that the step detection algorithm performed quite well with PD patients without further adaptation.
2.4.3 Music Manipulation: phase matching and manipulation

D-Jogger uses music alignment algorithms to match the beat of the music to external stimuli such as footsteps. The mechanism to manipulate the timing of a beat to an external moment is phase matching. This section documents several tests performed to verify the correct functioning of this mechanism.

**Protocol:** Typically songs recorded without a clicktrack have high inter-beat variability, while electronic songs have low variability. For this test we selected four songs with high variability because they tend to be the most difficult to perform phase matching. The songs were processed using BeatRoot to determine tempo and beats. D-Jogger was used to play them back again matched to a predetermined time series with varying sources. The first test was making all inter-beat intervals constant, i.e. flattening the groove of a song. The second test was matching the intervals to a 1/f series which is similar to a natural gait pattern. Finally, the resulting audio was recorded and beat-tracked. By comparing the processed time series and the 'theoretical' requested or desired time series, we were able to assess the valid functioning of the time stretcher and algorithms. In this case, beat tracking results were manually verified using BeatRoot’s graphical interface.

**Example:** Figure 2.20 shows the result of a song with a mean BPM of 150 or a mean inter-beat interval (IBI) of 397 ms. The original song IBI series is shown in black, fluctuating around the mean, showing a variable beat pattern. The blue line shows the de-grooved song (identical to the plot above). The light-gray line indicates the requested IBI interval for a
Figure 2.20: Validation tests to verify the time stretching and phase matching subsystem.

certain beat of the 1/f series. The red line is the IBI of the resulting recording. One can see that the requested and perceived IBI time series correlate very closely, albeit with some beats delay. This example makes it clear that the processing is not instant but requires some time to change the original interbeat interval to the desired one.

Figure 2.21 shows a more in-depth view of this delay. We can see that the delay is constant; and the resulting IBI series correlates very well with the requested IBI. It is however not an exact match; there are still deviations in the range of 10ms, which is to be expected with a real-time system.

Results: this test tried to re-apply a new time series to the interbeat variations so they all match the intended IBI as close as possible. In this case, we apply a fixed and 1/f time series.

The fixed tempo test shows a 75% reduction in variability (see table 2.1), but also shows that the procedure is not completely accurate and a certain amount of variability remains. For some songs this is limited and thus usable; but other songs (eg Ike Turner - River Deep) the remaining difference from the mean is too high. For this reason, an exclusion criteria was added to our music pre-selection limiting initial variation.
For interpreting the results of the 1/f test (see table 2.2), we look at the cross correlation between the requested and the detected IBI time series. Cross-correlation measures the similarity between x and shifted (lagged) copies of y as a function of the lag. A significant correlation at a small lag indicates that the application of the new time series is indeed correct. The lag indicates the response time of two beats for the system. It is clear that the song played back with a new time series as interbeat intervals indeed matches the intended target, and thus is played back correctly, however with a lag of two beats.

<table>
<thead>
<tr>
<th>Song</th>
<th>BPM</th>
<th>Original IBI variation</th>
<th>Processed IBI variation</th>
<th>Reduction of variation</th>
</tr>
</thead>
<tbody>
<tr>
<td>Steppenwolf - Born to Be Wild</td>
<td>146</td>
<td>75.8 ms</td>
<td>20.07 ms</td>
<td>74%</td>
</tr>
<tr>
<td>Guns N’ Roses - It’s So Easy</td>
<td>150</td>
<td>113.57 ms</td>
<td>5.85 ms</td>
<td>96%</td>
</tr>
<tr>
<td>The Beach Boys - Surfin’ USA</td>
<td>157</td>
<td>39.67 ms</td>
<td>14.48 ms</td>
<td>64%</td>
</tr>
<tr>
<td>Ike Turner - River Deep...</td>
<td>170</td>
<td>123.19 ms</td>
<td>50.41 ms</td>
<td>60%</td>
</tr>
<tr>
<td>Means</td>
<td></td>
<td></td>
<td></td>
<td>73.5%</td>
</tr>
</tbody>
</table>

Table 2.1: Validation test to match variable music to a fixed interval (flattening out the groove).

2.4.4 Validation of the prototype in real environments

Finally, now most components have been tested and checked; we can test the system as a whole in a real-life test. We try to validate a ‘prototype’ by comparing the internal measurement systems (the log files produced during an experiment) with an external, already validated system (Delsys sensors and ADC’s). This will indicate whether the system effectively ‘does’ what is programmed to do and if this can be confirmed using external validated systems. Three variables are checked with external Delsys recordings: steps per minute,
beats per minute, and the relative phase. Of particular interest is the phase variable, which is logged internally on the prototype but can also be calculated independently when recording the audio stream and the footsteps. The phase variable is interesting to validate because it is calculated based on all other components (beat tracking, step detection, calibration, etc.) and would only match with independent calculations (from the Delsys) when everything functions correctly. If even one component would not function correctly, the log files and recording would not match. Our methodology for this validation is therefore based on the comparison between Delsys recordings and internal recordings of the phase variable. Several of these initial tests have revealed problems in our setup which were then corrected. Here we present the last test of a ready system, which was one of the latest iterations of D-Jogger, namely BeatRun.

**Protocol:** A runner is equipped with a full BeatRun installation (7" tablet, sensors, etc.), in addition to secondary sensors (accelerometers, gyroscopes, FSR’s in the heel) connected to the validated Delsys capture system. For ease of data interpretation, fixed-tempo metronomes were used. Audio from the tablet is duplicated to an analogue input on the Delsys system to have a synchronised independent recording of the beats. The equipment is configured for a short warm-up, followed by two conditions each lasting 4 minutes: fixed tempo (determined in warm-up) and adaptive tempo. The experiment was on a treadmill in the lab. Synchronised data capture was started at the start of the experiment. Four different runners were tested for the validation. Synchronised data capture was started at the start of the experiment.

**Data processing & analysis:** The tablet log files were ready for interpretation. The analogue Delsys signals were processed in Matlab using peak-finding methods on the audio- and pressure sensor channels. This determined the timing of the ’ground truth’ actual footfall and beats. All signals (BPM, SPM, and phase) were linearly interpolated at 100 Hz so it was possible to compare them. The final data analysis measured the difference between both recordings for each variable.

<table>
<thead>
<tr>
<th>Song</th>
<th>BPM</th>
<th>Cross correlation</th>
<th>Correlation at optimal lag (beats)</th>
<th>Optimal lag (beats)</th>
<th>Correlation at optimal lag significance</th>
</tr>
</thead>
<tbody>
<tr>
<td>Steppenwolf - Born to Be Wild</td>
<td>146</td>
<td></td>
<td></td>
<td>2</td>
<td>Yes, p &lt; 0.001</td>
</tr>
<tr>
<td>Guns N’ Roses - It’s So Easy</td>
<td>150</td>
<td></td>
<td></td>
<td>2</td>
<td>Yes, p &lt; 0.001</td>
</tr>
<tr>
<td>The Beach Boys - Surfin’ USA</td>
<td>157</td>
<td></td>
<td></td>
<td>2</td>
<td>Yes, p &lt; 0.001</td>
</tr>
<tr>
<td>Ike &amp; Tina Turner - River Deep</td>
<td>170</td>
<td></td>
<td></td>
<td>2</td>
<td>Yes, p &lt; 0.001</td>
</tr>
</tbody>
</table>

*Table 2.2: Validation test to match variable music to a 1/f time series.*
Figure 2.22: This plot shows the three variables (BPM (top), SPM (middle), phase (low)) measured by both the tablet and the Delsys system. It is clear that all measurements agree very well.

Example: Figure 2.22 shows the resulting recording of a test including a fixed-tempo music alignment and an phase-matching adaptive alignment. The plots show that the music follows the requested tempo music; the internal steps-per-minute calculations match the externals and that the internal relative phase correlates with the external analysis.

Results: To quantize the results, we calculate the mean difference between the two recordings at sample-interval. The difference should be close to zero to confirm the validity. Table 2.3 shows the results. Both the independent recording and the internal recording indeed do very well agree. The plots show a very high correlation and similarity (other than noise) for all relevant variables (SPM, BPM, and phase) between the internal & external recording. If the prototype were to function incorrectly, this would not be the case. The prototype thus
provides correct stimuli and is verified with a validated external data capture. This also shows the internal logging results can be used for possible data-analysis and publications.

<table>
<thead>
<tr>
<th>Runner</th>
<th>Mean SPM difference +/- SD</th>
<th>Mean BPM difference +/- SD</th>
<th>Mean Rel. Phase difference +/- SD</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>0.87 SPM (+- 3.12 SPM)</td>
<td>0.16 BPM (+- 0.46 BPM)</td>
<td>-0.43 ° (+- 40 °)</td>
</tr>
<tr>
<td>2</td>
<td>-0.003 SPM (+- 0.31 SPM)</td>
<td>-0.03 BPM (+- 0.72 BPM)</td>
<td>-1.36 ° (+- 49 °)</td>
</tr>
<tr>
<td>3</td>
<td>0.04 SPM (+- 0.44 SPM)</td>
<td>-0.14 BPM (+- 0.48 BPM)</td>
<td>-0.30 ° (+- 49 °)</td>
</tr>
<tr>
<td>4</td>
<td>0.05 SPM (+- 0.22 SPM)</td>
<td>-0.11 BPM (+- 0.39 BPM)</td>
<td>-4.15 ° (+- 24 °)</td>
</tr>
<tr>
<td>Mean</td>
<td>0.24 SPM</td>
<td>-0.03 BPM</td>
<td>-1.56 ° (+- 40 °)</td>
</tr>
</tbody>
</table>

Table 2.3: Results of the validation test of a complete BeatRun prototype. The data shows the difference in timings between internal and external recordings. Lower differences indicate that the external recording agrees well with the internal system.

2.5 Conclusion

We presented our soft- and hardware framework for our adaptive music player D-Jogger. All individual components were described: step detection, sensors, playlist, music processing, and music alignment strategies which will be further elaborated in the next chapter. Finally, we summarised validation experiments performed with the individual components and the functional implementations of D-Jogger. Results of the validation tests show that:

- iPod sensors are sufficient for gait analysis; step detection holds up well when compared to Mobility Lab and a ground truth determined by pressure sensors.
- Algorithms for adding and removing interbeat variation work correctly.
- Step detection with iPods for PD patients detects most of the steps correctly. A slight person-dependant delay was detected and was corrected using personal calibration.
- Tested D-Jogger & BeatHealth prototypes function correctly (with some errors found and corrected during testing).
- Internal logging results of D-Jogger correlate with external readings and can be used for data-analysis and publications.

The following chapters present experiments using D-Jogger or BeatHealth systems.
Alignment strategies for gait-synchronised music

This chapter documents the main five alignment strategies created with D-Jogger. A paper was published about the iterative development of the first four strategies. One additional alignment strategy was added to this chapter, which forms the core body of this dissertation. We document five different experiments, for which we collaborated with different departments and universities.

Publication title  Encouraging Spontaneous Synchronisation with D-Jogger, an Adaptive Music Player That Aligns Movement and Music

Status  Published as Moens et al. (2014, Plos One).

Authors  Bart Moens (1), Chris Muller (1), Leon Van Noorden (1), Marek Franěk (2), Bert Celie (3), Jan Boone (3), Jan Bourgois (3), Dobri Dotov (4), Marc Leman (1)

Affiliates  This work was a collaboration between (1) IPEM (Department of Art, Music and Theatre Sciences, Ghent University, Belgium), (2) Department of Management, University of Hradec Králové, Czech Republic, (3) Department of Movement and Sports Sciences, Ghent University, Belgium and (4) EuroMov (Université de Montpellier, France).
3.1 Introduction

In this study we explore how music can entrain human walkers to synchronise to the musical beat without being instructed to do so. For this, we use an interactive music player, called D-Jogger, that senses the user’s walking tempo and phase. D-Jogger aligns the music by manipulating the timing difference between beats and footfalls. Experiments are reported that led to the development and optimisation of five alignment strategies. 1) The first strategy matched the music’s tempo continuously to the runner’s pace. 2) The second strategy matched the music’s tempo at the beginning of a song to the runner’s pace, keeping the tempo constant for the remainder of the song. 3) The third alignment starts a song in perfect phase synchrony and continues to adjust the tempo to match the runner’s pace. 4) The fourth strategy additionally adjusts the phase of the music so each beat matches a footfall. 5) The fifth and last strategy uses continuous adaptive oscillators instead of a discrete algorithm. The first two strategies resulted in a minor increase of steps in phase synchrony with the main beat when compared to a random playlist, the three two strategies resulted in a strong increase in synchronised steps.

These results may be explained in terms of phase-error correction mechanisms and motor prediction schemes. Finding the phase-lock is difficult due to fluctuations in the interaction, whereas strategies that automatically align the phase between movement and music solve the problem of finding the phase-locking. Moreover, the data show that once the phase-lock is found, alignment can be easily maintained, suggesting that less entrainment effort is needed to keep the phase-lock, than to find the phase-lock. The different alignment strategies of D-Jogger can be applied in different domains such as sports, physical rehabilitation and assistive technologies for movement performance.

An alignment strategy controls the interaction between a person and the machine. In what follows, five alignment strategies will be described and evaluated with an experiment. We describe the experiments and alignments in order of execution: starting from a basic alignment in 2009, to more advanced alignments in 2015. Each experiment builds upon the knowledge and experience learnt from the previous experiments conducted to improve the alignment strategies. Our goal is to maximise uninstructed synchronisation using such an alignment.

Figure 3.1 presents an overview of the first four algorithmic alignment strategies, using beat and footfall as measurement points for timing, music and person. Beat and footfall is represented by the short vertical lines on a horizontal line that represents time. The double arrows on top of a horizontal line represent period, while those below the horizontal line represent relative phase. The oval shape draws attention to the moment where the music begins. In the first two alignment strategies the relative phase is not controlled (and thus random), while in the last two alignment strategies the relative phase is in-phase. The
different alignment strategies also suggest which kind of entrainment we may expect. For example, in alignment strategy 2, it is assumed that the person will converge to zero degrees relative phase, similar to that seen in alignment strategy 3. However, in alignment strategy 4, it is the music player that converges its phase with the person. Further details of the alignment strategies are discussed below.

3.2 Strategy 1: period-adaptive phase-random

Algorithm description

Our first alignment strategy is rather naive in its approach when it comes to encouraging entrainment. We simply match the tempo of the music (tempo = number of musical periods per minute, or Beats Per Minute, or BPM) with the observed tempo of the gait (tempo = number of gait periods per minute, or Steps Per Minute, or SPM), as shown in Figure 3.1. The relative phase is neglected, which means that the music starts at whatever time interval taken between two steps, and the phase of the music is not adapted during the song. The observed gait tempo (and therefore the music temp) is updated each step and is based on the average inter-step interval of the last 5 steps. Steps are detected using an input sensor and step detection algorithm as described in the previous section. The strategy allows the participant to adjust the relative phase by taking smaller or bigger steps. We denote $\Delta \omega$ as the value for the difference between the tempo of the musical beat and the tempo of the actual (non-averaged) gait.

The pseudo-code in table 3.1 describes the alignment strategy and its parameters. The period-adaptive strategy seeks to minimizes $\Delta \omega$. When the participant changes gait tempo, it takes five seconds for the system to realign itself. During this time, $\Delta \omega$ will be non-zero. When the participant holds a steady pace, $\Delta \omega$ will converge to zero, meaning both frequencies match. When the adjustment needed to minimise $\Delta \omega$ is either smaller than $-10\%$ or greater than $+10\%$, a new song is chosen to prevent an audible deformation of the song. A new song then begins at a random time between footsteps, resulting in a random relative phase at the beginning of a song.

Hypothesis

We assumed that if the strategy has an influence on the participants’ behaviour, then the resulting distribution of the relative phase will be different from a uniform (random) distribution. In addition, there will be a statistically significant mean relative phase angle close to $0^\circ$, indicating that more than random steps are taken close to the main music beat.
Figure 3.1: Four different alignment strategies. 1. The song starts in tempo but not in-phase. During the song, the music period is adapted to the walking period. 2. The song starts in tempo but not in-phase. During the song, the music period is kept fixed. The human entrains to the phase of the song. 3. The song starts in tempo and in phase. During the song the phase is kept fixed, while the music period is adapted to the walking period. The human entrains to the phase of the song. 4. The song starts in tempo and in phase. During the song, the period and phase are adapted. The music player follows human changes in period and phase.
Pseudocode for alignment strategy 1 (Period-adaptive phase-random)

1: for all steps do
2: \( SPM \leftarrow \text{avg gait frequency of last 5 steps} \)
3: \( MTM \leftarrow \frac{SPM}{BPM} \)
4: \( \text{if } MTM \leq 0.9 \text{ or } MTM \geq 1.1 \text{ then} \) (Tempo outside 10% stretch)
5: \( \text{if for more as 5 seconds then} \) (Avoid too many song changes)
6: \( \text{choose new song} \) (BPM sufficiently close to \( SPM \))
7: \( \text{end if} \)
8: \( \text{end if} \)
9: \( \text{end for} \)

Table 3.1: Algorithm 1. \( MTM \) is the resulting music tempo modifier.

Experiment and Participants

Two public exhibition demonstrations of the system took place in Belgium and participants volunteered to take part in the experiment with the demonstration system. They gave their consent for their walking behaviour to be recorded. In total, 150 participants were recruited (age = 21.9 ± 12.9 STD, 82 male, 68 female) of whom 119 participants were included in the analysis. 31 datasets were neglected because the participant spent less than a minute on the treadmill. After a short explanation of the treadmill’s operation and safety mechanism, participants could choose to either walk or run on the treadmill. Once the participant was comfortable with the treadmill and its operation, the headphones were given, and the data capture and auditory feedback was set in motion.

Setup

The experimental setup consisted of a basic treadmill, a computer running the smart music player with the above described TA-PR strategy, a Sennheiser HD62TV headphone and a Wii-motion plus a sensor used for step detection. Only one sensor was used per participant, and this was attached comfortably to the right leg above the ankle using elastic Velcro straps. Due to the location of the sensor, footfall impacts were easily detected in real time using peak detection algorithms on the accelerometer signal. The resulting gait frequency was then doubled before transmitting it to the music alignment algorithm. All data was logged for analysis after the experiment, however exclusion criteria for the analysis included participants with potentially asymmetrical gait pattern (eg participants with a gait impairment) and participants who did not feel comfortable at a treadmill.
Stimuli

The music used for the two public demonstration events was identical. As the target audience was taken from a broad section of the general public, the tempo-annotated music library contained 150 pop songs selected from recent commercial radio charts. Only songs with a basic 4/4 rhythmical pattern and a clear main audible beat were included. For any given gait frequency between 80 SPM and 200 SPM, several songs were available in a range of ± 5 BPM. The volume of participants’ headphones was limited to 75 dBA.

Task

The task given to participants was to freely experiment with the demonstration system. The experiment/demonstration was unrestricted in terms of walking speed and time. Participants were able to select a new treadmill speed or stop at will. The underlying experimental goals of the researchers were not disclosed to the participants prior to the experiment, and the participants were told that the prototype shown was for demonstration purposes. After the experiment, the participants completed a very short anonymous questionnaire requesting general information such as age, gender and it invited them to note down their experience with the system. After filling in the questionnaire, the participants also provided written consent allowing us to use the resulting data for research purposes and further development of the system.

Results

In total, we recorded 51689 valid right footfalls or steps. The resulting distribution is described in Table 3.5, the angular histogram is shown in Figure 3.2. The histogram shows a clustering of phase angles around $0^\circ$, while a minor cluster is visible around $-180^\circ, +180^\circ$. The distribution can therefore be interpreted as bimodal. We found that the distribution is not uniformly dispersed (Omnibus test for non-uniformity, $p < 0.001$). However, because the secondary cluster - around $180^\circ$ - is barely visible, we can also interpret the distribution as unimodal. In this case, we find a statistically significant mean phase angle of $5.6^\circ$ ($z_{1487.7322}, p < 0.001$).

Both results confirm our hypothesis that the music-to-movement alignment algorithm has a significant influence on the participants’ behaviour. Had this not been the case, we would have seen a uniform distribution. The resulting vector length $|R|$, or measure of synchrony, equals 0.17, showing a higher concentration of angles around the circular mean.

Individual analysis showed that 71.8% of the 119 participants had a significant mean angle, determined using the Rayleigh test. The individual resultant vector lengths are shown in figure 3.12.
Discussion

The results show that the distribution is not uniform, with a slightly higher concentration of phase angles around 0°. However, while the increase is noteworthy, we expected a higher concentration around 0° (i.e. more steps close to the beats). Several factors may be account for this. We should first consider the instability of the human gait: it rarely remains constant and the average frequency continuously fluctuates around a mean. Therefore, $\Delta \omega$ never really converges to zero, in contrast with what was expected, due to the averaging of the gait frequency. A second factor is that the interaction is unstable in the sense that a music tempo and the gait tempo tend to 'wobble' or alternate around the mean. See Figure 3.3A and 3.3B for an illustration of this phenomenon. This wobbling may be a consequence of the used gait tempo; a byproduct resulting from the following method. Music adjustment lags several seconds behind, the result being a loss of the phase alignment with every small period change. An in-depth data analysis reveals that participants subsequently try to readjust their pace in an attempt to get back in time with the music. However, the system reacts again to this change and phase alignment is again lost. This pattern often repeats itself and therefore the interaction seldom stabilises, as illustrated in Figure 3.3A and 3.3B. A larger step detection window might solve this problem but that would result in more stable music stimuli, which is the topic of our second alignment strategy. A third plausible factor for the lower synchronisation rate is the restriction imposed by the treadmill. This device may restrict the movement of the participant (Mendonça et al., 2014b). However, he or she is still free to change gait parameters for any given speed, most notably the step length and thus the steps per minute. It can be argued that this action might feel somewhat unnatural.
**Conclusion**

To sum up, the results show that alignment strategy 1 has indeed an influence on the gait of the user. More steps were synchronised than unsynchronised, but the strategy suffers either from very low phase stability or high circular variance. The results suggested making a change in the alignment strategies such that the interaction would increase stability.

### 3.3 Strategy 2: period-fixed phase-random

**Algorithm description**

In this alignment strategy, the music period is kept stable once it has been chosen. This is done by playing the music back using a tempo that corresponds to observed gait tempo. Similar to the first alignment strategy, the relative phase is not used in the alignment, as shown in Figure 3.1. After a song is finished, a new song is selected based on the most recent measurement of the gait tempo. The pseudo-code found in table 3.2 describes the alignment strategy and its parameters.
**Pseudocode alignment strategy 2**

1: \textbf{for all} steps \textbf{do}
2: \hspace{1em} \textit{SPM} \leftarrow \text{avg gait frequency of last 5 steps}
3: \hspace{1em} \textbf{if} current song ending \textbf{then}
4: \hspace{2em} \text{choose new song} \hspace{5em} (BPM as close to \textit{SPM} as possible)
5: \hspace{2em} \textit{MTM} \leftarrow \textit{SPM} / \text{newBPM} \hspace{5em} (change tempo only on song change)
6: \hspace{1em} \textbf{end if}
7: \hspace{1em} \textbf{end for}

*Table 3.2: Algorithm 2. MTM is the resulting music tempo modifier.*

**Hypothesis**

We assumed that alignment strategy 2 would be more stable than alignment strategy 1 because the musical tempo is kept stable once the playback starts. This would make it easier to synchronise to, thereby establishing a stable synchronisation interaction. We assume that if the strategy has an influence on the participants behaviour, then the resulting distribution of the relative phase will be different from a uniform (random) distribution. In addition, we foresee a statistically significant mean phase angle close to $0^\circ$, indicating that more steps were taken close to the main beat.

**Participants**

The experiment took place in the Czech Republic at the Univerzita Hradec Králové, where 112 students voluntarily participated in the experiment. However, 12 students did not complete the task successfully or had bad data and so were discounted in the further analysis. This resulted in the inclusion of 100 valid participants (age $= 20.2 \pm 0.8$ STD, 56 male, 44 female) in the analysis.

The participants signed a consent declaration which stated that have participated in the experiment of their own free will, were informed in advance about the task, the procedure and the technology used for measurement. They had the opportunity to ask questions and agreed that recordings of their actions would be made. They agreed that the recorded data would be used for scientific and educational purposes, only. In accordance with the general standards at the Univerzita of Králové, and the faculty of Department of Management, their privacy is respected. Owing to the fact that the experiment was conducted in public spaces around the city Hradec Králové, permission from the municipality to conduct this study was required and given.
Setup

A mobile implementation was made allowing us to experiment with the alignment strategy while walking in an open field. The experimental setup consisted of a mobile implementation of the music synchronisation framework using the aforementioned music alignment strategy. The hardware used was a Samsung Galaxy Y (2011) phone, running Android 2.3. The device was equipped with inertial sensors used to capture step detection. The device was placed on a belt worn around the hip; steps could be detected using peak detection methods on the accelerometer signal of the axis, positioned perpendicular to the earth (where the hip absorbs the shock of the footfall, and changes direction from downwards to upwards). Participants listened to the provided stimuli using a Sennheiser HD62TV headphone. The device also logged all available information for later analysis.

Stimuli

Participating students were asked beforehand to submit their favourite songs. From this list, a selection of 40 songs was made, each with a tempi that fell within the typical walking range of 80 to 140 BPM. Additional selection criteria were then applied to achieve stimuli that are more or less similar to the previous experiment. This is, stimuli in 4/4 metre with a clearly audible main beat. As no phase vocoder was available on the mobile system, several versions of each song were created beforehand with varying tempi, namely -3%, -2%, -1%, 0%, +1%, +2% and +3%. This resulted in an annotated library of 280 songs normally divided in the tempo range of 80 to 140 BPM. As the average human walking tempi in a natural setting is around 110—120 SPM (MacDougall and Moore, 2005a), more songs were available in this range. Once a song had been played, all other versions of the song were removed from the library to prevent users would hearing the same song twice. Each song’s intro was manually removed (if there was one) and then cropped to a duration of two minutes, resulting in a broad enough range of songs for the user, and which immediately began with an audible beat to encourage spontaneous entrainment. The volume of participants’ headphones was limited to 75 dBA.

Task

The task for the participants was to follow a predetermined outdoor path of 1.8 km taken at their own preferred speed, while listening to music. The path was clearly marked using orange indicators on the ground, in addition to a map which they could study beforehand. The participants were not informed about the goal of the experiment, nor were they told to synchronise or adapt to the music. Instead, they were told that the experiment was about the perception of the environment during free walks. Individual spontaneous gait frequencies
were determined during the first two minutes of the walk, without auditory feedback. After the initial phase, music was provided with tempi matched as close as possible to the users’ gait frequency. Each song excerpt played for two minutes, after which a new song was chosen, matched closely to the most recent gait frequency. Upon completion of the track, participants filled in a questionnaire about their experience and the music.

**Results**

In total, we recorded 25,454 valid footfalls. The resulting distribution is described in Table 3.5, the angular histogram is shown in Figure 3.4. The histogram shows a clustering of phase angles around 0°. The distribution can therefore be interpreted as unimodal. We found that the distribution differs from a uniformly distributed one with a statistical significant mean phase angle of 4.7° (Rayleigh $z_{1907.8163}$, $p < 0.001$).

The results illustrate that the alignment strategy has a significant influence on the participants’ behaviour because otherwise we would have seen a uniform distribution. The resulting vector length $|R|$, equals 0.27, which indicates a higher concentration of angles around the circular mean and it also hints at a higher synchronisation rate than our previous alignment strategy.

Finally, individual analysis showed that 89.0% of the 100 participants had a significant mean angle, determined using the Rayleigh test. The individual resultant vector lengths are shown in Figure 3.12.
Discussion

The relative phase distribution shows the same pattern as our previous experiment, although a slight improvement in the distribution of the relative phase over the previous algorithm is noticeable. However, the in-depth data-analysis of individual relative phases and tempo plots reveals interesting recurring patterns. Figure 3.5 shows four examples of different participants. The first example (Fig. 3.5, A and B, 0-2 min) shows initial phase synchronisation which is momentarily lost, but the participant eventually falls back in sync with the music again for the remainder of the song. The second example (Fig. 3.5, A and B, 3-5 min) shows that the participant does not appear to adjust to the stimuli. However, each time the steps coincide with the beat of the music, the participant keeps the same relative phase region for a few steps and gets temporarily 'locked' in-phase. However, the participant is not permanently held, and can continue on in their own preferred locomotor tempi. By the end of the song however, the participants gait period is matched more closely to the music. The third example (Fig. 3.5, C and D, 6-8 min) shows that there is initially no synchronisation between participant and music due to a tempo difference. However, once close to the in-phase range, the user gets caught up by the main attractor and remains in phase for the remainder of the song. The fourth example (Fig. 3.5, C and D, 9-11 min) shows initial anti-phase synchronisation when the song starts, and this is maintained for several steps. However, after a while the participant gets locked into the beat and remains in-phase for the remainder of the song. The data suggests that the music has a certain attraction force: once in-phase synchrony is obtained, the synchronisation was usually maintained until the end of the song. This observation became the starting point for our next alignment strategy.

We also observe that the initial music tempo selection is often several BPMs off target. This is due to the fact that gait frequencies tend to be very variable on their own. During the five seconds needed for music player adaptation, the actual gait frequency will most likely be changed and the music selection will no longer be optimal. This problem is inherent with real-time step detection, and especially when the music player is non-adaptive.

Another disadvantage of this alignment strategy is its insensitivity to sudden gait period changes. These occur frequently in our test due to environmental factors such as road crossings (although these were limited to a minimum), obstacles such as other pedestrians or participants looking and stopping to find the next directional marker. In such cases the new gait period rarely matched the gait period before the obstacle, creating a substantial difference between music and gait period, and thus, less synchronisation.

Conclusion

To sum up, the results show that alignment strategy 2 has an influence on the gait of the user. The algorithm facilitates entrainment and the resulting synchronisation is more stable than
Figure 3.5: Excerpts from the experiment of alignment strategy 2 (period-fixed phase-random). Figure A and C show tempo plots, figures B and D show the phase evolution per step. The figure shows several examples of recurring patterns throughout the experiment.
alignment strategy 1. We observed interesting recurring patterns in the data, most notably that once phase lock was obtained, it was seldom lost. We also noted two disadvantages to the alignment strategy. First, due to the gait frequency variability and the delay in the step detection, non-optimal stimuli was sometimes selected (based on old SPM values), thus lowering the chance of synchronisation and dragging down stability means. Secondly, the proposed method is impervious to large gait period changes. Improvements can be made by considering an in-phase lock at the start of a song, and by the re-introduction of period-adaptation.

3.4 Strategy 3: period-adaptive phase-starting $0^\circ$

Description

This alignment strategy takes the relative phase into account, as well as the period, as shown in Figure 3.1. Music is played with an adaptive period based on the average gait period of the last 5 seconds, which is identical to the first alignment strategy. In addition, this alignment strategy introduces a song start based on the users gait phase. The song starts playing when the relative phase is equal to the desired starting phase. Based on our findings in alignment three, we tested both a $0^\circ$ starting phase to maximise stability and a $180^\circ$ starting phase for comparison. The pseudocode found in table 3.3 describes the alignment strategy and its parameters.

<table>
<thead>
<tr>
<th>Pseudocode alignment strategy 3 (tempo-adaptive phase-starting $0^\circ$)</th>
</tr>
</thead>
<tbody>
<tr>
<td>1: for all steps do</td>
</tr>
<tr>
<td>2: $SPM \leftarrow$ avg gait freq of 5 last steps</td>
</tr>
<tr>
<td>3: $MTM \leftarrow SPM/BPM$</td>
</tr>
<tr>
<td>4: if $MTM \leq 0.9$ or $MTM \geq 1.1$ then (Tempo outside 10% stretch)</td>
</tr>
<tr>
<td>5: if for more as 5 seconds then (Avoid too many song changes)</td>
</tr>
<tr>
<td>6: queue new song ($BPM$ close to $SPM$)</td>
</tr>
<tr>
<td>7: end if</td>
</tr>
<tr>
<td>8: end if</td>
</tr>
<tr>
<td>9: if song in queue then</td>
</tr>
<tr>
<td>10: Skip to first beat in song</td>
</tr>
<tr>
<td>11a: Start playing song when</td>
</tr>
<tr>
<td>11b: desired phase is reached (Calculate based on inter-steptime)</td>
</tr>
<tr>
<td>12: end if</td>
</tr>
<tr>
<td>13: end for</td>
</tr>
</tbody>
</table>

Table 3.3: Algorithm 3. $MTM$ is the resulting music tempo modifier.
Hypothesis

For both the $0^\circ$ and $180^\circ$ starting phase, we assumed that the alignment strategy would have an influence on the participants’ behaviour. In particular, we expected that both resulting distributions would be different from a uniform (random) distribution, with a statistically significant mean phase angle, close to the starting phase of either $0^\circ$ or $180^\circ$, indicating that more steps were taken close to the main beat or off-beat. Furthermore, for the $0^\circ$ condition we expected a more stable interaction resulting in more footsteps taken in synchrony with the music compared to the previous alignment strategies. Finally, a different behaviour was expected when the starting phase was set to $0^\circ$ versus $180^\circ$. This included a higher enjoyability for the $0^\circ$ starting phase and a lower resultant vector length for the $180^\circ$ starting phase (i.e. more deviation from the starting phase because of the lower attraction force of the offbeat phase compared to the main beat). We also expected a difference in performance (the distance travelled).

They were given the opportunity to ask questions and agreed that anonymous recordings of their actions would be made for scientific purposes, only. In accordance with the general standards set by our university and our faculty, security was guaranteed (the indoor task carries no risk), and privacy is respected. According to Belgian law for experiments aimed at research performed to further the development of biological or medical knowledge (cf. 7 May 2004 Law concerning experiments on the human person (Ch.II, Art.2, Par.11)), means our research is exempt from the requirement to obtain ethical approval because the study only involves behavioural knowledge.

Participants

The experiment took place in Belgium at the University of Ghent. In total, 12 participants (mean age = 21.2 ± 1.7, all female) volunteered for the experiment. Two participants did not complete the trial; all the recorded data for the remaining 10 participants could be used in the analysis. After a short explanation of the treadmill’s operation and safety mechanism was given, participants could freely walk or run on the treadmill. Once the participant was comfortable with the treadmill and its operation, the headphones were given, and the data capture and auditory feedback was set in motion. The ten remaining participants alternated freely between running and walking.

Setup

The experimental setup was similar to the first experiment: a treadmill, a computer running the music framework with the above algorithm and a Sennheiser HD62TV headphone. Step detection was done using a pressure sensor located below the front of the treadmill. The
resulting signal indicated the weight in front of the treadmill, where a sharp increase indicated a footfall. This resulted in very accurate gait phase information, a necessary item for this experimental setup.

**Task**

Participants were asked to freely walk and run on a treadmill for 15 minutes. Each participant tested the system twice, but not on the same day, in counterbalanced order. The only difference between both trials was the starting phase: either 0° or 180°. After each trial, a short survey about the physical enjoyment during the exercise was filled in by the participants. For this, we used the Physical Activity Enjoyment Scale (PACES) (Kendzierski and DeCarlo, 1991a), a questionnaire of 17 questions to be answered on a 7-point Likert scale. The PACES scale is verified with a similar population (Motl et al., 2001). Participants were free to change the treadmill speed as they wished. Again, they were not informed about the underlying synchronisation goal nor the differences between both conditions, but were instead told the experiment was about the subjective enjoyment experienced when walking or running on music.

**Stimuli**

The music used for both trials was identical to the first experiment where we tested the tempo-adaptive strategy. That is, 150 pop songs selected from recent commercial radio charts, with a 4/4 rhythmical pattern and a clear main audible beat. For any given gait frequency between 80 SPM and 200 SPM, several songs were available. The volume of participants’ headphones was limited to 75 dBA.

**Results for the 0° starting phase**

In total, we recorded 19,875 valid footfalls. The resulting distribution is described in table 3.5, the angular histogram is shown in Figure 3.6. The histogram shows a clustering of phase angles of around 0°. The distribution can therefore be interpreted as unimodal. We found that the distribution is not uniformly distributed with a statistical significant mean phase angle of 4.7° (Rayleigh $z_{10721.3} < 0.001$).

The alignment strategy has a significant influence on the participants’ behaviour, if this had not been the case we would have seen a uniform distribution. The resulting vector length $|R|$, equals 0.73. This indicates a high concentration of angles around the circular mean and also hints at a higher synchronisation rate than in our previous alignment strategies. Finally, individual analysis showed that all of the 10 participants had a significant mean angle, determined using the Rayleigh test. The individual resultant vector lengths are shown
Results for the 180° starting phase

In total, we recorded 20,348 valid footfalls. The resulting distribution is described in Table 3.5, the angular histogram is shown in Figure 3.6. The histogram shows a clustering of phase angles of around 180°. The distribution can therefore be interpreted as unimodal. We found that the distribution is not uniformly distributed with a statistical significant mean phase angle of $-175°$ (Rayleigh $z_{3999.88}, p < 0.001$).

The alignment strategy has a significant influence on the participants’ behaviour, if this had not been the case we would have seen a uniform distribution. The resulting vector length $|R|$, equals 0.44. Finally, individual analysis showed that all of the 10 participants had a significant mean angle, determined using the Rayleigh test. The individual resultant vector lengths are shown in Figure 3.12.

Comparing the 0° and 180° starting phase conditions

We compared both distributions using the Watson’s U2 test, which computes the probability that, according to the null hypothesis, 2 samples of circular data come from the same population, or from 2 populations that have the same direction (Zar, 1999). Analysis reveals the distributions differ significantly (Watsons $U_{2541.05}, p < 0.001$), indicating that a different starting phase has an effect on the participants walking behaviour. We note that the resultant vector length is much higher for the 0° condition ($|R| = 0.73$) than the 180° condition ($|R| = 0.44$).
= 0.44), indicating that participants deviated more from the 180° starting phase. There was a significant difference in the PACES scores for 0° starting phase (Mean = 95.6; SD = 10.6) and the 180° starting phase (Mean = 87.9; SD = 13.2) conditions; t(9) = 2.37, p = 0.042. There was no significant difference in the distance travelled for 0° starting phase (Mean = 1650m; SD = 314) and the 180° starting phase (Mean = 1630m; SD = 261) conditions; t(9) = 0.347, p > 0.5.

Discussion

The likelihood of entraining with the music, using the third strategy, is much higher compared to random music stimuli (i.e. a random playlist with various BPM values), and even the other alignment strategies. Yet, the only difference with alignment strategy 1 is a fixed starting relative phase angle. The best synchronisation is obtained when starting in the 0° phase angle at the start of the song. As mentioned in the discussion of strategy 2, participants do seem to remain in phase once a low relative phase angle is obtained (see Figure 3.7 A and B). This alignment, specifically the 0° start angle, therefore appears to be very effective when trying to encourage stable synchronisation. Participants react differently with the 180° condition. Figure 3.7 C and D shows a 7 minute excerpt from the experiment. In this case, the participant seems to have two reactions: either try to go in-phase (e.g. 440s - 530s), which seems a conscious effort by slowing down/speeding up, or remaining in anti-phase (e.g. 330s - 440s). When starting in 0° however, one rarely goes to the 180° starting phase. This indicates that the 0 degree attractor is stronger than the 180 degree. Figure 3.12 shows the resultant vector length distribution (calculated per person). The 0° condition has a higher mean resultant vector and lower standard deviation than the 180° condition. This indicates that the 0° starting phase results in a more stable interaction with the system. Lastly, the PACES score (physical enjoyment) was significantly higher in 0° starting phase, indicating a higher enjoyment when running in phase-synchrony. Participants kept a more stable pace and had less tempo changes, i.e. participants were more likely to maintain the same pace when the musical beat corresponded with the footfall - and started in-phase - than when the music started in anti-phase. When starting in anti-phase, some participants sought to get in sync, but while doing so, they changed gait frequency and thus the system resets itself to 180 degrees. This ‘frustration’ could have caused the lower PACES. However, it did not influence the total distance travelled (the performance).

Note that this study has a lower participant number than previous studies (N=10). Furthermore, the participants were all female, which makes it difficult to generalise about the results in relation to a larger population. However, the effects are so significant that we believe that this alignment algorithm will have similar results on a larger population.
Figure 3.7: Excerpts from the same participant using alignment strategy 3 (period-adaptive phase-starting). A and B show the $0^\circ$ starting phase, C and D show the $180^\circ$ starting phase condition from the experiment using the phase-aware stimuli. Figures A and C show tempo plots, figures B and D show the phase evolution per step. The examples show the influence of the starting phase: when starting in sync, the phase lock is mostly maintained while in the offbeat condition, there is a higher chance of deviating from the starting phase towards the $0^\circ$ phase.
Conclusion

To sum up, the overall data and examples show that the likelihood of having a stable synchronisation is very high when using the $0^\circ$ starting phase compared to the previous strategies. When a new song was chosen, participants started in phase, which resulted in a much more stable synchronisation. The proposed alignment strategy does seem to solve the problem of finding the in-phase alignment that affected the previous alignment strategies. However, there will always be people who are unable to synchronise. For them there is the option to go one step further by using both phase-adaptation and a period-adaptation.

3.5 Strategy 4: period-adaptive and phase-adaptive to $0^\circ$

Algorithm description

This alignment strategy adapts the relative phase analysis continuously, as shown in Figure 3.1. This happens when the allowed synchronisation range from -30° to 30° is exceeded. If this deviation persists, then an extra period adjustment is applied to enable the phase alignment to converge towards the $0^\circ$ relative phase angle. The pseudocode in table 3.4 describes the alignment strategy and its parameters in more precise detail.

<table>
<thead>
<tr>
<th>Pseudocode alignment strategy 4 (tempo-adaptive phase-adaptive to $0^\circ$)</th>
</tr>
</thead>
<tbody>
<tr>
<td>1: for all steps do</td>
</tr>
<tr>
<td>2: $SPM \leftarrow \text{avg gait freq of 5 last steps}$</td>
</tr>
<tr>
<td>3: $Tempo \leftarrow SPM/BPM$</td>
</tr>
<tr>
<td>4: if Tempo $\leq 0.9$ or Tempo $\geq 1.1$ then (Tempo outside 10% stretch)</td>
</tr>
<tr>
<td>5: if for more as 5 seconds then (Avoid too many song changes)</td>
</tr>
<tr>
<td>6: Queue new song (BPM as close to $SPM$ as possible)</td>
</tr>
<tr>
<td>7: end if</td>
</tr>
<tr>
<td>8: end if</td>
</tr>
<tr>
<td>9: if Phase $\leq -30$ then (Step after beat: speed music up)</td>
</tr>
<tr>
<td>10: Tempo $\leftarrow$ Tempo + 0.03</td>
</tr>
<tr>
<td>11: else if Phase $\geq 30$ then (Step before beat: slow music down)</td>
</tr>
<tr>
<td>12: Tempo $\leftarrow$ Tempo - 0.03</td>
</tr>
<tr>
<td>13: end if</td>
</tr>
<tr>
<td>14: MusicTempoModifier $\leftarrow$ Tempo (Set the final music tempo)</td>
</tr>
<tr>
<td>15: if song in queue then</td>
</tr>
<tr>
<td>16: Skip to first beat in song</td>
</tr>
<tr>
<td>17a: Start song when desired</td>
</tr>
<tr>
<td>17b: phase is reached (Calculate based on inter-step time)</td>
</tr>
<tr>
<td>18: end if</td>
</tr>
<tr>
<td>19: end for</td>
</tr>
</tbody>
</table>

Table 3.4: Algorithm 4. MTM is the resulting music tempo modifier.
**Hypothesis**

In this alignment strategy the phase and the period are continuously adapted to the participants’ phase and period. Accordingly, by definition, the participant will be synchronised with the music. If the technology works, there should be a statistically significant mean phase angle, close to $0^\circ$. As a matter of fact, there will be more footsteps in synchrony with the music compared to all previous alignment strategies.

**Participants**

The experiment took place in Belgium at the Department of Movement and Sports Sciences of Ghent University. 12 students from Physical Education and Movement Sciences (Ghent University) were recruited for the study participation on a voluntary basis. All participants were recreational but non-professional runners. The experiment took place in the context of another experiment where we tried to determine whether there is a difference in ergogenic parameters (such as blood pressure, heart rate, lactate, oxygen consumption, etc.) when training on phase-synchronised music versus regular (unsynchronised and random) music. However, the physiological results are not reported in the present paper. Proper safety precautions were taken due to the high intensity of the tests. A large red panic button that automatically stops the treadmill was made easily accessible, and participants wore a safety harness to prevent them from hitting the ground in case of a fall. A doctor was present during the VO2 max tests, to examine the participants beforehand and judge them fit for the tests. After the completion of all the trials, participants were rewarded with a 5 euro shopping card gift voucher. 2 of the 12 participants dropped out due to injuries unrelated to the experiment. 10 participants (age 23 ± 3 SD; 6 female, 4 male) were included in the analysis. Only the two (anaerobic and aerobic) synchronous music conditions are used for further analysis, as only those are relevant in this context.

**Setup**

The experimental setup consisted of a professional treadmill, a computer running the music framework with the above algorithm and a Sennheiser HD62TV headphone. Step detection was done using two iPods, located at the participants’ ankles, streaming accelerometer and gyroscope data wirelessly to the computer at 100 Hz. Steps were detectable by analysing both the gyroscope and accelerometer signal. By using the gyroscope, forward to backward leg movement was detected, which occurs a fraction prior to the footfall. The gyroscope signal was used to predict a small footfall window ($\pm 50 ms$) in which the first peak in the accelerometer signal from the axis perpendicular to the earth was denoted the footfall. This method has proven to be very accurate as no more dubious peaks were detected.
Task

The task consisted of 6 thirty-minute sessions of running on a treadmill, and a pretest. The pretest comprised a BRMI2-test used to determine individual motivational music. This was followed by a VO2-Max test in order to determine individual treadmill speeds for the anaerobic and aerobic threshold. A medical doctor was also present during these tests. Two treadmill speeds were thus determined: a high-intensity speed and a medium-intensity speed. For each speed, three musical conditions were tested: no music, random music with a tempi of around 120 BPM (thus no synchronisation would be possible) and the forced phase synchronisation music. The six conditions were tested in counterbalanced order. The trials were spread evenly over three weeks, a break of at least 48 hours was given between each session to allow the participant to recover. Participants were also asked to follow the same lifestyle pattern and perform the test at roughly the same time of day for each test. Participants were instructed to run for thirty minutes at a given treadmill speed. They were informed that the study concerned the influence of music on running, but were not informed, beforehand, of the different conditions. The secondary goal for evaluating the relative phase distribution was also not mentioned.

Stimuli

A pre-selection of 100 songs from the pop music repertoire was made by the experiment supervisors. Before the VO2-Max pretest, each participant rated all 100 songs using the BMRI2 questionnaire/survey (Karageorghis and Priest, 2006). The BMRI2 is a scale used to assess the motivational power a song has upon a participant. This resulted in two playlists per individual, one for the synchronised condition (150 - 200 BPM) and one for the regular condition (110-130 BPM), containing only motivational songs. The volume of participants’ headphones was limited to 75 dBA.

Results

In total, we recorded 104334 valid footfalls. The resulting distribution is shown in Table 3.5, the angular histogram is shown in Figure 3.8. The histogram shows a clustering of phase angles around 0°. The distribution can therefore be interpreted as unimodal. We found that the distribution is not uniformly distributed with a statistical significant mean phase angle of −0.14° (Rayleigh z_{88674}, p < 0.001). The results confirm the hypothesis that this alignment algorithm shows the best results in terms of synchronisation. The resulting vector length |R|, equals 0.92. This indicates a high concentration of angles around the circular mean and also hints that this is the highest synchronisation rate out of all of the alignment strategies. Finally, individual analysis showed that all of the 10 participants had a significant
mean angle, determined using the Rayleigh test. The individual resultant vector lengths are shown in figure 3.12.

**Discussion**

The results show that the alignment strategy is very effective in maintaining synchronisation. Steps taken outside the synchronous range are automatically corrected, although due to the delay caused by the step detection, it may take a few seconds to give an effect. Although some of the steps included abrupt step length changes (due to experimentation of the participants) and small pauses made to take blood samples from the participant, this had little or no effect on the outcome. It is also logical that almost no steps were taken in off-beat synchronisation, because the alignment algorithm tries to push participants towards the in-phase angles. Figure 3.9 shows the effect of the alignment strategy on the phase angle.

The bottom graph includes three lines: 0°, -30° and +30°. The latter two are the boundaries from which the system starts adjusting the music tempo in order to manipulate the relative phase. It is clear that, once the phase angle steps outside of the boundary, the music tempo chances 3% to push the relative phase back to 0°. We sometimes observe a small after effect, in the sense that the adjustment results in a reverse tempo adaptation (slowing the music down after accelerating) in order to minimise the relative phase. This is a recurring pattern, which indicates that by tweaking the arbitrary chosen parameters, the algorithm could be improved. In that regard, both systems influence each other; and would thus qualify as a form of entrainment. Interestingly, with this alignment strategy there is basically no human entrainment to get in-phase. Instead, the entrainment is done by the
music player. What is left for the participant is 'being in-phase', without 'getting in-phase'. This effect requires further study as some participants reported that this type of synchronisation felt rather synthetic and mechanical. We do believe that a fine-tuning of this alignment strategy may lead to even more stability and decrease the mechanical feeling of the system. For example, the values $-30^\circ$ and $+30^\circ$ were somewhat artificially chosen and they could be optimised. In addition, a sudden 3% shift in tempo might be noticeable to users.

**Conclusion**

As expected, alignment strategy 4 has the highest amount of steps that were in synchrony with the musical beat. The main reason is that the music player adapts to human movement so that there is a constant in-phase situation. However, more study is needed to consider the psychological effects of this type of alignment. These issues will be addressed in further research, where we will also address the optimisation of this alignment strategy.
CHAPTER 3.6

3.6 Strategy 5: Kuramoto - dynamic phase coupling using adaptive oscillators

Based on the feedback of our first four algorithmic approaches, a more dynamic approach was needed. Ideally, the last alignment strategy would

- allow the user to go out of phase for some time and experience phase cycles; hoping to reduce the 'mechanical feel' reported earlier and simulate a more natural interaction
- avoids sudden 3 percent tempo changes
- results in a higher degree of freedom for participant
- a higher enjoyment

Algorithm description and theory

The last new alignment strategy is, in contrast to previous strategies, based on adaptive oscillators and limit cycles (i.e. continues adaptation), and not algorithmic logic (i.e. discrete adaptation). The Kuramoto system is the most paradigmatic formal system used in the study of synchronisation processes throughout nature (Strogatz, 2000). This dynamic approach also inspired by WalkMate (Miyake, 2009b; Hove et al., 2012), a cueing device for Parkinson Patients.

We selected to implement the alignment strategy as a phase oscillator receiving a coupling term from the gait dynamics in terms of a sine function of the step phase. The following equation depicts the Kuramoto model for N oscillators:

\[
\frac{d\theta_i}{dt} = \omega_i + \frac{K}{N} \sum_{j=1}^{N} \sin(\theta_j - \theta_i), i = 1...N \tag{3.1}
\]

In our case, we only have two oscillators: the music system and the human. We can only (directly) manipulate the music, but it is reasonable to assume the user also acts as a coupled oscillator towards the music given our previous results in terms of phase locking to the beat and being attracted to $0^\circ$ phase angles. Using the above formula in our simplified context with only a human an machine oscillator ($N = 2$), we get the following model:

\[
\dot{\theta}_{\text{machine}} = \omega_{\text{machine}} + \frac{k_{\text{machine}}}{2} \sin(\theta_{\text{machine}} - \theta_{\text{human}}) \tag{3.2}
\]

This instantiation has two configurable parameters: $\omega_{\text{machine}}$ is the intrinsic preferred frequency of the musical player, usually matching the human frequency, and $k_{\text{machine}}$ is the coupling gain and depicts the phase attraction strength. These two parameters of the machine phase oscillator can lead to a varying degree of so-called individuality of the music...
oscillator, both controlling its tendency to phase-lock to the rhythm of the user. Other
input is the continuous step phase $\theta_{\text{human}}$ which is linearly extrapolated from the last two
footfalls, the continuous machine phase $\theta_{\text{machine}}$ is linearly extrapolated from the last two
beats.

The phase oscillator approach has several advantages over the algorithmic approach: it
has been studied extensively, it is easy to control parametrically and its behaviour predicted
(Buchli et al., 2006), an essential property for our purposes.

Furthermore, when we assume that the human acts as an adaptive oscillator and is drawn
to a stable phase lock; these parameters can be adjusted so that the adaptive machine stimulus
will have the tendency to increase (or decrease) the cadence of the user while maintaining
frequency matching and relatively stable phase locking. This could be used to entrain run-
ners, walkers or even Parkinson Patients to a particular cadence in a natural way. We will
not explore these options in this chapter, however they form a central topic in the European
Beathealth project.

This chapter will focus on only one set of parameters: an empirically determined $K = 1$
(trade-off between adjustment range and response time) and $\omega_{\text{machine}}$ matching a smoothed
SPM. This would theoretically allow a certain degree of freedom for the user but eventually,
both oscillators will always obtain a phase lock in a more natural way.

What does the model do exactly to the music? When the relative phase angle is between
-90 and 90 degrees, it will adapt the tempo of the music so that the next beat will occur
closer to the step. The coupling parameter indicates the maximum tempo change (compared
to the music oscillators frequency, matching the SPM). A high coupling will result in faster
synchrony but higher music tempo oscillations which we want to avoid. When the relative
phase goes outside the -90 to 90 degree range, it will attempt to synchronise by skipping
one relative phase cycle (speeding up to sync to the next beat).

Algorithm implementation

Our previous alignment strategies were based on a set of rules, which were applied at dis-
crete time intervals, such as a detected beat or a detected step. However, the dynamical
Kuramoto model required a different approach. Both the music and the walker were repre-
sented as phase oscillators $\theta_{\text{machine}}$ and $\theta_{\text{human}}$, which were updated at specific intervals
$\Delta t = 10 ms$. At such an update, the phase was calculated based on the current time $t$ and
last available steps ($s_n$ and $s_{n-1}$) or beats ($b_n$ and $b_{n-1}$). To calculate the phase of each
oscillator, we divide the time since last step/beat by last inter-step/beat interval and convert
this fraction to radians, using the following formulas:

$$
\theta_{\text{machine}} = \frac{t - b_n}{b_n - b_{n-1}} \ast 2 \ast \pi
$$

(3.3)
\[ \theta_{\text{human}} = \frac{t - s_n}{s_n - s_{n-1}} \times 2 \times \pi \] (3.4)

This however implies a certain inaccuracy: because phase is linearly extrapolated from the last two steps/beats, music tempo changes are not taken into account. Specifically, the time between the two last beats will not exactly match the time between the following two beats. However, the above formulas self-correct after each beat or step, which can result in small phase jumps at the first intervals \( \Delta t \) after a beat or step. The self-correcting dynamical phase oscillators are then used to calculate the current relative phase between music and gait.

The machine or music player has a pre-defined preferred or goal frequency, denoted \( \omega_{\text{machine}} \) and expressed in radians/second. The machine will manipulate its phase oscillator (by manipulating music tempo) to minimize the relative phase between music and footsteps. To use this as an alignment strategy which matches the music to the gait, the machine frequency has to match the current SPM value (for highly coupled oscillators) or a smoothed SPM value (i.e. average of the last 10 steps, for a weaker coupling). Given the feedback on our previous strategies, we preferred to test a weaker coupling (smoothed SPM, \( K = 1 \)).

This adaptive goal frequency is converted from steps per minute to radians/s:
\[ \omega_{\text{machine}} = \frac{\text{goal spm}}{60} \times 2 \times \pi \]

The relative phase between human and music is based on the two oscillators: \( \theta_{\text{relative}} = \theta_{\text{machine}} - \theta_{\text{human}} \) We then calculate the desired machine oscillator frequency using the following formula, with \( K \) being the coupling strength of the machine oscillator:
\[ \dot{\theta}_{\text{machine}} = \omega_{\text{machine}} + \frac{k}{2} \sin (\theta_{\text{relative}}) \] (3.5)

\( \dot{\theta}_{\text{machine}} \) is then converted to the more usable format in BPM:
\[ BPM_{\text{machine}} = \frac{\dot{\theta}_{\text{machine}} \times 60}{2\pi} \] (3.6)

Finally, the desired tempo is calculated by dividing the songs’ original BPM value by the desired BPM tempo.

**Hypothesis**

In this alignment strategy the phase and the period are continuously adapted to the participants’ phase and period. Accordingly, by definition, the participant will be synchronised with the music. If the technology works, there should be a statistically significant mean phase angle, close to 0°. We expect there will be more footsteps in synchrony with the music compared to all previous alignment strategies.
Participants
Thirty-eight healthy, adult participants (20 males) took part in the study. The participants were all recreational runners and had an average age of 31.00 years (SD = 8.27), a mean body mass of 69.82 kg (SD = 11.14), and an average height of 1.75 m (SD = 9.49). Every participant reported to be fit to run about 30 minutes continuously. Of all participants, 39.47% had received musical training. All participants reported that running is an activity that forms a part of their lives, with varying degrees of frequency (65.79% runs multiple times a week; 34.21% runs about once a week; 0% runs about once a month or less). Of all participants, about half (55.26%) reported to typically train without music, 23.69% generally runs with music, and 21.05% runs both with and without musical accompaniment.

Setup
The measurement system consisted of a 7” tablet (Panasonic FZ-M1) strapped to a backpack, several sensors, a pair of headphones, and a management computer. The tablet was the main hub that handled incoming sensor data, provided auditory stimuli, and was controlled remotely from the control desk via the management computer. During experiments, the tablet was sending sensor data to the management computer in order to be able to monitor the experiment in real-time.

To measure strides, participants were equipped with two iPods (4th generation); one attached at each ankle. Using the Sensor Monitor Pro application on the iPods, data from accelerometers and gyroscopes was streamed wirelessly at 100 Hz to the tablet.

Music tempi were manipulated using a phase vocoder, which time-stretched the music without pitch modification. The system logged all data and calculations in real-time. Finally, the resulting auditory stimuli were sent back to the participant using a Sennheiser HD60 headphones connected to the tablet.

The wireless connection between the tablet, iPods, and management computer was provided through a WiFi router (TP-Link M5360) strapped firmly to the backpack. The small router used a battery as power source. Strapping it to the backpack had the advantage that all the crucial components were close to each other and could communicate reliably. Only the management computer could have fallen outside of the WiFi range, which would have made it temporarily unable to monitor sensor data in real-time, without any further consequences for the rest of the experiment.

Task
The experiment took place in the Flanders Sports Arena of Ghent, Belgium. Participants were equipped with the iPods, the wireless headphone, and the backpack with sonar. Each
participant was asked to run on a 200 m running track 5 minutes continuously, for 6 times. One of these sessions they ran with the Kuramoto based alignment strategy and the rest of this chapter focuses only on this condition. Participants were instructed to run at their own comfortable tempo. No information was distributed concerning the real purpose of the experiment and all participants ran in solo conditions.

Each of the six 5 minute runs consisted of: 1) 25 seconds of running during which no music was presented, and 2) 4 minutes 35 seconds of running during which music was presented. In the first 25 seconds, the participant ran at his/her self-paced cadence without musical accompaniment. In the following 4 minutes 35 seconds, five songs of 50 seconds were played through the headphones. Songs were chosen with a tempo (BPM) close to the average cadence (SPM) of the final seven detected steps recorded during the previous song (or, in case of the first song, during the silence). After the song was selected, its tempo was adjusted using the Kuramoto based alignment strategy.

Stimuli

A music database consisting of songs in the tempo range of 120-200 beats per minute (BPM) was created, since natural running cadence (SPM) for recreational runners lies approximately in the same range. The list consisted of music from a previous running experiment (Van Dyck et al., 2015a) which scored high on the Brunel Music Rating Inventory 2 (BMRI-2) test (Karageorghis et al., 1999). In this previous test, in order to have an idea about the motivational qualities of the music, participants were asked to rate all items of the music database by answering six questions about the motivational aspects of each song. Each item referred to an action, a time, a context, and a target (e.g., 'The rhythm of this song would motivate me during a running exercise') (Ajzen and Fishbein, 1977). Participants responded on a 7-point Likert scale anchored by 1 ('strongly disagree') and 7 ('strongly agree'). Besides these songs, some more recent songs were added to the list of stimuli in order to make the list more up-to-date. In total, 43 songs with a clear beat and correct tempo range were pre-selected. In the course of the selection process, it was verified that the tempo of each song remained stable throughout the entire track. Using Audacity software (http://audacity.sourceforge.net), intros without clear beats were cut from the stimuli. BeatRoot (Dixon, 2007) was applied to track the beats of each song in order to ensure that only songs between 120-200 BPM were included, while ReplayGain was used to normalize perceived loudness and minimize possible imbalances in sound pressure level.

Results

In total, we recorded 28081 valid footfalls. The resulting distribution is shown in Table 3.5, the angular histogram is shown in Figure 3.10. The histogram shows a clustering of phase
angles around 0°. The distribution can therefore be interpreted as unimodal. We found that the distribution is not uniformly distributed with a statistical significant mean phase angle of $-6.20°$ (Rayleigh $z_{24902} = 1.1$, $p < 0.001$). The results confirm the hypothesis that this alignment algorithm shows the best results in terms of synchronisation. The resulting vector length $|R|$, equals 0.94. This indicates a high concentration of angles around the circular mean and also is the highest synchronisation rate out of all of the alignment strategies. Finally, individual analysis showed that all of the 38 participants had a significant mean angle, determined using the Rayleigh test. The individual resultant vector lengths are shown in figure 3.12.

**Discussion**

The results show that the alignment strategy is very effective in maintaining synchronisation. When looking at the resulting distributions, there does not seem to be much difference with our algorithmic approach (strategy 4); however in-depth data-analysis does reveal some interesting aspects of this model.

Figure 3.11 shows two in-depth data excerpts indicating the effect of the alignment strategy on the music tempo and phase angle.

First, we notice that the music tempo does not show any sharp increases or decreases when the participant goes out of sync; in contrast to our previous alignment strategy which often jumped 3% in tempo. The adjustments are much more subtle and result in phase angles very close to 0; except when gait tempo changes occur.

Secondly, while gait and music tempo do seem to correlate, we do not notice an exact
Figure 3.11: Excerpt from two participants during the experiment using alignment strategy 5 (Kuramoto). Figure A and C show the tempo plots, where the smoother tempo adaptation from the algorithm is clearly visible. Figure B and D show the resulting relative phase.
correlation with a certain lag (like strategy 2); but it looks more like an independent tempo follower. This results in more ‘freedom’ for the user - the music does not match immediately what the user does. An example can be seen when looking at a sudden increase in SPM or gait frequency (see fig 3.11 A&B at 95 seconds): the music tempo did not increase as much as the SPM, but it slowly increased towards the SPM. This resulted in a phase cycle (i.e. skipping one beat to catch up in the next cycle) and took about 10 seconds. This interaction is typical for the Kuramoto model as it allows for the individuality of each oscillator.

Example C and D show a relatively stable gait tempo. The resulting relative phase oscillates around 0°, as intended, whilst not influencing the music tempo with sudden jumps (in contrast to strategy 4, where even a stable tempo could still lead to tempo jumps due to phase drift).

The model thus seems to react fluently and loosely to the user, resulting in smoother audio playback (less tempo jumps). Again, there is no human entrainment needed to get in-phase. However, the increase in steps in sync indicates that the entrainment might be mutual: the additional freedom from the weak coupling allows the user to synchronise to the music themselves, resulting in more steps in sync. Using the Kuramoto model, both music and user synchronise with each other to form a stable system.

Unfortunately, subjective data (such as appreciation and motivation) is difficult to compare to other alignment strategies because the methodological differences between experiments. However, participants did not indicate the negative effects mentioned for strategy 4 (synthetic and mechanical feel). Subjective data will be analysed in future experiments comparing the different strategies in a more systematic experiment (see chapter 4.2).

**Conclusion**

The Kuramoto model can indeed be used as a music alignment strategy, leaving it up to the system to entrain to the user but allowing mutual entrainment due to the weaker coupling between user and music. This weaker coupling does not seem to decrease the amount of synchronised steps, nor were any negative effects experienced by participants with other strategies mentioned.

**3.7 General Results and comparison**

Table 3.5 summarises the alignment strategies and the related experimental context for each strategy according to the following contextual parameters: period adaptation, phase adaptation, number of participants, age, setup, walking area, stimuli, tasks, duration, and total of recorded valid steps. Table 3.5 also summarises the findings for spontaneous synchronisation for each experiment, according to the following statistical parameters: mean angle,
Figure 3.12: Resultant vector lengths of individual participants for all alignment strategies. The box plots show the distribution and mean of the resultant vector lengths.

upper 95% confidence limit, lower 95% confidence limit, resultant vector length $|R|$, variance $CV$, angular deviation $s$, circular skewness $b$ and circular kurtosis $k$. Table 3.6 gives a summary of the major results of this step-by-step development of the alignment strategies. Finally, figure 3.12 shows the distribution of the resultant vector lengths for individual participants.

Alignment strategy 1 leads to a ‘wobbling behaviour’ or an unstable synchronisation. The reason being is that the person adapts to the system, probably in attempt to try to align themselves to find a stable relative phase (see Discussion below), but the systems interprets this as a period change and adjusts it accordingly. We should also mention that the environment in which the D-Jogger system was tried out, namely a demonstration during an exhibition, may have stimulated a person’s explorative behaviour. The context may have stimulated an explorative attitude to test how D-Jogger would respond to different tempi. This explorative attitude could have had a negative effect on the stability of the synchronisation.

To overcome the wobbling effect, alignment strategy 2 uses a fixed period once the song is chosen. Note, this only occurs in this strategy where the tempo is not changed during the song. However, the phase is not controlled, which means that getting into the in-phase synchronisation is a task left to the participant. This strategy is successful once the participant accesses the stable phase synchronisation. However, getting in-phase appears more of a challenge than keeping the in-phase alignment. It should be noted that during the outdoor walk, there may have been some obstacles (e.g. stepping up and down a footpath,
Table 3.5: Summary of the five alignment strategies, algorithm descriptions, methodological differences and resulting phase distributions. φ is represented from -179° to +180° to increase consistency with earlier plots.

<table>
<thead>
<tr>
<th>Alignment Strategy</th>
<th>Period Adaption</th>
<th>Phase Adaption</th>
<th>Valid Participants (N)</th>
<th>Participants Age</th>
<th>Setup</th>
<th>Walking Area</th>
<th>Stimuli</th>
<th>Tasks</th>
<th>Duration</th>
<th>Recorded Valid Steps</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>Adaptive</td>
<td>Adaptive</td>
<td>119</td>
<td>22 ± 12</td>
<td>PC</td>
<td>Treadmill</td>
<td>pop selection</td>
<td>Any tempo</td>
<td>Voluntary</td>
<td>52,050</td>
</tr>
<tr>
<td>2</td>
<td>Adaptive</td>
<td>Adaptive</td>
<td>100</td>
<td>20 ±0.8</td>
<td>Mobile</td>
<td>Outdoor</td>
<td>pop selection</td>
<td>Any tempo</td>
<td>2 km walk</td>
<td>29,419</td>
</tr>
<tr>
<td>3</td>
<td>Adaptive</td>
<td>Adaptive</td>
<td>10</td>
<td>21 ±2</td>
<td>PC</td>
<td>Treadmill</td>
<td>pop selection</td>
<td>Any tempo</td>
<td>15 minutes</td>
<td>19.875 (0°)</td>
</tr>
<tr>
<td>4</td>
<td>Adaptive</td>
<td>Adaptive</td>
<td>10</td>
<td>21 ±2</td>
<td>PC</td>
<td>Treadmill</td>
<td>pop selection</td>
<td>Any tempo</td>
<td>15 minutes</td>
<td>20.348 (180°)</td>
</tr>
<tr>
<td>5</td>
<td>Adaptive</td>
<td>Adaptive</td>
<td>38</td>
<td>23 ±3</td>
<td>Tablet</td>
<td>Indoor Running Track</td>
<td>motivational pop</td>
<td>Run</td>
<td>30 minutes</td>
<td>104.334</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Alignment Strategy</th>
<th>Circular Variance CV</th>
<th>Residual vector length</th>
<th>Circular Skewness s</th>
<th>Circular Kurtosis k</th>
</tr>
</thead>
<tbody>
<tr>
<td>0°</td>
<td>1.7°</td>
<td>0.92</td>
<td>0.015</td>
<td>0.066</td>
</tr>
<tr>
<td>180°</td>
<td>0.3°</td>
<td>0.44</td>
<td>0.015</td>
<td>0.066</td>
</tr>
<tr>
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</tr>
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<td>0.015</td>
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<td>0.44</td>
<td>0.015</td>
<td>0.066</td>
</tr>
<tr>
<td>0°</td>
<td>0.3°</td>
<td>0.83</td>
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<td>0.066</td>
</tr>
<tr>
<td>180°</td>
<td>0.3°</td>
<td>0.44</td>
<td>0.015</td>
<td>0.066</td>
</tr>
</tbody>
</table>
other people walking) that disturbed the regularity of the gait.

In order to facilitate the entrainment, alignment strategy 3 sets the music in-phase to begin at the start of a song. During the remainder of the song, the tempo is adaptive, while the relative phase is neglected. Although this experiment was conducted under laboratory conditions on a treadmill, it suggests a major improvement over the phase-random approach of alignment strategy 1. The main finding is that being in-phase at the beginning of the song helps to maintain stable synchronisation immediately. And when the tempo changes, the phase will also change, but it will remain in synchrony with the participant.

Alignment strategy 4 is a special case because the music player is now entirely adapted to the person. This implies that there is no entrainment on the part of the person, only alignment. If the person changes phase or period, then the music player will respond immediately. This was experienced as forced and mechanical and has ample room for improvement.

Alignment strategy 5 uses another approach with adaptive oscillators, using a weaker coupling between music and user but resulting in even more steps in synchrony due to mutual entrainment.

To sum up, we can conclude that spontaneous human entrainment seems to be most effective in alignment strategy 3 for reasons that can be attributed to the in-phase lock at the beginning of the song. Interestingly, human entrainment to find the beat can be eliminated and replaced by machine entrainment, as shown in alignment strategy 4. The optimal system seems to be one that entrains the music to the user using a weak coupling, allowing for mutual entrainment, as shown in strategy 5.

<table>
<thead>
<tr>
<th>Alignment</th>
<th>Effect on entrainment and alignment</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>Person entrains to phase, but with unstable alignment</td>
</tr>
<tr>
<td>2</td>
<td>Persons entrains to phase, difficult but with possibility of stable alignment</td>
</tr>
<tr>
<td>3</td>
<td>Person entrains to phase, with stable alignment</td>
</tr>
<tr>
<td>4</td>
<td>Machine entrains to phase, no human entrainment, forced alignment</td>
</tr>
<tr>
<td>5</td>
<td>Machine entrains to phase, human entrainment possible (mutual entrainment)</td>
</tr>
</tbody>
</table>

*Table 3.6: Effect of strategy on entrainment and alignment*
3.8 Discussion

The results of the present paper suggest that the spontaneous entrainment between a person and music (D-Jogger) can be influenced by manipulating the period and the phase of the music.

3.8.1 Coupled rhythms

The results show that all strategies resulted in a significantly higher amount of steps in phase synchrony with the main beat (=phase-lock), when compared to a random playlist. However, the strongest synchronisation was obtained with strategies involving period and phase manipulation, so that songs start in perfect synchrony. The weakest synchronisation was obtained with strategies involving period manipulation, but not phase manipulation.

We assume that strategies that immediately lock the subject in-phase with the music (at the start of each song) are superior because they allow the subject to adopt a stable sensorimotor scheme (with phase-error correction mechanism) that predicts the beat more accurately right from the start of a song. Strategies that require the subject to find the in-phase lock are more difficult due to fluctuations in the interaction. Finding stable synchronisation requires more pull and push to effectively lock into a fluctuating attractor. If one injects too much effort, it may overshoot the balance, while injecting too little may result in a failure to attain the attractor. Instead, to keep stable synchronisation requires that once it is locked, some degree of tweaking and re-adjustment will be required to ensure it remains locked into the beat. In other words, less effort is needed to keep the alignment, than to find the alignment. Note that alignment strategy 4 and 5 not only eliminates the human task of finding the beat, it also eliminates the task of keeping the beat, and the subject stays aligned in-phase with the music.

The interacting rhythms should be seen as the result of a layered interplay of several factors. Our manipulations here are confined to timing only, leaving all other parameters of the music unaffected. However, due to the complex character of the human response, other factors may influence the entire interaction dynamics. Factors that determine the human rhythm are, among others, variability (Stergiou and Decker, 2011), motor resonance (Styns et al., 2007), and attending (Large and Snyder, 2009; Madison, 2014). Factors that determine the music rhythm are the intrinsic musical features that define the differences between songs, and the extrinsic manipulatory features that define how songs are played back using a music player. In light of the recent results produced by Leman et al. (Leman et al., 2013; Fritz et al., 2013), we are aware of the fact that musical style and physical exertion may have an strong motivational effect on music-movement interactions. Music style can either speed up or slow down walking velocity, even when the music has the same tempo. Although aspects of style and effort, as well as motivation in general, have not been
considered in the present study, we believe that an interactive personal-music system opens up promising new possibilities in our understanding of how music empowers people.

### 3.8.2 The influence of the starting phase

The coupled oscillator model suggests differences between the attraction force of the in-phase attractor and the anti-phase attractor (Haken et al., 1985a; Kelso et al., 1990). We have collected data on this difference from the third experiment, where we tested the period-adaptive phase-aware strategy. Recall that this alignment has a starting phase parameter, set to either 0° or 180°. More steps were located in the starting attractor basin when the starting relative phase was 0°, rather than when the starting relative phase was 180°. Again, less effort was needed to keep the alignment, than to find the alignment.

This shows that an attractor at 0° is much stronger than an attractor at 180°. Moreover, participants were more likely to maintain the same pace when the musical beat corresponded with the footfall - and started in-phase - than when the music started in anti-phase. The difference between the 0° and 180° condition is also visible in the individual analysis (see figure 3.12). We also found that all participants had a significant mean angle (using the Rayleigh test), similar to the 0° condition. However, due to the low number of participants in this experiment (N=10, all female) more research is needed before generalisations can be made about these results.

### 3.8.3 Limitations

The development of D-Jogger is based on an approach where experiments provided feedback for further development and optimization. For example, the strategy taken with the adaptive phase was, at first, not present in the music player. It was developed and tested only after having realised that the period-adaptive strategy was insufficient, and was not as efficient as the fixed period. Nevertheless, we believe that the development of D-Jogger followed a logical path. As with the adaptive phase, after having first tested the period adaptation strategy, we then introduced the phase adaptation strategy. The results led to consistent general findings about entrainment and alignment. However, a major limitation to this approach is that each of the experiments cannot really be compared alongside each other. The experiments were placed in different contexts for different versions of the strategy. Moreover, there were exhibition conditions and laboratory conditions, and differences in the size of the groups tested. A follow-up study (see next chapter) with a balanced control of conditions is needed to provide further comparison.

As to making comparisons of our work with the work of others, it should be noted that our emphasis on spontaneous entrainment is not the same as most of the walking-running studies that have been conducted thus far. When participants are requested to syn-
chronise with music played back, by means of a non-adaptive music player, one typically finds that synchronous music has numerous advantages related to ergogenic, physiological and/or psychophysiological aspects (Simpson and Karageorghis, 2006; Lane et al., 2011; Terry and Karageorghis, 2012; Bacon et al., 2012; Hoffmann et al., 2012; Karageorghis and Priest, 2012a). This requires that the participant engages with the music in an intended way, which might alter the participants natural gait pattern. However, we believe that in many applications, instructed entrainment is not always realistic. We also believe that it is important to understand the subliminal effects of entrainment and alignment, but here too, further research is needed.

3.8.4 Strengths of D-Jogger and open questions

The above results suggest that D-Jogger can serve as an assistive technology to motivate people to exercise physically. One application domain that has already been mentioned in the introduction is recreation, such as providing beat-locking during walking or running activities. However, D-Jogger can also be used as an assistive technology in the clinical context (e.g. as smart walkman for Parkinson patients), or for physical rehabilitation. Apparently, not everybody can synchronise to music, even when instructed to do so (Phillips-Silver et al., 2011; Styns et al., 2007; Leman et al., 2013). This group of people can be helped with a system that adapts to them. This shows the potential for an alignment strategy in which the entrainment problem is facilitated by the adaptability of the music player (alignment strategy 4). The merits of the strong, one-sided coupling are that there will always be synchronisation alignment, even if the user lacks a sense of rhythm or ignores the stimuli completely. Note that this approach makes objective comparisons between synchronised and unsynchronised music possible. For example, in endurance training literature, synchronised music requires participants to consciously synchronise to music and thus adapt their walking or running habits. This might result in biased comparisons as the participant, in order to synchronise to the music, under the controlled conditions may have run at a tempo that s/he would not have otherwise have run at. With this alignment strategy, one could determine whether there is a pure ergogenic or psychophysiological effect of the phase-synchronous music during exercise. In short, D-Jogger generates a number of new research questions such as: Which strategy is actually the best, and in what respect? What is the exact difference between spontaneous synchronisation and intended synchronisation in relation to performance? What is the role, the task, the context, the motivation, and the musical stimulus? D-Jogger thereby offers a new platform that allows such questions to be addressed in a manner that is straightforward.
3.8.5 Conclusions

The goal of the present paper was to develop and optimise the alignment strategies of D-Jogger, an adaptive music player that facilitates the elicitation of spontaneous entrainment. We showed that different alignment strategies can indeed have an effect on spontaneous entrainment behaviour. We found that entrainment may be less effective if the attractor (zero relative phase) fluctuates (which is often the case in an interactive setup). The solution is that the relative phase should be set close to zero right from the start of the interaction. This ‘being in-phase’ at the start seems to dramatically enhance the possibility of obtaining a stable synchronisation (‘keeping in-phase’), as it reduces the effort of ‘finding in-phase’. From a theoretical point of view, this means that entrainment is most effective when it maintains a given stable alignment between movement and music. Finding this stable alignment is much harder to achieve.

The reason for wanting to produce an adaptive music player is that it would empower people to walk or run at their own pace, using a music player that automatically adapts to that tempo. In addition, there are several applications in the domain of assistive technologies and physical rehabilitation, even for people that cannot entrain to an external auditory stimulus. We believe that our technology and the implied results offer interesting perspectives for further study, providing useful applications in the area of sports and physical rehabilitation.
Main research questions tested using D-Jogger technology

4.1 Introduction

In the previous chapters, we introduced the D-Jogger framework and five alignment strategies developed over the years. Using this framework, we were able to conduct a wide range of interdisciplinary experiments, the practical or theoretical applications of synchronous music. This work challenged us to leave our musicology and engineering domain; into sports and health - such as rehabilitation, Parkinson disease, sports physiology, music therapy, etc.

In this chapter, we present extended abstracts of experiments in which we were directly involved in all stages: conceptualising the experiment, methodology, execution, design and programming. The experiments directly followed our research questions presented earlier; and often are a collaboration with different faculties or universities because of their interdisciplinary nature. Additional details of the experiments can be found in the referenced paper.
4.2 Stratego: Does synchronous music influence runners’ motivation, cadence or velocity?

The first experiment we present is a comparison between the five presented alignment strategies. In the previous chapter, we’ve shown the iterative process and experiments but the experimental settings were not identical between strategies; making it difficult to compare.

This chapter, aptly named ‘Stratego’, compares the strategies with the same conditions, participants and music using a mobile version of D-Jogger in an indoor athletic track.

Publication title Various music-to-movement alignment techniques have different impact on beat-synchronised running and motivation

Status Submitted in February 2018 to Plos One.

Authors Jeska Buhman (1), Edith van Dyck (1), Bart Moens (1), Dobri Dotov (2), Marc Leman (1)

Affiliates This work was a collaboration between (1) IPEM (Department of Art, Music and Theatre Sciences, Ghent University, Ghent, Belgium) and (2) EuroMov (Université de Montpellier, Montpellier, France).

Introduction The previous chapters introduced alignment strategies in different settings and conditions. The logical next step was to compare the resulting strategies in ecologically and methodologically valid settings. Ecologically, we want to use a setting which is familiar to runners, namely free-running on an indoor running track instead of using a treadmill in a laboratory. Technical implications for this requirements resulted in our first mobile or transportable version of D-Jogger.

The aim of the experiment is to compare synchronisation parameters such as the phase distribution and resultant vector lengths (‘does it actually work in free-running?’), but also validate the impact of different music-to-movement alignment strategies on running behaviour in terms of motivation, cadence and velocity.

Methods The study was approved by the Ethics Committee of the Faculty of Arts and Philosophy of Ghent University and all procedures followed were in accordance with the statements of the Declaration of Helsinki.

Thirty-eight healthy, adult participants (20 males) took part in the study. The participants were all recreational runners and had an average age of 31.00 years (SD = 8.27), a mean body mass of 69.82 kg (SD = 11.14), and an average height of 1.75 m (SD = 9.49).
Every participant reported to be fit to run about 30 minutes continuously. Of all participants, 39.47% had received musical training. All participants reported that running is an activity that forms a part of their lives, with varying degrees of frequency. Of all participants, about half (55.26%) reported to typically train without music, 23.69% generally runs with music, and 21.05% runs both with and without musical accompaniment.

A music database consisting of songs in the tempo range of 120-200 beats per minute (BPM) was created, since natural running cadence (SPM) for recreational runners lies approximately in the same range. The list consisted of music from a previous running experiment (Van Dyck et al., 2015a) which scored high on the Brunel Music Rating Inventory 2 (BMRI-2) test (Karageorghis et al., 1999). Music was preprocessed using the procedure described in chapter two somewhere.

The measurement system consisted of a 7" tablet (Panasonic FZ-M1) strapped to a backpack, several sensors, a pair of headphones, and a management computer. The tablet was the main hub that handled incoming sensor data, provided auditory stimuli, and was controlled remotely from the control desk via the management computer. During experiments, the tablet was sending sensor data to the management computer in order to be able to monitor the experiment in real-time. Figure 2.3 in chapter 2 shows the experiment setup.

To measure strides, participants were equipped with two iPods (4th generation); one attached at each ankle. Using the Sensor Monitor Pro application on the iPods, data from accelerometers and gyroscopes was streamed wirelessly at 100 Hz to the tablet. Speed measurement was done using sonar and marker rods placed at a regular interval (see figure 4.1).
The wireless connection between the tablet, iPods, and management computer was provided through a battery powered WiFi router (TP-Link M5360) strapped firmly to the backpack. Strapping it to the backpack had the advantage that all the crucial components were close to each other and could communicate reliably. Incoming sensor data was processed by a customised version of D-Jogger (Moens et al., 2014). The adapted prototype contained new alignment algorithms to match the experimental protocol. Finally, the resulting auditory stimuli were sent back to the participant using a Sennheiser HD60 headphones connected to the tablet. The experiment took place in the Flanders Sports Arena of Ghent, Belgium (see figure 4.2).

![Figure 4.2: An ecological setting for runners: the Flanders Sports Arena (Ghent, Belgium)](image)

**Procedure** Each participant was asked to run on a 200 m running track 5 minutes continuously, for 6 times. Participants were instructed to run at their own comfortable tempo. No information was distributed concerning the real purpose of the experiment and all participants ran in solo conditions. After each 5 minute run, participants were allowed to have a break for several minutes in order to enable them to recover sufficiently. Meanwhile, they were asked to indicate how heavy the effort had been during the exercise. This was rated on a Rating of Perceived Exertion (RPE) Scale (Borg, 1998), ranging from 6 (‘no exertion at all’) to 20 (‘maximal exertion’). Besides, they were also asked to rate the level of physical enjoyment of the previous run on the 8-item version of the Physical Activity Enjoyment Scale PACES (Kendzierski and DeCarlo, 1991b; Mullen et al., 2011), a single factor scale to assess enjoyment of physical activity in adults across exercise modalities. Higher PACES scores reflected greater levels of enjoyment.
Each of the six 5 minute runs consisted of: 1) 25 seconds of running during which no music was presented, and 2) 4 minutes 35 seconds of running during which music was presented. In the first 25 seconds, the participant ran at his/her self-paced cadence without musical accompaniment. In the following 4 minutes 35 seconds, five songs of 50 seconds were played through the headphones. The tempo (BPM) of each song was based on the average cadence (SPM) of the final seven detected steps recorded during the previous song (or, in case of the first song, during the silence). The musical stimuli consisted of songs with tempi closest to the cadence of the runner and differing maximally 5% from the running cadence of the participant. After the song was selected, its tempo was adjusted to exactly match mean running cadence.

In each of the six 5 minute runs, a different alignment strategy was tested. The different conditions were randomized over the experiment in such a way that each participant performed all conditions but no participants performed the conditions in the same order. Afterwards, participants filled out a questionnaire on personal background, music education, and sports training.

Alignment Strategies / conditions  Six different strategies were compared:

1. Control: condition in which the tempo is not aligned with running cadence, but is 20 BPM faster or slower than the participant’s running cadence (SPM)
2. Adaptive tempo & random phase: condition in which the music tempo is adapted to the initial running cadence of the participant, without phase-locking the beat and footfall
3. Fixed tempo & random phase: condition in which the tempo of the music is continuously adapted to the runner’s cadence, without phase-locking the beat and footfall
4. Adaptive tempo & in-sync phase start: condition in which the music tempo is continuously adapted to the running cadence of the participant, with phase-locking the beat and footfall at the start of the condition
5. Adaptive tempo & adaptive phase: condition in which the tempo of the music is continuously adapted to the runner’s cadence, with phase-locking the beat and footfall continuously
6. Kuramoto: condition using the Kuramoto model for continuous tempo alignment, with phase-locking the beat and footfall continuously.

It was tested whether the different strategies would affect running synchronisation, cadence, running speed and motivation.

Main Results  In this experiment, the effect of the different conditions on the runners’ cadence (SPM), speed (km/h) and resultant vector length (a measure of tempo entrainment,
ranging from 0 to 1 with 1 representing perfect entrainment) was examined.

Repeated measures ANOVA revealed a significant main effect of condition on cadence, $F(5, 185) = 11.81, p < .001$, but not on speed, $F(5, 180) = 0.88, p = .50$. A repeated measures ANOVA with a Greenhouse-Geisser correction showed a significant main effect of condition on resultant vector length, $F(2.53, 91.05) = 387.16, p < .001$. Post hoc tests using Bonferroni correction for both cadence and resultant vector length, showing significant results ($p < .003$), are shown on the figures 4.3 and 4.4.

Wilcoxon signed-rank tests (comparing each strategy with the control strategy) were performed on the scores of the PACES scale. A Bonferroni correction was applied and so all effects are reported at a .01 level of significance. The motivational scores were higher when participants ran with strategy 6 ($Mdn = 71.38$) than with the control strategy ($Mdn = 67.25$), $T = 187, p = .008, r = -.31$. None of the other strategies showed differences in motivation when compared to the control condition.

\begin{figure}
\centering
\includegraphics[width=\textwidth]{sync_scores.png}
\caption{Synchronisation score or resultant vector lengths of each condition, where $R$ is calculated per song (not per condition); as different songs may have different mean phase angles complicating the interpretation. Error bars are 1SE.}
\end{figure}
Discussion

Not only can moving in synchrony with music have psychophysical and physiological benefits (Ramji et al., 2016; Bood et al., 2013; Lim et al., 2014; Terry et al., 2012), it might also evoke a sense of agency (Fritz et al., 2013). Figure 4.5 shows a slightly negative average phase angle in strategy 6 (Kuramoto), which tells us that footfall instants occur just prior to the beats and that this happens with great consistency, as reflected by a large resultant vector length. Although participants are not producing the music themselves, such a stable and slightly negative phase might evoke a feeling as if they are in control of the beats, often referred to as agency. In combination with a certain amount of physical exertion, this feeling of agency might contribute to a perceived positivity bias (Fritz et al., 2016) or a feeling of homeostasis (Leman, 2016) which could possibly explain the higher motivational ratings in strategy 6 compared to the allochronic strategy. However, more research on this matter is needed in order to draw more definite conclusions.

Conclusions

It was shown that the alignment strategy does have a significant effect on running cadence, synchronisation and motivation. However, no effect was noted on velocity (speed). As has been shown above, compared to the control, the adaptive tempo & random phase, the fixed tempo & random phase, and the adaptive tempo & in-sync phase start conditions, both the adaptive tempo & adaptive phase and the Kuramoto conditions
have been shown to result in a decrease in mean running cadence, although running speed did not change (thus, bigger steps were taken in these two conditions). With regard to tempo entrainment, compared to the other four conditions, again both the adaptive tempo & adaptive phase and the Kuramoto conditions proved to result in better entrainment with the tempo of the music. In this case, it was revealed that the Kuramoto strategy obtained the highest entrainment levels of all.

Figure 4.5: Phase distributions of the Stratego experiment.
4.3 Is synchronous music useful for Parkinson’s disease rehabilitation?

This section documents our initial tests in 2012 using the D-Jogger alignment strategies as music therapy for Parkinson Disease patients. During the European project BeatHealth, an additional analysis was applied on the data (DFA), eventually leading to this paper.

**Publication title** Effects of adaptive-tempo music-based RAS for Parkinson’s disease patients

**Status** Published as Moens et al. (2017, Proceedings of the ESCOM 2017 conference)

**Authors** Bart Moens (1), Leon Van Noorden (1), Wim de Wilde (2), Micheline Lesaffre (1), Dirk Cambier (2), Dobri Dotov (3), Patrick Santens (4), Jana Blomme (2), Heleen Soens (2), Marc Leman (1)

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**Introduction** Parkinson’s disease is characterised by an impaired basal ganglia function (Braak et al., 2003; Buhusi and Meck, 2005), which can lead to problems of movement timing and rhythm (Grahn and Brett, 2009; Graybiel et al., 1994; Schwartze et al., 2011). This loss in the ability to produce a steady gait can cause gait disturbances, such as shuffling steps, start hesitation and freezing. These debilitating symptoms of Parkinson’s disease (PD) have been associated with increased risk of falling (Hausdorff, 2009; Hove et al., 2012).

Pharmacological (i.e. medication) and surgical (i.e. deep brain stimulation) can positively influence gait cadence and velocity (Chen et al., 2013). In addition, patients can be helped with a non-invasive method: Rhythmic Auditory Stimulation (RAS), such as playing metronomes or marching music. RAS has been shown to be an effective method in improving gait in PD patients (Ashoori et al., 2015) and reducing costs associated with falling. Positive effects of the RAS cueing can even lead to benefits beyond gait (Benoit et al., 2014; Bella et al., 2015), such as improvement of quality of life. There are several different approaches for RAS, based on the type of stimuli (metronomes, marching songs, music) and tempo (fixed tempo, adaptive or interactive tempo).
Fixed tempo RAS has been researched the most, and has shown to improve many aspects of gait timing (Thaut and Abiru, 2010; Rubinstein et al., 2002; McDonough et al., 2001). Most notably, the fixed tempo RAS can increase gait tempo and stride length (McIntosh et al., 1997) and decrease the magnitude of stride-time variability (Arias and Cud-eiro, 2008; Hausdorff et al., 1996). Despite these results, the use of fixed tempo RAS in Parkinson rehabilitation has limitations because it requires synchronisation to a metronome or music. PD patients, however, have an impaired ability to synchronising gait with the RAS (O’Boyle et al., 1996). Synchronising gait with auditory rhythms presents attentional demands, which can be problematic for PD patients, for example due to difficulties with multitasking (Rochester et al., 2004). The task to synchronise walking to external stimuli is sometimes even hard for healthy population (Styns et al., 2007).

It has been suggested that RAS that adapts to patients’ movements may be more effective than fixed tempo RAS (Ashoori et al., 2015). Adaptive RAS uses feedback from human walking rhythm to determine cueing or RAS rhythm. A cueing system that aligns to the patients’ movements could reduce attention demand and could improve gait more than with fixed, non-adaptive cueing (Hove and Keller, 2015). Walk-Mate (Miyake, 2009b), for example, is an adaptively timed metronome used as adaptive RAS (Uchitomi et al., 2011; Hove et al., 2012). They found positive results on spatiotemporal parameters (cadence, velocity, step length) for all RAS types. Additionally, they showed that the isochronous metronome introduced unnatural random variation in the gait timings, but that the adaptive RAS raised the patients’ gait timings to almost normal or healthy levels.

It is easy to see that the D-Jogger alignment strategies are, in fact, RAS strategies in rehabilitation contexts. Therefore, the aim of our study is to test if the same positive kinematic effects of using fixed and adaptive RAS are also present when used with music (as compared to the metronome approach by Walk-Mate).

DFA: Fractal scaling exponent  Gait dynamics can be analysed using Detrended Fluctuation Analysis (DFA) (Peng et al., 1995; Goldberger et al., 2002). The resulting fractal-scaling exponent alpha is associated with gait adaptability and is one of the best measures of predicting falling (Herman et al., 2005; Bartsch et al., 2007; Hausdorff et al., 2000). The main goal of RAS is to improve gait patterns and reduce falling, therefore the alpha DFA value seems an important tool to assess RAS systems, in addition to conventional measures such as stride length, cadence, etc.

DFA analyses long-range correlations in time-series, or in this case, stride interval timings. The method, in contrast to standard variability, determines whether the gait pattern is predictable, based on previous steps. The result of the analysis is called the DFA fractal-scaling exponent or the ‘alpha value’ which has a useful meaning between 0 and 2.

The alpha value is an intuitive measure: based on previous steps (e.g. short, long) we
should be able to predict the next step (similar, following a speedup or slowdown trend, etc). If the pattern is not predictable, a step interval could be followed by any unrelated step interval, which would seem unnatural. We note the following alpha levels (Hausdorff et al., 2000) with the interpretation to the gait:

- Alpha < 0.5: anti-persistent stride intervals: long steps are often followed by small steps and vica versa (Beran, 1994).
- Alpha ≈ 0.5: stride intervals are random distributed and unpredictable, seemingly white noise.
- Alpha ≈ 1.0: stride intervals represent a $1/f$ sequence. This is a common pattern for self-organizing systems (Bak et al., 1987) and indicates long-term correlations in the data. The previous strides can be used to predict the next steps. Strides are most likely followed by strides of about the same interval; but over time the interval tends to fluctuate. This is most similar to healthy walking (Jordan et al., 2007).
- Alpha ≈ 1.5: stride intervals represent Brownian noise.

Healthy people show a value of around 1.0 in normal walks. PD patients often exhibit a fractal scaling value around 0.5 in normal walks without RAS (Bartsch et al., 2007; Hausdorff et al., 2000) depending on the advancement in functional impairment.

Fixed-tempo metronome RAS has been show to decrease the alpha value away from healthy levels (Delignières and Torre, 2009), as stride-time variability becomes organized around a single frequency. Hove et al. (Hove et al., 2012) have shown that using adaptive metronome-based RAS, patients’ alpha value increased towards healthy levels, reducing the risk of falling. However, this was only tested with metronomes.

**Methods**  This trial was ethically approved by the Ethical Committee of the University Hospital of Ghent.

29 patients, 17 men and 12 women, (age M = 66.16, SD = 8.18) with an idiopathic form of Parkinson’s disease were included. Patients’ disease severity was Hoehn and Yahr Stage 2.5 to 4, nine patients reported freezing on the NFOG questionnaire and the mean duration of disease was 6.84 years (SD = 3.52). All patients were able to walk two minutes repeatedly. Patients with deep brain stimulation, severe gait disorders and Parkinson-plus syndromes were excluded. All patients were tested while ‘on’ medication.

Before the actual testing procedure began, participants completed an intake questionnaire including the unified Parkinson’s disease scale (UPDRS) and the new freezing of gait questionnaire (NFOG-Q) (Nieuwboer et al., 2009). A Borg scale was taken before and after conditions to evaluate the influence of fatigue (Borg, 1982; Chen et al., 2013).
The participants walked around a rectangular shaped trail (15 m long and 3.02 m wide, see figure 4.6) whilst allowing for big turns. Participants walked for two minutes in four different conditions, alternated with six minutes of rest. After the experiment a short interview was taken by the experiment supervisors to gather information on participants’ experience.

![Figure 4.6: Location of the experiment](image)

A GAITRite mat, a sensor-augmented mat of 9 metres long, measured spatial and temporal gait parameters such as cadence, step length and gait variance (McDonough et al., 2001; Bilney et al., 2003). Auditory stimuli were provided using a modified version of the D-Jogger system (Moens et al., 2014). Custom music alignment algorithms were implemented to match this experiment RAS requirement. The D-Jogger software was running on a Dell Latitude i7 laptop (Dell E6520). Two iPods (4th generation) attached at each ankle were used for real-time gait analysis. The wireless connection between was provided through a WiFi router (TP-Link M5360). Finally, the selected and aligned music was sent back to the participant using wireless Sennheiser HD60 headphones with the base-station connected to the computer. A music database was generated a priori based on Li et al’s (Li et al., 2010) recommendations (based on tempo, cultural, and beat strength features). We selected popular and stimulating radio songs, which we believed to be familiar to the patients; with stable tempi in the range of 80-130 BPM.

**Data capture and statistics** Spatiotemporal data was captured by the GAITRite system, synchronisation data was provided by the D-Jogger system. The D-Jogger system also provided step and stride times for each trial used in DFA analysis. To calculate the DFA alpha values, the left stride times were used because this was the most complete dataset. In some cases, sensor data was corrupt (i.e. due to low batteries) and the right stride times were used instead. For each trial, the first 20 and last 5 strides were ignored, as well as outliers that indicate a missed step in the data processing. On average, 123 ± 15 strides were used
from each trial to calculate the alpha value. The DFA alpha values were calculated using the algorithm described by Peng et al. (1995). The implementation in Matlab used a maximum bin size of 100 and an advancement of 10 steps. Synchronization scores were calculated using the Circular Statistics Toolbox in Matlab Berens et al. (2009). All data were processed in Matlab and analysed in SPSS using repeated measures ANOVA with post hoc test using Bonferroni corrections.

Spatiotemporal data was captured by the GAITRite system, synchronisation data was provided by the D-Jogger system. The D-Jogger system also provided step and stride times for each trial used in DFA analysis. To calculate the DFA alpha values, the left stride times were used because this was the most complete dataset. Synchronization scores were calculated using the Circular Statistics Toolbox in Matlab (Berens, 2009). All data were processed in Matlab and analysed in SPSS using repeated measures ANOVA with post hoc test using Bonferroni corrections.

**Music alignment strategies / conditions** The only instruction, given in the different conditions, was to walk for two minutes around the rectangle, enabling to determine the effect of RAS on their gait. No instructions or explanations about synchronisation were given before or after the experiment.

First, participants walked on a comfortable pace without RAS as a baseline step rate measurement (= no RAS condition). Afterwards, there were three conditions, which were counterbalanced to exclude the influence of fatigue. A first RAS condition was walking with the use of a metronome with a tempo that matched the baseline step rate (= fixed tempo metronome condition). A second RAS condition used music with a tempo that matched the baseline step rate (= fixed tempo music condition). Finally, a third interactive RAS condition used music with a tempo and phase that matched the step rate during the walking task (= adaptive-tempo music condition).

**Population** Out of the 29 participants, four had a missing value in one of the conditions registered by GAITRite. The results of these four participants were not included in the data processing or statistical analysis, resulting in 25 participants (15 men and 10 women). The mean age was 66.7 (SD 8.2), height 168.6 cm (SD 8.6), weight 74.8 kg (SD 16.9), were diagnosed 6.8 years (SD 3.5) and scored on UPDRS part 1 on average 2.8 (SD 1.4); on the UPDRS part three 41.0 (SD 11.3). There were 9 freezers (based on the NFOQG).

**Results** Using repeated measures ANOVA tests with a Greenhouse-Geisser correction, we found significant main effects on the velocity ($F(2.08, 49.98) = 4.0, p < .05$), stride length ($F(2.26, 54.21) = 8.63, p < .001$), fractal scaling ($F(2.36, 51.53) = 11.06, p < .001$) and synchronisation ($F(2.00, 48.00) = 5.332, p < .01$). No significant differences were found
for cadence and fatigue. Table 4.1 and figures 4.7 and 4.8 show the details of these results. We note some relevant post-hoc (Bonferroni corrected) results:

- Patients walked significantly faster in the fixed metronome ($p < .05$) and fixed music ($p < .05$) condition when compared to the no RAS condition.

- Stride length also increased significantly for fixed metronome ($p < .01$), fixed music condition ($p < .01$) and adaptive music condition ($p < .05$) compared to the no RAS condition.

- Patients had a more natural DFA scaling value using adaptive music when compared to fixed metronome ($p < .01$) and fixed tempo music ($p < .01$).

- Interestingly, no significant difference was found between adaptive music and the baseline (no RAS). With the fixed metronome RAS, patients’ stride had a lower fractal scaling than during the silent-control condition ($p < .05$).

- There was significantly less synchronisation in the fixed music condition than in the music adaptive condition ($p < .02$). We note that, while not statistically significant, the resultant vector length for the fixed metronome condition is lower than for the adaptive music condition but higher than the fixed music condition. This indicates that the adaptive system increased step-beat synchronisation (as it was designed to do); and that music at a fixed tempo is slightly more difficult or less intuitive to synchronise to than metronomes. However, spontaneous synchronisation to metronomes is still lower than the adaptive system.

<table>
<thead>
<tr>
<th>n = 25</th>
<th>Velocity (cm/s (SD))</th>
<th>Cadence (SPM (SD))</th>
<th>Stride Length (cm (SD))</th>
</tr>
</thead>
<tbody>
<tr>
<td>No RAS</td>
<td>119.27 (20.71)</td>
<td>113.92 (12.88)</td>
<td>124.29 (17.76)</td>
</tr>
<tr>
<td>Metro, fixed</td>
<td>124.77 (20.53)</td>
<td>115.19 (11.61)</td>
<td>129.69 (17.81)</td>
</tr>
<tr>
<td>Music, Fixed</td>
<td>124.65 (21.35)</td>
<td>116.10 (11.65)</td>
<td>129.31 (18.19)</td>
</tr>
<tr>
<td>Music, Adaptive</td>
<td>124.55 (17.88)</td>
<td>116.36 (12.02)</td>
<td>129.26 (16.27)</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>n = 25</th>
<th>BORG (cm/s (SD))</th>
<th>R (SPM (SD))</th>
<th>Alpha DFA (cm (SD))</th>
</tr>
</thead>
<tbody>
<tr>
<td>No RAS</td>
<td>9.64 (2.66)</td>
<td>0.00 (0.00)</td>
<td>0.67 (0.29)</td>
</tr>
<tr>
<td>Metro, Fixed</td>
<td>10.20 (2.53)</td>
<td>0.59 (0.33)</td>
<td>0.41 (0.30)</td>
</tr>
<tr>
<td>Music, Fixed</td>
<td>10.20 (2.57)</td>
<td>0.50 (0.31)</td>
<td>0.51 (0.23)</td>
</tr>
<tr>
<td>Music, Adaptive</td>
<td>10.12 (2.22)</td>
<td>0.72 (0.19)</td>
<td>0.84 (0.37)</td>
</tr>
</tbody>
</table>

Table 4.1: Results

Discussion The results of our study largely agree with other recent studies (Uchitomi et al., 2011; Hove et al., 2012; Rubinstein et al., 2002; del Olmo and Cudeiro, 2005).
Basic kinematic measures (velocity, cadence and step length) did not differ significantly between RAS conditions. However, the addition of adaptive music together with the measurements of the DFA alpha (as a falling predictor) and the resultant vector length (as a measure of synchronicity) opened up some interesting viewpoints, especially towards the use of metronomes vs. music in a RAS system.

**Metronomes: not as efficient as hoped?** Fixed metronome-based RAS provides a significant benefit in terms of spatiotemporal gait structure for PD, increasing stride lengths and velocity. However, we also noted a negative effect of metronome-based RAS: the fractal scaling value was lowered significantly, from slightly correlated inter-stride times (a = 0.65) to anti-persistent inter-stride times (a = 0.4); while optimal walking patterns show an alpha of around 1. Lower values have been linked to falling (Herman et al., 2005; Bartsch et al., 2007), so this can be seen as a negative effect of metronome-based RAS. Anti-persistent means that large steps are often followed by small steps. This could be a result of humans’ tendency to synchronise to rhythms close to our own (Moens et al., 2014; Van Dyck et al., 2015a), while walking to fixed tempo RAS: we tend to 'self-correct' so our steps match the metronome tick; even when not instructed to synchronise. The reasoning is also strengthened by the negative correlation found between the amount of spontaneous synchronisation (R) and the alpha value: when the patient did not synchronise to the RAS, alpha values returned towards the baseline level but high synchronisation scores lead to
lower alphas. There was a strong, negative (Spearman’s rank-order) correlation between R and alpha for the metronome condition, which was statistically significant ($r(26) = -0.718, p < .001$), meaning that, if the patient spontaneously synchronised to the metronome, the fractal scaling became worse and increased the risk of falling. The negative correlation was not present with fixed music or adaptive music. Spontaneous entrainment or synchronisation is only possible when gait and music cadence don’t differ much (Van Dyck et al., 2015a), so this could be a reason why metronome RAS is often used at +10% tempo compared to baseline (Willems et al., 2006): to avoid synchronisation which reduces fractal scaling.

- Adaptive music: less efficient to influence cadence and velocity but potential decreasing the risk of falling. we can confirm the positive effects of music RAS on velocity (fixed-tempo) and stride length (fixed-tempo / adaptive-tempo). However, the effects of musical RAS were less significant than fixed metronome based RAS. We note that with these results, the adaptive tempo RAS seems the least efficient: it only significantly raises stride length. The lesser efficacy of music could be partially explained by the individual preference for music, a more complex stimuli than metronomes. For example, it has been shown that the familiarity with the music has a significant effect on the changing of the gait parameters (Leow et al., 2015;
Ashoori et al., 2015). With both music conditions, we found no correlation between the synchronisation score $R$ and the alpha value, whereas for metronomes, a negative correlation was found. The advantage of adaptive-tempo music RAS stimuli becomes clear when looking at the alpha value. The metronome lowered the alpha value compared to the no-RAS condition, indicating an increased risk of falling; but the adaptive-tempo music significantly increased the alpha value compared to the metronome condition. This indicates that adaptive-tempo music is significantly better in reducing falling risk than regular metronome RAS. Furthermore, walking on music was the most preferred condition, which is in line with findings of de Bruyn et al. (de Bruyn et al., 2010) who showed that walking on cadence-matched music is feasible and enjoyable for PD Patients,

- **Adaptive cueing could lower the cognitive tasks to synchronise.** No explicit instructions to synchronise to the music were given. The resulting intuitive synchronisation scores are the highest for adaptive music, followed by fixed metronome, whereas fixed music had the lowest $R$ score. The adaptive tempo music RAS was designed to synchronise to the patient and also phase-correct, resulting in a high synchronisation score. In the non-adaptive RAS conditions, the patient needed to synchronise (sometimes unsuccessful) to the music to obtain a high $R$. Music is more complex and often deviates small fractions from the mean tempo when compared to metronomes, which could explain the lower synchronisation rate to music compared to metronome (yet insignificant). This might indicate that spontaneous synchronisation to music induces a higher cognitive load than synchronisation to metronomes, and that adaptive cueing lowers the cognitive tasks to synchronise. This can be advantageous especially for freezers. Nieuwboer (Nieuwboer, 2008) concluded that freezers have less effect of cueing when attention is overloaded (e.g. during therapy). Interestingly, the synchronisation result $R$ of the fixed metronome condition correlates with the fractal scaling alpha of all three conditions. There is a negative correlation for the fixed metronome (see earlier) but also for music ($r(26) = -0.378, p < .05$), while there is a positive fractal scaling correlation ($r(26) = 0.485, p < .01$) for the adaptive music condition. This could indicate that spontaneous 'synchronisers' (with a high $R$ on the metronome) have the most benefit of adaptive music (a high value of alpha).

**Limitations** We are aware of multiple limitations of this presented study. To begin with, the lack of a healthy control group makes it difficult to know if the results are generally applicable or only valid for PD patients. Second, the amount of time per participant was restricted, limiting the RAS conditions to three. However, an adaptive metronome should have been included in the study allowing better comparisons between RAS standards. A third constraint is that we did not differentiate between freezers and non-freezers, or gender,
as the resulting groups was quite small. Finally, we did not take into account possible carry-over effects of the different conditions (it has been shown that positive cueing effects persist for a short while after the training sessions (McIntosh et al., 1997; Hausdorff et al., 2007; Benoit et al., 2014). Finally, the music selection was not standardized which could have had an influence on the gait velocity of the patients (Buhmann et al., 2016a).

Conclusion Our main conclusion is that metronome-based RAS should not always be considered the best cueing stimuli for Parkinson Disease patients. Music shows less pronounced effects on typical measures such as cadence and velocity, but it has a positive effect on the gait predictability or the fractal scaling. Adaptive music even increased the fractal scaling towards healthy-gait variability, potentially lowering fall risk. In contrast, metronomes make inter-step intervals unpredictable, which increases risk of falling.
4.4 Does running on synchronous music reduce energy consumption?

This section documents our earliest experiment in sport sciences. From the conceptualization of D-Jogger, we were curious as to what effect synchronous music (in our definition as phase-synchronised) would have on a runner. Together with the Sports Faculty of UGhent, the first interdisciplinary collaboration made with D-Jogger, an experiment was designed to assess the influence on the running economy of synchronous music.

**Title**  Synchronous and asynchronous musical influence on psychophysical variables during prolonged exercise running

**Status** Unpublished. We did not find any physiological effects of synchronous music; but we saw ‘responders’ with positive effects and ‘non responders’ with null effects. The submissions were rejected because these groups were to small to be conclusive. While this paper is not published, we feel it is an important part of our research as these results could not confirm popular findings that list positive physiological effects of synchronous music (Terry et al., 2012; Bourgois and Vrijens, 1997); which might be partly due to difference in participant selection and synchronisation method.

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**Affiliates** This work was a collaboration between (1) Department of Movement and Sports Sciences, Ghent University, Ghent, Belgium, (2) Institute for Psychoacoustics and Electronic Music (IPEM), Department of Musicology, Ghent University, Ghent, Belgium and (3) Centre of Sports Medicine, Ghent University Hospital, Ghent, Belgium

**Introduction** On February 18th, 1998, Haile Gebrselassie ran a new 5000m world record on the beats of the ‘Scatman’ song. Starting from that moment new research questions arose about the possible influence of music on sports performance. Music is a well know motivational tool that is used in recreational sports or athletical training. Main reasons are its possible ergogenic effects on performance as well as increased exercise enjoyment. Karageorghis reports: ’of the 32 studies that have been performed, 24 reported ergogenic effects of asynchronous and synchronous music on different sports performances (rowing, running, cycling,...)’ (Karageorghis and Priest, 2012b). Well selected motivational music increases the exercise enjoyment(Wininger and Pargman, 2003) or the mood scales towards an exercise task(Karageorghis et al., 2009). This effect seems to be more beneficial in an
untrained population (Mohammadzadeh et al., 2008) and in low to moderate intensities as no differences in rate of perceived exertion (RPE) were found in high intensity conditions (Tenenbaum et al., 2004; Yamashita et al., 2006).

The tempo of the music also plays a major role in the effects. Asynchronous (SPM and BPM differ) and synchronous (SPM and BPM are very similar) music have similar psychophysical benefits, but the ergogenic effects in the synchronous music condition exceed those in an asynchronous music condition. E.g. in the motivational synchronous music conditions treadmill walking endurance increased with 15% and a strong positive influence was found on post exercise mood scales (Karageorghis et al., 2009). One of the few studies that combined physiological measurements such as gas analysis and lactate measurements with different music conditions and performance is Terry et al. (Terry et al., 2012) who found a longer time to exhaustion in a neutral and motivational music condition in Eleven elite triathletes. Oxygen consumption ($VO_2$) and Heart Rate (HR) was lower with music (1.0-0.7%) and both music conditions were associated with better running economy (REC).

Music seems to play an important role in exercise enjoyment and/or perception (Wininger and Pargman, 2003), however the underlying mechanisms of the effects of music are not well known. Also the extent in which different motivational music conditions (asynchronous and synchronous) influence the psychophysical benefits towards health outcomes are currently unknown. Karageorghis and Priest (2012b) express the need to study the effects of self selected music that would automatically adjust the rhythm to the exercise (synchronised music). However, to our knowledge this has not been done so far. Moreover, almost all past researches focused on performance (e.g. time to exhaustion, 400m performance) comparison between no music and music conditions. In contrast, examining fundamental physiological variables in a protocol with standardized intensity and no performance measurements would be very useful (Karageorghis and Priest, 2012b).

In short, we believe that the study of the effect of non-synchronised and synchronised music, and the measurement of physiological variables during prolonged exercise (no performance measurement) can add new insight into the role of music in sports activities and performances. From this perspective our purpose was to investigate fundamental physiological and perceptual variables during a Prolonged Exercise Test (PET) at two different submaximal intensities in three music conditions. With the use of the D-jogger device, it was possible to synchronise the motivational music to the running frequency (Moens et al., 2010).

**Methods** 10 physical active males and females (4 male, 6 female) were recruited from the Physical Education and Movement Sciences Institute from Ghent University. Their age, height and body weight were respectively 24 (SD 3) years; 174 (SD 10) cm and 66 (SD 10) kg (mean values and standard deviation). The subjects were fully informed of any
risk associated with the experiments and had a medical checkup preceding any testing and before giving their written consent for participation. The study was approved by the ethics committee at the Ghent University Hospital.

Seven treadmill running conditions were performed by each participant, at a maximum rate of 2 per week. The conditions included a pretest and 6 music conditions. Measurements of interest were running efficiency determined using oxygen consumption, heart rate and Rate of Perceived Exertion (RPE, BORG). Blood analysis were done by means of a radiometer (ABL-90 radiometer, Bronshof, Danmark). Oxygen uptake was registered by means of a metabolic measurement system (Jaeger Oxycon Pro, Hochenhausen, Germany).

The pretest was one to determine medium and high running intensities (MIC and HIC), as we hypothesised the influence of the music might differ significantly between running intensities.

Given the complexity and safety requirements of this setup, it was not feasible to perform this experiment in ecological settings and was therefore performed in the sports science laboratory (see figure 4.9).

**Figure 4.9: D-Jogger Energy Consumption experiment setup**

**Alignment Strategies / Conditions** Prior to the protocol, we used the BMRI-2 inventory (Karageorghis et al., 2006) to let all subjects compose their individual motivational music selection. 80 pop songs were available from recent all-time high radio charts. The most motivating songs per participant were divided into two playlists: the asynchronous music, containing music with moderate BPM values (110-130 BPM) and the synchronous
music, containing music with higher BPM values (150-180 BPM).

The D-jogger device (Moens et al., 2010) was used to synchronise the motivational synchronous music to the running frequency. There were three music conditions or alignment strategies:

- No-music control condition.
- Asynchronous music: music with a lower BPM was used without tempo modifications, making it practically impossible to run in step synchrony with the music as the gait tempo (150-180 SPM) did not match the music’s tempo (110-130 BPM).
- Synchronous music: faster music was used, and the tempo of the music was adapted so each footfall coincided with a beat, independent of the rhythm response of the participant. Because the synchronised music contained only high-tempo music (150-180 SPM), the required music tempo adaptation to match the runner’s frequency was relatively small (< 10% tempo adaptation).

All three conditions were performed at two different running intensities: medium intensity condition (MIC) and high intensity condition (HIC), both determined in a $VO_{2peak}$ pretest. This resulted in 7 different conditions. A repeated measures ANOVA analysis was used to compare the physiological and perceptual variables (5) between different music condition at the registration moments (33) in the MIC and HIC.

**Results** We found no significant differences for both the MIC and HIC conditions between all music conditions for all variables (heartrate, lactate, running economy, energy consumption and even perceived rate of exertion). While this was a fairly disappointing result, it is interesting to note that it is in contrast with other studies. However, an in-depth data exploration showed that almost every subject responds consistently positive or negative for both asynchronous and synchronous music. These contradictory findings are further explored in the discussion. Tables 4.10 and 4.11 show the results in detail at the four different measurements during the protocol. We can see that these follow very logical trends: eg RPE and HR increase significantly as the exercise progresses and are higher in the HIC than MIC conditions, etc. This partly shows that the measurements are correct - but that we just did not get the results we expected.

**Discussion** Despite the fact that Karageorghis et al. (Karageorghis et al., 2009) found a stronger positive effect of musical influence using the synchronous application, we found no differences between both music conditions (asynchronous and synchronous). A possible explanation could be the different approach of study design as we decided to use prolonged exercise instead of exhaustive exercise (Karageorghis et al., 2009). Also, the imposed task
was treadmill walking instead of treadmill running which is also an important difference. Another important aspect to mention is the different approach towards synchronous musical stimuli in comparison with other studies. In our study music adapted to the participant so each footfall coincided with a beat, requiring no adaptation whatsoever from the participant to be and perceive synchronicity with the music. The ability to be synchronised was therefore also independent from the rhythmical response ability of the participant. This is important because it has been shown not everybody can synchronise to musical stimuli, even when instructed to do so (Styns et al., 2007). In other studies, a preferred gait tempo was measured during a pretest to which the music was adapted so the participant could run in sync. This could imply that the participant had to adapt him/her herself in order to be in sync - running at an unnatural frequency during the actual test which could explain the differences found in other studies (Karageorghis et al., 2009) between synchronous and asynchronous music as well. When a subject synchronise his running frequency to music that has slightly higher beats per minute, the performance could be improved.

The deviations of both music conditions with respect to the condition without music shows that almost every subject responds consistently positive or negative for both asynchronous and synchronous music. Based on RPE it is possible to make a distinction between 'positive' and 'negative' responders especially when their RPE differs remarkably towards a 'no music' condition. In our global analysis, we found that these differences resulted in insignificant results. Unfortunately, the resulting groups of responders and non-responders were too small for any statistically valid analysis.

We also found that in the MIC and the HIC-protocol, RPE-values did not differ significantly between conditions. However, a general negative response in the MIC and HIC music conditions towards the 'no music'-condition can be observed. The lower RPE-values (in %) for asynchronous and synchronous music in almost every individual indicate a higher exercise enjoyment (Wininger and Pargman, 2003) and/or potential differences in perception of certain physiological stimuli. Despite the fact that all physiological variables show that the exercise intensity in the HIC conditions is strenuous, RPE values are lower in the music conditions. A possible explanation for the lower RPE-values in general could be the fact that music is an exogenous stimulus which possibly diverts the attention from the activity itself. This shows that during prolonged exercise perception of exertion (RPE) can be positively influenced with music.

Conclusions  With this research we tried to fill in a lack of information carrying out physiological measurements in a protocol with standardized intensities. To conclude we can suggest that the group of subjects is composed of positive and negative responders towards musical influence. In general the perceptual parameter (RPE) was positively influenced by asynchronous and synchronous music in the MIC and HIC condition. However, no diff-
ference was found between asynchronous and synchronous music. Physiological variables like the HR and $VO_2$ were not significantly different but slightly higher values were found indicating that the exercise enjoyment and excitement are minimally influencing the physiological stimuli during MIC. These findings can be relevant towards the use of music in sports activity and performance, whereas perception is the parameter that varied positively in the musical conditions.

**Practical Implications:**

- Synchronous and asynchronous music influence slightly positive perception of exercise
- No difference was found between asynchronous and synchronous musical influence.
- Positive and negative responders towards musical influence could be recognized.
Figure 4.10: Physiological responses to 30 min treadmill running in de No music (N), Asynchronous music (A) and the Synchronous (S) music in the MIC condition (mean and SD) of 10 subjects are presented. Significant main-effects were pointed out with: $0.1 > p > 0.05$, $p < 0.05$, $p < 0.01$, $p < 0.001$. Post hoc pairwise differences between different time measurements are shown by the letters a,b,c. The same letter indicates that the parameter did not differ between the bouts. Bouts with a different letter significantly differ ($p < 0.05$ was used as the level of significance). Post hoc pairwise differences between different music conditions are shown by the symbols δs,Κ,θ s.
Figure 4.11: Physiological responses to 30 min treadmill running in de No music (N), Asynchronous music (A) and the Synchronous (S) music in the HIC condition (mean and SD) of 10 subjects are presented. Significant main-effects were pointed out with: $0.1 > p > 0.05$, $p < 0.05$, $p < 0.01$, $p < 0.001$. Post hoc pairwise differences between different time measurements are shown by the letters a,b,c. The same letter indicates that the parameter did not differ between the bouts. Bouts with a different letter significantly differ ($p < 0.05$ was used as the level of significance.) . Post hoc pairwise differences between different music conditions are shown by the symbols $\delta_1, \delta_2, \delta_3$.

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<th>HR (BPM)</th>
<th>La (mmol.l)</th>
<th>REC (ml/km.kg)</th>
<th>VO2(ml/min.kg)</th>
<th>RPE</th>
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<td>175 ± 11</td>
<td>5.2 ± 1.7</td>
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<tr>
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<td>178 ± 13</td>
<td>178 ± 13</td>
<td>6.1 ± 2.8</td>
<td>217 ± 21</td>
<td>16 ± 1.7</td>
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<td>183 ± 12</td>
<td>181 ± 12</td>
<td>6.6 ± 2.3</td>
<td>218 ± 18</td>
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<tr>
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<tr>
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4.5 Can we manipulate runners’ cadence by changing only the music tempo?

So, if we cannot establish a link between running economy, heart rate or oxygen consumption using music alignment strategies, could it provide other benefits for runners?

This paper, published in 2015, uses the D-Jogger system described in a novel way to slow down or speed up participants using tempo-based methods. We hypothesised that by playing back music slightly faster or slower, the user would align him or herself to the music and thus increasing or decreasing cadence - which might, in turn lead to speedup or slowdowns.

**Title**  Spontaneous Entrainment of Running Cadence to Music Tempo

**Status**  Published as Van Dyck et al. (2015b, Sports Med Open. 2015 Dec)

**Authors**  Edith Van Dyck (1), Bart Moens (1), Jeska Buhmann (1), Michiel Demey (1), Esther Coorevits (1), Simone Dalla Bella (2), and Marc Leman (1)

**Affiliates**  This work was a collaboration between (1) IPEM (Department of Art, Music and Theatre Sciences, Ghent University, Ghent, Belgium) and (2) EuroMov (Universite de Montpellier, Montpellier, France).

**Background**  Since accumulating evidence suggests that step rate is strongly associated with running-related injuries, it is important for runners to exercise at an appropriate running cadence. As music tempo has been shown to be capable of impacting exercise performance of repetitive endurance activities, it might also serve as a means to (re)shape running cadence. The aim of this study was to validate the impact of music tempo on running cadence.

**Methods**  Sixteen recreational runners ran four laps of 200 m (i.e. 800 m in total); this task was repeated 11 times with a short break in between each four-lap sequence. During the first lap of a sequence, participants ran at a self-paced tempo without musical accompaniment. Running cadence of the first lap was registered, and during the second lap, music with a tempo matching the assessed cadence was played. In the final two laps, the music tempo was either increased/decreased by 3.00, 2.50, 2.00, 1.50, or 1.00 % or was kept stable. This range was chosen since the aim of this study was to test spontaneous entrainment (an average person can distinguish tempo variations of about 4 %). Each participant performed all conditions.
Alignment Strategies used  A variation was created on the fixed tempo strategy, where the tempo could be changed to any percentage from a reference tempo.

Results  Imperceptible shifts in musical tempi in proportion to the runner’s self-paced running tempo significantly influenced running cadence ($p < .001$). Contrasts revealed a linear relation between the tempo conditions and adaptation in running cadence ($p < .001$). Figure 4.12 shows this result.

![Figure 4.12: Mean tempo and cadence adaptation for the different conditions. Data presented are mean ± 95% CI. It can be clearly seen in the plot that the cadence adaptation is correlated with the tempo adaptation.](image)

In addition, a significant effect of condition on the level of entrainment was revealed ($p < .05$), which suggests that maximal effects of music tempo on running cadence can only be obtained up to a certain level of tempo modification. Finally, significantly higher levels of tempo entrainment were found for female participants compared to their male counterparts ($p < .05$).
Entrainment basin  A measure of interest concerned the percentage of tempo-entrained steps during the laps with tempo-changed music. A step taken in a tempo sufficiently close to the music tempo (max. 1% difference between SPM and BPM) at that specific moment is regarded as a tempo-entrained step. The tempo entrainment score is the percentage of tempo-entrained steps of the total amount of steps. Figure 4.12 shows the tempo entrainment for this experiment; where it can be clearly seen that the +1%, 0% and -1% conditions have the highest ’entrained’ steps. The ’tempo attraction force’ of the music seems therefore similar when not diverging more than 1% away from the self-selected preferred cadence.

When going outside this 1% range; we notice that this entrainment drops - and this lesser steps are taken in sync. This looks very similar to the Haken-Kelso-Bunz model (HKB) (Haken et al., 1985b), a model for motor coordination and relative phase attraction force. Visually, the HKB model shows the relative phase attraction force as a ’pit’ with its deepest point at 0°; visually a ’basin’. Hence the name of this section: entrainment basin.

In order to statistically trace a possible basin for entrainment, the effect of the conditions on the level of tempo entrainment was tested. A Friedman’s ANOVA (due to non-normal data) showed a significant effect of condition on tempo entrainment, \( p < .05 \). Wilcoxon tests were used to follow up this finding and all conditions were compared against the control condition (0% of tempo change). A Bonferroni correction was applied and all effects are thus reported at a .005 level of significance. It appeared that, compared to the control condition, tempo entrainment was significantly lower in the +2.50% condition \( p < .05 \) and tended to be lower in the +3.00% and -3.00% conditions \( p < .05 \). Figure 4.13 represents the mean tempo entrainment for every single condition.

Responders vs non-responders?  In depth analysis also showed that, similar to the energy consumption study, we also have responders (eg figure 4.14) and non-responders (eg figure 4.15); do not seem to react on the music. However, we could not find a variable to split up our groups even though we did several tests in advance specifically for this goal (eg the BASTA test for testing rhythmical abilities, personal questionnaires, etc).

Conclusions  The applicable contribution of these novel findings is that music tempo could serve as an unprompted means to impact running cadence. As increases in step rate may prove beneficial in the prevention and treatment of common running-related injuries, this finding could be especially relevant for treatment purposes, such as exercise prescription and gait retraining.
Figure 4.13: Entrainment basin displaying mean tempo entrainment for the different conditions. Data presented are mean ± 95 % CI.

Figure 4.14: Example of a 'responder'. In this case, the participant has a stable tempi around 185 and keeps in sync with the music. After the music changes tempi (+2%); the participant also increases cadence after a little delay. Towards the end of the example, we can see the participant reverting to their natural cadence; either due to tiredness or anticipation of the end.
Figure 4.15: Example of a 'non-responder'. In this case, the participant has a stable tempi throughout the exercise, although the music did change tempo from round 3 and onwards.
4.6 Can we manipulate runners’ cadence by shifting the beat forward or backward?

The previous section manipulates runners’ cadence using tempo-adaptations compared to the steps per minute. We also briefly referenced the HKB model, which depicts attraction forces of the $0^\circ$ relative phase angle. An interesting follow-up question would be if we could use this concept to influence runners’ cadence by manipulating the phase, and not the tempo?

In other words, if we change the time of the beat (of tempo-matched music) forwards (i.e. just before the footfall) or backwards (i.e. just behind the footfall); would the participant try to synchronise and therefore speed up (to catch the beat) or slow down (to let the beat catch up)? If so, would it be more or less effective than the less complicated tempo-based method? These questions are answered in the last experiment in this chapter.

**Title**  Shifting the Musical Beat to Influence Running Cadence

**Status**  Published as Buhmann et al. (2017a, Proceedings of the ESCOM 2017 conference)

**Authors**  Jeska Buhmann (1), Bart Moens (1), Valerio Lorenzoni (1), Rudi Villing (2) and Marc Leman (1)

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**Background**  Humans have a tendency to synchronise repetitive motion with each other (i.e. during walking) or with machines (i.e. dancing to the beat on music). This phenomenon is called entrainment, and can occur spontaneously. In this experiment, we analyse if we can use this tendency to manipulate the cadence of runners by playing back tempo-synchronised music which is slightly misaligned so beats either occur just before or just after the footfall. The approach is similar to the tempo based manipulation strategy, which was already shown to be able to manipulate the cadence to one percent; and in some cases up to 2.5%.

**Aims and hypothesis**  Instead of influencing running cadence by manipulating the musical tempo, we explored the possibility of spontaneously affecting cadence by shifting the phase of the musical beat in ecological settings.

We hypothesise that:
Main Research Questions with D-Jogger

- Positive relative phase results to increased cadence. In other words: beats occurring before the footfalls will result in an increase of cadence (‘catching up to the beat’).
- Negative relative phase results to decreased cadence. Or: beats occurring after the footfalls will result in a decrease of cadence (‘slowing down to letting the beat catch up’).
- The effect of this manipulation is stronger than the simpler tempo-based manipulation strategy.

Methods

Twenty-six recreational runners ran four minutes, nine times on a self-selected pace in an ecological setting (indoor running track). The first minute of each 4-minute sequence consisted of running without musical accompaniment. Running cadence was measured and the average cadence of the final 15 sec was used to select a musical track with matching tempo. In the following three minutes we tried to increase or decrease the runner’s tempo up to 5% by setting the target frequency 5% above or below the measured preferred frequency. Three different phase shifting strengths, meaning a small, medium or big timing difference between the beat and the footfall, were tested.

Based on pilot results, we tested 3 types of phase ‘shifting’:

- Subconscious or low: a subtle phase shift which is not perceivable by the participant, around 25° maximum (23ms at 170 BPM).
- Barely noticeable or medium: a phase shift which is most likely not perceivable by the participant, around 50° maximum (46ms at 170 BPM).
- Conscious or high: a phase shift which should be perceivable by the participant, around 75° maximum (69ms at 170 BPM).

Alignment Strategies used

Music and gait signals were synchronised so music tempo matched the cadence of the participant. The relative phase (timing offset between step & beat) was configurable using a special alignment strategy based on the Kuramoto model described in chapter three. A phase shift, either positive or negative, was introduced in the model. This shift gradually decreased when the actual running frequency approached the target frequency. Therefore three new parameters were introduced: maximum phase shift (the ‘strength’ or notability of the manipulation), target frequency (frequency at which both runner and music should be in perfect sync - as a reward) and the maximum allowed tempo difference to react to. Figure 4.16 illustrates the concept.

The formula for the oscillator becomes:

\[
\dot{\theta}_{\text{machine}} = \omega_{\text{machine}} + \frac{k_{\text{machine}}}{2} \times \sin (\theta_{\text{machine}} - \theta_{\text{human}} + \theta_{\text{offset}}) \quad (4.1)
\]
$\theta_{offset}$ is the relative phase shift (i.e. the timing of the beat compared to the footfall) and is based on the experimental condition (25, 50 or 75°). The phase shift is gradually decreased to 0° (perfectly synchronised) when actual running frequency approaches the target frequency.

**Figure 4.16:** Illustration of a responder adapting their cadence towards the target frequency. It can be seen that the relative phase gradually is reduced to zero, so beat-step matched synchrony is obtained (as a reward) when target frequency is reached.

**Results** Shifting the beat forwards or backwards with respect to the footfall influences runners’ velocity (fig 4.17) & cadence (fig 4.18) ($p < 0.05$). It appears that low phase shifts are the most effective, higher manipulations (> 75°) appear to confuse the participant and have an adverse effect. No significant effects were found on exertion or enjoyment ($p > 0.05$).

For the low manipulation strategy, participants reached an increase cadence of 1% and a decreased cadence of 2%. It therefore does not appear to be more effective than the tempo-based approach, although this statement could not be verified statistically due to a slightly different setup.

**Discussion and conclusion** We note that this approach is the first one to influence both cadence and velocity, the tempo based approach did not have a significant effect on velocity. Hence, to influence running performance (in terms of km/h, distance, etc) this approach might be favoured over the tempo based approach.

Being able to influence runners’ cadence, velocity, and enjoyment through phase-shifted music is an interesting finding in the light of preventing common running-related injuries.
Figure 4.17: Velocity adjustments over different conditions

Figure 4.18: Cadence adjustments over different conditions
Summaries of interdisciplinary work using D-Jogger technology

5.1 Introduction

The previous chapter focussed on our own research questions and experiments. However, the use of D-Jogger’s core idea and technology was not limited to our own experiments and questions. In this chapter, we present several summaries of experiments using revised prototypes of D-Jogger. It shows the concept of music alignment strategies can be used in even broader contexts. In this chapter, our role was mainly focussed on programming the devices, which has lead us to another set of interesting domains to explore synchronous music.

This chapter also contains a summary of the European project BeatHealth. Our main role in the project was to develop prototypes based on the D-Jogger technology for use in experiments performed in Ghent and Montpellier. The experiments were focussed on using gait synchronised auditory stimuli for two distinct groups: healthy runners (‘BeatRun’) and Parkinson Patients (‘BeatPark’). We briefly present the prototypes, experiments and results obtained.
5.2 Spontaneous velocity effect of musical expression on self-paced walking

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Authors Jeska Buhmann, Frank Desmet, Bart Moens, Edith Van Dyck, Marc Leman (IPEM, Department of Art, Music and Theatre Sciences, Ghent University, Ghent, Belgium).

Abstract The expressive features of music can influence the velocity of walking. So far, studies used instructed (and intended) synchronisation. But is this velocity effect still present with non-instructed (spontaneous) synchronisation? To figure that out, participants were instructed to walk in their own comfort tempo on an indoor track, first in silence and then with tempo-matched music. We compared velocities of silence and music conditions. The results show that some music has an activating influence, increasing velocity and motivation, while other music has a relaxing influence, decreasing velocity and motivation. The influence of musical expression on the velocity of self-paced walking can be predicted with a regression model using only three sonic features explaining 56% of the variance. Phase-coherence between footfall and beat did not contribute to the velocity effect, due to its implied fixed pacing. The findings suggest that the velocity effect depends on vigour entrainment that influences both stride length and pacing. Our findings are relevant for preventing injuries, for gait improvement in walking rehabilitation, and for improving performance in sports activities.

Figure 5.1: Velocity effect of self paced walking setup
5.3 Effect of synchronised and non-synchronised music on runners’ foot strike impact

Status Published in Proceedings of the ESCOM 2017 conference.

Status Published as Lorenzoni et al. (2017, Proceedings of the ESCOM 2017 conference)

Authors Valerio Lorenzoni, Edith van Dyck and Marc Leman (IPEM, Department of Art, Music and Theatre Sciences, Ghent University, Ghent, Belgium).

Background Running is a widespread and growing physical activity with known positive effects on health. However, the severity of foot strike impact on the ground is a known cause of lower limb injuries for runners (van Gent et al., 2007). The Department of Movement and Sport Sciences of UGent in collaboration with IPEM, is working on the reduction of foot strike impact, through music and sonification of movements.

Aims This work aims at investigating the effect of different music synchronisation strategies on runners’ foot strike impact, specifically on the effect of the alignment of music beats with footfalls. The results of the present tests will be used in later experiments to investigate the feasibility of impact reduction through embodied music sonification.

Methods Experiments were carried out on the outside track of the Topsporthal Vlaanderen in Gent (330 metres) with 28 non-professional experienced runners (average age: 24 (SD 5)). For each participant, a test consisted of five different conditions of the duration of 210 seconds. For each condition the g-force on both legs, SPM and speed were recorded. The first 30 seconds of each condition featured no music and were used to calculate the average runner’s speed. The runner was then requested to keep this speed constant throughout the condition. Visual feedback of the speed and deviation from the reference speed, were provided by three screens placed along the track. The five conditions consisted of:

1. a reference condition without music
2. ‘adaptive synch’, an adaptive BPM and phase synchronisation based on the D-Jogger technology (Moens et al., 2014)
3. ‘initial synch’ a tempo synchronisation condition based on the initial step-per-minute (SPM) of the runner
4. ‘plus 30%’ a non-synch condition with music BPM constantly 30% higher than the runner SPM
5. ‘min 30%’ a non-synch condition with music BPM constantly 30% lower than the runner SPM

Conditions were randomized across participants to minimize fatigue effects. After each condition, participants were asked to fill in questionnaires (BORG, PACES and BMRI) to rate: perceived exertion, enjoyment and music motivational qualities.

**Results**  The mean values of the g-force, SPM and speed are calculated respectively from the start of the experiment to the start of the music (30 seconds) (part1) and after 30 seconds from the start of the music for a duration of two minutes (part2) for each participant. The differences and ratios of the means (with music / without music) are used to evaluate the effect of the different synchronisation strategies for all participants separately. From statistical analysis, no significant effect on the average g-level and SPM with and without music could be observed among the different synchronisation conditions. By paired comparison between part1 and part2, it could be observed that music has the general effect of increasing impact level with respect to the no music phase (part1) for all conditions except the no-music reference, in particular for high BPM (plus30%). No significant differences in SPM were observed across conditions and with or without music. From the questionnaires, the ‘initial synch’ condition appears to be the most motivating and pleasant. People with musical background rated highest the ‘adaptive synch’ and the ‘plus 30%’ in terms of pleasantness. No significant differences due to gender and training level were found.

**Conclusions**  From the analysis, synchronisation of music with foot falls seems not to cause an increase of foot strike impact. The music onset seems to lead to a slightly increased impact level, compared to running without music. This increase could also be ascribed to the specific music choice; further research will be devoted to investigate the effect of specific music features on runner’s foot strike impact. The motivational effect of music is particularly evident when the BPM of the music matches the comfort tempo of the runner, not necessarily the phase.
Figure 5.2: Picture of the experimental set-up. Accelerometers installation and pre-stretching (left), backpack and poles positioning (middle), speed feedback system: raspberry pi and screens (right).
5.4 Sound-induced stabilization of breathing and moving

**Status**  Published as Bardy et al. (2015, Annals of the New York Academy of Sciences)

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**Abstract**  In humans and other animals, the locomotor and respiratory systems are coupled together through mechanical, neurophysiological, and informational interactions. At a macroscopic observer environment level, these three types of interactions produce locomotor respiratory coupling (LRC), whose dynamics are evaluated in this paper. A formal analysis of LRC is presented, exploiting tools from synchronisation theories and nonlinear dynamics. The results of two recent studies, in which participants were instructed to cycle or exhale at a natural frequency or in synchrony with an external rhythmic sound, are discussed. The metronome was either absent or present (study 1) and close to or far from the natural frequency of the cycling and breathing systems (study 2). The results evidenced a stabilization of cycling, breathing, and LRC when sound was present compared to when it was absent. A decrease in oxygen consumption was also observed, accompanying the increase in sound-induced LRC stabilization. These results obtained with a simple rhythmic metronome beat have consequences for exercising while listening to music; the consequences are further explored here.
5.5 Music therapy for multiple sclerosis patients

**Status**  Unpublished, experiment in progress.

**Authors**  Lousin Moumdjian (1), Bart Moens (2)

**Affiliates**  This work was a collaboration between (1) Hasselt University and (2) IPEM, Department of Art, Music and Theatre Sciences, Ghent University, Ghent, Belgium.

**Summary**  Multiple sclerosis (MS) is an inflammatory demyelinating and neurodegenerative disease of the central nervous system (Peterson and Fujinami, 2007). To date, there are no cures for MS, however there are two treatment approaches. The first treatment approach is pharmacological, and this has two aspects: a) therapy targeting underlying pathophysiological disorder and b) therapies to relieve or modify symptoms which result from the disease (Hauser and Oksenberg, 2006). The second approach is rehabilitation, as rehabilitation for PwMS aims to improve these symptoms and it remains a key solution in the disease management (de Sa et al., 2011).

More specifically, motor and cognitive functions are frequently impaired in persons with multiple sclerosis (PwMS). Motor impairments such as muscle weakness, hypertonia, incoordination and balance, have a negative impact on walking (e.g. reduced cadence and step length) and functional mobility (McLoughlin et al., 2014). Cognitive deficits are also frequently present, in up to 60% of PwMS in the domains of working memory, learning, sustained attention, information processing speed and executive functioning (Denney et al., 2005).

Rehabilitation aims to improve motor and cognitive symptoms, in order for PwMS to perform activities of daily living and have a high quality of life. Yet current rehabilitative approaches do present with limitations. For example, exercise therapy has shown to be effective in MS for improving physical fitness as well as for mood regulation, but its benefits may be dependent on the intensity of the training (Motl et al., 2016). PwMS find training at adequate intensities difficult, as they have co-founding symptoms such as fatigue and fatigability (Dobkin, 2008). Additionally, adherence to therapy remains an issue persons with PwMS (Heesen et al., 2014).

The D-jogger is used in light of these reasons. As the D-Jogger technology facilitates sensorimotor prediction (due to synchronisation), it works as a motivating device for walking, especially when preferred musical stimuli are used. The prediction mechanism also leads to feeling in control, which is also known as music agency, promoting music-induced reward. This feeling of reward (satisfaction and pleasantness) may increase the adherence of PwMS to therapy. As Musical agency has shown to contribute to reduced perceived ex-
ertion during strenuous physical exercise (Fritz et al., 2013), then it may be assumed that training with music may also decrease feelings of perceived fatigue, and allow PwMS to exercise at adequate intensities.

The apparatus includes a custom version of the D-Jogger software (see figure 5.4) and uses gyroscopes as step sensors. For validation purposes, the clinically valid Mobility Lab Gait system (Mancini et al., 2012) is also used for external data logging.
5.6 BeatHealth 1: Effects of RAS on performance and breathing in laboratory and ecological settings

**Status**  Prototype finished, experiments finished, one poster presentation on the Sports Plaisir 2017 conference. Publication in progress.

**Authors**  Programmed by B. Moens (4), Experiments by L. Damm (1), D. Varoqui (1), F. Blondel (1), P. Ihalainen (1), S. Dalla Bella (1,2,3) and B.G. Bardy (1,2).

**Affiliates**  This work was a collaboration between (1) EuroMov Laboratory, University of Montpellier, Montpellier, France; (2) Institut Universitaire de France, Paris, France; (3) International Laboratory for Brain, Music, and Sound Research (BRAMS), Montreal, Canada; (4) Institute for Psychoacoustics and Electronic Music, University of Ghent, Ghent, Belgium;

**Description**  This was the first experiment performed in the project European project BeatHealth. The goal was to test the effect of rhythmic auditory stimulation on performance during running over ground when stimuli were manipulated using several music-to-movement alignment strategies. Measurements include energy consumption and locomotor-respiratory coupling (LRC). Special attention was directed to the user-friendliness of the software because the experiments were performed without the developers present.

**Apparatus**  The 10” Panasonic Tablet (FZ-G1) was chosen to use during the experiment due to its long battery life and robustness. It was called 'transportable' as it was not truly mobile but it could be transported during the experiment in the backpack. Step detection was done using gyroscopes from iPod 4th generation. They streamed the sensor data using a wireless connection to the tablet. Finally, a custom-made breath sensor (thermistors connected to Arduino Nano) was connected to the tabled using USB connection. The sensor was placed in a breathing mask. While inhaling, cool air entered the mask thus lowering temperature, breathing out resulted in an increase in temperature. This signal was used to determine breathing frequency. To determine the energy consumption, a portable gases exchange analyser was used independently of the tablet. Figure 5.5 shows the setup.

**Software and alignment strategies**  The software contains several components: individual motivational music databases per participant, metronomes, time stretching module for adjusting tempo without pitch, step detection for a gyroscope, a logging subsystem, experimental methodology and several music-to-movement alignment algorithms:

- Periodic: music tempo-matched to reference tempo measured in earlier round
Figure 5.5: Illustration of the experimental setup used for testing on the athletic track. (a) iPods (accelerometers, gyroscopes), (b) tablet PC (real time computation, data logging), (c) gases exchanges analyser and (d) thermistor

- Periodic with added interbeat variability: music tempo-matched to reference tempo measured in earlier round with added random interbeat variations (Coefficient of variation = 2)
- Adaptive or forced synchronisation: both tempo and phase aligned.

Prior to the experiment, we extended our existing D-Jogger database with radio hits known in the Montpellier area where the experiments occurred. We converted all audio to 44Khz stereo wave files, followed by loudness normalization, manual beat annotation using Beatroot, verification of the resulting BPM and finally, the resulting files were sorted in a folder structure so both the BMRI test (motivational test) and the prototypes can access the songs. Additionally, we developed an automated pre-test for participants to individually assess the motivational aspects of the music using the BMRI2 questions. Each song was rated from 7 (demotivational) to 42 (highly motivational).

Experiments One experiment was conducted in order to test the effect of RAS (i.e., metronome vs. music) adaptively synchronising to the motor performance of the individual on the running behaviour (motor performance and energy consumption). The experiment was conducted in controlled laboratory conditions on a treadmill. A secondary goal of the experiment was to test the Adaptive stimuli prototype implementing beat-movement alignment strategies. The test and data analysis was conducted by Charles Hoffmann, at that time PhD student at UM1 Montpellier. In this experiment 14 healthy young participants
were asked to run together with adaptive and nonadaptive RAS while both movement kinematics and oxygen consumption were measured.

A second experiment has been devised in which the design implemented in the previous experiment has been mostly replicated, but in more ecological conditions (i.e., with participants running over ground instead than on a treadmill). The test and data analysis is conducted by Dr. Loic Damm, post-doctoral researcher at UM1 Montpellier. 15 healthy young participants finished the experiments.

In addition to pleasure and motivation reinforcement during running, music may sustain locomotor and respiratory rhythms, as well as their coupling. This experiment explored the effects musical entrainment on locomotor and respiratory systems. We hypothesize the reinforcement of locomotor-respiratory coupling with auditory cueing and the associated energy cost saving.

**Results**  The results show large individual differences of the effect of music on running efficiency: across experiments and manipulations, there was no significant effect at the level of the whole group. However subgroup of responders, who benefited from the cueing, and of non-responders, insensitive to cueing, could be distinguished. We note that this is similar to our earlier findings and also in contrast with popular literature.

The entrainment between locomotor and respiratory systems was asymmetric: Irrespective of the running modality on a treadmill or over ground, and of the population recreational or expert runners, auditory cueing with tempo matching step frequency elicited an increase of respiratory frequency.

Biological variability in the inter-beat-interval of the presented stimuli increases the effectivity of RAS (i.e., leading to a better compromise between gait stability and flexibility). Again, a link between beat variability and gait stability was found; similar to our results with the RAS for Parkinson Disease patients.

Rhythmically salient musical stimuli show a more beneficial effect on gait when compared to a simpler rhythmic stimulus (i.e., a metronome).

Through a reinforcement of locomotor respiration coupling, RAS is beneficial for runners’ performance. Lower energy consumption is observed with RAS, an effect particularly visible with musical stimuli. This result is consistent with our hypotheses. The effect was not present when the breathing was unregulated.

The present data provide new insights into the dynamics of physiological rhythms under the influence of music. Breathing appears to be flexible, with the same level of efficiency noticed for a large range of frequencies. Runners are more prone to modulate their breathing than their kinematic tempo when listening to auditory stimulations. The present data are discussed within the framework of sport performance and new music technologies.
5.7 BeatHealth 2: Effects of RAS variability on motor-auditory synchronisation

**Status** Prototype finished, experiments finished, one poster presentation on the Sports Plaisir 2017 conference. Publication in progress.

**Authors** Programmed by Bart Moens (4), Experiments by L. Damm (1), D. Varoqui (1), F. Blondel (1), P. Ihalainen (1), S. Dalla Bella (1,2,3) and B.G. Bardy (1,2).

**Affiliates** This work was a collaboration between (1) EuroMov Laboratory, University of Montpellier, Montpellier, France; (2) Institut Universitaire de France, Paris, France; (3) International Laboratory for Brain, Music, and Sound Research (BRAMS), Montreal, Canada; (4) Institute for Psychoacoustics and Electronic Music, University of Ghent, Ghent, Belgium.

**Description** The second experiment for BeatRun entailed the experimentation with tempo-adaptive stimuli on an indoor running track. The goal was to test the effect of rhythmic auditory stimulation (RAS) (i.e. metronome, motivational music) with added interbeat variation on performance during running over ground when stimuli was manipulated using several music-to-movement alignment strategies. The first Beathealth experiment showed interesting results when adding variation, therefore the second experiment was focussed on that aspect. Measurements include: energy consumption and locomotor-respiratory coupling (LRC).

The focus of this version was the timing variability between the beats. With a natural gait pattern, inter-step-interval is neither random nor fixed; it has a fractal scaling of about 1 - it resembles a 1/f sequence. Basically, this means that a step interval is based on the previous steps, i.e. there is a long-term correlation. This is logical in a sense; if one takes big steps, it stands to reason that the next step will also be a big one. However, when applying fixed tempo metronomes or music, this long-term correlation in the step intervals diminishes and resembles a more Gaussian-noise like distribution. This has negative impact on certain gait aspects, for example with PD patients this can lead to falling.

This explains the necessity for this variability prototype: if we change the fixed stimuli to match 1/f or Gaussian noise sequences, what will happen?

**New alignment strategies for inter-beat variation** Several music-movement alignment algorithms were implemented. The beat variability prototype supports the following strategies:

- None: original songs’ tempo
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Figure 5.6: Beathealth variability setup

- Periodic (fixed)
- Periodic + 1/f noise (pre-generated sequences in Matlab)

The interbeat intervals using a Periodic strategy can be manipulated so that they either represent a Gaussian distribution or a 1/f distribution (which implies a long term correlation). A normal healthy gait sequence usually represents a 1/f inter-step-interval series, while unhealthy (PD) gait generally resembles a Gaussian series. Therefore, the prototype was made to see if these interbeat variations could influence the participant.

**Apparatus** The smaller version of the Panasonic Touchpad was used for this prototype (Panasonic Touchpad FZ-M1); a 7” windows tablet which weights around 1kg. We used the iPods again as sensors. This allowed us to re-use more code between experiments, which increased stability and familiarity. Finally, a custom-made breath sensor was connected to the tabled using USB connection.

Additionally, a new portable WiFi router (TP-Link M5360) was used as a hotspot to connect sensors to the tablets. The router allows a lot of configuration parameters such as the channel and WiFi standard (IEEE 802.11 b/g/n), which resulted in more stable connections and less jitter from the sensors compared to ad-hoc. This also allowed more resources for the computer as it did not need to setup an ad-hoc network.
Experiment  This experiment was designed to identify the effects of RAS variability on motor-auditory synchronisation, and the potential associated benefits in terms of running economy. Stimulation, which does not embed variable intervals between beats, is unlikely to be optimal. This experiment was conducted on young healthy adults. We proposed in the present study to test two types of RAS, which differed by their type of variability while participants were running on the treadmill.

The first condition used long-range correlated noise with a Gaussian distribution (pink noise, 1/f) as a variability source. Variability was introduced in the stimuli by scaling each successive inter-beat interval to match the successive values in simulated pink noise series. The simulated series were scaled in magnitude and a constant was added to them such that they have the appropriate mean inter-beat interval and coefficient of variation. 2% was chosen as the coefficient of variation similar to the one observed during running.

The second condition was periodic (no variability). The inter-beat interval matched the average inter-step interval of the runner measured in an earlier trial.

Both types of RAS were compared to silence.

Results  Kinematic, LRC and energy consumption related variables were globally stable across all experimental conditions, and we could not find any benefit of RAS variability on our variables. Various and contrasting effects can explain this lack of significance across participants: the energy spent increased with RAS for some participants but decreased for others. We note that this is the third experiment confirming the inter-personal difference in reaction to RAS. Globally, half of the participants benefited from the RAS when considering running economy. It is difficult to draw definitive conclusions due to the lack of effects of the long-range correlation embedded in RAS. This last-type of stimuli should be tested on a larger population of responders to validate or invalidate its specific benefits.
5.8 BeatHealth 3: Long-term optimization of healthy runners’ cadence

Status Experiment finished (Ghent, Montpellier), one poster presentation on the Sports Plaisir 2017 conference. Publication in progress.


Affiliates This work was a collaboration between (1) EuroMov Laboratory, University of Montpellier, Montpellier, France; (2) Institut Universitaire de France, Paris, France; (3) Institute for Psychoacoustics and Electronic Music, Department of Musicology, Ghent University, Ghent, Belgium; (4) International Laboratory for Brain, Music, and Sound Research (BRAMS), Montreal, Canada; (5) Maynooth University, Maynooth, Ireland.

Description The last experiment of the BeatRun project was the result of three years research and implementation by all partners, and can be seen as the biggest ecologically valid RAS running experiment as of yet. Using results of previous experiments, a new mobile implementation (both hard- and software) of the BeatHealth platform was created. Participants were allowed to take the equipment home and use it in their spare time, which results in a long-term (two months) study of running behaviour with RAS. The goal was to optimize running cadence using music alignment strategies. The ‘phase basin’ experiment was a pilot or proof of concept in light of this experiment.

Objective During running, music whose the tempo is matching runner’s cadence is often advocated as a factor of performance and motivation. Running cadence is indeed a macro-variable affecting directly the kinematics: higher stride frequency than the one usually adopted by shod-runners has been reported to be less prone to elicit injuries and to favour better energy efficiency (Lieberman et al., 2015). We developed a specific technological architecture, which continuously measures foot strikes in real time, and allows the manipulation of musical beats according to kinematics. The objective was to entrain the runner toward a target cadence, considered as ideal in terms of biomechanical constraints. We compared the entraining ability of two beat manipulation algorithms, an adaptive one, which follows runner’s tempo, and a periodic one, which consists in assigning the same constant musical tempo matching the target tempo.
Participants and Methods  21 young adults participated in a 9-week training program including 17 running sessions in ecological conditions. Pre-training consisted in four running sessions in ecological conditions without any auditory stimulation. During pre-test, the target cadence was determined during barefoot running. Participants had to complete 5 training sessions.

They were listening to music whose tempo was manipulated using either a fixed-tempo alignment strategy (periodic); or a Kuramoto-based phase-shifting music alignment strategy aimed to increase cadence. They completed the first post-test session before embarking on the second training period also consisting in 5 running sessions with musical samples manipulated with the other strategy. The second post-test ended the experiment. Participants experienced 15 minutes of silence and 10 minutes of auditory stimulation during the two post-tests sessions.

Gait related data were collected with inertial motion sensors. A GPS recorded the speed. Data collected during pre- and post-tests were compared. We hypothesized that the adaptive algorithm would attract runners toward the target cadence more efficiently than the periodic one.

Hardware  Each participant received a package with the following equipment: 1 Android Phone, 2 Inertial motion units (created by Maynooth University), gait-related sensors, 1 Zephyr HxM heart rate sensor, earphones, 3 USB cables, 1 base station for heart rate sensor charging, 1 belt pouch, 2 ankle straps, 1 chest belt for the heart rate sensor. Figure 5.7 shows the setup.

Software  Maynooth University created an application to run on an Android phone implementing the experimental protocol. Several pitfalls and issues were found and solved, resulting in a stable and phase-accurate mobile version using the D-Jogger concept and architecture. Figure 5.8 shows the application.

Results  The experiment resulted in the following dataset:

- 463 sessions with 29 participants
- 222 hours of running
- Almost 2200 km covered
- Robust performance and comprehensive real time data logging

5 participants were excluded from the analysis because their average shod running cadence during pre-test was not higher than their barefoot cadence. Post-tests silence did not
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Figure 5.7: BeatRun mobile version hardware and usage instructions

Figure 5.8: BeatRun mobile application User Interface
reveal any significant effect of algorithms. Cadence with adaptive algorithm was significantly higher (3.71 ± 2.98 SPM) than cadence with periodic algorithm during post-tests music (0.49 ± 3.6 SPM) whereas speed did not differ statistically. Comparisons between pre and post-tests are show in figure 5.9.

![Graphs showing cadence and speed comparisons](image)

Figure 5.9: Preliminary results of the BeatRun proof of concept experiment. The two upper right plots show the difference between both alignment strategies: the periodic alignment strategy did not increase the cadence while the Kuramoto-based strategy had a significant effect.

**Conclusions**  The increase of stride frequency following training with the adaptive algorithm was obtained at constant running speeds. It means that participants associated higher stride frequency with shorter stride length. Among the hypothesised advantages of this combination reported in the literature we can cite: less mechanical energy absorption by lower limb joint (Heiderscheit et al., 2011; Hobara et al., 2012), higher leg stiffness (Farley and Gonzalez, 1996) and shorter contact time (Morin et al., 2007). Our adaptive algorithm was able to attract runners in a higher interval of stride frequency, in the absence of any instruction given to the participant relative to beat-step synchronisation. This music-based strategy appears to be an efficient way to manipulate runner’s cadence in a subliminal way.
To conclude, BeatRun had the goal of improving running performance through the use of wearable sensors and rhythmical auditory stimulations. The technology developed is appropriate to manipulate runners’ cadence. This factor emerged recently in the literature as being a macrovariable that can have a strong influence on the biomechanical constraints experienced by runners. As such, the use of BeatRun, by entraining runners to adopt better kinematics through the use of music, could represent a promising way to promote a safe and enjoyable practice of running.

**Valorisation**  The alignment strategy created by BeatHealth consortium was shown to be successful in adapting users’ cadence towards optimal levels and resulted in a provisional patent application: *Mobile system allowing adaptation of the runner’s cadence, co-inventor (first inventor Benoît Bardy), filed on July 27 2017.* Potential benefits of this strategy include reduced injury risks and increased motivation. IPEM and the authors of this section share inventorship and co-ownership of the patent application.
Conclusion

In this dissertation we've presented D-Jogger: a soft- and hardware framework aimed at synchronising music to gait. The core idea, how music is synchronised to the gait, is called a music alignment strategy. We presented and compared five music alignment strategies that encourage entrainment: uninstructed or spontaneous synchronisation during self paced walking or running.

Several experiments have been done with D-Jogger, testing out the influence of different music alignment strategies. In these experiments, we try to answer our main research questions in different domains such as sports and rehabilitation. This chapter provides a global overview of the results. We also present some limitations of our studies and give a short note on valorisation.

6.1 Contributions to the research field

The development of D-Jogger has resulted in a fully documented and validated system. While none of the individual components is ground-breaking nor 'new' itself, the combination of these components forms part of valuable know-how. Details of its development are published in this dissertation and several papers, allowing the re-creation of a D-Jogger device.

The concept of music alignment strategies, as introduced in chapter 3, is a notable contribution to both entrainment and human-computer interaction research. The term has been
used in multiple publications (e.g., van Dyck et al. (2017); Leman (2016); Maes et al. (2016)). We've shown that details (i.e., the exact moment when a song starts, timing offsets) have a big influence on the outcome and user appreciation. These details should be paid attention to or controlled when designing musically-based synchronisation experiments. We've documented alignments that allow most users to synchronise to music (e.g., chapter 3.2). When full phase synchronisation is required, strategies from chapter 3.4 and 3.5 can be used providing automatic phase alignment. These strategies are useful for a part of the population that is unable to synchronise (Styns et al., 2007) or if double tasks are to be avoided, such as in Parkinson Disease rehabilitation (Nombela et al., 2013).

Another aspect we feel as a contribution is our focus on ecological settings. This starts with using uninstructed synchronisation and self-paced walking or running. In entrainment and tapping literature, this is quite common. However, for walking or running experiments there is a limited amount of literature about self-selected cadence and uninstructed synchronisation. The use of self-selected cadence could lead to interesting new experiments and results that better reflect real-world scenarios. Due to hard- and software developments, we were able to test in 'ecological setting': running on an indoor athletic track, walking tests in the rehabilitation centre, outdoor running... While it is preferred, the logistic hassle is higher and even in these settings, it is difficult to generalise results to a broader public. But we hope to emphasise the importance of going outside the lab - especially for empirical and applied research questions such as ours.

We also feel that we contributed to the field of music therapy and specifically Parkinson Disease (PD) rehabilitation. It has already been shown that metronomes can greatly improve the gait of PD patients (Ashoori et al., 2015). Music has similar but less pronounced effects. However, music arguably feels more comfortable and motivational for the patient. Our alignments and interactive approach with music focus on the patient’s comfort by using pleasant stimuli and reducing double tasking (the task is just walking instead of synchronising). This approach might better reflect a real application for PD patients and we feel it as a recommendation to consider music as viable rhythmical auditory stimuli in addition to metronomes.

Finally, we have shed a bit of light on the empowering effect of music when walking in the beat (Leman et al., 2016). Using the right music alignment could increase motivation during exercises (see chapter 4.2). This adds to the recent findings that the sense of agency might have an additional empowering effect (Wöllner, 2017) and could potentially strengthen the effect of activating and relaxing music (Buhmann et al., 2016b; Leman et al., 2013).
6.2 Main results: answering the research questions

In this dissertation, we answered several empirical research questions about the effects of music alignment strategies on spontaneous synchronisation, sports and rehabilitation. In our experiments, we use uninstructed synchronisation, i.e. the effects of music when the participant was not given any instruction related to the music. In most domains, uninstructed and self-paced synchronised trials are novel and only made possible by the developments of systems like the D-Jogger. We can sum up our results by looking back at the main research questions in the following sections.

**Does synchronous music influence runners’ motivation, cadence or velocity?**

Yes: motivation and cadence can be influenced by specific music alignment strategies. Aligning music to the gait using adaptive oscillators appears to be the most effective and appreciated strategy (chapter 4.2).

**Is synchronous music useful for Parkinson’s disease rehabilitation?**

Yes, synchronous music shows a positive effect on the gait predictability or the fractal scaling, possibly reducing risk of falling. However, typical measures such as cadence and velocity increase are less pronounced compared to metronomes. Moreover, music was found to be more motivating and stimulating than metronomes (chapter 4.3).

**Does running on synchronous music reduce energy consumption?**

It appears that, for a subset of participants, there is indeed a positive influence. However, we could not generalise these findings nor confirm positive results found in literature. For the non-responders, there is no difference between synchronous and asynchronous music (chapter 4.2).

**Can we manipulate runners’ cadence by changing only the music tempo?**

Yes, when the tempo of the music is shifted away from the runners spontaneous cadence, the runner tends to follow small changes. Tempo differences up to 1% are followed unknowingly by almost all participants. The ‘tempo basin’ effect is measurable from -2.5% to +2.0%. No significant effect on performance has been found. Using this strategy, non-followers will experience ‘phase cycling’: getting in and out of sync with the music. This might be experienced as frustrating or demotivating (chapter 4.4).
Can we manipulate runners’ cadence by shifting the beat forward or backward?

Yes, we can change the offset of the tempo-matched beats slightly forwards (i.e. just before the footfall) or backwards (i.e. just behind the footfall). As a result, the runner tries to synchronise and therefore speed up (to catch the beat) or slow down (to let the beat catch up). The 'phase basin' effect is measurable from -2.0% to +1.0%. Velocity or performance can also be influenced using this method. Smaller phase shifts (tens of milliseconds) are more effective than large shifts (larger than 50 milliseconds), showing that attraction force of the beat is related to the relative phase (chapter 4.5).

6.3 Valorisation

One question often received during talks about D-Jogger was whether there was a 'D-Jogger application for smartphones'. After initial tests, we realised that the work for such an app (conceptualisation, programming, maintenance, support...) would not be in line with our research interests or capabilities. Therefore, external parties were contacted to create such an application. This was the beginning of the smartphone era and the technical challenges for programming low-latency sensor-based audio-apps on mobile platforms were great (most notably step detection that worked for everybody and low-latency audio time-stretching).

One company from Ghent managed to create a working prototype in 2012 on iPhone OS 3.0 (later iOS 4.0). It was tested on a general population (50 participants), followed by a survey. While the app worked fine for most, it was decided in June 2013 they would not continue with the development for two reasons: (1) 'Concerns that streaming apps will increase in importance which would make the market for an app such as D-Jogger smaller’ and (2) 'lack of time to handle the project with care in all its aspects’. Some public demonstrations and talks on national media again increased interest to create such an app by other parties, however none got further than initial talks because it quickly became clear that there were technological obstacles to overcome. Eventually we did not continue our efforts on commercialisation because we felt the amount of time given to this valorisation was proportionally high compared to the most likely outcome.

However, the BeatHealth project resulted in a different type of valorisation. The alignment strategy created by BeatHealth consortium was shown to be successful in adapting users’ cadence towards optimal levels (see chapter 5.8) and resulted in a provisional patent application: Mobile system allowing adaptation of the runner’s cadence, co-inventor (first inventor Benoît Bardy), filed on July 27 2017. Potential benefits of this strategy include reduced injury risks and increased motivation. Each IPEM BeatHealth member is listed personally as co-inventor of the patent application.
6.4 Limitations

During our research, we’ve found several interesting outcomes and practical use cases for using synchronous music. However, some results lack a fundamental theoretical explanation and were focussed on the empirical results. Building and using such a theoretical framework could improve our results and understanding of synchronous music and entrainment. Such a theoretical framework could also help in generalising the results to a broader public.

In most of our experiments, we noticed ‘responders’ and ‘non-responders’. Responders had a positive influence (either motivational or physiological) of synchronous music, while non-responders often had a null effect. This sometimes resulted in insignificant results on the general data - while it is clear that a subgroup potentially benefits from synchronous music. The solution seems simple: split up the participants based on responder or non-responder. This is generally bad practice because due to smaller subgroups, changed methodological approach and ‘bad statistics’ - it would be like creating a subgroup of participants who don’t comply with the hypothesis in this case. No correlations between (non)responsiveness and other quantitative or qualitative data were found, but this aspect merits more research and experiments.

In more recent experiments we were well aware in advance of this (non-)responder aspect and therefore we ‘searched’ for different predictive measures to generate two groups prior to the experiment. However, we could not find any such measure we took prior to the experiment that correlate with the result of (non-)responder. This includes pre-tests such as one’s ability to synchronise to music; survey data such as musical preference, running experience (with or without music), music education, experience with instruments, personal interests and also personal physical aspects such as gender, age, length of the legs, etc. We found interesting differences between gender (Buhmann et al., 2017b) but this did not correlate to the responder/non-responder question. This (non-)responder issue is one of the biggest open questions in our research; and in retrospect is not handled enough.

Another issue relates to the music selection. In our experiments we try to control as much variables as possible, however this is not trivial for music. Individuals respond differently to the same songs. Their emotional state, hour of the day, number of repetitions, physical exertion all influence the judgement of a song. This leads to an individualised music selection, for example using pre-tests such as the motivational scale BMRI-2 (Karageorghis et al., 1999, 2006). This is possible on smaller scale experiments but is not easily feasible on large scale databases. We’ve always taken great care for our music selection - but improvements to this aspect could again help generalise the results.

The Parkinson study (chapter 4.3) has some of the most notable results and discussions, but also multiple limitations. The lack of healthy control group, a non-standardised music
selection and the lack of an adaptive metronome condition make it is difficult to generalise
the findings. New studies, such as the study by the BeatHealth consortium, are looking at the
longer term effects on health of using rhythmical auditory stimuli and alignment algorithms.

Music alignment strategies that influence gait cadence (chapters 4.5, 4.6 and 5.8) also
raise concerns about its applicability. By changing the cadence incorrectly, one might in-
crease the risk of injury or exertion. A decreased cadence could lead to higher risk injury
due to higher impact forces (Luedke et al., 2016), or participants could ignore physical
warnings of the body due to musical enjoyment or distraction. Possible positive perfor-
ance effects of musical stimulation have not gone unnoticed for competitive running, in
some cases leading to a ban on music playing equipment for contests or even disqualifi-
cations (Van Dyck and Leman, 2016). It is however still unclear whether regulations are
required given some contradictory results; but it is reasonable to avoid these devices and
headphones in case of championships for professional athletes.

6.5 General conclusion

In this dissertation, we presented the D-Jogger music alignment framework and several
interdisciplinary applications and experiments. We examined the effects of different music
alignment strategies in entrainment, sports and rehabilitation research. We can conclude
that music synchronisation strategies are very useful for several different scenario’s. Our
main results show that spontaneous running cadence can be influenced, Parkinson gait can
be improved and runners can experience more motivation using the correct music alignment
strategies.

The applicability of music alignment strategies in music therapy is especially promis-
ing. Parkinson Patients can be helped with specific stimuli, and such a finding could be
easily transformed into a concrete or usable device for patients. Finally, a range of training
applications for runners can be created using the music alignment strategies that influence
runners cadence. They could be used for reducing injuries, but it is not difficult to image
applications that are coupled with the heartrate for example, which can be applicable for
start to run or endurance training, kind of like a subliminal or non instructing coach.
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