A Successive Wavenumber Filtering Approach for Defect Detection in CFRP using Wavefield Scanning

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Abstract—Owing to the high sensitivity of carbon fiber reinforced polymer (CFRP) to internal damages, defect detection through Non-destructive testing (NDT) is deemed an essential task. One of the common methods in NDT to achieve this aim is measuring and analyzing the full-field guided waves propagation in CFRP plates. Scattered waves corresponding to deep defects are usually obscured by other waves due to their weak amplitude. A successful method to highlight these waves is to use wavenumber filtering (WF). However, WF suffers from the assumption that the optimal frequency range of excitation signal is known beforehand, which is not always available. Another drawback is that when more than one type of guided waves mode exist, this method is not capable of highlighting desirable waves or vibrations sufficiently. In this paper, full wavefield images are first constituted by exciting the guided waves via broadband chirp signal and registering them with scanning laser Doppler vibrometry (SLDV). Then, a successive wavenumber filtering (SWF) approach is introduced, which efficiently removes undesirable higher order guided wave modes, and removes the need to know a priori the optimal excitation frequency. Moreover, it is qualitatively and quantitatively shown that the proposed approach could lead to better discrimination between damaged and healthy area than conventional WF.

Keywords—Carbon fiber reinforced polymers, non-destructive testing, wavenumber filtering, scanning laser Doppler vibrometry, guided waves, defect detection;

I. INTRODUCTION

High stiffness and strength, as well as low weight cause Carbon Fiber Reinforced polymers (CFRP) to be preferred to other types of components in applications where high performance structures are required such as aerospace industry, automotive engineering, and civil engineering. However, due to their typical layered structure, CFRPs are susceptible to the formation of internal damages. Considering this fact, nondestructive testing (NDT) methods are required to identify these damages, which could occur during the manufacturing process.

Exciting the CFRP under investigation with high-frequency acoustic waves and then analyzing the elastic wave propagation registered from the specimen’s surface is a renowned NDT method for damage detection in composite structures. These generated elastic waves are referred to as Lamb waves or guided waves. In a specimen having free boundaries, Lamb waves can be created with an endless number of symmetric and antisymmetric modes accounting for the symmetric and antisymmetric displacement within the layer. In literature, each mode is indicated with S or A, which stands for symmetric and antisymmetric, along with their order. The excitation of the CFRPs and then measurement of the results could typically be done in different ways [1]-[4]. These two steps are done in order to attain full wavefield, showing guided waves as they propagate in the plate in conjunction with their interaction with edges of the inspected plate, or defects.

The most significant advantage of Lamb wave is its ability to propagate over long distances, thereby, defects existed in large structures could be localized [5]. On the contrary, due to dispersion and multimodal behavior, their analysis aiming to localize defects in full wavefield is a complicated task, especially when deep defects are present. This is because the incident wave, which is the wave attributed by the transducer before it reaches any discontinuities, has a higher amplitude than the waves reflected off deep defects. In addition, the more different Lamb wave modes propagate in the plate, the more processing is needed for localizing defects.

To overcome these problems, incident waves should be removed from full wavefields whereby only the vibrations regarding defective areas remain. Several researches have been done in recent years for this aim. In [6], to highlight the waves propagating in the opposite course of incident waves, frequency-wavenumber filtering through three-dimensional discrete Fourier transform (3D DFT) is conducted in the application of thin-walled aluminum plates. Another method proposed in [7] developed wavenumber filtering (WF) using 2D DFT to separate scattered waves corresponding to defects from incident wave in the wavenumber domain.

Two aforementioned approaches have used narrowband toneburst signal centered on a specific frequency to excite the plates, which is considered a downside. This is due to the fact that the selection of the center frequency (f_c) that leads to a proper distinction between defect and sound area is highly dependent on the depth and shapes of defects [8], which is mainly unavailable prior to the experiment. To address this issue, authors in [9] suggested using broadband linear chirp signal rather than toneburst signal in defect detection algorithms, and proposed a filtering approach in the frequency-wavenumber domain based on mode removal concept, where optimal frequency range was assumed unknown. Furthermore, the
method introduced in [7] has another disadvantage, namely, if more than one mode of Lamb wave is present in the recorded data, which is highly possible in high excitation frequency, it could not achieve good contrast for deep defects.

In this work, it is attempted to develop a successive wavenumber filtering (SWF) based on WF proposed in [7] which not only takes into account the effect of different $f_c$’s due to using chirp excitation signal, but also is able to detect shallow and deep defects in both low and high frequencies, where more than one mode of lamb wave exists.

The contribution of this paper can be summarized as follows: in section II, the setup used in this research is briefly presented. Section III accounts for the methodology used for damage map construction wherein the proposed SWF is elaborated. Then, qualitative and quantitative comparison is made between the SWF and conventional WF in section IV. At last, conclusion and future work are brought in section V.

II. MATERIAL AND MEASUREMENT

The experiment of this research is performed on one CFRP sample, CFRP1, with the size of 330x330x5.52 mm$^3$, which is formed from unidirectional CFRP laminate with layup [(45/0/-45/90)]$_1$ containing 11 distinctive flat bottom holes (FBHs) defects with different diameters, $d$, and relative thicknesses, $u$. The plate under investigation along specification of FBHs are illustrated in Fig. 1. For excitation, a surface-bonded piezoelectric (PZT) transducer and for vibration measurement, a 3D scanning laser Doppler vibrometer (SLDV) are employed, respectively. In order to excite the plate, a broadband linear chirp signal from 5 KHz to 300 KHz amplified to 50 Vpp using a Falco system WMA-300 voltage amplifier is applied utilizing PZT. SLDV measures the vibration velocity of each scan point in predefined grids at the inspection surface in 3 directions. This work is just based on the out-of-plane component. The detailed specification of the sweep signal and data acquisition system, as well as the schematic setup are shown in Fig. 2. In this figure, spatial coordinate of each scan point is indicated by $x$ and $y$, and $t_0$ is the discrete time variable where $n = 1, 2...L$, and $L$ is the number of time samples. $U_{exc}(x,y,t,n)$ and $V_z(x,y,t,n)$ denotes, respectively, the voltage amplitude of the excitation signal and the out-of-plane velocity amplitude in time domain. According to the number of time samples, $L$, horizontal scan grid, $N$, and vertical scan grid, $M$, a 3D dataset with the size of $(M\times N \times L)$ is derived, which is indicated by SLDV data in Fig. 2. Moreover, full wavefields of SLDV data are constructed with taking time slice at each time instant.

III. PROPOSED METHODOLOGY FOR DAMAGE DETECTION

For reference, Fig. 3 illustrates the summary of the damage detection methodology proposed in this paper, which is detailed in the following subsections.

A. Deriving toneburst responses

To obtain toneburst responses at different $f_c$’s, the method introduced in [10] is used, in which the whole system including PZT, instrumentation, and the plate is assumed linear. Thus, it is possible to compute the frequency response function (FRF) of each scan point, $H(x, y, f_c)$, by means of DFT, denoted by $F$:

$$H(x, y, f_c) = \frac{F \{V_z(x,y,t,n)\}}{F \{U_{exc}(x,y,t,n)\}}$$

(1)

\[u = 100 \frac{T_r}{T_{Base}}\]

<table>
<thead>
<tr>
<th>Defect name</th>
<th>#1</th>
<th>#2</th>
<th>#3</th>
<th>#4</th>
<th>#5</th>
<th>#6</th>
<th>#7</th>
<th>#8</th>
<th>#9</th>
<th>#10</th>
<th>#11</th>
</tr>
</thead>
<tbody>
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<td>d (mm)</td>
<td>7</td>
<td>15</td>
<td>15</td>
<td>15</td>
<td>12.5</td>
<td>15</td>
<td>20</td>
<td>15</td>
<td>25</td>
<td>15</td>
<td>15</td>
</tr>
<tr>
<td>u (%)</td>
<td>29</td>
<td>30</td>
<td>31</td>
<td>30</td>
<td>29</td>
<td>30</td>
<td>31</td>
<td>30</td>
<td>49</td>
<td>31</td>
<td>58</td>
</tr>
</tbody>
</table>

where $f_k$ represents discrete frequency variable with $k = 1, 2...L$. According to having FRF of each scan point, toneburst response at desired $f_c$ for each scan point, $V_z^{f_c}(x,y,t,n)$, could be derived:

$$V_z^{f_c}(x,y,t,n) = F^{-1}\{H(x, y, f_k)\cdot F\{U_{exc}^{f_c}(x,y,t,n)\}\}$$

(2)

where $F^{-1}$ stand for inverse DFT, and $U_{exc}^{f_c}(x,y,t,n)$ is desired toneburst excitation signal. In this research, 9 five-cycle toneburst signals having $f_c$ that ranges from 30 KHz to 190 KHz with the step of 20 KHz are used. Through frequency filtering mentioned above, our initial dataset with the size of $(M\times N \times L)$ is converted to the 4D array with the size of $(C \times M \times N \times L)$, consisting $C \times 3$D cubic concerning different $f_c$, where $C$ is the number of different $f_c$ that is employed. Hereafter, each of these 3D cubes, indicated by burst dataset in Fig. 3, is shown with TBC where $c = 1, 2...C$. In the next step, the process related to filtering in wavenumber domain is stated with the objective of mitigating undesirable vibrations in each burst dataset.
B. Initial filtering

In this subsection, an initial filter is constructed based on the WF procedure introduced in [7]. First, the function showing the entire energy of each full wavefield consisting TBc should be computed:

\[ E(t_n) = \sum_{y=1}^{N} \sum_{x=1}^{M} V_{zc}(x, y, t_n)^2 \]  

(3)

Then, 2 points should be found in \( E(t_n) \), the time instant in which \( E \) has maximum value, \( T_M \), and 10% of maximum value, \( T_S \). The period between \( T_S \) and \( T_M \) is named excitation period since incident waves occupy the great amount of the full wavefields placed in it. As such, if a filter is made based on the full wavefields placed in the excitation period, it could be a good representative of incident waves. Next, all of the full wavefields making TBc are transformed into the wavenumber domain through 2D DFT, \( F_{2D} \):

\[ V_{z}^{f}(k_x, k_y, t_n) = F_{2D} \{ V_{zc}(x, y, t_n) \} \]  

(4)

\( k_x \) and \( k_y \), respectively, stands for wavenumber in horizontal and vertical direction, and \( V_{z}^{f}(k_x, k_y, t_n) \) is full wavefield spectrum at time instant \( t_n \). Now, using the spectrums of full wavefields placed in the excitation period, a filter mask, \( M_{S} \), is needed to be constructed in order to remove undesirable waves corresponding to damage-free area. The procedure of making it could be abridged as below [7]:

1) Compute the average image of the spectrums of full wavefields placed in excitation period.

2) Obtain the normalized Cumulative distribution function (CDF) of the image resulted from step1.

3) Specify the intensity value, \( THR \), where CDF reaches 0.95.
4) Make a filter mask, \( M \), with assigning 0 to pixels obtained from step 1 whose intensity are more than \( THR \), and 1 to the pixels not satisfying the condition.

5) Smooth \( M \) by means of symmetric Gaussian low pass filter.

Then, the spectrum of each full wavefield at time instances \( t_n \) should be filtered by \( M \) and returned to the space-time domain by inverse 2D DFT, \( F_{2D}^{-1} \):

\[
\hat{V}_s^f(x, y, t_n) = F_{2D}^{-1} \{ V_s^f(k_x, k_y, t_n) \cdot M_z(k_x, k_y) \},
\]

where \( \hat{V}_s^f(x, y, t_n) \) is filtered full wavefield at time instant \( t_n \). It is important to mention that all steps described in the subsection B is the same as the work of [7].

C. Constructing damage map

In order to obtain one single damage map from filtered full wavefields, WRMS is utilized, simply computing the vibrational energy of each scan point [11]. This damage index is preferred to energy-based root mean square index (ERMS), introduced in [7], because ERMS has a drawback, namely, it is assumed that dispersion relations of the plate are known beforehand, which is not possible always [9]. The equation of WRMS is defined as:

\[
WRMS(x, y, w) = \sqrt{\sum_{n=1}^{N} \hat{V}_s^f(x, y, t_n)^2} \cdot n^w
\]

Generally, vibrational energy is higher in defect’s surrounding compared to sound area due to the reflection waves existing near the location of damages, and WRMS could take into account this increased vibrational energy and reveals the defects. Moreover, the weighting factor \( n^w \) is employed to deal with the decrease of propagation wave’s amplitude as it departs from the excitation point. The optimum value of \( w \) yielding to best distinction between defects and sound area could be determined by the algorithm introduced in [9]. In this paper, the mentioned algorithm is slightly modified in that it leads to better performance in the case of the method proposed in this paper. The algorithm could be summarized as below:

1) Compute damage maps using (6) for \( w \) ranges from 0 to 6 with the step of 0.25.

2) Remove pixels having intensity value higher than the \( m+\alpha \cdot \sigma \) from damage maps obtained from step 1, where \( m \) and \( \sigma \) are the mean and standard deviation of each damage map, respectively. The value of \( \alpha \) is set to be 2.5 based on experiments.

3) The above step is repeated \( \beta \) times until no more change is observed in the number of scan points satisfying the above mentioned condition.

4) Compute the \( \sigma \) of damages map outputted by step 3, denoted as \( \sigma_R \).

5) Choose the damage map having the lowest \( \sigma_R \), denoted as DM.

It should be mentioned that \( \alpha \) was set to be 3 in [9], but it is altered to 2.5 in order to remove high intensity pixels that could be defects or noises from the images outputted by step 2 with higher possibility. Furthermore, step 3 is added to increase this possibility, which causes that only scan points that are most likely in the sound area remain.

D. Successive filtering

In this step, filtered full wavefields are returned to the beginning part of the filtering process and filtered by the procedure mentioned in subsection B, so that remaining vibrations corresponding to the damage-free area that could not be eliminated from the full wavefields of TBc become suppressed. Physical reason for this step is detailed in next section. Then, a damage map should be constituted, and the process of making it is the same as the one mentioned in subsection C. Next, a stop condition for the successive algorithm should be designed so that the filtering procedure stops when adequate vibrations belonging to sound area are filtered, which is as follows: if the \( \sigma_R \) of damage map resulted from (6) is higher than the \( \sigma_R \) of the former constituted damage map outputted by previous iteration of filtering, the algorithm will be stopped, and the former damage map will be selected as the output of the algorithm. Otherwise, the last filtered full wavefields should be returned to the beginning of the filtering process again. Therefore, this process proceeds until the \( \sigma_R \) of the last damage map exceeds the \( \sigma_R \) of previous one.

In summary, following modifications are applied to the damage detection methodology proposed in [7]:

1) The proposed damage detection method takes into account the effect of different \( f_i \)'s, while the conventional method was designed based on optimal \( f_i \).

2) WRMS is utilized instead of ERMS for damage map construction, where the conventional algorithm for finding the optimum value of \( w \) is slightly modified.

3) The non-iterative conventional WF is converted to an iterative WF.

IV. EXPERIMENTAL RESULTS

Fig. 4 (a-i) illustrates damage maps constructed by conventional WF on the TB1 to TB9. Noted that, WRMS is used instead of ERMS in order to construct damage map in Fig. 4 (a-i) because our purpose is to compare the SWF and WF when similar method is used to obtain single damage map from filtered full wavefields. As is observable, this method could only attain acceptable contrast between deep defects and healthy area when the \( f_i \) of the applied toneburst signal is 30 or 50 KHz. The reason for this performance could be ascertained by investigating the plate’s dispersion curve, which could be obtained by applying 3D DFT on the broadband chirp response, as shown in Fig. 5. Since the frequency used to excite a plate in guided wave detection techniques typically ranges from 5 to 300 KHz, just the first three modes of Lamb wave have enough energy to be distinguished from this figure, \( A_0 \), \( A_1 \), and \( S_0 \). The highlighted modes are those traveling in the healthy area because the great part of the plate is associated with healthy area of similar thickness, and the modes related to defects are obscured by the ones corresponding to healthy area.

Based on Fig. 5, it could be argued that conventional WF can only detect three deepest defects in burst datasets therein the only dominant mode is \( A_0 \) (i.e., TB1 and TB2) by removing this mode. However, in TB3 to TB9, \( S_0 \) and \( A_1 \) has also remarkable
amplitude, which is equivalent to the fact that a larger area of their full wavefields are filled with incident waves compared to full wavefields belonging to TB1 and TB2. This fact negatively affects the performance of the conventional WF in detecting deep defects in TB3 to TB9 because the main parameter of the built filter, $THR$, was set to only remove $A_0$ by the authors in [7], but this fixed $THR$ is not able to filter enough amount of coefficients belonging to incident waves existing in the wavefields' spectrums of TB3 to TB9. Hence, setting 0.95 as the threshold value in CDF for building $M_s$ is not a good choice. To address this problem, there are two simple ways, reducing the threshold value for burst datasets relating to higher $f_c$’s or designing a SWF technique. The second suggestion is preferred since otherwise, for each burst dataset a fixed threshold would have to be determined, which could also vary in different datasets.

Fig. 6 shows the $M_s$’s made in each iteration of SWF for the case of TB3 and TB4, as well as their corresponding damage maps. For the both of these burst datasets only four iterations are needed. In Fig. 4 (j-r) the resulting damages map are illustrated for all burst datasets. As expected, the suggested algorithm leads to appropriate contrast between deep defects and sound area in TB3 to TB6, while this wasn’t possible in the non-successive WF. It should be mention that in the case of TB1 and TB2, the SWF has the same result with the conventional method because
if more than one iteration of filtering was done for them, the filter would start to eliminate the vibrations related to damages, and the contrast between defects and sound area would be decreased.

In Table I, the proposed method is compared with the conventional one based on contrast to noise (CNR) criteria:

$$\text{CNR} = 20 \log_{10} \left( \frac{M_{\text{defect}} - M_{\text{sound}}}{\sigma_{\text{sound}}} \right)$$  \hspace{1cm} (7)

where $M_{\text{defect}}$ denotes the mean of defective area, and $M_{\text{sound}}$ and $\sigma_{\text{sound}}$ are the mean and standard deviation of the sound area, respectively. The CNR is computed for three deepest defects in TB3 to TB6. Noted that, CNR is computed locally around three mentioned defects, not globally. As could be observed in the Table I, proposed method achieves higher CNR than the conventional one for deep defects in TB3 to TB6, which was predictable according to Fig. 4.

Albeit more acceptable results are achieved with the use of the proposed procedure for TB3 to TB6, but still no clear distinction between deep defects and sound area is determined in TB7 to TB9. There could be two main reasons for this. First the proposed filter is not dependent to frequency, and has the same form throughout the whole bandwidth of the toneburst excitation signal. Hence, while a large amount of incident waves related to modes traveling in the sound area are removed from the damage-free area during the first filtering cycle, considerable vibrations induced by damages are also filtered, which is deemed a significant disadvantage [9]. The second reason is that because all filters used in the proposed approach are linear, meaning that all pixels in a full wavefield contribute equally to filter construction. In conclusion, it is explained how we plan to mitigate mentioned drawbacks in future work.

### V. Conclusion

In this work, the conventional wavenumber filtering made based on an optimal toneburst excitation signal has been converted to a successive wavenumber filtering based on chirp response, which is capable of detecting both shallow and deep defects when more than one mode of Lamb wave exists in the recorded data. It is shown that compared to the wavenumber filtering, better distinction between defects and sound area is achieved via successive wavenumber filtering when the center frequency of the toneburst excitation signal is between 70 KHz and 130 KHz. However, not considerable difference was shown in the results from 150 KHz onwards.

In order to achieve acceptable results even in very high frequencies, we are trying to propose a nonlinear filter altering with frequency or time so that different areas of a full wavefield could have a different impact on making its corresponding filter.

### References


