Effects of Edge Detection on Least-squares Model-image Fitting Algorithm

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Abstract: Fitting the projected wire-frame model to the detected edge pixels on images by using least-squares approach, called Least-squares Model-image Fitting (LSMIF), is the key of the Model-based Building Extraction (MBBE). It is implemented by iteratively adjusting the model parameters to minimize the squares sum of distances from the extracted edge pixels to the projected wire-frame. This paper describes a series of experiments and studies on various factors affect the fitting results, including the edge detectors, the weighting rules, the initial value of parameters, and the number of overlapped images. The experimental result is not only helpful to clarify the influences of each factor, but is also able to enhance the robustness of the LSMIF algorithm.

Keywords: Least-squares Adjustment, Model-image Fitting, Edge Detection, Model-based Building Extraction

1. Introduction

Fitting the projected wire-frame model to the detected edge pixels on images by using least-squares approach, called Least-squares Model-image Fitting (LSMIF), is the key of the Model-based Building Extraction (MBBE). Although the feasibility of LSMIF has been proven by previous researches [2-4], we also found that there are various factors affecting the performance need to be studied. For example, (1) various edge detectors will extract different edge pixels, which may lead the fitting to a varied result. (2) The width of the buffer along the projected wire-frame model will determine how many edge pixels should be count in the LSMIF, thus, affect the pull-in range of model parameters. (3) The weighting rules for each edge pixel in the buffer will have dramatic influence on the adjustment. (4) The observation number increases with the number of overlapped images. Therefore, using more images for LSMIF should be able to increase the reliability. To study the effects of these factors on LSMIF algorithm, a series experiments are designed. The first experiment is to compare the performance of three edge detectors: (1) Sobel operator, (2) Canny edge detector[1], (3) Laplacian of Gaussion (LoG) by extracting the building edges from the same image. The edge pixels extracted by each detector are used as the subjects of LSMIF to test which detector is the most suitable. The second experiment is to test three different weighting rules for each edge pixel in the buffer: (1) weighted by the gradient vector, (2) weighted by the gradient intensity, (3) filtered by gradient vector then weighted by the gradient intensity. By analyzing the results from the first and second experiments, the most

suitable edge detector and weighting rules are integrated into LSMIF. The third experiment is to test the pull-in range of each model parameter by the improved LSMIF. The fourth experiment is to evaluate the effect on the number of overlapped images. The same building is extracted by LSMIF from 2 images, 3 images, and 4 images in sequence, and the fitted model parameters are compared with one another. The experiments and analysis in this paper are very helpful to clarify the effects of various factors in the LSMIF algorithm especially the effects of edge detection. The building extraction would be more efficient and robust by using the improved LSMIF.

2. Edge Detection

Since the edge detection is one of the most fundamental procedures both in Computer Vision and Digital Photogrammetry, plenty of edge detectors have been developed for various applications. To test their suitability for LSMIF, we select three commonly-used edge detectors to extract the building edges from the same image (Fig.1(a)): (1) Sobel operator, (2) Canny edge detector and (3) Laplacian of Gaussian (LoG) edge detector. Each detector has its own parameters. In this research, these parameters are determined by try and error. The criterion is extracting most edge pixels of the bottom edge below the left-side of the building shown in Fig. 1a, but the minimum number of non-edge pixels. The optimal extracted result of Sobel, Canny, and LoG are shown in Fig.1(b), Fig. 1(c), and Fig. 1(d). The Sobel operator extracts the most pixels, but also includes many non-edge pixels. The Canny detector extracts the least pixels, but most of them can be connected into lines. The LoG extracts fewer pixels than Sobel operator, but also includes a few isolated non-edge pixels. Moreover, it extracts the least pixels on the criterion edge.

3. Weighting Rules

Since the detected edge pixels are used as the fitting subject of the model projection in LSMIF algorithm, the quality of detection is crucial to the fitting result. The distinct edge pixel usually has higher gradient intensity, which can be extracted by most of the edge detectors. However, the indistinct edge pixel may not be detected or, be detected with other non-edge pixels together. If all



extracted pixels are equally treated as the fitting subject, the non-edge pixels could lead the fitting to wrong position. Therefore, it is more reasonable to give different weight to each detected pixel in the LSMIF process according to their quality. Three kinds of weight rules are introduced and compared: (1) weighted by the gradient vector, (2) weighted by the gradient intensity, (3) filtered by gradient vector then weighted by the gradient intensity.

3.1 By Gradient Intensity

The edge pixel usually has higher gradient intensity than non-edge pixels, which is the basic idea of Sobel operator and Canny detector. Therefore, the gradient intensity could be used as the index of the detection quality. For the weights should have the same range, it must be normalized between $0\sim1$. That is, the pixel with maximum gradient intensity should be weighted as 1, while the pixel with minimum gradient intensity should be weighted as 0. After the detection of Sobel operator or Canny detector, the gradient intensity image G and the maximum intensity g_{max} are computed from the original image I. Divide every pixel of G by g_{max} to derive a new gradient intensity image P. Then, the normalized weight w(x, y) of the detected pixel I(x, y) is the intensity of P(x, y), as Eq. (1).

$$w(x, y) = P(x, y) = G(x, y) / g_{max}$$
 (1)

3.2 By Gradient Vector

The gradient vector is also useful to evaluate the detected edge pixel, because it symbolizes the direction of the extracted edge on that pixel. If the fitting is without error, the projection of the wire-frame model should be overlapped exactly on the detected edge pixels. The angle between the projected edge and the gradient vector should be 90° or 270°. Therefore, the angle between the projected edge of the wire-frame model and the gradient vector of the detected edge pixel can be taken as the second index of the detection quality. Since the image orientation is known, the wire-frame model can be projected onto the image by using the collinear condition equations. The gradient vector can be computed from gradient intensity after the detection of Sobel operator or Canny detector. Thus, the angle \ddot{e} between the projected edge and the gradient vector can be solved. To weight the pixel of 1 when $\ddot{e}=90^{\circ}$ or 270° and 0 when $\ddot{e}=0^{\circ}$ or 180° , the weight function w(x, y) of

the detected pixel I(x, y) must be normalized as Eq. (2) shows.

$$w(x, y) = [sin(2\ddot{e} - 90^\circ) + 1] / 2 \qquad (2)$$

3.3 By the Integration of Intensity and Vector

Although the previous two weighting rules have already decreased the influence of extracted non-edge pixels, the pixel with poor \ddot{e} still affects the fitting more or less. Therefore, the third weighting rule integrates the previous two rules into consideration. The extracted pixel is first filtered by vector difference \ddot{e} , and then weighted by gradient intensity. With carefully chosen threshold value of \ddot{e} , this rule can effectively decrease the number of non-edge pixels extracted. The LSMIF process will be faster and more accurate due to less influence from the non-edge pixels.

4. Experiments

In order to evaluate how these factors affect the fitting result, a series experiments are implemented. The aerial images are photographed by Zeiss LMK Aerial Survey Camera at 1600m height with focal length 305.11mm lens, as a result, the average photo scale is about 1:5000. The photographs are then digitized by Vexel Photogrammetric scanner in 25ì m resolution. The edge pixels are detected by corresponding Matlab modules of the three edge detectors.

4.1 Average Correctness Analysis

The first experiment is to test the suitability for LSMIF of three edge detectors: (1) Sobel, (2) Canny, (3) LoG by extracting the building edges from the same image. The second experiment is to test three different weighting rules for each edge pixel in the buffer: (1) weighted by the gradient vector, (2) weighted by the gradient intensity, (3) filtered by gradient vector then weighted by the gradient intensity. The evaluation index of the two experiments is the average correctness rate AC, which is the percentage of the correctly fitted edge number \hat{Q}_i over all visible edge numbers \hat{Q}_i in all overlapped images, as Eq. (3) depicts.

$$AC = (\hat{\mathbf{Q}}_{i}^{'} / \hat{\mathbf{Q}}_{i}^{'}) * 100\%$$
(3)

In which, l_i is the number of correctly fitted edges on image *i*, while l_i is the number of all visible edges on image *i*. Fig. 2 is the chart of average correctness rates

for the three edge detectors by applying three different weighting rules. The three edge detectors almost have the same performance, but the integrated weighting rule does improve the average correctness rate. Therefore, the rest experiments adopts the Canny edge detector and the integrated weighting rule.



Fig. 2. The average correctness rates of the three edge detectors by applying three weighting rules.

4.2 Pull-in Range Test

The pull-in range is the range from the initial value to the convergent value of each parameter. It can be taken as a reference of the maximum error that the fitting function can tolerate, or the least accuracy the initial value should achieve. The pull-in range of dZ and h are wider than other parameters, which means it is possible to give coarser initial values but still achieve optimal fitting. The pull-in range of the rotation angle è is about ± 5 degree, and other parameters are about 2 meters, which is a small improvement to the previous work.



4.3 Overlapped Image Number

Increasing the overlapped image number would provide different views of the same building, so the probability to see the occluded edges is increased. Take the box-like building for example; there are at most 9 edges visible in one image, the other 3 edges are occluded by itself. But these three edges might be seen from another view point. Therefore, the most benefit from adding overlapped images into LSMIF is increasing the reliability. Fig. 4 shows that the average correctness rate has the slightly grow from 2 images to 3 images, and 3 images to 4 images.



Fig. 4 The correctness grows up with overlapped image numbers.

5. Conclusions

This paper discussed several factors that affect the LSMIF: the edge detectors, the weighting rules, the initial values, and the overlapped image number. From a series of experiments, we know that the edge detector based on the first derivative, such as Canny, will achieve better fitting result without complicated computations. The weighting rule integrates gradient intensity and vector also improves the correctness rate. Using this modified edge detecting and weighting policy with multiple overlapped images can increase the efficiency and reliability of the original LSMIF algorithm

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References

- Canny, J. F., 1986. A Computational Approach to Edge Detection, *IEEE Transactions on Pattern Analysis and Machine Intelligence*, 8(6), pp. 679-698.
- Tseng, Y.-H. and S. Wang, 2003. Semiautomated Building Extraction Based on CSG Model-Image Fitting, *Photogrammetric Engineering & Remote Sensing*, 69(2), pp. 171-180.
- Wang, S. and Y.-H. Tseng, 2001. Least-squares Model-image Fitting for Model-based Building Extraction, *Proceedings* of the Asia GIS 2001, Tokyo, Japan, Vol. pp. 1-8.
- Wang, S. and Y.-H. Tseng, 2001. On the Accuracy Assessment of Least-Squares Model-image Fitting for Building Extraction from Aerial Images, *Proceedings of The 22nd Asian Conference on Remote Sensing*, Singapore, Vol. II, pp. 1085-1090.