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3D BUILDING RECONSTRUCTION IMPROVEMENT BASED ON GIVEN GROUND PLAN INFORMATION AND SURFACE MODELS EXTRACTED FROM SPACEBORNE IMAGERY

ABSTRACT

3D surface models have gained field as an important tool for urban planning and mapping. However, urban environments have a complex nature to model and they provide a challenge to investigate the current limits of automatic digital surface modeling from high resolution satellite imagery. An approach is introduced to improve a 3D surface model, extracted photogrammetrically from satellite imagery, based on the geometric building information embodied in existing 2D ground plans. First buildings are segmented from the extracted DSM based on the 2D polygonal building ground plans. To generate prismatic shaped structures with vertical walls and flat roofs, building shape is retrieved from the cadastre database while elevation information is extracted from the DSM. Within each 2D building boundary, a constant roof height is extracted based on statistical calculations of the height values. After buildings are segmented from the initial surface model, the remaining DSM is further processed to simplify to a smooth DTM that reflects bare ground, without artifacts, local relief, vegetation, cars and city furniture. In a next phase, both models are merged to yield an integrated city model or generalized DSM. The accuracy of the generalized surface model is assessed according to a quantitative-statistical analysis by comparison with two different types of reference data.

4.1 INTRODUCTION

3D city models have been increasingly applied as data source or visualization/communication method in a growing number of fields such as urban planning and city management, architecture, archaeological reconstruction, tourism, civil engineering, mobile telecommunication, energy supply, navigation, environmental simulation, disaster management, game industry, etc. A wide range of applications exist: sustainable urban development, water flow modeling, city climate studies, map updating, environmental evaluations, surface analysis, architectural design, 3D visualizations, etc. Although these application fields share the common demand for 3D information, their special requirements with regard to accuracy, detail, actuality and interoperability differ considerably.

Concerning the detail and accuracy of the 3D model, different Levels of Detail (LoD) can be distinguished, each corresponding to a certain degree of generalization (Meng & Forberg, 2007). An urban object or feature can be modeled differently depending on the LoD. Since August 2008, City Geography Markup Language, CityGML version 1.0.0 has been adopted as a standard by the Open Geospatial Consortium, Inc. (OGC) for modeling 3D urban objects, especially 3D buildings. CityGML is a common information model for the representation of 3D urban objects. It defines the classes and relations for the most relevant topographic objects in cities and regional models with respect to their geometrical, topological, semantical and appearance properties. CityGML differentiates 5 consecutive LoDs, with at LoD0 a map or image draped over a Digital Terrain Model (DTM) and at the finest level a 3D city model consisting of architectural building models with all details enriched with 3D interior structures (Kolbe *et al.*, 2005). Evidently, a higher LoD demands bigger efforts and costs to produce, while the level of automation drops.

The presented approach aims at extracting an approximated LoD1 city model based on stereo Ikonos High Resolution Satellite Imagery (HRSI) and an external dataset of 2D ground plans with building delineations. LoD1 is the well-known blocks model comprising prismatic buildings with flat roofs and without roof or wall texture (Kolbe *et al.*, 2005). The elevation information is generated according to machine-based photogrammetric extraction from spaceborne stereo imagery, while the building position, orientation and shape information, embodied by the eaves polygon, are gathered from the 2D cadastre database.

Urban surface reconstruction based on stereo imagery is a complex problem and is extensively researched for many decades. Only a few are reported, dealing with DSM extraction from high resolution satellite imagery (Zhang, 2005; Baltsavias *et al.*, 2006; Jacobsen, 2006; Zhang & Gruen, 2006; Crespi *et al.*, 2007; Krauss & Reinartz, 2010).

A lot of research is specifically devoted to the automation of 3D building extraction and reconstruction, based on dense 3D point clouds extracted from LiDAR data and aerial imagery. A distinction between semi-automatic approaches, which require a certain amount of human operator interactions, and automatic approaches can be made. The Merging Method (Jensen *et al.*, 1994), CC-Modeler (Gruen & Wang, 1998) and inJECT (Gülch & Mueller, 2001) are prominent examples of semi-automatic approaches. The automatic approaches are generally model-based and try to detect, segment and extract the building ground plan, followed by 3D reconstruction of the roof shape. Mostly, they reconstruct LoD2 polyhedral building structures based on determination of a model primitive that will fit a dense and detailed 3D roof point cloud best. Weidner & Förstner (1995), Fischer *et al.* (1998), Baillard & Zisserman (1999), Nevatia & Price (2002), Vinson & Cohen (2002) and Kim & Nevatia (2004) are interesting works that can be cited here.

In literature, a few approaches can be found that inject additional knowledge into the extraction strategy. Given 2D building delineation maps, e.g. 2D GIS data or cadastral data, provide essential building ground plan information and constrain the main shape. In Haala & Brenner (1999), Maas & Vosselman (1999), Stilla & Jurkiewicz (1999) and Kada & McKinley (2009), an accurate and dense LiDAR point cloud is processed in combination with 2D ground plans to extract building models, while in Haala & Anders (1996), Jibrini *et al.* (2000), Flamanc *et al.* (2003), Suveg & Vosselman (2004) and Taillandier (2005), buildings are reconstructed based on stereo aerial imagery and 2D ground plans.

Only a few approaches are reported, investigating the 3D building reconstruction issue based on satellite imagery. In Fraser *et al.* (2001) buildings are reconstructed based on Ikonos stereo imagery and the CC-Modeler workflow. In Guo & Yasuoka (2002) Ikonos imagery and laser scanning data are jointly used for snake-based building extraction and reconstruction. Lafarge *et al.* (2008) extracts building footprints by a reversible jump Markov chain Monte Carlo sampler embedded in a simulated annealing scheme. In Alobeid *et al.* (2010) a

semi-global matching approach is applied to improve 3D building reconstruction. The method discussed in Woo & Park (2011) is based on the extraction and grouping of 3D line segments.

Although the automatic approaches are robust and perform well in most situations, a fully automated procedure in operational state and generally applicable for surface reconstruction from large-scale (aerial and satellite) imagery over dense urban areas remains an unsolved problem, in spite of the many efforts in the photogrammetric and computer vision fields (Zhang, 2005). Cities are made up of a dense and complex mixture of artificial and natural urban features with an immense variety in size, shape, composition and arrangement (Mesev, 2003). This diversity often hampers automation processes.

In the presented work, an applicable, cost-effective and highly automated approach is proposed to produce a generalized LoD1 city model, based on photogrammetric processing of 1 m resolution satellite imagery and fusion with given building ground plans. Surface reconstruction, and especially building reconstruction, is addressed. If a DSM and 2D ground plan information is available, the approach is able to reconstruct the terrain surface and buildings in a fast and reliable way and also for a large coverage. The approach is applied on a large, densely built-up urban region covering approximately 90 km² and consisting of a varying urban morphology and high diversity in building types.

Compared with most of the previously mentioned automatic building reconstruction methods, the most fundamental difference of this work is that buildings are extracted from high resolution satellite imagery and not from aerial or LiDAR data. This has both benefits and drawbacks. The coverage of satellite images is much larger and sometimes a whole city can be captured in one stereo pair. On the other hand, 1 m Ikonos imagery does not provide a level of detail and 3D point cloud density to reconstruct a complex building roof shape. Partly because of the low 3D point density, the emphasis is on LoD1 prismatic building models and not on LoD2 polyhedral models with roof structure. The more generalized LoD1 models are also preferred in this particular study area as most buildings have a flat base, stuffed with covered terraces, water tanks, elevator shafts, antennas, etc. The generalization of this local roof height variation boosts the visual comprehension and reduces information overload and cognitive problems.

The use of given 2D building delineation maps provides essential building ground plan information, also in the case of small and complex buildings. They provide strong geometric constraints, useful for accurate reconstruction of the main building shape. In most countries, cadastre data is available nationwide. On the downside, the quality of the building reconstruction strongly depends on the quality and completeness of the external dataset. Missing buildings or erroneous building shape, position and orientation are possible flaws that can occur. Also, the generalized roof does not always approximate the construction in a correct way, e.g. the dome of a mosque. Suchlike landmarks can better be reconstructed according to a semi-automatic approach.

Objectives are:

- (i) testing the operability and general applicability of a cost-effective, highly automated method for LoD1 3D city model generation on a dense urban core;
- (ii) improving building modeling, as buildings are the key features in 3D city models. In general, it implies a transformation or generalization from the blob shaped buildings in the initial surface model to prismatic shaped structures with vertical walls and flat roofs;
- (iii) filtering and generalization of the DSM, after segmentation of the buildings, to a smooth, continuous and visual comprehensive DTM;
- (iv) optimal representation of a hybrid raster-vector city model for visualization and interpretation applications.

Research is conducted within the framework of the MAMUD project (Measuring And Modeling of Urban Dynamics), launched in 2007 and funded by the STEREO (Support to The Exploitation and Research of Earth Observation data) program of Belgian Science Policy. First, an overview is given of the used dataset and study field. Next, the machine-based surface model extraction methodology from the HRSI is discussed briefly. In next part, the methodology is outlined to improve building block modeling and to generalize the surface model after segmentation of the buildings. Section 4.5 focuses on visualization of the hybrid raster-vector model. Then the accuracy of the generalized surface model is assessed according to a quantitative-statistical analysis by comparison with two different types of reference data. The paper concludes with a brief summary and discussion of the applied methodology and obtained results.

4.2 IMAGE DATASET & STUDY FIELD

At the start of the MAMUD project, Ikonos imagery is selected as the most suitable for conducting the research because of its high radiometric and geometric capacities. The Ikonos platform, launched in 1999, was the first commercial satellite with a high spatial resolution acquiring panchromatic (0.45-0.90 μm) and multispectral imagery at approximately 1 m and 4 m respectively. The VHR Ikonos platform is able to rotate the pushbroom sensor up to an angle of 26° off-Nadir, so the satellite can acquire images of the same location from two different view points on the same orbital track. A surface model is extracted from an Ikonos along-track stereo pair acquired in March 2002.

Table 4-1. Characteristics of the along-track stereo pair acquired over the study field.

Image ID	Acquisition date	Elevation angle	Collection azimuth	Sun elevation	Sun azimuth
Forward	2002-03-01	67.59°	1.6°	39.1°	158.3°
Backward	2002-03-01	75.59°	214.1°	39.1°	158.3°

Both acquisitions are cloudless. The panchromatic images are resampled to a spatial resolution of 1 m by the image vendor and provided with the Rational Polynomial Coefficients (RPC) camera model file. The 1 m resolution of Ikonos panchromatic imagery supplies a level of detail that makes the identification and 3D reconstruction of individual structures, such as buildings, possible. According to GeoEye (2006), the map-oriented Ikonos GEO product has an overall horizontal positional accuracy of 25 m Circular Error 90 (CE90) without any ground control information. This indicates that a feature is imaged within 25 m of its actual planimetric position, at 90% probability or for 90% of the well-defined, photo-identifiable features. For altimetric accuracy, the Linear Error 90 (LE90) in vertical dimension is defined at 22 m in case of an along-track Ikonos stereo pair. With reliable Ground Control Point (GCP) information, the horizontal and vertical accuracy can be increased by eliminating bias errors to 4 m CE90 and 5 m LE90, corresponding with a Root Mean Square Error (RMSE) of 2 m and 3 m respectively (Dial, 2000). LE90 and CE90 are typically US accuracy expressions while RMSE is a standard error measure in photogrammetric research.

Figure 4-1. Overview map with (i) study area, delineated by the red polygon. (ii) GCPs, illustrated by red dots, used to refine the RPC sensor model; (iii) black dashed polygons indicating 3D building vector validation dataset (Ikonos MS image, 2005-05-16, RGB).

The study field covers a part of the city Istanbul, Turkey (figure 4-1). It is a city characterized by an intense urban growth, with a prominent densification concentrated along the Bosphorus strait. The study area covers approximately 90 km², containing the city core and reaching to the urban fringe in the North. The land cover is quite homogeneous and consists of a densely built-up area with a height range of 162 m with the lowest point at sea level. Geomorphologically, the area is characterized by a rugged landscape. Most building types within the study area are connected multi-family townhouses and apartment blocks, yet they are built rather in an irregular way and building size and shape may vary strongly. Within a block of houses, a roof landscape of high diversity occurs. Most roofs within the city core have a flat base but are stuffed with sealed terraces, water tanks, elevator shafts, antennas, etc. Taken also the narrow streets and the

rugged landscape into account, it makes the area quite challenging to model. At the western fringe of the study area, a zone with large rectangular industrial building types occurs while at the northern fringe a region with more residential, free-standing buildings can be found.

4.3 3D SURFACE MODEL EXTRACTION ALGORITHM

As the core topic of this paper is not the photogrammetric extraction methodology of the surface model but the refinement of it, the authors restrict the discussion of the extraction to the elementary aspects. Prior to processing of the VHR imagery, a contrast enhancement and radiometric normalization is applied to improve texture in shadowed areas and to reduce radiometric dissimilarities due to different illumination and atmospheric conditions. To enhance the contrast for each image individually and to equalize the radiometric differences between the imagery, an LCE Wallis filter is applied (Wallis, 1976). As most correlation algorithms are sensitive to image noise and the Wallis filter enhances also the noise, prior to contrast enhancement an adaptive smoothing filter, proposed by Saint-Marc *et al.* (1991), is applied.

To establish the relationship between 2D image and 3D object space and to calculate the position of the sensor (X_0, Y_0, Z_0) and the rotation along the three axes (ω, φ, κ) during image acquisition, a block bundle adjustment process is executed, based on a set of Rational Polynomial Coefficients (RPCs) and the Rational Functional sensor Model (RFM) (Grodecki & Dial, 2003). As RPCs are solely derived from satellite ephemeris and satellite attitude angles calculated by an on-board GPS/INS system, the RFM model suffers from biases in the sensor exterior orientation and is further refined with ground control information. Operated with a C-Nav Differential GPS system, clearly visible GCPs were measured, homogeneously distributed over the study area. The system provides sub-10 cm horizontal accuracy and sub-20 cm vertical accuracy. In total, 15 points with known map coordinates, homogeneously distributed and unambiguously identifiable in the images, were used to describe the relationship between imagery and terrain. The point distribution is illustrated in figure 4-1. The a priori geometric accuracy for the DSM extraction consists of an overall RMSE value of 0.68 m for X residuals, 0.72 m for Y residuals and 2.44 m for Z residuals. Prior to image matching, the original images are resampled and

rectified to an epipolar geometry based on the orientation parameters of the block bundle adjustment process.

The image matching process is considered as the core of the photogrammetric extraction and is capable to detect conjugate features between the overlapping images automatically, so these corresponding points are projections of the same physical feature in object space. The surface model can be processed afterwards by calculation of height differences based on the measurement of the disparity between corresponding pixels. The applied algorithm works according to a coarse-to-fine hierarchical matching strategy. Image pyramids consist of different versions of an image at exponentially decreasing resolutions. The bottom level of the pyramid contains the original image. The matching results of each higher pyramid level are used as approximations in the successive, lower level. At each level also an intermediate DSM is generated from the matched features and is refined through the image pyramid. Based on all data in each pyramid level, the matching parameters are determined and fine-tuned progressively, following a method proposed by Kanade & Okutomi (1994).

The matching algorithm is in essence a combination of feature point, grid point and 3D edge matching. This redundancy leads to additional constraints and more reliable results as blunders and mismatches can be further detected and removed according to a least-squares matching. Feature and grid point extraction generate dense 3D point clouds while 3D line features are complementary to point correlation as they comprise more geometric and semantic information and are less dependent on image noise.

The Lue operator, a local interest operator, is used to detect feature points that have a neighborhood with a maximum grey level variance (Lue, 1988). Grid point matching is especially valuable in areas with less texture where conjugate feature points are hard to detect. Instead of the rather randomly dispersed feature points, grid points are uniformly distributed over the image. For each grid point to be matched in the first image, the Area-Based Matching (ABM) algorithm searches for the conjugate pixel in the other image that correlates the most by shifting a kernel of certain size along the epipolar line. A correlation coefficient is used to identify possible matching candidates. The Geometrically Constrained Cross-Correlation or GC³ method is an extension of the standard cross-correlation technique (Zhang & Gruen, 2006). Edges are detected by the

Canny edge operator and approximated by connected straight line segments (Canny, 1986).

At a final stage an extended Least-Squares Matching method (LSM), called modified Multi-Photo Geometrically Constrained least-squares matching (MPGC), is performed using all matched features as precise approximations to check for consistency, to detect outliers and to further refine matching results. The MPGC algorithm combines the matched points with geometrical constraints, derived from image ray intersection conditions, epipolar constraint and knowledge about the image orientation. The algorithm is developed by Baltsavias (1991) and based on the LSM method described in Gruen (1985).

To generate a connected and continuous surface, the large amount of extracted discrete point measurements is interpolated. The extracted line features serve as breaklines to model natural and artificial surface discontinuities such as ridges and vertical building walls. Prior to DSM extraction, water bodies and areas that may be excluded from the model are masked out. The generated surface model is processed at a grid size of 3 m. The chosen resolution provides a dense 3D description of the covered surface and leads to the best equilibrium between detail and reduction of noise or information overload.

4.4 DSM IMPROVEMENT METHODOLOGY

The 'raw' surface model will be inflicted by artifacts, noise and outliers caused by errors of different origin such as physical limitations of the image sensor, limited model geometric accuracy and matching errors due to occlusion, shadow and sun reflection. The errors manifest themselves in the raster DSM as flaws, elevation inconsistencies, spikes or pits. Moreover, due to sparse matching results around buildings and subsequent interpolation, applying smoothing constraints, buildings have blob-like shapes in the model instead of rectilinear block geometry and small bystreets are not detected.

Figure 4-2. Flowchart for improving terrain and building modeling in a DSM, extracted photogrammetrically from satellite imagery.

An approach is proposed (see figure 4-2) to reduce noise and errors in the surface model and improve building block modeling by segmentation of the buildings and further processing of first the building layer, secondly the remaining DSM to generalize to a smooth DTM, modeling only bare ground. A Digital Elevation Model (DEM) is in essence a digital model or 3-D representation of a terrain's surface, created from terrain elevation data. A DEM is often used as a generic term for DSMs and DTMs. In the most cases the term DSM represents the Earth's surface and includes all objects on it (Li *et al.*, 2005). A DSM actually represents the highest detected points such as tops of trees and roofs of buildings and only indicates the height of the terrain where it is not covered by objects. A DTM on the other hand represents the bare ground surface without any objects like vegetation and buildings (Li *et al.*, 2005). A Digital Building Model (DBM) or building layer is a digital representation of only the building features within the dataset.

The availability and use of an existing, external database of 2D roof boundaries has great potential, particularly to delineate and improve building modeling in DSMs derived from satellite imagery, and also to extract smooth terrain. Distinction between a terrain model layer and a building model layer allows to apply spatial filtering on the elevation values adapted to the specific properties of the layer and to model the discrepancy between the smoothness of the continuous terrain surface and sudden occurrence of height discontinuities from vertical walls. After processing, both models can be merged to yield a refined DSM or an integrated LoD1 city model.

4.4.1 DBM

A method is developed to further optimize building shape in the raster DSM extracted from stereoscopic HRSI, as these are the key features in 3D city models. In essence it implies a transformation or generalization from the blob shaped buildings in the surface model to prismatic shaped structures with vertical walls by eliminating the smooth transition between terrain surface and roofs and the rounding of building edges. The DBM will consist of prismatic building models, which describe a structure by its polygonal ground plane and a calculated height (Herman & Kanade, 1986). Prismatic models are a generalized form of polyhedral models, thus suggesting planar roof structures. Most roofs within the study area have a flat base but are stuffed with covered terraces, water tanks, elevator shafts, antennas, etc.

In case of a model-driven approach it would be very hard to determine suitable polyhedral model primitives for such roof morphology. Simplification of the local roof height variation to a constant height boosts the visual comprehension and reduces noise and information overload. The assumptions that building roofs are quasi parallel to the terrain surface while walls tend to be perpendicular to it, geometrically constrain the final building shape and count for a large part of the man-made objects. Based on these assumptions of orthogonality and parallelism, the complex building reconstruction problem can be reduced to the reconstruction of planar roof delineation or its polygonal projection on the terrain surface in first phase and calculation of its mean height.

4.4.1.1 Building segmentation

The approach combines the information from the 3D surface model with a dataset consisting of 2D building contours. The simplified building shape is derived based on the geometric information from the 2D roof boundaries while structure height information is extracted from the DSM. The buildings within the study field are assumed to have planar polygonal roof structures.

An available 2D cadastral database is used to segment the buildings within the dataset. The dataset contains detailed building footprint ground plans at the level of individual structures, e.g. building shape polygon, planimetric position, orientation and topology useful to discriminate buildings from the digital surface model. Suchlike cadastre data is available in digital format for urban areas in most countries, while 3D descriptions are not. The data is gathered by digitizing existing maps and plans, by photogrammetry and by field measurements and was last updated in 2005, regarding the used dataset.

In a first phase, the 2D building footprints are fitted on the generated raster surface model, constraining the building blobs and allowing to extract portions or patches of pixels that correspond with building structures. All pixels or Z point measurements within or crossing the 2D building footprints are subsetted into groups describing the roof surface height of a particular building. To avoid saw-edged delineations for the buildings, the DSM extracted from the matching point cloud at a spacing of 3 m is resampled to a 0.5 m grid. As both datasets are in the same cartographic projection system, a transformation was not necessary and positional shifts did not occur. Discriminating buildings from other features and the terrain greatly reduces the complexity of 3D reconstruction.

4.4.1.2 Volumetric building model generation

The objective of this step is to assign a constant height value to each building, to model the elevation of a planar roof in accordance to the LoD1 definition. For each 2D building boundary a constant roof height value will be computed via zonal statistical calculations on the roof height values of each extracted patch of connected pixels. Different zonal statistics, such as average, median, lower and upper quartile height are tested and the approach described below aims at selecting the statistical height which is the best approximation of the correct

building height. If there are many outliers in the DSM, the average height will be much more influenced than the median or the quartiles. The lower quartile value can be of interest if the DSM is biased, overestimating building height. The same count for the upper quartile in case of underestimation. To determine which height parameter is the best approximation for correct building height, the statistical roof heights are compared with a 3D reference database consisting of manually measured building delineation and height, provided by IMP-Bimtas, the partner in Istanbul. As this article aims at the generation of a LoD1 city model, the generalized prismatic buildings in the reference dataset, which have a constant height at cornice level, are considered as correct building height.

For two parts of the study area, reference buildings were collected. Both areas are illustrated in figure 4-1 by a black dashed polygon. Zone UA1 covers 5.8 km² and is located in the South of the study area. The area contains the city core with mainly blocks of connected multi-family townhouses and historical buildings. Zone UA2, located in the Southwest, covers 9.4 km² and consists of an industrial area in the South and a recent residential area in the northern part. Prismatic buildings with planar roofs were collected: a constant height was collected for each building with Z-map photo software on stereo aerial imagery by digitizing the outlines of the building at cornice level. The aerial flight has been conducted with an analogue JenOptik LC0030 camera ($f= 305$ mm) in July 2006. Each image has a photo scale of 1:4500 with a GSD of 0.10 m and covers almost 1 km². We assume that the reference dataset has a much higher quality than the automatically generated DSMs as skilled operators can more accurately extract height information, than an automatic algorithm. For each building in the reference dataset, the (measured) constant roof height is compared with the statistical height parameter calculated for the particular building. The comparison is done by subtracting reference height from the statistical height value. In table 4-2, the difference between each statistical roof height parameter and reference roof height is summarized by six descriptive parameters and given for both reference zones separately. 12.769 building heights are compared in area UA1 and 43.712 in zone UA2.

Table 4-2. Quantitative measures for four different statistical building height parameters compared with measured building height from reference (UA1 / UA2). Both areas, UA1 and UA2, are illustrated in figure 4-1 by a black

dashed polygon. Q1 and Q3 are respectively the lower and upper quartile or 25% and 75% percentile of the roof heights within a building footprint.

	Building height statistics (UA1 (n=12.769) / UA2 (n=43.712))			
	<i>Average Z</i>	<i>Q1 Z</i>	<i>Median Z</i>	<i>Q3 Z</i>
Min dZ (m)	-20.78/-34.84	-22.43/-44.25	-21.20/-37.38	-21.20/-30.15
Max dZ (m)	26.16/43.78	26.16/44.24	26.16/44.24	26.16/44.24
Mean dZ (m)	-1.23/0.12	-1.75/-0.56	-1.29/0.08	-0.79/0.62
St.dev. (m)	3.31/3.58	3.38/3.63	3.33/3.62	3.43/3.68
MAE (m)	2.48/2.65	2.63/2.70	2.48/2.66	2.49/2.74
RMSE (m)	3.53/3.58	3.81/3.67	3.57/3.62	3.52/3.73

The mean dZ or bias can be interpreted as a signed parameter indicating whether the statistical height is biased and if so, in which direction. It is an indicator for the magnitude of overall under- or overestimation of building elevation in the surface model. This bias is usually a consequence of different factors, such as the stereo constellation, quality of GCPs, accuracy of the image orientation process and performance of the matching algorithm. It can be stated that the overall bias is small for all four statistics. As the reference height is subtracted from the statistical height, building elevation is slightly underestimated for all statistics in zone UA1, while there is a slight overestimation for zone UA2, except for the lower quartile. The magnitude of the dZ dispersion or random error of the height differences is measured by the standard deviation. The height differences are not spread out over a large range of values but tend to be relatively close to the mean. The Mean Absolute Error (MAE) parameter describes the average magnitude of the height differences without considering their direction. The MAE is a linear score which means that all the individual differences are weighted equally in the average. The RMSE is a common used error parameter in earth science model analysis. It is a quadratic scoring rule which also measures the average magnitude of the deviation.

In general, all four statistical height parameters perform quite similar in approximating the reference building heights. The biggest MAE difference is only 0.15 m for zone UA1 and 0.09 m for zone UA2, while the biggest RMSE difference is 0.29 m for zone UA1 and 0.15 m for zone UA2. As only small differences can be noticed between the results of the quartiles, the roof height values in the ‘raw’ surface model seem to be quite constant within the Inter Quartile Range (IQR). However the average Z yields the smallest deviation from the reference heights,

the median height parameter is preferred as the parameter is generally less sensitive to outliers than the average Z. The preference for the median Z can also be justified since the differences between average Z and median Z are not significant. MAE difference is zero for UA1 and 0.01 m for zone UA2, while RMSE difference is 0.04 m for both zones. In case of another dataset or other surface model with much outliers, it can be assumed that the average Z will deviate more from the reference height than the median Z.

As the median Z parameter is considered to be the best approximation for the building heights in the reference, it is assigned as an attribute for roof elevation to each 2D building vector. Transformation of the footprints to a raster format assigning the height value to each corresponding pixel yields a DBM raster layer. For each building, the raster has pixels with same elevation values, assuming flat roofs and removing local relief and bell shape. 'No data' values are assigned to the non-building areas in the DBM.

4.4.2 DTM

In addition to a building layer (DBM), a terrain model layer (DTM) can be extracted after buildings, the most prominent objects in an urban surface model, are segmented from the initial 'raw' surface model. The remaining surface model without buildings is not a smooth, continuous surface. It does not only reflect bare ground but also errors due to poor matching, vegetation and small features such as cars, fences, lampposts and other city furniture. These features induce local relief, spikes and pits in a model extracted from 1 m resolution imagery. In a LoD1 city model these are experienced as noise or information overload and give rise to cognitive problems.

First, significant errors and problematic areas are detected and removed from the initial DSM. Afterwards the model is filtered, simplified and interpolated to fill the gaps, to apply smoothness constraints and to abstract meaningful to yield a continuous, visual comprehensive DTM layer.

4.4.2.1 Removal of problematic areas

Due to the existence of high-rise objects and the Earth's position relative to the sun, shadows occur in the imagery. Areas of very poor or no texture are a

significant source of matching errors and consequently height errors. On the other hand, geometric displacement of high-rise objects conceals portions of the surface in the 2D imagery and hampers 3D reconstruction. Due to the lack of image texture in case of shadow and the lack of image information in case of a concealed area, matching and modeling in these areas is complex and often incorrectly or simply impossible. Beside shadow and occlusion, significant height errors are common in vegetated areas. Below the applied strategies are discussed to remove these problematic areas from the initial DSM.

A shadow and occlusion map is produced according to a pixel-based approach to assist the detection and removal of both phenomena from the terrain layer. Once the building modeling is improved by fusion with 2D cornice polygons and removal of local elevation variations, smoothing and artifacts, the DBM serves as a reliable database to detect building shadow and occlusion patches on the terrain. Based on the information in the image metadata file about sun elevation angle and sun azimuth at the time of image acquisition, building shadow can be modeled.

A standard ray tracing approach is applied to model the direction and declination of the light source, illuminating the surface model. The light source is considered at infinity. A binary shadow map is created for each Ikonos image, indicating a shadowed or non-shadowed area. Shadow in both images coincides as the acquisition of the backward image is less than one minute later than the acquisition of the forward image. As the images are acquired early in the year, shadows are quite long due to small sun elevation angle. Within the study area, 20.2% of the terrain surface is covered by building shadow. Binary occlusion maps are produced according to the same approach based on the satellite azimuth and elevation angle at the acquisition time. In case of the Ikonos along-track stereo pair, 11.6% of the terrain surface is occluded by building displacement.

The remaining DSM subtracted by the segmented building patches can be overlaid by the shadow and occlusion binary maps to identify the respective areas. Based on this information, building occlusion and shadow is masked out from the DSM. The combination of shadow and occlusion covers 24.2% of the study area, which is a considerable proportion. Due to the problematic nature of vegetated areas, a vegetation mask is generated based on a high-resolution Land

Use / Land Cover (LULC) classification process (Binard *et al.*, 2010) and used to assign a 'no data' value to pixels belonging to this class.

4.4.2.2 DTM interpolation & filtering

After removal of buildings, significant errors and problematic areas, the remaining DSM needs to be interpolated and filtered: holes without height information need to be filled and off-terrain points need to be removed to extract out of the DSM a smooth and generalized DTM, which approximates only the terrain surface. Morphological filters are applied to execute both operations according to a method proposed by Chen *et al.* (2007). Morphological closing is applied to fill data holes, while opening removes off-terrain points.

In essence, morphological filters rely upon the height relation of neighboring points to identify off-terrain points or holes. Only main heights are kept as a rough approximation of the terrain. The filters in mathematical morphology are based on erosion and dilation, which are performed over a neighborhood specified by a moving window or structural element (Soille, 2003). Erosion and dilation are respectively defined by equation (4-1) and (4-2):

$$[E_S(I)](x) = \min \{x_b\} \quad (\text{Eq. 4-1})$$

$$[D_S(I)](x) = \max \{x_b\} \quad (\text{Eq. 4-2})$$

where E is erosion; D is dilation; I is the DSM or greyscale image; S is the structural element; x is the centre pixel of moving window; and x_b is the neighborhood of x , defined by the structural element.

Morphological closing is defined as $E(D(I,S),S)$ while opening is defined by the function $D(E(I,S),S)$. First to fill all empty data in the surface model a closing operation is iteratively applied, which executes a dilation followed by an erosion to compensate for height overestimation. The kernel is parameterized at seven pixels and the filter is set conditionally, to restrict the application to only empty data cells.

Next, to produce a continuous, generalized surface and to remove all remaining off-terrain points and outliers, an opening operation is applied which executes an erosion followed by dilation. The kernel is parameterized at seven pixels and a threshold of 2 m is set. Defining the optimal structural element size

can be challenging: if it is set too small, the filter will miss its effect as not all off-terrain features will be removed. If it is set too large, detail will be lost as more terrain will be flattened. As the most prominent off-terrain features (buildings and vegetation) are already removed from the DSM as well as problematic areas (shadowed and occluded areas) which give rise to significant outliers or spikes, the kernel size could be kept small. This reduces the flattening of the terrain. The threshold of 2 m is necessary to differentiate terrain points from off-terrain points or to detect height jumps. If the difference between old and newly calculated pixel value is bigger than the threshold, then the point is not considered as a terrain point and the new value will be assigned to the pixel. In case of a terrain point, the original value is retained.

Finally, the generated DTM is smoothed to reduce step effects caused by the morphologic operators by convolving the DTM layer iteratively with a low pass filter.

4.4.3 Refined DSM

After processing of the DBM and DTM, both models can be merged into an integrated and refined DSM. Prior to fusion of both models, the DBM and DTM elevation information is compared to detect possible anomalies. In the event that the DBM height is lower than the DTM height or if the difference is smaller than a certain threshold, the actual building is deleted from the DBM layer. To parameterize the threshold, it is assumed that a building must be at least 3 m high. Some anomalies can occur due to the temporal shift between the datasets.

In presented case the 2D vector dataset, last revised in 2005, is more recent than the acquisition of the Ikonos imagery. In case of a newly constructed building which is not yet in the imagery but digitized in the 2D vector dataset, the median height statistic, assigned to the building as roof height attribute, will actually be calculated based on a set of terrain points. The concerning building will be deleted, as the height will be slightly lower or higher than the filtered terrain height of the DTM. An overview of the refined DSM for the whole study area is illustrated in figure 4-3. A zoom on 2 parts in map and perspective view is given in figure 4-4.

Figure 4-3. Merge of DTM and DBM to a final DSM, covering the study field.
Two DSM enlargements are delineated and illustrated in figure 4-4.

Visual-qualitative analysis indicates that the refined city model reconstructs the terrain, buildings as well as the street-house pattern veracious and in a detailed way. The main types of buildings, occurring within the dataset, are modeled correctly, although generalized according to the LoD1 model definition. The models of close-set apartment blocks and townhouses in the city centre as well as detached houses and large industrial/commercial buildings, approximate the main building shape. Instead of a blob shape, buildings have a prismatic

shaped structure with quasi vertical walls, planar roof and a sharp transition between the base of the building and the terrain. Small alleys are reconstructed correctly and are clearly recognizable in the model, while in the raw DSM bystreets are often not modeled and close-set buildings are merged due to building shadow and occlusion. Removal of shadow and occlusion and subsequent morphological filtering of the terrain layer has yield a smooth surface, stripped of noise, outliers, vegetation and off-terrain points. Meaningful abstraction of local relief, spikes and pits results in a visual comprehensive surface. The reconstruction problem of very small dwellings persists nonetheless in the refined DSM. Due to the limited resolution of the imagery, often too few elevation data is captured on small dwellings which prevent an adequate modeling. Sometimes they appear as a small peak or are not modeled at all.

Figure 4-4(a) & 4-4(b). A zoom in map and perspective view respectively on an area, consisting mainly of industrial/commercial buildings and on a part of the dense city core. The delineation for both areas, as well as the perspective viewing direction is indicated on the overview map in figure 4-3.

4.5 HYBRID RASTER-VECTOR CITY MODEL

Further analytical analysis requires the 3D information generally in a raster format, however a 3D vector-based, volumetric representation for buildings has greater potential for visualization applications and interpretation. On the other hand, the continuous terrain surface can be visualized more understandable by a raster DTM, instead of vector representations such as a TIN or height contours. Integration of both results in a hybrid model using raster and vector data simultaneously.

The hybrid model requires first a transformation of the DBM layer to a vector description with 3D building block geometry or solids. Each building must be described by an individual object with a cubic, rectilinear geometry to which multiple attributes can be linked. In first phase, the median height value for each building, derived from the initial surface model, is assigned as an attribute for roof elevation to the objects of the external 2D vector dataset consisting of 2D building delineations. In next phase, the 2D roof polygons are extruded to solid prismatic structures onto the raster DTM layer based on the roof elevation attribute. The hypothesis that eaves height is constant, building roofs are quasi parallel to the terrain surface while walls tend to be perpendicular to it and are planar, geometrically constrain the final building shape and allow to reconstruct a solid out of the 3D roof boundary. Building walls are determined by the eaves lines and approximated by vertical planes and can be extended vertically to the DTM. The volumetric building models in this research case are linked only with geometric and indexing attributes but can be extended with semantics or thematic attributes, such as building function, number of residents, etc.

For important landmarks within the study area, LoD3 architectural models with detailed wall and roof structures and mapped with high-resolution textures are designed by the Istanbul Metropolitan Planning centre, based on laser and optical data (Baz *et al.*, 2008). In figure 4-5, a LoD3 architectural model of the

Suleymaniye mosque, Istanbul is illustrated. Evidently, higher LoD models demand much more manual input from an operator.

Figure 4-5. LoD3 architectural model design of Suleymaniye mosque in Istanbul study area (3D Studio Max model produced by IMP-Bimtas).

The interpolated and filtered DTM is draped with a pan-sharpened ortho-image for photorealistic representation and assisting natural interpretation. First, the panchromatic and multispectral image bands are ortho-rectified. During ortho-generation phase the sensor geometry of the images, characterized by a parallel projection in along-track direction and perspective projection in across-track direction, is transformed to map geometry based on the generated surface model. Transformation of raw to geo-corrected imagery produces planimetrically corrected images that represent each pixel or feature in its correct geometric position. Ortho-generation reduces not only geometric errors due to camera orientation and characteristics but copes also with terrain-related distortions, e.g. topographic relief displacement and Earth curvature. As a DSM is available instead of a DTM, also topographic features such as buildings can be corrected for their height displacement. Back-projection from the DSM to the image, based on the orientation parameters from the bundle adjustment, supplies the grey value or texture information for each pixel. The ortho-photo quality depends

highly on the accuracy of the DSM as gross altimetric errors will result in planimetric errors in the generated ortho-photo. Ortho-images are extracted at a ground sample distance of 1 m or 1 pixel.

In addition to ortho-rectification, the 1 m panchromatic band is pan-sharpened by combining with the 4 m low-resolution multispectral bands to produce an RGB, 1 m high-resolution image. The pan-sharpening takes advantage of the complementary spatial/spectral resolution characteristics of both image bands. A Gram-Schmidt (GS) spectral sharpening is applied, developed by Laben & Brower (2000).

Based on experimental results, The GS pan-sharpening method performs the best in terms of preserving spatial and spectral information of the features (Yuhendra *et al.*, 2010). The GS algorithm is based on a rotation similar in nature to a Principal Component Analysis (PCA). First, The GS fusion simulates a lower spatial resolution panchromatic image from the low-resolution multispectral bands. In general, this is achieved by averaging the multispectral bands. Based on the image orientation data, all bands can be co-registered. As a next step, a GS transformation is performed for the simulated panchromatic band and the multispectral bands, with the simulated panchromatic band employed as the first band. The statistics of the original panchromatic image are adjusted to match the statistics of the first transform band resulting from the Gram-Schmidt transformation to produce a modified higher spatial resolution panchromatic image. Then, the first Gram Schmidt band is substituted by the high-resolution panchromatic band to produce a new set of transformed bands. Finally, an inverse Gram Schmidt transformation is applied to create the pan-sharpened multispectral bands (Laben & Brower, 2000).

An extract of the final hybrid model, consisting of building vector-based solids and a raster DTM, draped with a pan-sharpened ortho-image, is given in figure 4-6.

Figure 4-6. Perspective view on an extract of the rendered hybrid model, consisting of building solids and raster DTM draped with pan-sharpened ortho-image.

4.6 QUALITY & ACCURACY ASSESSMENT

The accuracy of the integrated and generalized surface model is assessed according to a quantitative-statistical analysis by comparison with two different types of reference datasets. The accuracy of the model can be defined as the difference between a calculated or modeled position and a measured or observed position while an error can be defined as a lack of quality or level of accuracy (Podobnikar, 2009).

In a first approach the elevation model is assessed by comparison with reference check points. In the second approach, the extracted DSM is compared with a reference consisting of 3D building contours, digitized manually on high resolution aerial imagery. Both assessment approaches have their specific strengths and weaknesses and can be considered as complementary as different aspects of the surface model quality and accuracy are assessed.

The quality of reference points is expected to be higher than of rooftops contours or a reference DSM as the latter are derived from remote sensing data

while reference points are measured directly on the terrain and can be considered as ground truth. On the other hand, the number of reference points is limited by financial and logistical constraints. They also do not provide any information on the building modeling quality. The reference model applied in the second approach is of high quality as the buildings are captured by well-trained operators. However, the method assesses exclusively the modeling of building height. To get an insight into the overall model accuracy for all land cover types, the extracted surface models could not be compared with a continuous reference DSM as none is available at present time for the study area with an adequate accuracy and level of detail, e.g. derived from LiDAR data. In both analysis methods, the statistical parameters for the ‘raw’ and generalized or refined surface model are compared with each other.

4.6.1 3D validation points

In a first approach the elevation model is assessed by comparison with validation check points. A dataset of 35 check points, distributed as uniform as possible over the study area, is used to check the height accuracy of the refined surface model. Check points are independent ground control points, meaning that they are not used in the photogrammetric processing of the model. The Z residuals are expressed in terms of a root mean square error and summarized in table 4-3. The assessment is also performed for the raw DSM, which is not refined based on 2D building outlines.

Table 4-3. Geometric accuracy analysis with reference points.

	A priori geometric accuracy (m)			
	<i>No. of GCP</i>	<i>RMSX</i>	<i>RMSY</i>	<i>RMSZ</i>
Along-track	15	0.68	0.72	2.44
DSM geometric accuracy (m)				
Raw DSM	35	-	-	2.61
Refined DSM	35	-	-	2.84

In table 4-3, first the a priori geometric accuracy is given, which reflects the quality and robustness of the image orientation process. RMS error values in X, Y and Z are given for the total of 15 ground control points that were used to fix the mathematical relationship between image and object coordinate space. For X and

Y, sub-pixel accuracy is obtained. RMSE for the Z component is less than three pixels. 35 independent check points are used to calculate the RMSZ error between measured positions and the predicted values by both models. The altimetric error is in the same range but slightly bigger for the refined DSM (0.23 m). This is due to the interpolation and morphological filtering of the model, applying generalization and global smoothing constraints. The quantitative accuracy check with reference points does not reflect any advantages for the refined DSM approach. This is because the major improvements of the refined method are situated on and in the vicinity of buildings and elevation discontinuities. On the other hand, the assessment represents optimal conditions at check points which are easily identifiable, highly contrasted in the image and located in open terrain to have a sufficient satellite constellation for GPS measurements and to prevent that points are invisible in the imagery due to occlusion and shadow. The refined as well as the raw surface model yields good and comparable results within these non-complex areas. For both DSMs, the measured accuracies are better than the specified CE90 and LE90 theoretical accuracies claimed by the image vendor. The a priori geometric accuracy predicted the model accuracy well, as the predicted errors are highly correlated with the statistics that are calculated based on independent check points.

4.6.2 3D building contour reference

In the second approach, the surface model before and after filtering/generalization is investigated. Only vertical positional accuracy of building roof height is assessed. The buildings in the raw DSM, generated from the along-track Ikonos stereo pair, as well as the buildings in the refined DSM are compared with a reference dataset, consisting of manually measured building delineation and height. It concerns the same 3D rooftop vector dataset, used for the determination of the most appropriate statistical height parameter. For each building in the reference dataset, reference height is compared with modeled height. The comparison is done by subtracting reference heights from model heights. Statistical parameters are summarized for the building height differences within the 95% confidence interval in table 4-4. In total, 11.999 buildings are compared in zone UA1 and 41.757 buildings in zone UA2.

Table 4-4. Descriptive statistics of respectively ‘raw surface model minus reference and refined surface model minus reference model’ for $\mu \pm 2\sigma$.

	Raw DSM		Refined DSM	
	<i>Zone UA1</i>	<i>Zone UA2</i>	<i>Zone UA1</i>	<i>Zone UA2</i>
# Compared buildings	11999	41757	11999	41757
Min dZ (m)	-11.51	-12.89	-7.72	-7.03
Max dZ (m)	5.81	11.16	5.35	7.12
Mean dZ (m)	-3.05	-1.56	-0.97	0.05
St.dev. (m)	3.39	4.56	2.41	2.89
MAE (m)	3.75	3.89	2.00	2.30
RMSE (m)	4.56	4.82	2.60	2.89

The bias is smaller for the refined DSM and nearly zero for zone UA2. In zone UA1 and in both zones for the raw DSM, model height underestimates reference height. The magnitude of the dZ dispersion or random error of the height differences is measured by the standard deviation. The standard deviation can also be interpreted as a measure of preciseness. The preciseness of the refined DSM for building height estimation is better than for the raw surface model. Both, the MAE and RMSE measure the average magnitude of the deviation without considering its direction. The MAE(95) is improved 1.75 m for zone UA1 and 1.59 m for UA2. Unlike the MAE, where the differences are weighted equally, the RMSE gives a relatively high weight to large deviations and makes the measure more sensitive to outliers, as the height differences are squared before they are averaged. Either for zone UA1 as for zone UA2, the RMSE(95) is significantly better for the refined DSM. The RMSE(95) for the refined DSM is 1.96 m lower for zone UA1 and 1.93 m lower for UA2. For the raw DSM, RMSE(68) is 3.83 m and 3.52 m for zone UA1 and UA2 respectively. For the refined DSM, RMSE(68) is respectively 1.88 m and 1.82 m.

4.7 CONCLUSION & DISCUSSION

3D city model generation from space imagery by highly automated photometric methods has great potential but still urban scene and especially building modeling is considered as an extremely complex problem. During image acquisition, the 3D object scene is projected onto the 2D image plane. As the

projection causes information loss due to the convergent viewing angle and presence of urban features such as buildings, the reconstruction of the 3D scene is an inverse, ill-posed problem (Terzopoulos, 1986). The most prominent distortions that hamper the 3D reconstruction from 2D imagery are image dissimilarities, occlusion, shadow and steep changes in slope. Without external geometric building information or manual feature extraction, it is extremely difficult to reconstruct strictly vertical building walls, narrow streets, small dwellings and to remove visual noise and information overload from the model. Flaws mainly occur in the densely built-up urban core, where close-set buildings are often merged into building blocks and blob-like shaped building models are still present, due to residual shadow and occlusion.

A fast, reliable and cost-effective approach is proposed to produce a LoD1 city surface model, based on photogrammetric processing of a 1 m resolution Ikonos stereo pair, refined by fusion with given cadastre data. The approach is tested on a 90 km² wide urban environment, consisting of a varying urban morphology and several building types. The availability and use of an existing, external database of 2D roof boundaries has great potential to delineate and improve building modeling in DSMs derived from satellite imagery. 2D building polygons provide strong geometric constraints, useful for reconstruction of the main building shape in first place but also for segmentation of buildings from the DSM and spatial filtering of elevation values in DBM and DTM separately. Based on the median height parameter, the buildings in the resulting DBM yield good approximations for the main building types occurring within the whole dataset. The DTM is generalized, based on morphological filtering, to a smooth continuous surface, modeling only bare ground.

The obtained RMSE for the refined surface model are within the boundaries of the CE90 and LE90 theoretical accuracies claimed by the image vendor, for both quantitative assessment approaches. However, this is not the case for the raw surface model in the quantitative-statistical analysis based on a 3D rooftop vector reference. The raw DSM yields an RMSE(95) of 4.56 m in zone UA1 and 4.82 m in zone UA2.

At the start of the MAMUD project in 2007, Ikonos imagery was considered the most appropriate HRSI type for conducting the research because of its high radiometric and geometric capacities. VHR earth observation satellite systems evolve to capture images with a more stable radiometry and geometry and at

increasingly finer resolutions. At present, a wide variety of earth observation sensors are operational with a GSD finer than half a meter, e.g. Worldview-1, Worldview-2 and GeoEye-1. GeoEye-2, planned to be launched in early 2013, is a third generation earth observation satellite and will attain a resolution of 0.25 m in panchromatic mode. From a technical point of view, the presented approach has a generic character and is easily applicable on DSMs derived from these sensors. Evolution in geometry, radiometry and resolution will improve the building reconstruction approach as the basic input, the DSM, will yield a much denser and more accurate 3D point cloud.

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