IMAGE CLASSIFICATION WITH SPECTRAL AND TEXTURE FEATURES BASED ON SVM

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1. INTRODUCTION

It is well known that high classification accuracy is usually difficult to be obtained if only spectral feature is considered, because of the phenomenon that different geographical objects may have the same spectrum and the same geographical objects may have different spectrum. The classification methods that rely only on spectral information may result in misclassification. In high-resolution remote sensing images, the geographical objects show distinctive textures. So the geographical objects can be classified by their texture features, and this method has received a lot of attention in the literature. In this paper, we propose a three-step classification method for high-resolution remote sensing images with the spectral and texture features based on the Support Vector Machine (SVM) classifier. The image is first segmented into regions with the spectral features. Then, texture features are extracted from each independent region by the wavelet transform. Third, the SVM is used to classify the image with these extracted texture features.

The image is first segmented by the mean shift algorithm. The mean shift is a nonparametric feature-space analysis technique. This estimator of density gradient is employed in the joint, spatial-range domain of images for discontinuity preserving filtering and image segmentation. In this paper, we use the mean shift algorithm to segment the image into regions with the spatial-spectral feature.

After the segmentation is completed, texture features are extracted from these independent regions by using the wavelet transform. It is well known that the wavelet transform provides a precise and unifying framework for the analysis and characterization of a signal at different scales. But in the commonly used discrete wavelet transform (DWT), which was proposed by Mallat, it is known that at each decomposition step, downsampling (keeping only one point out of two in the output samples) is used. So the the decomposed coefficient sequences at higher levels would be half the length of its previous level signals. This is not good for image texture analysis, especially to the signals at high decomposition scales, which are of small size. In our approach, the undecimated discrete wavelet transform (UDWT) is used. The UDWT is very similar to the DWT except that the decomposed coefficient sequences are not decimated at each decomposition stage. Although the results of UDWT lead to a redundant representation of the original signal, the UDWT has a valuable property of “time invariance”. So, it can yield a more detailed texture characterization and a better estimation of the texture statistics than DWT. The output of UDWT is done by filtering the image with a bank of filters that have specific frequencies and orientations. The texture features are then extracted from the filtered images. In this paper, we rearranged the output of UDWT into a N-component vector

$$Y(k,l) = (y_i(k,l))_{i=1,\dots,N} = [CA_I(k,l)\ CD_I^h(k,l)\ CD_I^v(k,l)\ CD_I^d(k,l) ... CD_1^h(k,l)\ CD_1^v(k,l)\ CD_1^d(k,l)]^T$$

where the number of feature channels $N = 1 + 3I$ is calculated from a 2-D separable wavelet transform with a depth I; CA_I is the scale coefficients; CD^h, CD^v and CD^d are wavelet coefficients in the horizontal, vertical and diagonal directions, respectively; (k,l) is a given spatial index. The texture is then characterized by the set of N first-order probability density function p(y$_i$)$, i = 1, \dots N$. Alternatively, we can get a more compact representation by a block representation of the coefficients centered on the (k,l) position. In practice, we estimate the variances from the average sum of squares over a region of interest R of the given texture type

$$v_i = \frac{1}{\#R} \sum_{(k,l)\in R} y_i^2(k,l)$$

Where #R denotes the number of pixels in R. So we can get a N dimension vector as the texture feature.

The texture feature vectors of each independent region that are obtained in the previous step are used by the SVM for image classification. SVM is a new technology of machine learning. This state-of-art pattern recognition technique stems from statistical learning theory. It is based on the concept of structural risk minimization(SRM), which has proved the capacity is better than the traditional learning machines like multi-layer neural networks that are based on the concept of empirical risk minimization. There are many scholars who have introduced SVM into image classification and received good results. The SVM classifier has many advantages in the image classification, such as: 1. the same classification operation has a ability to process several data source, 2. the possibility to adapt to the available data through the use of the kernels, 3. neither its complexity nor the computation time is not affected when process large amounts of data.

We have tested our method on an aerial remote sensing image and got satisfying classification results. The precision of classification is better than spectral feature used only. Experiment results show that our method is feasible and it can exert the virtues of both spectral and texture features.

2. REFERENCES

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