Title: Adaptive Region Merging Segmentation of Airborne Imagery for Roof Condition Assessment

Abstract:

In order to perform residential roof condition assessment with very-high-resolution airborne imagery, an adaptive region merging method for roof image segmentation is presented. This algorithm was initialized by the simple linear iterative clustering (SLIC) superpixel algorithm. Region merging segmentation was performed. The optimal result was adaptively selected by an unsupervised evaluation index, Q. We ran our method on airborne data collected by Pictometry International. Comparison of our method with the state-of-the-art region merging segmentation compression-based texture merging (CTM) method is presented. Based on visual evaluation, our algorithm provides a more optimal result.

1 Introduction

As an important step of damage claim processing in the insurance industry, roof condition inspection is done by humans which is an expensive and time-consuming processing. Thus, automated roof condition assessment from aerial images is of great interest. The mission for a researcher is to convert the knowledge of how an expert inspects roof condition into the language of computer vision techniques.

There is little research has been published specifically on roof condition assessment. The closest field we could find is building damage assessment. In the European Macroseismic Scale 1998 (EMS98) (Grünthal, 1998), building damage is classified into five damage grades and heavy damage grades in EMS98 are detectable (Dong and Shan, 2013). The challenge is to identify lower damage grades (Dong and Shan, 2013). Roof condition assessment is a more sophisticated task because its emphasis is placed on identification of lower damage grades compared to building damage assessment.

The data for this study was collected by Pictometry International. Considering the complexity of residential roofs, roof condition assessment using features covering the entire rooftop can not provide a promising result. Thus, a better approach is to divide the task into two stages: roof segmentation; followed by roof segments classification. We focus only on the roof segmentation in this paper.

An adaptive region mering segmentation method for roof condition assessment is proposed in this paper. This algorithm was initialized with simple linear iterative clustering (SLIC) superpixel (Achanta *et al*., 2012). Color features were extracted to represent each superpixel. A similarity measure was defined to measure color similarity. The most similar adjacent regions were merged iteratively. The series of merging steps are evaluated by an unsupervised evaluation metric, Q and the result corresponded to the minimal value of Q.

The paper is organized as follows. Section 2 introduces the Pictometry data set. Section 3 presents the proposed region merging algorithm. Section 4 gives experimental results and disscussion. Section 5 concludes the paper.

2 Data

The data for this research was one inch resolution color airborne imagery collected by Pictometry International. We manually extracted the roof images as shown in Fig. 1. Rooftops of interest were cut out and a rotation is followed by additional cropping to obtain the experimental sample images.

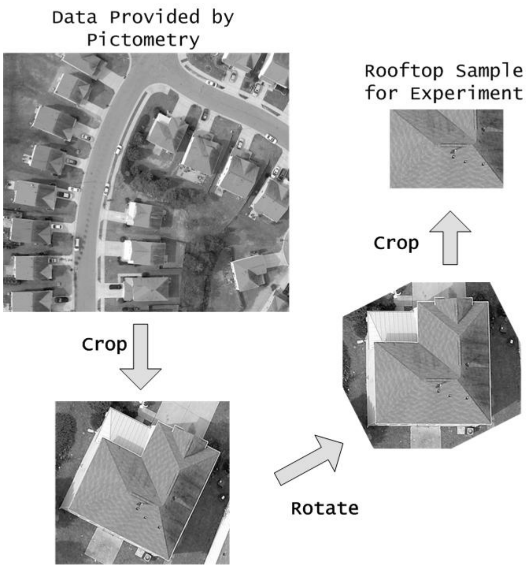
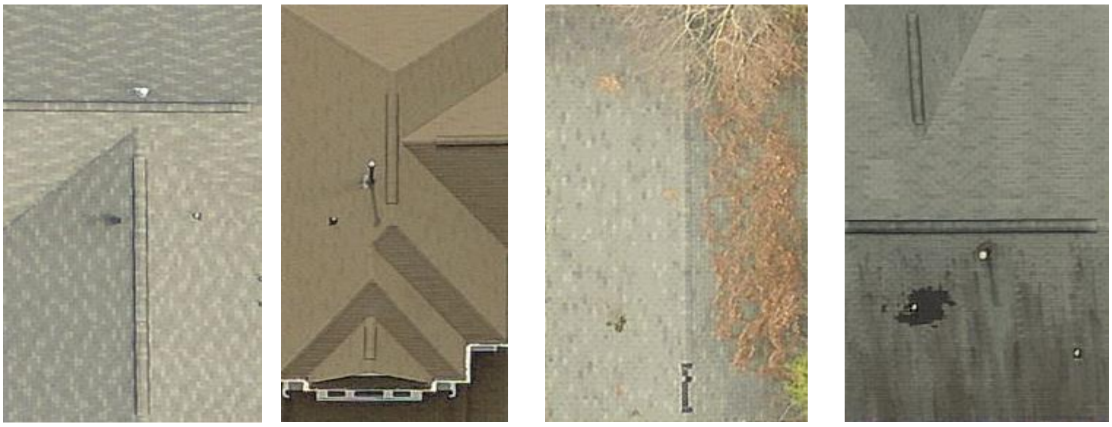


Figure 1: Manual residential roof extraction

110 intact roofs and 164 damaged roofs were manually extracted. Fig. 2 shows typical roof sample images. Fig. 2 (a) is an intact roof with a relative uniform texture. Fig. 2 (b) is a “structured” rooftop with several ridges and windows. Fig. 2 (c) is a roof covered by dust and trees. Fig. 2 (d) is a damaged roof with cosmetic damage and missing shingles.



(a) (b) (c) (d)

Figure 2: Pictometry rooftop sample images. (a) Intact roof. (b) “Structured” roof. (c) Roof with tree and dust. (d) Roof with cosmetic damage and missing shingle.

The challenge is the high within-class diversity in roofs. Features extracted from the entire rooftop are not sufficient enough for roof condition assessment. Thus, roof segmentation, followed by segments classification is proposed. We focus on the roof segmentation in this paper.

3 Algorithm

In this section, we will detail our proposed algorithm. First, the image was over-segmented by SLIC superpixel. Color features were extracted from each superpixel and a similarity measure of color feature was defined. The most similar neighboring regions were merged at each iteration. An unsupervised evaluation metric Q quantified the merging steps into a score list. The result of algorithm corresponded to the segmentation achieved the minimal Q.

3.1 Over-segmentation using SLIC superpixel

The proposed region merging method is initialized by the SLIC superpixel method. The excellent boundary adherence (Achanta *et al*., 2012) of SLIC superpixel algorithm is a necessary prerequisite to eventually obtain the accurate shape and area of missing shingles or cosmetic damage. SLIC was applied to color images in the CIELAB color space. We set the nominal size of the superpixel to 15×15 instead of determining the number of desired superpixels in each roof image. The compactness parameter is used to control the tradeoff between superpixel compactness and boundary adherence (Achanta *et al*., 2012) which is empirically set to 7 in this study.

3.2 Color feature computation

After the SLIC segmentation, the image was divided into homogenous regions. Color histograms which have been widely used for image retrieval (Belongie *et al*., 1998; Deng and Manjunath, 1997) were used as the features for region representation. Each color channel in RGB space is quantized into 16 bins and each region is thus represented by a vector of dimension 4096.

3.3 Similarity measure

The order of merging is controlled by the similarity measure between adjacent regions. In our algorithm, the Bhattacharyya coefficient (Kailath, 1967) was adopted to measure the color similarity Sim_c between adjacent regions p and q

$$Sim_c = BC(p,q) = \sum_{i=1}^{n} \sqrt{CH_p^i \cdot CH_q^i} \tag{1}$$

where CH_p^i and CH_q^i represent the normalized color histograms of region p and q. The superscript i means the ith element and n is the dimension of the color histogram.

The region merging processing were then performed by iteratively merging the most similar adjacent regions. The color features and similarity ranking were updated after each merging.

3.5 Unsupervised segmentation evaluation

The series of merging steps was compiled into a score list by an unsupervised evaluation metric Q (Borsotti *et al.*, 1998) which is defined by

$$Q = \frac{\sqrt{R}}{10000(N \times M)} \sum_{i=1}^{R} \left[\frac{e_i^2}{1+\log A_i} + \left(\frac{R(A_i)}{A_i}\right)\right] \quad (2)$$

where $N \times M$ is the size of the image, R represents the number of regions, A_i is the area in number of pixels and e_i^2 is the squared color error of the ith region v_i, respectively. The squared color error of the ith region v_i for each color band is defined as

$$e_i^2 = \sum_{p \in v_i} (C(p) - \hat{C}_i)^2 \quad (3)$$

where $\mathrm{C(p)}$ denotes the value of pixel p and $\hat{\mathrm{C}}_\mathrm{i}$ represents the average value of ith region. $\mathrm{R(A_i)}$ represents the number of regions that have an area equal to $\mathrm{A_i}$ (Borsotti *et al.*, 1998) . Lower Q values mean better segmentation quality. The final segmentation result corresponded to the step with minimal Q value.

5 Experimental results and discussion

In this section, we demonstrate the segmentation results of our proposal algorithm on manually extracted roof sample images from the one-inch-resolution Pictometry data set. The proposed algorithm was compared with the well-known compression-based texture merging (CTM) method (Yang *et al.*, 2008) . Representative results are provided in Figs. 3.

An intact roof example is shown in the first row of Fig. 3. Compared with the the CTM algorithm, the proposal algorithm produces a relative clear result around the structure region. CTM works well on the shadow area, however, it produces a weird boundary around the ridge. A roof with dust, tree and missing shingle is shown in the second row of Fig. 3. Our algorithm isolates the missing shingle and the dust area accurately. CTM suffers an under-segmentation problem around the dust and over-segmentation problem around the missing shingle. A “structured” roof is shown in the thrid row of Fig. 3. Compared with our algorithm, CTM algorithms does not isolate the ridge and two small chimneys. Another “structured” roof is shown in the fourth row of Fig. 3. CTM produces a weird boundary around the chimney.

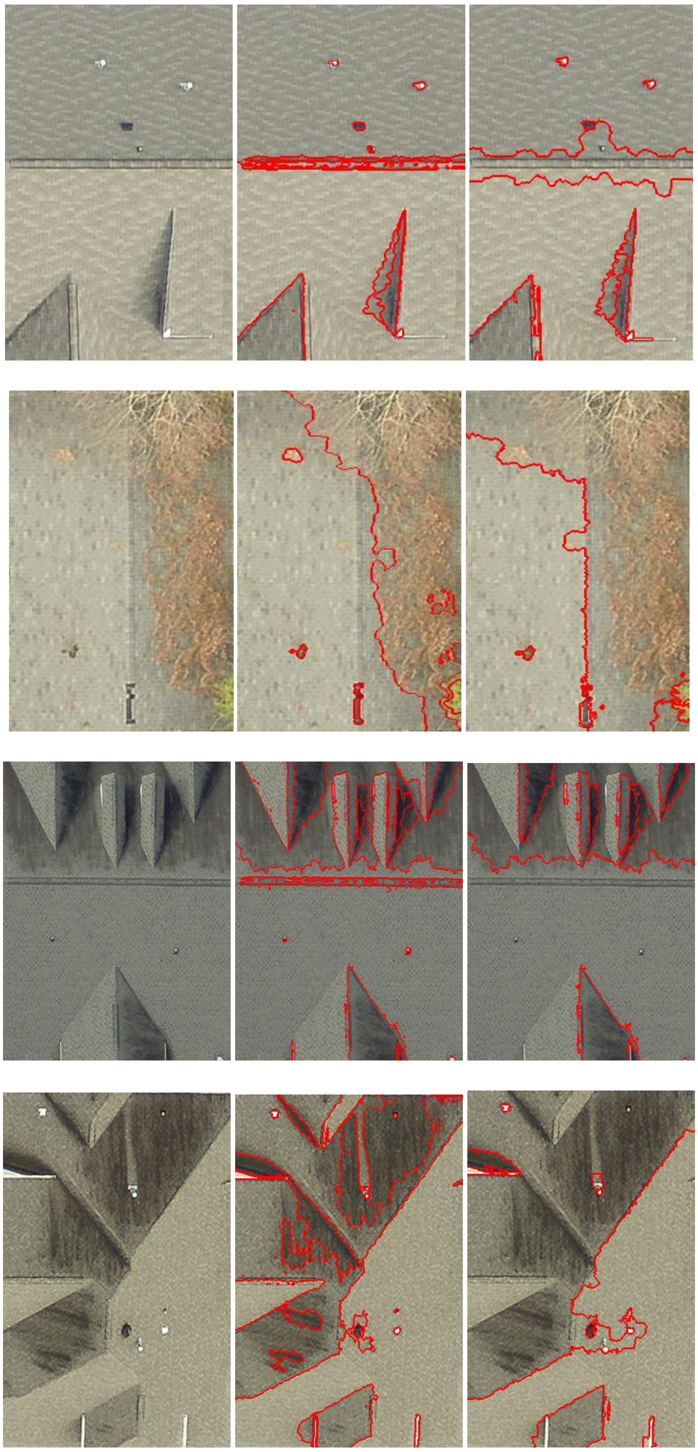
In summary, the proposal algorithm produces better results compared with the CTM method. The CTM algorithm produces sinuous boundaries around ridges and chimneys. Meanwhile, CTM is not robust. It isolates cosmetic damage areas on some data and ignores them on other data.

7 Conclusion

An adaptive region merging segmentation method is proposed as a step in the assessment of roof condition with very-high-resolution airborne imagery.

The algorithm started from a SLIC over-segmentation result. Adjacent superpixels were progressively merged. The merging order was controlled by a similarity measure of color histogram. The series of merging steps were monitored by an unsupervised segmentation evaluation metric, Q. The result of the algorithm corresponded to the step with minimal value of Q.

Extensive visual demonstration was shown to validate the proposed method as a pre-processing step for subsequent segment condition assessment. Future work on segment classification will be conducted to complete the roof condition assessment.



(a) (b) (c)

Figure 3: Segmentation results by proposed modified algorithms and CTM. (a) Original image (b) Proposed algorithm result (c) CTM result

References

Achanta, R., A. Shaji, K. Smith, A. Lucchi, P. Fua and S. Susstrunk, 2012. SLIC superpixels compared to state-of-the-art superpixel methods, Pattern Analysis and Machine Intelligence, IEEE Transactions on, 34 (11): 2274–2282.

Belongie, S., C. Carson, H. Greenspan and J. Malik, 1998. Color-and texture-based image segmentation using em and its application to content-based image retrieval, In Computer Vision, Sixth International Conference on. IEEE, pp. 675–682.

Borsotti, M., P. Campadelli and R. Schettini, 1998. Quantitative evaluation of color image segmentation results, Pattern recognition letters, 19 (8): 741–747.

Deng, Y. and B. Manjunath, 1997. Content-based search of video using color, texture, and motion, Image Processing Proceedings International Conference on IEEE, pp. 534–537.

Dong, L. and J. Shan, 2013. A comprehensive review of earthquake-induced building damage detection with remote sensing techniques, ISPRS Journal of Photogrammetry and Remote Sensing, 84: 85–99.

Grünthal, G., 1998. European macroseismic scale 1998 (ems-98), Conseil de l'Europe.

Kailath , T., 1967. The divergence and bhattacharyya distance measures in signal selection, Communication Technology, IEEE Transactions on, 15 (1): 52–60.

Yang, A. Y., J. Wright, Y. Ma and S. S. Sastry, 2008. Unsupervised segmentation of natural images via lossy data compression, Computer Vision and Image Understanding, 110 (2): 212–225.