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To cite this article: Liang Huang *et al* 2019 *IOP Conf. Ser.: Earth Environ. Sci.* **234** 012022

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Unmanned Aerial Vehicle Remote Sensing Image Segmentation Method by Combining Superpixels with multi-features Distance Measure

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Abstract. Image segmentation is the foundation and key step of object-level classification and change detection. In this paper, a segmentation method of UAV remote sensing image based on multi-features distance measure and superpixels is proposed. First, the simple linear iterative clustering (SLIC) algorithm is used to segment the unmanned aerial vehicle (UAV) remote sensing image to obtain the initial superpixels. Then the distance measures of the spectral, texture, shape and area features are used as the criterion for initial superpixels merging. Finally, merger termination when the number of regions reaches the set number. Two groups of UAV remote sensing images are selected to evaluate the experimental results through visual evaluation. The experimental results show that the proposed method can be used to aggregate objects of different scales, and the segmentation effect is satisfactory.

1. Introduction

At present, unmanned aerial vehicle remote sensing system has become one of the most important technical means of global earth observation technology, and it has been widely used in mine monitoring [1], precision forestry [2], automatic mapping of land surface elevation changes [3], precision agriculture [4], and disaster damage assessment [5] and so on. In order to better serve all trades and professions, it is necessary to extract all kinds of thematic information from the unmanned aerial vehicle (UAV) remote sensing image, that is, objectified extraction from the data to the information [6]. Image segmentation is the transition part and key step of UAV remote sensing image information extraction and target recognition [7].

Pixels are usually as the basic processing unit in traditionally image segmentation methods. But with the continuous improvement of the spatial resolution of remote sensing image, the size of the target image is becoming larger and larger. It is difficult to meet the application requirements when the pixel-based image segmentation method is used directly in very high spatial resolution remote sensing images [8]. In order to solve this problem, many scholars have used the superpixels segmentation method to segment image and get the over segmentation results, which can greatly reduce the complexity of the subsequent image processing tasks. Superpixel [9] is the first concept proposed by Ren X and Malik J in 2003, the superpixels refer to the local, consistent, sub region of the image that can maintain the local structural characteristics of a certain image. The superpixels segmentation is a



processing technology that aggregates pixels into superpixels. At present, the superpixels segmentation method can be roughly divided into two broad categories [10-11]: 1) Graph-based algorithms; 2) Gradient-ascent-based algorithms. Graph-based algorithms generate superpixels by minimizing a cost function defined over the graph [12], the representative algorithms based on graph area as following: 1) Normalized cuts algorithm (NCUTS) [13]; 2) Minimum spanning tree methods (MST) [14]; 3) ERS algorithm [15]. Gradient-ascent-based algorithms start from a rough initial clustering of pixels and iteratively refine the clusters until some criteria are met to form the superpixels [10,12]. The representative algorithms based on gradient-ascent are as following: 1) Mean shift algorithm; 2) Watershed algorithm; 3) Turbopixels; 4) SEEDS algorithm; 5) Spatial-constrained watersheds (SCoW); 6) DBSCAN; 7) SLIC algorithm. These methods have different methods to obtain segmentation results, and their respective advantages and disadvantages are different. Among them, SLIC superpixels algorithm is one of the most popular superpixels segmentation method. This method has the advantages of more smooth regular-sized superpixels, higher boundary recall and faster segmentation speed [10].

The SLIC algorithm can obtain more satisfactory superpixels, but there are different sizes of ground objects in the UAV remote sensing images. For small size objects, the ground objects can be extracted and identified by directly calculating the features of superpixels. However, for large scale objects, super pixel results are too broken. Using super pixel as the basic unit of information extraction and target recognition, it has to face the problem of low computing efficiency. In order to solve this problem, a remote sensing image segmentation method based on multi-features distance measure and superpixels is proposed. In this paper, we first used SLIC algorithm to obtain superpixels in unmanned aerial vehicle (UAV) remote sensing image, and take superpixel as the basic unit of image processing; and then calculate the distance of spectral, texture, shape and area characteristics between superpixels, and use it as the criterion of superpixels merging. Finally, the merge is terminated according to the number of blocks in the merging regions.

The second section introduces the proposed method, introduces the theoretical background of SLIC superpixels segmentation, the superpixels merging based on the multi-features distance measure; the third section introduces the experimental results and analysis, describes the data sets, the contrast experiments and the analysis of the experimental results; the fourth section introduces the conclusions, and describes the main results and the existing problems.

2. A segmentation method of combining multi-features distance measure and superpixels

The main steps of the proposed method in this paper are as follows: 1) the SLIC algorithm is used to generate the initial superpixels by over segmentation of unmanned aerial remote sensing image; 2) the spectral, texture, shape and area features distance between the superpixels are calculated; and 3) the spectral, texture, shape and area features distance are used as the superpixels merging criteria, and the number of merged region blocks are set as the condition of merging end; 4) accuracy evaluation. The flowchart of proposed method is shown in Figure 1.

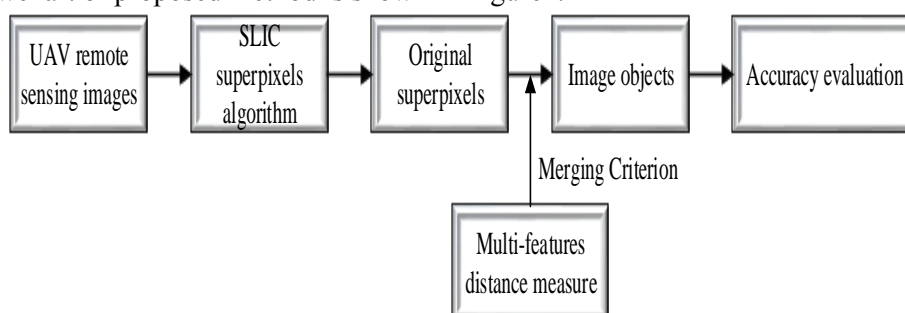


Figure1. The Flowchart of proposed method

2.1 SLIC superpixels segmentation

Achanta et al. proposed a SLIC algorithm in 2010. The SLIC superpixels algorithm mainly used *K*-means clustering algorithm to carry out superpixels clustering processing. It is an improved clustering

algorithm based on color and space information. Use CIELAB (*Lab*) color space L , a , b color characteristics and pixel space coordinates x , y to construct the five dimensional feature vectors under the color space of *Lab*. Therefore, the K superpixels clustering center can be described as a standard to measure the five dimensional feature vectors to determine the size of the local feature difference between pixels. Finally, the pixels are clustered to generate the SLIC superpixels.

The algorithm steps are described as follows:

(1) Initialization of seed points

An image contains N pixels. If the N pixels of the image are clustered into k superpixels blocks, each superpixel size is equal to each pixel if the length and width of each superpixel block are evenly equal $S = \sqrt{N/k}$.

(2) Measure similarity

The similarity measure between each pixel point and the nearest seed point is calculated. The label of the seed point with the highest similarity is assigned to the pixel, and the process is iterated until the convergence, and the relation of the similarity is measured as follows:

$$d_{lab} = \sqrt{(l_k - l_i)^2 + (a_k - a_i)^2 + (b_k - b_i)^2} \quad (1)$$

$$d_{xy} = \sqrt{(x_k - x_i)^2 + (y_k - y_i)^2} \quad (2)$$

$$D_S = \sqrt{(d_{lab})^2 + (d_{xy}/S)^2 m^2} \quad (3)$$

In the formula, d_{lab} represents the distance from the color space; d_{xy} represents the distance of the plane space, D_S represents the space distance of the five dimensional color features, and m represents the balance parameter. In the similarity measure, it is used to weigh the proportion of the color characteristic value and the spatial feature information, and the range is [1,40]; S is the distance between adjacent seed points; The bigger the value of D_S , it means that the two pixels are more similar or the two pixels are closer to each other.

The SLIC superpixels algorithm used the above formula (1) - (3) to measure the K superpixels and the i superpixel similarity; then, the mean $[l, a, b, x, y]^T$ of each pixel in each superpixels block are used as the new clustering center, and the residual error is calculated. Finally, repeat the above two steps until the stop standard is reached. Unlike other super pixel segmentation algorithms, SLIC super pixels do not specify whether or not a connection must be forced. At the end of the clustering process, some "isolated" pixels that do not belong to the cluster center may be retained.

2.2 Superpixels merging method

The superpixels segmentation algorithm is a very popular fast segmentation algorithm for image. The segmentation obtains the superpixels block with uniform size and high degree of edge fitting, but the phenomenon of over segmentation is followed by the high efficiency image processing. In order to solve the problem of over segmentation, the superpixels which appears after the SLIC over segmentation is proposed. And deal with the formation of new regions.

(1) Merger criterion

The combination of spectral and texture weighting is recorded as [16]:

$$h_1(m, n) = \omega_G h_G + \omega_T h_T \quad (4)$$

h_G indicates that the distance of spectral histogram in two regions is called spectral distance, that is, the heterogeneity of the spectrum. h_T combines texture structure and texture strength to measure

the joint probability distribution histogram of LBP and LC, that is, texture heterogeneity, ω_G and ω_T represent the corresponding weights.

The heterogeneity of the adjacent two regions is expressed as:

$$h(m, n) = \frac{h_1(m, n)}{l^\lambda} \quad (5)$$

l^λ represents the common edge length of i in adjacent regions and regional j , and λ represents the influence coefficient of the common side. When λ equals 0, l^λ is equal to 1, indicating that the public edge does not affect the measurement of regional heterogeneity. When λ is not 0, the longer the public edge is, the smaller the heterogeneity.

The combined value is expressed as [17]:

$$C_{i,j} = \frac{N_i \cdot N_j}{N_i + N_j} \cdot h(m, n) \quad (6)$$

$C_{i,j}$ represents the combined generation value of area i and area j . N_i represents the area of the area i , N_j represents the area of the area j , $h(m, n)$ represents the heterogeneity of the two regions.

Bring $h(m, n)$ into the form (6) to get

$$C_{i,j} = \frac{N_i \cdot N_j}{N_i + N_j} \cdot (w_G G_G + w_T G_T) \cdot \frac{1}{l^\lambda} \quad (7)$$

The combined cost of the above formula not only incorporates the spectral, texture and shape features of the region, but also takes into account the area characteristics of the region.

(2) Regional merger stop criteria

There are two ways to stop the merging of regions. The first is to terminate the merger by setting a threshold, and the second is to terminate the merger by the number of merged region blocks set.

3. Experimental results and analysis

3.1 Experimental data

In order to verify the reliability and effectiveness of the proposed method, two data sets of experimental data are selected. The two sets of data are remote sensing images of UAV in local area of Yiliang County of Kunming city, including 3 bands of red, green and blue. The main ground objects in the image include buildings, vegetation, bare land, roads and so on. The first scene image size is 979×586 pixels, the spatial resolution is 0.05m, as shown in Figure2; Figure3 is the reference image obtained by artificial vectorization of the first scene image. The second scene image size is 726×468 pixels, the spatial resolution is 0.05m, as shown in Figure4; Figure 5 is the reference image obtained from the second scene image by artificial vectorization.



Figure2. First scene image

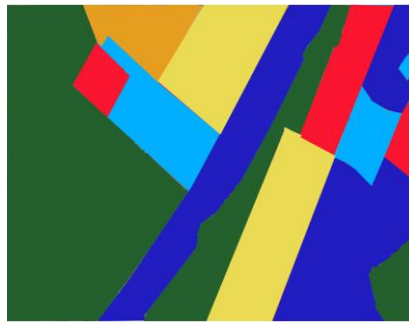


Figure3. Reference image

**Figure4.** Second scene image**Figure5.** Reference image

3.2 Experimental results and analysis

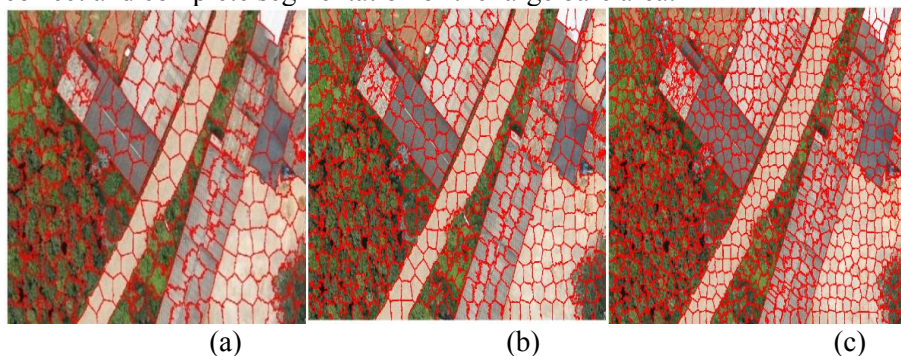
In order to evaluate the experimental results, a qualitative evaluation method is adopted. Visual evaluation was used in qualitative evaluation. At the same time, the results of the proposed method are compared with the results of the FNEA algorithm, and the effectiveness and reliability of the proposed method are compared with the popular image segmentation methods.

Figure6 shown the results of SLIC superpixels segmentation obtained from $K=300$, 600 and 1000 respectively for the first scene image. Figure7 is a segmentation result image obtained by merging the superpixels of the segmentation results of Figure6. Figure8 is a segmentation result image obtained by FNEA method. Its parameters are: *shape*=0.1, *compactness*=0.9 and *scale* are 100, 200 and 300 respectively.

In the arrowhead area of first scene image, the FNEA algorithm has an over segmentation phenomenon. With the increase of the segmentation scale, the over segmentation problem in the arrowhead area has not been solved well. At the same time, the partial segmentation results are under the phenomenon of under segmentation, and the method in this paper is better cut out the border area between the bare land and the vegetation.

Figure9 shown the results of SLIC superpixels segmentation obtained from $K=300$, 600 and 1000 respectively for the second scene image. Figure10 is a segmentation result image obtained by merging the superpixels of the segmentation results of Figure9. Figure11 is a segmentation result image obtained by FNEA method. Its parameters are: *shape*=0.1, *compactness*=0.9 and *scale* are 100, 200 and 300 respectively.

In the red circle area of second scene image, the FNEA algorithm has over segmentation. By increasing the segmentation scale, the segmentation problem is still not solved, and the partial segmentation results are also under the phenomenon of under segmentation, and proposed method is correct and complete segmentation of the large bare area.

**Figure6.** SLIC segmentation results in first scene image: (a) $K=300$; (b) $K=600$; (c) $K=1000$

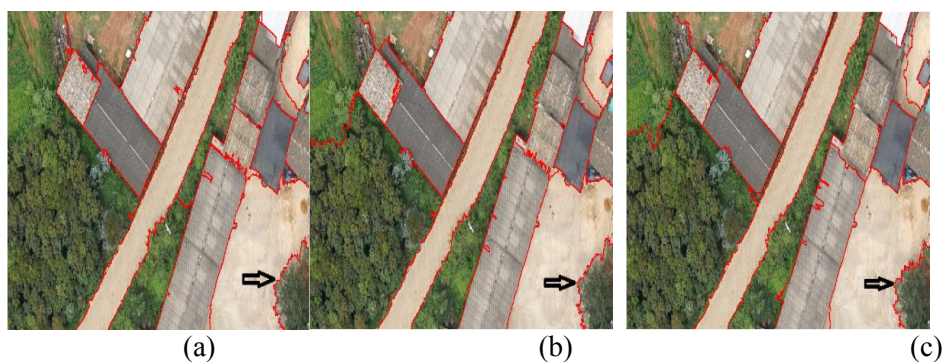


Figure7. Proposed method segmentation results in first scene image: (a) K=300; (b) K=600; (c) K=1000

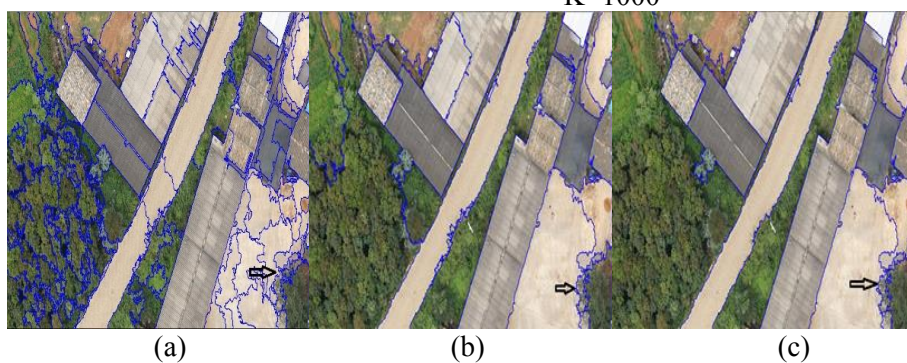


Figure8. FNEA method segmentation results in first scene image: (a) scale=100; (b) scale=600; (c) scale=1000

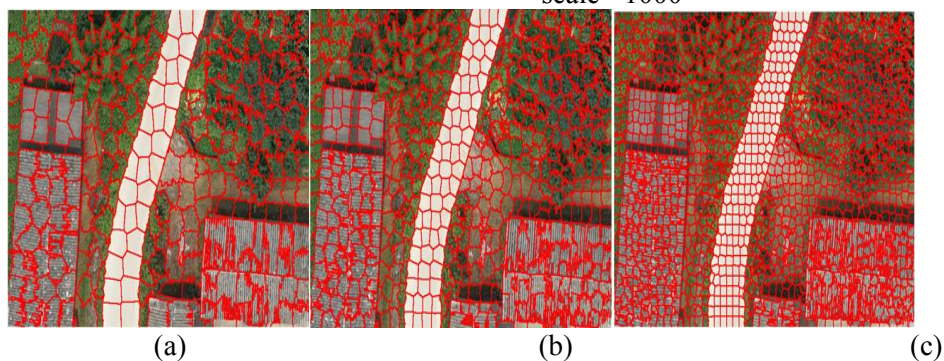
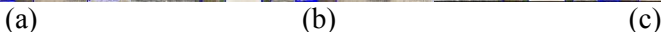


Figure9. SLIC segmentation results in second scene image: (a) K=300; (b) K=600; (c) K=1000



Figure10. Proposed method segmentation results in first scene image: (a) K=300; (b) K=600; (c) K=1000



scale = 1000

4. Conclusion

In order to give consideration to the generation of objects of various sizes in UAV remote sensing image, a segmentation method of UAV remote sensing image based on multi-features distance measure and superpixels is proposed. The method first segments the UAV remote sensing image into superpixels by using SLIC algorithm, and then used the measurement of spectrum, texture, shape and area distance as the merging criterion of superpixels, and combines the initial superpixels to form the final image segmentation results. Finally, the precision of the segmentation results is evaluated. Through two groups of experimental data, proposed method and the FNEA algorithm are qualitatively compared and evaluated. The proposed method can better solve the problem of over segmentation and under segmentation in image segmentation, and the results are satisfactory. The next step will be how to select the optimal region merging criteria and optimize the efficiency of the algorithm.

5. Acknowledgments

This research work was supported by the National Natural Science Foundation of China (no. 41601476), the Applied Basic Research Programs of Science and Technology Department of Yunnan Province (no. 2018FB078), the Talent Cultivation Foundation of Kunming University of Science and Technology (no. KKS201521040) and the Science Research Foundation of Yunnan Educational Committee (no. 2016ZZX051).

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