EDGE FINING ALGORITHM OF TEXTURE CLASSIFICATION FOR HIGH RESOLUTION REMOTE SENSING IMAGES

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ABSTRACT:

In order to improve the classification accuracy of the high resolution remote sensing images, the algorithm based on texture features is proposed in this paper. The image is classified initially by texture features which are derived from gray level co-occurrence matrices. And the suitable weights of these features are given to form the feature vector. Secondly, the edge fining method, which can reclassify the edge pixels to proper classes, is introduced. This method adopts texture features with different parameters to reclassify the edge pixels when the edge blocks are large. And when the edge pixels blocks are small, the spectral feature is taken into consideration. Finally, two different original images are chosen to verify the algorithm. And from the results it can be seen that this algorithm is effective for high spatial resolution RS images classification.

1. INTRODUCTION

The spatial resolution of remote sensing images has reached 0.6m or higher level. It brings us more information and higher accuracy for our applications. In addition to rich spectral information, the structural, figure and textural features appear more obvious in high resolution image (LIU, 2003). The key problem focused on how to extract useful information automatically and efficiently from high resolution remote sensing images.

In order to increase the classification accuracy, the texture analysis and other methods had been applied to the remote sensing image classification for several decades. However, the past algorithms were mainly dealt with the low and middle resolution remote sensing. Now, an obvious improvement had been gotten in the field of high spatial resolution remote sensing image processing. The structural and textural features are commonly used in information extracting. Texture analysis methods could be classified as statistic method, geometry method, model-based method and signal process method. In the last decades, different texture analysis methods have been applied to high spatial resolution remote sensing image processing. A RS image segmentation algorithm based on simplified random field model was proposed in (Ming, 2004). Texture analysis method based on wavelet transform has been applied to high spatial resolution RS image Classification (HUANG, 2006). A new texture method has been proposed and applied to residential area half-automatic extraction from high spatial resolution RS image (Su, 2004). However, the efficient texture analysis methods especially for high resolution remote sensing images are still lacking.

Therefore, an algorithm based on texture features is proposed to classify high resolution remote sensing images. The paper is organized as follows. The texture features based on gray level co-occurrence matrices are given in Section 2. Classification algorithm including initial classification and edge fining is discussed in Section 3 and, experimental results are given in Section 4. Finally, conclusions are drawn in Section 5.

2. CO-OCCURRENCE MATRICES

Gray level co-occurrence matrices suggested by Haralick have become one of the most well-known and widely used texture features. Texture could be seen as the spatial distribution and correlation between gray levels of image in this method. Given displacement d, direction θ, and original gray level i, $P(i,j\,|\,d,\theta)$ represents the probability of gray level j appearance.

Many texture features can be defined according to gray level co-occurrence matrix. Fourteen texture features have been defined by Haralick. In this paper, five of them are chosen to use in image segmentation. They are listed as the follows.

(1) Energy

$$f_1 = \sum_i \sum_j P_d^2(i,j) \tag{1}$$

(2) Entropy

$$f_2 = -\sum_i \sum_j P_d(i,j)\log P_d(i,j) \tag{2}$$

(3) Contrast

$$f_3 = \sum_i \sum_j (i-j)^2 P_d(i,j) \tag{3}$$

(4) Homogeneity

$$f_4 = \sum_i \sum_j \frac{P_d(i,j)}{1+(i-j)^2} \tag{4}$$

(5) Covariance

$$f_5 = \sum_i \sum_j P_d(i,j)^2 (i-\mu_x)(j-\mu_y) \qquad (5)$$

where

$$P_d(i,j) = \frac{P(i,j \mid d,0^o) + P(i,j \mid d,45^o) + P(i,j \mid d,90^o) + P(i,j \mid d,135^o)}{4}$$

μ_x = means of $P_d(x)$
μ_y = means of $P_d(y)$
$P_d(x) = \sum_j P(x,j)$
$P_d(y) = \sum_i P(i,y)$

3. CLASSIFICATION ALGORITHM

Before the classification, it should be supposed that the size of any connected texture area in RS images must be large than M ×M. Here M is the size of the image blocks which are divided in the following steps. It is because that texture feature is a property of area. Another supposition is that any texture area in image should include at least one foundational element of the texture(Zhou, 2001).

At the first step, the initial classification image will be gotten by the following process. First, the original image is divided into many sub-block with size of M×M. Texture feature of every sub-block is calculated by the equations above. Second, K-mean clustering algorithm is chosen to classify them to certain amount classes. And different classes are marked by different gray level. Edges between different areas in initial classification image are ladderlike. In order to get smooth and rational edge, it is necessary to perform the following edge fining algorithm. The algorithm, initial value and parameters of clustering should be confirmed in this step.

At the second step, a feasible edge fining algorithm is proposed to deal with the initial classification image. First, the boundary sub-blocks are distinguished by their classes and locations. Second, each boundary sub-block images are subdivided into four lower sub-blocks with size of (M/2)×(M/2). Texture feature of this level sub-block images are calculated with different parameter d. Finally, the distances of this level sub-block image to its adjacent classes are calculated. It will be marked as corresponding class according to distances. Actually, boundary sub-blocks should be altered to their neighbouring classes, which assured the integrality of the area of the segmentation.

The algorithm is given as follows.

Step 1: To divide the image I into sub-block images with size of M×M and calculate their texture features respectively.

Step 2: To classify the sub-block images into certain number of classes using K-mean clustering algorithm. And then, pixels in image are marked to corresponding classes according to their texture feature. After that, the initial classification image S(0) would be gotten.

Step 3: To distinguish the boundary blocks and divide them to lower sub-blocks with size of (M/2)×(M/2). Texture feature of this level sub-block images are calculated with the parameter d=d/2. These lower sub-blocks are marked to corresponding class according to their distances to the neighbouring classes. After that, the first fining classification S(1) will be finished.

Step 4: If S(t)=S(t-1) or M/2<size of the smallest texture foundational element, then to reclassify the small boundary blocks primarily by their spectral features and output the final segmentation image. Otherwise go to Step 3.

4. EXPERIMENT RESULT

4.1 Experiment

First, a standard texture image is used to testing the classification algorithms. The original image and the result image are given in the Figure 1 and Figure 2.

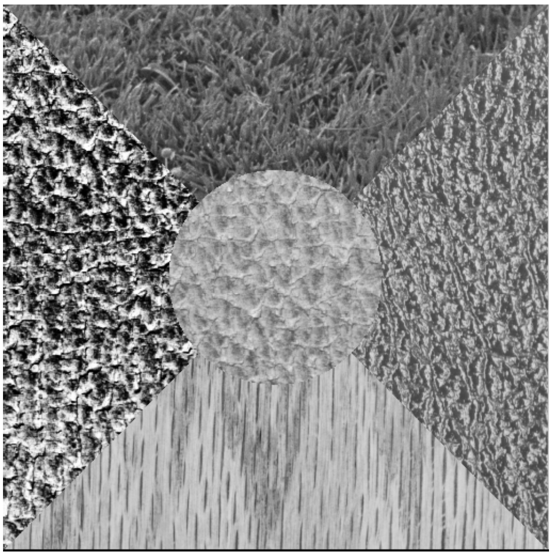

Figure 1. Original image

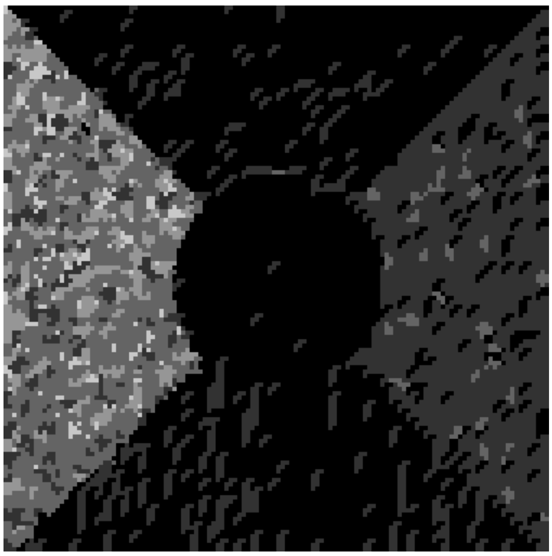

Figure 2. Classification result

Second, high spatial resolution RS image acquired by unmanned aerial vehicle is given as the original image. The Figure 3 is the original image. Figure 4 and Figure 5 are the initial classification result and the final result after edge fining, respectively.

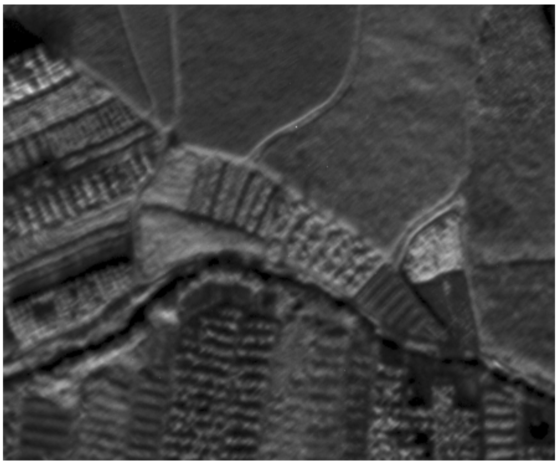

Figure 3. Original high resolution RS image

Figure 4. Initial classification result

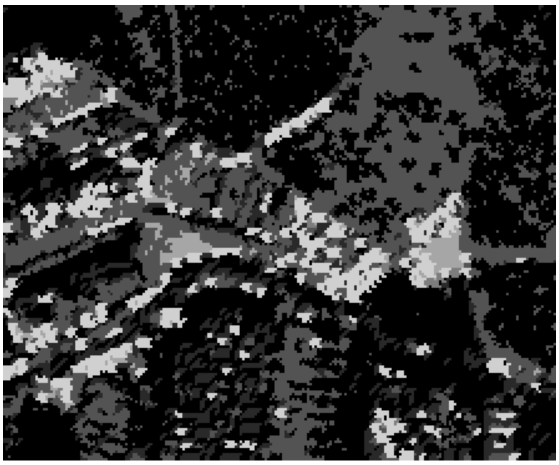

Figure 5. Final result after edge fining

4.2 Result analysis

From the processing result above, it could be seen that the classification algorithm proposed in this paper is feasible. The result after edge fining is better than that without this step. And the region which has similar texture is classified into the same class although the spectral features of its pixels are different obviously. However, it must be mentioned that there are still many small scraps in some region of the image, which should be a whole cluster region. So it is necessary to develop a method to merge them to suitable class.

5 CONCLUSIONS

By use of texture features, the algorithm proposed in this paper can overcome the shortcoming of the traditional classification methods. From the experiments of different original images, it can be seen that texture features are useful in high spatial resolution RS image processing.

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