AUTOMATIC HEIGHT ATTRIBUTE ASSIGNMENT FOR BUILDING POLYGONS: CITY MODELING WITH LEVEL OF DETAIL ZERO

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ABSTRACT
In recent years there has been a significant rise in interest in 3D city modeling and this is coupled with a need to quickly update 3D city models. It is essential to increase the speed and the level of automation of 3D data capture if costs are to be sufficiently low to make large scale production of 3D data viable. We assume that building footprints are available in advance. In our case, these are building polygons of the Ordnance Survey® OS MasterMap® Topography Layer. We propose an economically viable solution for extracting a basic roof description for city modeling based on a reliable estimation of a set of height attributes for each building roof. The height attributes can be estimated using a Digital Surface Model (DSM) that has been generated using photogrammetry or from aerial laser scanning. If a DSM is not available in advance, aerial images are used to extract a DSM of the building roof by image matching. Two steps are required in order to make the crude DSM more reliable for the height estimation. In the first step, blunders are eliminated using an efficient blunder detection method based on a local density function. In the second step, the points belonging only to the building roof are preserved. For this purpose, the local gradient is calculated and points falling on steep slopes, i.e. points on the building walls, are eliminated from the DSM. In this paper we present our design strategy and the results of automatically creating low level city models for a range of urban test sites. We also present first results of the quality assessment of the generated 2.5D city models.

1 INTRODUCTION

3D city models in urban areas are becoming more essential for applications such as disaster management, simulation of new buildings, updating and archiving cadastral data, change detection and virtual reality. In most of these cases the models of buildings and terrain surface are the primary features of interest. Since manual digitization of buildings and surface reconstruction is very costly and time consuming, the development of automated algorithms for feature extraction is of great importance. Automated methods often consist of two steps: 1) the extraction of building footprints, and 2) the 3D reconstruction of building roofs.

There have been a number of papers on the extraction of building footprints and 3D reconstruction of building roofs (Baillard et al., 1999; Heuel et al., 2000; Ameri and Fritsch, 2000; Scholze et al., 2002). However, in many cases the building footprints are available in advance, e.g. from Cadastral maps. Therefore, it is logical to make use of this information for the second step of reconstruction (Jibrini, 2000; Flamanc et al., 2003; Vosselman and Suveg, 2001; Brenner et al., 2001). Although successful results have been reported, the level of automation is not satisfactory. Furthermore, the results of automated reconstruction of roof shapes are not comparable to those from manual measurement by a human operator. However, in some applications, such as visibility analysis, an
approximate city model with single height value for each building footprint can provide sufficient input. In addition, if the level of automation is high and the model can be constructed in a reasonable time, it can also be used for applications such as disaster management where a rapid 3D reconstruction is demanded.

With the assumption that the building footprints are available in advance, we present a method with a high level of automation for estimating single height attribute values for each building. For the estimation of the height attributes, a DSM is used. In the case that a DSM is not available in advance, aerial images are used to extract the DSM for each individual building footprint. In this paper, we present the procedure and report the results of city modeling with a low level of detail, together with an analysis of the quality of the results.

2 SINGLE HEIGHT ATTRIBUTE ESTIMATION

Usually building footprints and DSMs are extracted using different methods and are acquired from different sensors. This can result in poor alignment between the two data sets. In order to eliminate (or reduce) this error, a buffer is defined for the building footprints. With this consideration, a quick search is performed over the point cloud to select the points that are inside the buffered building footprints.

The DSM (from photogrammetry or lidar) is crude and includes outliers. Therefore, in the first step, outliers should be detected. In addition, the DSM includes points that do not belong to the building roof. These points, like points on the walls, should also be detected. This processed point cloud is considered for the estimation of the height attributes. The height attributes are minimum, maximum, median, mean and standard deviation of the building roof height. Other height attributes can also be defined and estimated depending on the requirements.

2.1 Buffer Definition

Based on the accuracy of the location of the building footprints and DSMs a buffer is defined. Buffer operation refers the creation of a zone of a specified width around a polygon area. It is also referred to as a zone of specified distance around the coverage feature. There are two types of buffers: constant width buffers and variable width buffers. Both types can be generated based on the uncertainty zones. In our case we wish to exclude points that do not fall on the building roof. Therefore, we have created a buffer zone inside the building footprint. Points falling within this buffer are excluded from the building height calculations.

2.2 Selection of the DSM Points inside the Building Footprint

In order to have a quick access to each point via location-based querying, a 2D grid-based data structure is created. In the first step, the bounding rectangle of the footprint is considered and by a quick search the points inside this bounding rectangle are selected. In the second step, a modified X crossing algorithm (Haines, 1994) is used to select only the points inside the footprint. The implemented algorithm works for polygons with holes, for both convex and concave polygons, and it handles exceptional cases.

2.3 Outlier Detection

Successful results of using a density-based algorithm (Breunig et. al., 2000) for the detection of outliers in laser scanner point cloud was shown by Sotoodeh (2006). The characteristics of this algorithm are (Sotoodeh, 2006):

− it is not constrained by the preliminary knowledge of the object,
− it does not suffer from the varying density of the points.
Since this method does not consider the characteristics of the data acquisition method, it can be applied to DSMs that are acquired using different methods. Due to its capability, this algorithm was implemented and used.

2.4 Detection of Points on Steep Slope Surface

In order to preserve only the points of the building roof, the gradient vector of each DSM point is calculated. For this purpose, the points are triangulated using a 2.5D Delaunay method (Fang and Piegl, 1993). To calculate local gradient, the neighboring triangles of each point are considered. The resultant vector of the normalized normal vectors of neighboring triangles is used to define the gradient of the point. The building roof points are preserved by setting a slope threshold (Figure 1). The red dots in Figure 1 show the original DSM point cloud and the blue crosses show the processed point cloud after outlier detection and steep slope point removal.

![Figure 1. DSM point cloud of a building footprint. The red dot points are raw DSM point cloud and the blue cross points are processed through outlier detection/ and steep slope points removal. a) In XY-plane (planar) view and b) oblique view of the point cloud.](image)

3 DSM EXTRACTION BY PHOTOGRAMMETRY

If a DSM is not available or updated, aerial images are used to extract the DSM for each individual building. Here we use the Automatic Terrain Extraction (ATE) image matching engine of SOCET SET (version 5.3) from BAE Systems\(^1\). Access to the matching engine is achieved through the SOCET SET Software Development Kit (SDK). The SDK provides access to most functions of SOCET SET with the extended capability of developing new algorithms in C++. In summary, SOCET SET ATE:

- is based on image correlation (area-based technique)
- enables the handling of different strategies with pre-knowledge of the surface height variation
- enables the adoption of the above strategies automatically
- enables the use of multiple images (maximum 12 pairs) for image matching
- can handle seed points
- can provide both TIN and GRID format structure

As an input, the SOCET SET path, the data folder, the project path and the building footprint are given. The output of “Processing” (Figure 2) is the DSM of the given footprint in the internal format of SOCET SET. For access to the SOCET SET project parameters, such as image information, files and DSM, the SOCET SET SDK was used.

\(^1\) [http://www.socetset.com/](http://www.socetset.com/)
Input: SOCET SET path, the data folder, project path and building footprints

Processing:
1) A setting file for a batch process is created for a single building region.
2) The batch process starts immediately after creation: running the Automatic Terrain Extraction (ATE) of SOCET SET.

Output: DSM of the given bounding polygon (in SOCET SET internal format)

Figure 2. DSM generation with SOCET SET for each building footprint.

4 RESULTS

We report the results of low level of detail city modeling (2.5D city model) using our method and preliminary results of accuracy tests and quality analysis. We assume that the building footprints are available, which are building polygons of Ordnance Survey’s OS MasterMap Topography Layer. The aerial images and lidar that we use were also provided by Ordnance Survey. The results that we present here miss the post-processing part that eliminates the DSM points on steep slopes.

4.1 City Modeling with Level of Detail Zero

Four sites, each of 1 km² area, were selected for the following categories: industrial, residential, rural and urban. Table 1 shows the statistical information concerning the building distribution over these sites. Figure 3 shows the aerial images of the urban and residential sites.

Table 1. Statistical information of the studied sites.

<table>
<thead>
<tr>
<th>Parameters</th>
<th>Industrial</th>
<th>Residential</th>
<th>Rural</th>
<th>Urban</th>
</tr>
</thead>
<tbody>
<tr>
<td>Number of buildings</td>
<td>460</td>
<td>2,506</td>
<td>394</td>
<td>1,673</td>
</tr>
<tr>
<td>Total area of buildings (m²)</td>
<td>178,483.6</td>
<td>109,677.9</td>
<td>25,720.0</td>
<td>235,559.6</td>
</tr>
<tr>
<td>Mean area of buildings (m²)</td>
<td>388.0</td>
<td>43.8</td>
<td>65.3</td>
<td>140.8</td>
</tr>
<tr>
<td>Mean number of nodes in building footprint</td>
<td>7</td>
<td>6</td>
<td>7</td>
<td>12</td>
</tr>
</tbody>
</table>

Building footprints, DMC imagery and lidar point clouds were available for each site. The lidar data for the industrial, residential and rural sites had a point density of about 16 points per m². The interpolated lidar data for the urban site was 25cm grid. The lidar data was processed for three regions: industrial, residential and urban. The ground sampling sizes of DMC imagery were 10cm, 10cm, 10cm and 15cm for the industrial, residential, rural and urban sites, respectively.

A specific aerial block was flown for the urban site. The images were acquired with a large side overlap to increase the accuracy of the DSM. In order to investigate the influence of the aerial block configuration (flying regime), alternate strips were removed so that a very small side overlap was obtained. Two data sets were processed: one with a side overlap larger than standard, and one a side overlap smaller than standard.

At each site a photogrammetric operator measured in stereoview an eave height, an “average” height and a maximum height for every building defined by the vector data. Three automatic methods were also applied to each site using the developed method. Two of these were:
1. using the lidar point cloud to calculate the minimum, mean, median and maximum height within each building polygon ('lidar')
2. deriving a DSM for each building in the site and from this calculating the minimum, mean, median and maximum height ('On-The-Fly')

It should be noted that the density of the points obtained by On-The-Fly method adjusts the post spacing (density) depending on the size of the building and it varies between 33cm and 1m. The DSMs with a larger post spacing are for the larger size of the building.

The time taken to capture for each method and each site was recorded. The time was measured as interaction time (e.g. to set up an automatic process) and processing time (e.g. to run an automatic process). The time taken varied widely between the different sites (Figure 4). As would be expected, the industrial and rural sites were the quickest overall. For both, manual capture was the slowest method (5hrs and 3.3hrs, respectively) and the On-The-Fly method the second slowest (3hrs and 2.5hrs, respectively) The manual capture of the urban area took the longest overall (17hrs), followed by the On-The-Fly capture of the residential area (16hrs, almost all was processing time) and the manual capture of the residential area (14hrs). Factors that increased the processing times in the automatic methods seemed to include the higher point density and the larger number of images that were used in the image matching (large versus small side overlap).

The measured times were more precise for the automatic methods and also included the set up times, something that was not included in the manual method timings. All the timings for the automatic method were performed on a same machine.

Figure 5 shows a city model with 2.5D buildings created for the urban site with the On-The-Fly method. The heights are based on the median of the DSM point cloud.

4.2. Quality Control with Accuracy Test

In order to qualify the results of the automated method, accuracy tests were performed. For this purpose we assumed that the manual measurements were the most accurate measurements, and we used these as a reference for calculating RMSE (Root Mean Square Error) of the estimated height attributes. The RMSEs were calculated between corresponding heights in the data sets. Figure 6 shows the results of the accuracy test by method. The lidar and On-The-Fly methods appear to have similar results with almost identical values.

Lidar data may include heights of parts of the buildings that are not visible in imagery. In some cases, it was not possible to see that the lowest points actually fell within the building and so the
values for the lidar and the image-based methods were quite different. In addition, in some cases, small features sticking above the roof were visible only in the lidar data. In both these cases, the value added by using lidar data ultimately depends on the data specification. That is, what eave height and maximum height constitutes.

Figure 4. The interactive and processing time per method, per site.

Figure 5. A city model with 2.5D buildings of the urban site, corresponding to Figure 3a.

5 CONCLUSIONS

With the assumption that building footprints are available in advance, we proposed an economic solution for estimating height attributes for building footprints. The method is independent of the data source and can create DSM On-The-Fly if aerial images are the source of data.
Four different test sites were provided by Ordnance Survey for this investigation: industrial, residential, rural and urban. Building footprints from the OS MasterMap Topography Layer, DMC imagery and lidar point clouds were available for each site. Manual and automated methods were used to determine the eave, the median, the minimum and the maximum heights. The automated method requires less interaction than manual capture but the processing is time-consuming. The processing can be sped up by distributing the process over a network of computers.

The three techniques, manual capture, capture from lidar data and capture from image matching data are all good for different aspects of data capture. Manual capture is probably the best method for capturing eave height. However, the use of (current) image matching methods that include edge features is an alternative solution for a better capture of the eave height.

These results are only preliminary and a more thorough investigation is required to assess the costs and accuracies of 2.5D data capture on a large scale. This is an ongoing project and the suitability of other data sources and alternative solutions for the evaluation of the results is under investigation.

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