Classification of high resolution imagery based on fusion of multiscale texture features

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Abstract. In high resolution data classification process, combining texture features with spectral bands can effectively improve the classification accuracy. However, the window size which is difficult to choose is regarded as an important factor influencing overall classification accuracy in textural classification and current approaches to image texture analysis only depend on a single moving window which ignores different scale features of various land cover types. In this paper, we propose a new method based on the fusion of multiscale texture features to overcome these problems. The main steps in new method include the classification of fixed window size spectral/textural images from 3×3 to 15×15 and comparison of all the posterior possibility values for every pixel, as a result the biggest probability value is given to the pixel and the pixel belongs to a certain land cover type automatically. The proposed approach is tested on University of Pavia ROSIS data. The results indicate that the new method improve the classification accuracy compared to results of methods based on fixed window size textural classification.

1. Introduction
With the development of remote sensing technology, very high resolution satellite data such as hyperspectral remote sensing data which provides more detailed ground information have become readily available in recent years [1]. However, traditional classification methods using only the spectral information have proved to be inadequate for high resolution imagery due to the complex spectral characteristics within each land cover class and between different land cover classes. Fortunately, texture is considered as significant spatial information which discriminates different land cover class with the same spectrum. Incorporating textural and spectral information is a feasible method which effectively improves the classification accuracy of high resolution imagery [2, 3]. Many texture feature methods have been proposed and tested, and the grey-level co-occurrence matrix (GLCM) is one of the most popular methods to measure texture [4]. GLCM is used to get the texture feature in this paper.

In GLCM textural extraction process, window size, texture statistics, quantization level, inter-pixel distance and orientation are the factors that all contribute to the performance of the following textural classification [5, 6]. Among all the parameters in the textural analysis the window size is an important factor influencing the following classification process and overall classification accuracy [7]. In order to obtain the optimal fixed window size, a number of studies have been conducted on long window size experiments and through comparing all the overall accuracy under different window sizes conditions. Previous studies also indicated that different land cover types have their own optimal scale.
characteristic [8]. So it is difficult to describe the texture features using single window to demonstrate multiscale land cove types in the high resolution imagery. Some multiscale fusion methods based on different window size texture features have been proposed and the conventional fusion method was stacking the spectral bands and textural bands to a new imagery, and then the new imagery was utilized to be classified [9].

In order to improve the accuracy further and solve the problem of single textural classification and window size problem, a new multiscale textural classification method are proposed and compared with the traditional one.

2. Methodology

2.1. Study area and data
In our experiment we use the University of Pavia data sets which are acquired from the ROSIS-03 (Reflective Optics System Imaging Spectrometer) optical sensor. The airborne data are collected by the German Aerospace Center in the framework of the HySens project managed and sponsored by the European Union. The University is located in Pavia, northern Italy and the image is 610 by 340 pixels with the spatial resolution of 1.3m per pixel. There are 103 channels for the hyperspectral data as some channels have been removed due to noise. It has nine classes, including trees (deep green), asphalt (light grey), bitumen (purple), gravel (blue), metal sheet (pink), shadow (yellow), bricks (red), meadow (green) and soil (brown). The study area and test samples are shown in figure 1.

![University of Pavia study area](image)

Figure 1. University of Pavia study area (a) ROSIS data with three channels composite, (b) validation data.

2.2. Method
The new approach includes textural extraction, classification of spectral/textural integration images with fixed window size, and the fusion of multiscale texture features. The specific procedures are illustrated below.

2.2.1. Texture Extraction. The new spectral/textural images are the basis for the new method, and this process contains texture extraction of long window sequence. There are several factors such as window size length, texture feature which should be determined in advance in GLCM textural extraction process. Based on a series of previous studies on textural classification method, window size length in textural extraction in this paper is identified ranging from 3×3 to 15×15. Furthermore, according to the study of frequently-used GLCM texture features, Entropy and Homogeneity are selected as optimal features in this experiment. The traditional principal component analysis (PCA) method is utilized to the experiment data in order to reduce the data dimension and the front five bands
in the process of principal component analysis are employed as spectral bands. The GLCM texture features are calculated across the whole PCA first band image repetitively from small window size to larger one. For the border pixels in the image a mirror extension method is used to get the texture feature. In this way we obtain the entire textural feature under different window size condition.

2.2.2. SVM Classification. After extracting texture feature based on the long window sequence, the corresponding texture feature of fixed window size are stacked with spectral bands respectively, forming seven spectral/textural new images with the window size from 3×3 to 15×15. Every new spectral/textural image contains spectral bands and textural band obtained from a single window size. A supervised classifier is important for remote sensing image classification procedure. With the consideration of the characteristic of the classifier, the support vector machine (SVM) classifier is selected to classify all the new spectral/textural images. So the classification results and posterior possibility rule images of different window size are produced using SVM method. The posterior possibility rule images based on different window size represent the probability of a pixel belonging to different land cover types at that scale of window size.

2.2.3. Fusion of Multiscale Features. The classification of single window spectral/textural image neglects the scale characteristic of different land cover types existing in remote sensing image, so the fusion of multiscale texture features is proposed in the experiment. The classification map is hard classification result, by contrast, the posterior possibility rule map represents soft classification result. For every pixel in remote sensing image, there are several values of different land cover type’s posterior possibility and the sum of all the posterior possibilities equal one for one pixel in one single window size textural classification result. The hard classification map is the result of the comparison of the posterior possibilities in one fixed window spectral/textural classification. However, the new approach is based on the posterior possibility rule images of different window sizes. To be specific, the fusion method compares the posterior possibility rule images in all window sizes for each pixel, as a result, the biggest probability value is given to the pixel and the pixel belongs to a certain land cover type automatically according to that value. Moreover, in order to validate the new method, spectral classification method, fixed window size textural classification method and a traditional approach which stacks the spectral bands and all window size textural bands to a new imagery are all tested, and the traditional approach is called stacking method in this paper.

3. Result and Analysis
The classification processes and results with different methods are assessed with the same training sample and validation sample. Two statistics including overall accuracy (OA) and Kappa coefficient are selected to evaluate classification results. Table 1 illustrates the accuracy of spectral classification method, the stacking method and the new fusion of multiscale texture feature method. Obviously, according to the table, there is a dramatic accuracy difference between the spectral classification method and textural classification method. Introducing the textural information in the classification process can achieve higher accuracy result compared with the spectral information only, and this is mainly because adding texture feature can reduce the classification errors caused by similar spectral reflectance with different land cover types. The overall accuracy and Kappa coefficient of the spectral classification result are 68.02% and 0.5926 respectively. The window size selection has a considerable influence on the textural classification result.

| Different methods                  | Entropy | Homogeneity |
|------------------------------------|---------|-------------|
|                                    | OA      | Kappa       | OA      | Kappa   |
| Spectral image                     | 68.02%  | 0.5926      | 68.02%  | 0.5926  |
| Spectral+3×3 textural image        | 81.46%  | 0.7537      | 81.20%  | 0.7492  |

Table 1. Overall Accuracy and Kappa coefficient of Different Textural Methods.
For entropy textural feature, the overall accuracy reaches 81.46% and the Kappa coefficient is 0.7537 with window size of 3×3. As the window size increases, the overall accuracy and Kappa coefficient also tend to grow gradually then remain stable and then decrease slightly. Among the single window size textural classification results, the highest accuracy is obtained with window size of 7×7, and the overall accuracy is 83.96%, the Kappa coefficient is 0.7837. There is a slight fluctuation in the overall accuracy with window size of 9×9, 11×11, 13×13, 15×15. The traditional stacking method in this paper outperforms the classification with the window size of 7×7, it is found that the overall accuracy with the stacking method is 84.02% and the Kappa coefficient is 0.7831. This method allows all the window size textural information to participate in the classification process, and it is proved to be more effective than the single window size textural classification method. Apart from the stacking fusion method, a new fusion of multiscale texture feature method is tested and demonstrated the highest accuracy performance among all the classification results. To be specific, the overall accuracy is 85.50% and Kappa coefficient is 0.8022. It is obviously that the new method in this paper outperform the above two methods in terms of overall accuracy and Kappa coefficient. In addition, the new method is effective and meaningful especially considering the optimal window size is difficult to determine for textural classification.

For homogeneity textural feature, when the window size is 3×3, the overall accuracy and Kappa coefficient are 81.20% and 0.7492 respectively. There is an increase in the accuracy when the window size grow to lager one. Among the single window size textural classification results, the highest accuracy is obtained with window size of 13×13, and the overall accuracy is 84.50%, the Kappa coefficient is 0.7892. However, the accuracy using the traditional stacking method is lower than the classification with the window size of 13×13, and the new fusion method is still effective compared to other results although the traditional stacking method fails in the accuracy improvement. The overall accuracy of 85.74% in the new fusion method is still the best one among all the results for homogeneity textural feature. The classification maps are shown in figure 2. The first map demonstrates the spectral classification result, and the second and third one shows the classification maps of fusion method for entropy and homogeneity, respectively.

![Classification maps](image_url)

**Figure 2.** Classification maps with different methods (a) left
one: spectral classification map. (b) middle one: classification map of new fusion method with entropy textural feature. (c) right one: classification map of new fusion method with homogeneity textural feature.

4. Conclusion and Discussion
This paper has compared different textural classification methods and demonstrated the effectiveness of multiscale texture features for the improvement of high resolution data. Texture feature plays an increasing significant part in the classification of high resolution imagery. However, the classification process using a single window or a single scale texture feature cannot obtain satisfactory results, and the selection of optimal window size needs trial and error. In our experiment we propose and validate the new multiscale textural information fusion method. The new method avoids window size selection problem and consider multiscale textural information as well.

In the experiment on University of Pavia ROSIS image, the results show that different texture features have their own optimal windows size, among all the single window size textural classification results using entropy textural feature, the window size of 7×7 obtain the highest overall accuracy, and for homogeneity textural feature, the optimal window size is 13×13. Traditional multiscale texture method which stacks the spectral bands and all window size textural bands to a new imagery cannot achieve a relatively higher accuracy with homogeneity feature, however, the fusion of multiscale posterior possibility rule images methods with entropy or homogeneity all provide the best satisfactory results in terms of overall accuracy and Kappa coefficient.

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