3D BUILDING EXTRACTION FROM STEREO PAIR HIGH RESOLUTION SATELLITE IMAGERY

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ABSTRACT: In this paper, we will present a highly automated method of extracting 3D building information. Our approach set out to locate the vertices of building roof. For a start, we will limit our development to high rise buildings with approximately flat rooftop. If the main corners and intermediate vertices can be found, the 3D building model can be constructed. Our study is applying stereo pair satellite imageries; we first manually select a rectangular area of interest which contains our building of choice. This is the only manual process at the moment. We then compute the digital surface model (DSM) using normalized cross correlation template matching technique. Furthermore, we isolate the building of choice by discarding the non-building features according to the computed surface heights. If we just locate the edges of the DSM at this stage, we will end up with an unacceptable irregular geometry which is smaller than the actual roof and sometimes a building split up into a few parts. In order to find the correct building corner, we go back to the two images of the stereo pair to compute the edges from the pixel values. The rooftop found from the DSM is then expanded by a few pixels until edge pixels are detected. Clearly, there are still many false alarms such as when true edge did not show up as an edge pixel or edges picked up were not true roof edge. Using a series of rules, most of the false alarms were rejected and a series of roof edge pixels, but not sufficient to form the complete roof polygon, are retained. Subsequently, we developed an algorithm to search and extract the useful vertices of the building from the remaining edge pixels. Finally, the vertices with three-dimensional coordinates and the topological relations for each building are extracted and joined to form the roof polygon. The algorithm has been tested on stereo pairs of GeoEye-1 and WorldView-2 images.

1. INTRODUCTION

3D Building information is used widely in visualization, urban planning, pollution, traffic management, utility services, etc. 3D Building information is useful, but the creation of detailed wide-area models is a very difficult and tedious task. The most interest of generating 3D Building information is how to extract the exterior building boundary efficiently. It is observed that state-of-the-art algorithms are neither robust nor accurate enough to extract 3D building automatically while studying on available literature about 3D Building Extraction. In Shen and co-workers [3] paper, they describe a corresponding image object constrained registration method based on object oriented image segmentation. But in practice, some buildings cannot be segmented well and the accuracy of registration between the feature points of corresponding building is not good enough. Guo et al. [2] proposed an approach which can estimate the 3D building height from a stereo pair of satellite images. But user intervention is required to define outline of building top in the method. Xiong and Zhang [5] proposed a method for building boundary extraction apply edge detection in 2D images, then conduct edge connection to make the building edges become a closed block, finally extract information about 3D buildings based on stereo photogrammetry and image matching. However, the edge detection to form a closed block outline of building rooftop doesn’t work well on high resolution satellite imageries, especially over shadow areas. Ameri and Fritsch [1] introduce an algorithm for automatic 3D building reconstruction using plane-roof structures. The algorithm includes recognition, reconstruction and hypothesis verification. Some impressive results are shown in the proposed method. Nevertheless, in practice, sometimes the algorithm will fail to recognize the building, due to the presence of noise, shadow or low contrast which appears on rooftop. Dey and collaborators [4] apply a modified fuzzy logic based supervised (FbSP) approach to extract building in a multi-level segmentation. Their results shows the small buildings can be detected, but the building edges are not correctly identified. In this paper, we will present a highly automated method of extracting 3D building information. Our technique involves a novel way of detecting building edges in 3D space rather than the traditional edge detection are based only on 2D images.

2. DESCRIPTION OF ALGORITHM

2.1 Input Images and RPC Files

The input to the system is a pair of stereo high resolution satellite image. Only two mouse click on the left image to select a rectangular area of interest which contains our building of choice. For high resolution optical satellite imagery stereo pair, cameras' internal parameters and relative pose is represented by the rational polynomial coefficient (RPC). RPC is being widely used for representing the physical sensor models of recent satellite optical images. It has been demonstrated to be effective and robust that the adoption of RPC adjustment model as a preferred sensor orientation model for high resolution optical satellite imagery. It became almost standard sensor models of high resolution optical satellite images. Given an area of object on left image, it could match the area on right image by adjustment iteration according to parameters in the two corresponding RPC parameters files. RPC model is defined as following:

$$\begin{cases} s = \dfrac{Nums(P,L,H,c_{sn})}{Dens(P,L,H,c_{sd})} \\ l = \dfrac{Nums(P,L,H,c_{\ln})}{Dens(P,L,H,c_{ld})} \end{cases} \qquad (1)$$

Where *s* and *l* are normalized image coordinates; and each of the numerator and denominator above is related to RPC parameters:

$$\begin{aligned} f &= c_0 + c_1 L + c_2 P + c_3 H + c_4 LP + c_5 LH + c_6 PH + c_7 L^2 + c_8 P^2 + c_9 H^2 + c_{10} PLH \\ &+ c_{11} L^3 + c_{12} LP^2 + c_{13} LH^2 + c_{14} L^2 P + c_{15} P^3 + c_{16} PH^2 + c_{17} L^2 H + c_{18} P^2 H + c_{19} H^3 \end{aligned} \qquad (2)$$

Where *P*, *L* and *H* are normalized ground 3D coordinates, the formula is:

$$\begin{cases} \mathrm{P} = (\phi - \phi_0) / \phi_s \\ \mathrm{L} = (\lambda - \lambda_0) / \lambda_s \\ H = (h - h_0) / h_s \end{cases} \qquad (3)$$

Where ϕ , λ and h represent latitude, longitude and elevation respectively.

The image coordinates in pixel can be written as:

$$\begin{cases} x = s \bullet x_s + x_0 \\ y = l \bullet y_s + y_0 \end{cases} \qquad (4)$$

Each of RPC files (for both left and right images) provides 90 coefficients which are applied in above Equation (1)-(4).

2.2 Height Map Generation and Estimation of 3D Building Height

Our algorithm concerns a method of detecting building edges in 3D object space. But the height of the building is unknown before our processing. It is necessary to generate Height Map around the building by computing the digital surface model (DSM). From the Height Map generated, an approximate height of the building can be estimated. In this paper, we employ a normalized cross correlation template matching technique to construct a Height Map. The correlation matching is based on the equation below:

$$\rho = \frac{\sum_{i=1}^{m}\sum_{j=1}^{n}(I_{i,j} \bullet I'_{i,j}) - \frac{1}{m \bullet n}(\sum_{i=1}^{m}\sum_{j=1}^{n} I_{i,j})(\sum_{i=1}^{m}\sum_{j=1}^{n} I'_{i,j})}{\sqrt{[\sum_{i=1}^{m}\sum_{j=1}^{n} I_{i,j}^2 - \frac{1}{m \bullet n}(\sum_{i=1}^{m}\sum_{j=1}^{n} I_{i,j})^2][\sum_{i=1}^{m}\sum_{j=1}^{n} I'^2_{i,j} - \frac{1}{m \bullet n}(\sum_{i=1}^{m}\sum_{j=1}^{n} I'_{i,j})^2]}} \quad (5)$$

Where ρ is a correlation coefficient, *m* and *n* define the size of two dimensional search window, $I_{i,j}$ is a pixel intensity value at coordinate (*i, j*) in left image and $I'_{i,j}$ is a pixel intensity value at coordinate (*i, j*) in right image. After the correlation matching is iteratively calculated based on Equation (1)-(5), the Height Map around the building will be generated. Computing the histogram of heights distribution from Height Map, then a majority filter is applied on the Height Map, the 3D building height can be derived.

2.3 Correlation Map and Boundary Detection

At the moment, we limit our development to high rise buildings with approximately flat rooftop. It is possible to create a Correlation Map based on the derived height of the building and correlation coefficients. In order to construct a Correlation Map, we set a correlation coefficient threshold *Tc*. As mentioned in §2.1, a rectangular area of interest which contains our building of choice is selected. Hence, for the specified building height, the corresponding area of interest (AOI) around the building in 3D object space can be determined. Now starting for the AOI in 3D object space, we employ RPC model and apply Equation (5), the correlation coefficient ρ can be calculated. If ρ is greater than the correlation coefficient threshold *Tc*, the point on 3D object space will be segmented as building rooftop. Otherwise the point is considered as outside of building rooftop. After completing search matching for whole area of interest around the building in 3D object space, the Correlation Map will be produced. From the correlation map, the area outside the building can be removed. In the case of we isolate the building of choice by discarding the non-building features according to the building rooftop boundary detected from the Correlation Map only, we will end up with an unaccepted irregular geometry which is smaller than the actual rooftop and sometimes a building split up into a few parts. To overcome this problem, we go back to the two images of the stereo pair to detect the corners from the pixel intensity values. And the boundary of the building extracted at this stage is kept for use in the further process.

2.4 FAST Corner Detection

It is well-known, if the main corners and intermediate vertices of a building can be found; the 3D building model can be constructed. As mentioned above, if we just locate the corners of the building based on the boundary extracted from the Correlation Map, the position of the corners is not accurate enough. In order to find the correct building corners, we try to find a suitable corner detection algorithm to meet our application.
A corner can be defined as the intersection of two edges. A corner can also be defined as a point for which there are two dominant and different edge directions in a local neighborhood of the point. Various corner detection algorithms have been developed. For example, Moravec corner detection algorithm, but one of the main problems with this algorithm is that it is not isotropic, i.e. if an edge is present that is not in the direction of the neighbors, and then it will not be detected as a corner point. Harris and SUSAN are another two corner detection algorithms which were discussed by researchers. According to [5] experiment, use Harris and SUSAN to detect corners in the satellite image, the results are not accurate and usually gives many wrong corners.

FAST is an acronym standing for Features from Accelerated Segment Test. This test is a relaxed version of the SUSAN corner criterion. The segment test criterion operates by considering a circle of sixteen pixels around the corner candidate point. If *n* contiguous pixels are all brighter than the nucleus by at least *t* or all darker than the nucleus by *t*, then the pixel under the nucleus is considered to be a corner feature. This test is reported to produce very stable features. Our experimental tests show that the best results are achieved with *n* being 9. This value of *n* is the lowest one at which edges are not detected.

2.5 Edge with Checking Corner Detection

In this procedure, we locate a point along the boundary of the rooftop extracted from the Correlation Map in §2.3. Because this point is in 3D object space, we employ RPC model to project this 3D point to a corresponding 2D point in both left and right image space. Then search the neighbor points around the 2D point which is projected from 3D point in both left and right image space. If a corner feature point can be found within this 2D point neighbor area in both left and right image space. This 3D point is considered as edge pixel; otherwise this 3D point is not edge pixel. This process is repeated for each point along the boundary of the rooftop extracted from the Correlation Map until the first located point met again. Clearly, there are still many false alarms such as when the true edge did not show up as an edge pixel or edges picked up were not the true roof edge. Using the stereo pair imageries with corners feature information, expanding the rooftop extracted from Correlation Map a few pixels, and adjust the position of the 3D points based on the corners feature information in the stereo pair imageries, most of the false alarms were rejected and a series of roof edge pixels, but not sufficient to form the complete roof polygon, are retained. In the next vertices detection step, only the retained 3D edge points will be processed.

2.6 Vertices Detection

In this paper, a new algorithm is developed to search all the remaining edge pixels and extract the useful vertices of the building from the retained 3D edge points. We employ a polyline simplification method which is called Douglas-Peucker algorithm, besides checking the distance and angle between the edge pixels. The Douglas-Peucker (DP) algorithm uses the closeness of a vertex to an edge segment. This algorithm works from the top down by starting with a crude initial guess at a simplified polyline, namely the single edge joining the first and last vertices of the polyline. Then the remaining vertices are tested for closeness to that edge. If there are vertices further than a specified tolerance, $\varepsilon > 0$, away from the edge, then the vertex furthest from it is added the simplification. This creates a new guess for the simplified polyline. Using recursion, this process continues for each edge of the current guess until all vertices of the original polyline are within tolerance of the simplification. During the search progress, the sequence of searching is recorded. Consequently, the topological relations of these vertices are then determined. Finally, the vertices with three-dimensional coordinates and the topological relations for each building are extracted and joined to form the roof polygon. And also, there is a way to verify the accuracy of the results visually.

2.7 Results and Discussion

Our algorithm has been tested on stereo pairs of GeoEye-1 and WorldView-2 images. Figure 1 illustrates the results of the proposed algorithm. The WorldView-2 stereo pairs are employed in this experiment. Column (a) shows the extracted vertices of the rooftop, and each vertex comes with UTM coordinates and height. The topological relations of these vertices are represented in red line. The extracted 3D vertices are mapped back to left and right of stereo pair imagery for verification. The mapping results are shown in column (b) and column (c). From the results, we can find that most of the main corners and intermediate vertices can be detected, and the accuracy is within 2m. But there are several true roof corners not detected and a few vertices detected are away from the true roof corners. The reason is that the performance of our algorithm depends on the choice of the correlation coefficient threshold Tc; if set Tc lower, the Correlation Map will include some ground area; if set Tc higher, the building roof may be split off. Furthermore, the intensity gray distribution of building roof is not even or there are some attachments, such as water tank, etc. on the rooftop, which interfere with Correlation Map being generated correctly. For future work, we will research how to further improve the Correlation Map, filter the noisy features from rooftop and get back the missed true roof corners.

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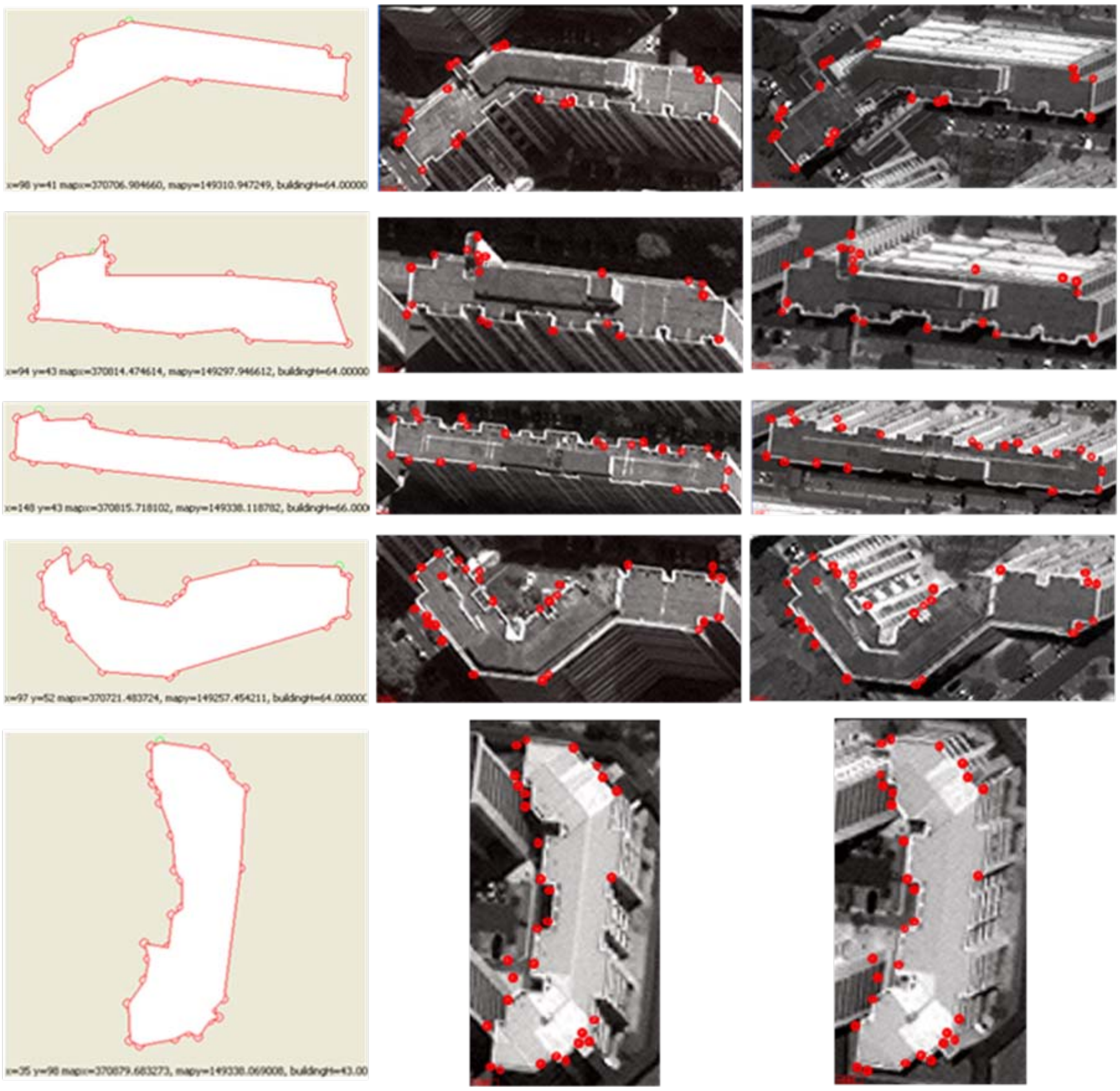

(a) (b) (c)

Fig.1 (a) Rooftop vertices with UTM coordinates, height are highlighted in circle dots, and building boundary extracted is colored in red line. (b), (c) Left and right image views of the building rooftop with the vertices which are associated with 3D vertices from (a).