REMOTE SENSING IMAGE TEXTURE ANALYSIS AND CLASSIFICATION WITH WAVELET TRANSFORM

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ABSTRACT:

One difficulty of texture analysis in the past was the lack of adequate tools to characterize different scales of textures effectively. Recent develmpments in multiresolution analysis such as the Cabor and wavelet transforms help to overcome this difficult. This paper intruducs a new approach to characterize texture at multiple scales. The performance of wavelet transform are measured in terms of sensitivety and selectivity for the classification of twenty remote sensing textures. The reliability exhibited by texture signatures of such transforms are beneficial for accomplishing segmention, classification and subtle discrimination of texture.

1. INTRODUCTION

Textures provide important characteristics for the analysis of many types of images including natural scenes, remote sensing data and biomedical modalities. The perception of texture is believed to play an important role in the human visual system for recognition and interpretation. Perious methods of analysis for accomplishing texture classification maybe roughly divided into three categories: statistical, structural and spectral [1][2][3]. These methods have been successful for many fields, but they share one common weakness. That is, the primarily focus on the coupling between image pixels on a single scale. More recently, the methods based on multichannal or multiresolution analysis have received a lot of attention. Recent developments in spatial/frequency analysis such as Gabor transform, Wigner distribution, DCT, and wavelet transform provide good mutiresolution analytical tools. Specifically, wavelet transform plaies an important part in texture analysis.

There were some studies for texture classification by wavelet tramform. Carter [4] first reported texture classification results using Morlet and Mexican hat wavelets. He achieved 98 percent accuracy on 6 types of natural textures. Andrew and Jian [5] stuied texture classification by wavelet packet signatures. They achieved more than 98 percent accuracy on 25 types of natural textures. In this paper, we introuduced a new approach to characterize remote sensing texture images at multiple-scales with wavelet transform. The performance of wavelet transform are measured for the classification of twenty aerial remote sensing texture images. Wavelet representions for twenty images in the same resolution were classified with few errors by a simple minimun-distance classifier. The classification for six images in different resolutions had been done, too.

2. THE METHOD OF CLASSIFICATION

2.1 Image Features by Orthonoral Wavelet Transform

By orthonoral wavelet transform, we mean the decomposition of an image into multiple levels framework. Each level and each portion represent themselves special properties of frequency and spatial. Fig. 1 shows a level wavelet decomposition, in which c represent low frequency information, d1 the vertical edge information, d2 the horizonal edge information, and d3 inclining edge information. Fig. 2 shows a 4-levels wavelet decomposition and obtains seventeen sub-images include original image. Here wavelet is selected for Daubechics wavelet [6] with filter length 4.

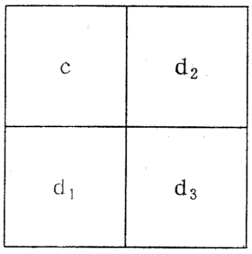

Fig. 1

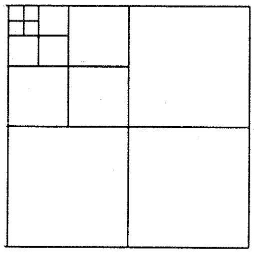

Fig. 2

2.2 Images Selection and Sampling

Twenty distinct aerial geomorphy texture images were selected from the albums of photogrammetry and remote sensing images. These images include desert, dune, loess dome, mountain, forest and so on. Each image was digitized on a scanner at 180dp. Some images were digitized at 150dp, 180dp and 230dp. Each image was stored as a 512×512 8bit/pixed digital image. Each image was broken down into forty sub-samples of size 256×256, in whcih twenty sub-samples for training and another twenty for testing.

2.3 Features Selection and Classification

Each sub-sample was decomposed into seventeen sub-images by a 4-levels orthonoral wavelet transform. The information entropy $H(x)$ of each sub-image was used as a feature of the sub-sample. Here $H(x)$ is defined by

$$H = -\sum_{i,j} |p(i,j)| \log |p(i,j)|$$

where

$$p(i,j) = \frac{|C(i,j)|^2}{\sqrt{\sum_{i,j} |C(i,j)|^2}}$$

and $C(i,j)$ is the number of image. Then each sub-sample was represented by a vector of seventeen features which are used for classification.

To decide the efficacy of wavelet transform for texture classification, the performance of a simple minimun-distance classificatier was evaluated.

3. Results and Discussion

3.1 Classification on the Same of Resolution

Supposing that decomposition levels of sub-sample are l_0, l_1, l_2, l_3 and l_4, we experimented for 400 training sub-samples and 400 testing sub-samples. In Table 1. we show the classification result.

Table 1

Features	Numble of features	Numble of errors	correct %
l_0, l_1, l_2, l_3, l_4	17	4	99.00
l_1, l_2, l_3, l_4	16	5	98.75
l_0, l_1, l_2, l_3	13	8	98.00
l_1, l_2, l_3	12	9	97.75
l_0, l_1, l_2	9	11	97.25
l_1, l_2	8	13	96.75

3.2 Classification on Different Resolutions

Six images digitized at 150dp、180dp、230dp were used for classfication under the condition of different resolutions. We experimented for 360 training sub-samples and 360 testing sub-samples. In Table 2, we show the result in our study.

Table 2

Features	Numble of features	Numble of errors	correct %
l_0, l_1, l_2, l_3, l_4	17	3	99.1667
l_1, l_2, l_3, l_4	16	4	98.8888
l_0, l_1, l_2, l_3	13	8	97.7777
l_1, l_2, l_3	12	11	96.9444

3.3 Disscussion

Table 1 and Table 2 show that remote sensing texture images could be classified by wavelet transform with high correct. And the highest correct is hased on 17 features. Our method of classification can be used for many regions such as imagery recognition, the application of remote sensing and computer vision.

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