Application of Texture Analysis Algorithms to Characterization of Complex Features in Urban Transportation Environment using High-Resolution Satellite Imagery

Kiwon Lee

Dept. of Information Systems Engineering, Hansung University, Seoul, 136-792, KOREA - kilee@hansung.ac.kr

Abstract – High-resolution satellite imagery has been regarded as one of important datasets to analyze urban environment composed of complex features. In this study, texture-based image analysis was applied to characterize urban features for regional planning, and firstly new implementation with user interface and main algorithms for this purpose was performed for texture image generation and wavelet image processing. As for quantitative texture analysis in the spatial domain, extraction and imaging of texture parameters based on GLCM (Grey Level Co-occurrence Matrix) was used: Homogeneity, Dissimilarity, Energy, Entrophy, ASM (Angular Second Moment), and Contrast. Results obtained by texture analysis in the frequency domain based on wavelet image processing framework provide useful indicator to delineate complex features within urban transportation environment. Through this study, experiment cases with actual satellite imagery such as KOMPSAT-EOC (6.6 M) were carried out to demonstrate and characterize complex types of urban features for regional planning, respectively. In urban remote sensing application with high-resolution imagery, it is concluded that these approaches based on integrated texture analysis in the both domain can be considered as one of practical application schemes for further multi-layer classification and recognition.

Keywords: High Resolution, Texture Image, Urban, Wavelet

1. INTRODUCTION

The remotely sensed image processing or interpretation using high-resolution level in most cities are somewhat complicated than conventional ones. Furthermore, urban features are normally complex type, so that it is very hard to obtain sufficient information with individual pixel values or layer-based approach. Texture image analysis was recognized as one of the effective schemes to solve these problems (Hamid *et al.*, 2004; Huang and Dai, 2004; Myint, 2004; Ruiz *et al.*, 2004). In this study, we attempted to study texture analysis with wavelet framework. Wavelet-based texture analysis is expected to provide texture information, because wavelet transform allows image decomposition in the different kind of coefficients preserving feature information. At first, we decomposed high-resolution imagery mainly using KOMPSAT imagery, using 2-D discrete wavelet transform (2-D DWT) and acquired coefficients. And then texture information, which considers a group of neighborhood pixels, is extracted from wavelet coefficients. GLCM (Grey Level Co-occurrence Matrix) texture variables, one of most useful techniques for texture image analysis in the space domain, such as Homogeneity, Dissimilarity, Energy, Entropy, Angular Second Moment, and Contrast are calculated in this process. For these approaches, new implementation for operation under MS Window OS was carried out. It is calculated GLCM texture variables in both schemes of the space domain and the wavelet domain, and those results were compared for further study. To avoid directional complexity in texture image analysis, the kernel size and direction for GLCM are basically 3*3 and circular mode, respectively.

2. BASIC THEORY

2.1 Texture Image Generation using GLCM

In remotely sensed image analysis, texture means the variability or uniformity of image tone or color (Avery and Berlin, 1992). It is characterized by the spatial distribution of gray levels in a neighborhood. No data set or sensor alone is able to capture the variability of an urban environment, because urban land cover features are composed of various materials. To extract the heterogeneous nature of urban features in high spatial resolution images, we need to consider the texture information contained in a group of neighborhood pixels instead of individual spectral values.

GLCM is a tabulation of how often different combinations of pixel brightness values occur in an image. GLCM texture has basically consideration for the relationship between two neighboring pixels in one offset, as the second order texture. Second order measures consider the relationship between groups of two pixels in the original image. GLCM considers relationship between pairs of pixels in the kernel after transformed to gray image. The kernel is moved through the data, and at each point the textural measure is evaluated and the result is stored as the probability form. When it is transformed the gray image space into the co-occurrence matrix space, neighboring pixels can be used the six defined directions; four directions such as 0°, 45°, 90°, 135° and circular, omni (Jeon *et al*., 2004). Therefore general GLCM texture measure depends on kernel mask, direction and measures. As known, measures such as contrast, entropy, energy, dissimilarity, angular second moment (ASM) and homogeneity are expressed as follows:

$$\text{Homogeneity} = \sum_{i=0}^{N-1}\sum_{j=0}^{N-1}\frac{1}{1+(i-j)^2}g(i,j) \quad (2)$$

$$\text{Contrast} = \sum_{i=0}^{Ng-1}\sum_{j=0}^{N-1}(i-j)^2\, g(i,j) \quad (3)$$

$$\text{ASM} = \sum_{i=0}^{N-1}\sum_{j=0}^{N-1} g^2(i,j) \quad (4)$$

$$\text{Entropy} = \sum_{i=0}^{N-1}\sum_{j=0}^{N-1} g(i,j)(-\ln(g(i,j))) \quad (5)$$

$$\text{Dissimilarity} = \sum_{i=0}^{N-1}\sum_{j=0}^{N-1} g(i,j)\,|\,i-j\,| \quad (6)$$

$$\text{Energy} = \sqrt{\sum_{i=0}^{N-1}\sum_{j=0}^{N-1} g^2(i,j)} \quad (7)$$

where i, j are coordinates of the co-occurrence matrix space, g(i, j) is the element of the i and j coordinate, and Ng is dimension of the co-occurrence matrix, which has gray value range of the original image. Before GLCM texture measure is applied, each value of g (i,j) is replaced to the probability value, which is evaluated to dividing by the sum of element values, as the normalization of GLCM.

2.2 Wavelet Processing Scheme

Wavelets are functions that satisfy certain requirements are to integrate to zero, wave above and below the x-axis and insure quick and easy calculation of the direct and inverse wavelet transform. Wavelets are used as basis functions in representing other functions, like sines and cosines in Fourier analysis. Signals are represented by translations and dilations of the wavelet, $\psi(\frac{x-b}{a})$.

$$f(a,b) = \frac{1}{|a|^{1/2}} \int \psi(\frac{x-b}{a}) f(x)dx \qquad (1)$$

The basic idea of the wavelet transform is to represent any arbitrary function as a superposition of wavelets (Fig. 1 and Fig. 2). Any such superposition decomposes the given function into different scale levels where each level is further decomposed with a resolution adapted to that level (Antonini et al., 1992).

The wavelet transform has been known to be particularly useful for analyzing signals and processing images. It provides a powerful and flexible set of tools for handling problems in denoising, signal or image compression, object detection, image enhancement and so on. Its ability to examine the signal simultaneously in both time and frequency in a distinctly different way from the traditional Fourier transform has spawned a number of sophisticated wavelet-based methods form manipulation and interrogation.

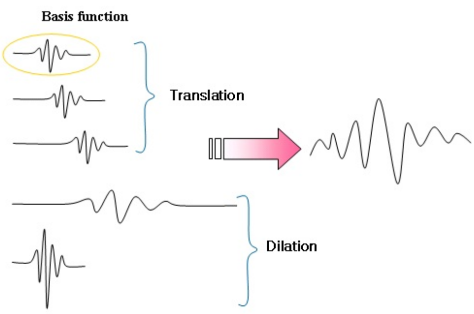


Figure 1. Basic concept of wavelet.

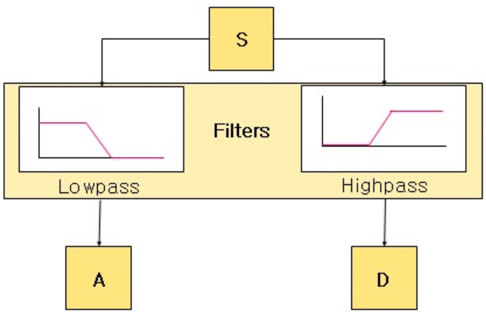


Figure 2. A two-band filter banks (Approximation and Detail) for one dimensional signal (S).

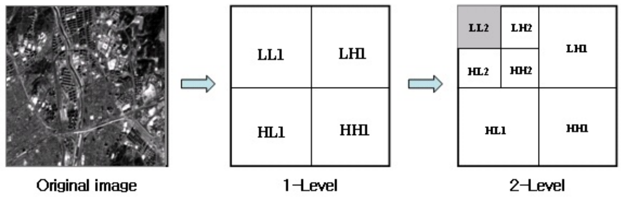


Figure 3. The 2D wavelet image decomposition in the down-level.

The discrete wavelet transform (DWT) is identical to a hierarchical sub-band system where the sub-bands are logarithmically spaced in frequency and represent octave-band decomposition. By applying DWT, the image is actually divided i.e., decomposed into four sub-bands and critically sub-sampled as shown in Fig. 3. These four sub-bands arise from separate applications of vertical and horizontal filters. The sub-bands labeled LH1, HL1 and HH1 represent the finest scale wavelet coefficients i.e., detail images while the sub-band LL1 corresponds to coarse level coefficients i.e., approximation image. To obtain the next coarse level of wavelet coefficients, the sub-band LL1 alone is further decomposed and sampled. Similarly, to obtain further decomposition, LL2 will be used. This process continues until some final scale is reached.

2.3 Implementation

The used approach for wavelet-based texture imaging is somewhat a new subject. Texture image, which is decomposed using one level DWT and GLCM, is derived for sub-bands (i.e., LL1, LH1, HL1, HH1) of wavelet decomposed image. The difference between wavelet-based texture imaging and traditional method is to use wavelet coefficients instead of the DNs of original image. Then, texture measures such as contrast, entropy, energy, dissimilarity, angular second moment (ASM) and homogeneity are computed from these GLCM using formulae given in Eqs (1)-(6). The results of DWT were normalized in scale of 0-16. A kernel size is 3 by 3 and direction is circular. We acquired 4 texture images (LL1, LH1, HL1, HH1) every texture measure consequently. These processing was performed by using new implemented program shown in Fig. 4.

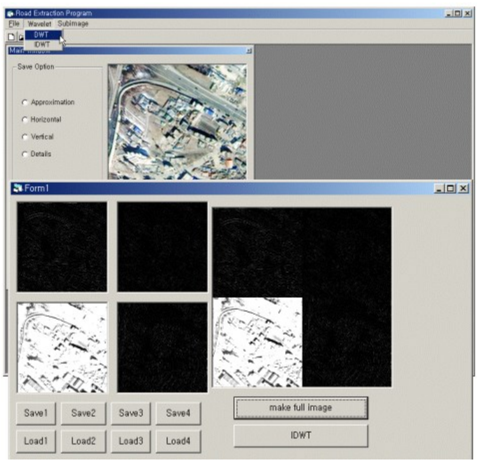
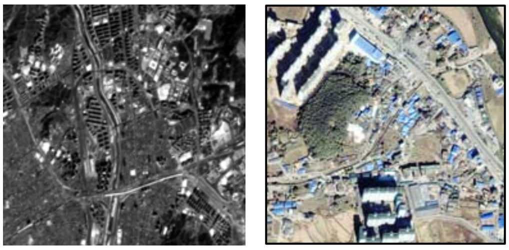


Figure 4. User interface implemented in this study for GLCM and wavelet image processing, loading IKONOS image.



(A) **(B)**

Figure 5. Data images: (A) KOMPSAT, (B) IKONOS.

2.4 Used Data

In this study, KOMPSAT 6.6m panchromatic imagery and IKONOS 4m color were used (Fig. 5). Study area is located in the Namyangju-city, nearby Seoul. The size of data image is 512 by 512, as sub image in the whole region, as an experiment case of the proposed scheme.

3. EXPERIMENTS

Texture images of 6 types were obtained by general GLCM computation scheme (Fig. 6).

Fig. 7 represents the texture measures of KOMPSAT image visually. In case of KOMPSAT image, big and systematic buildings' edges are revealed well at Homogeneity, ASM, Energy and Entropy of the full image. The difference of intensity is remarkable in wavelet sub bands. The road features appears on the LL band. And contrast images are very dark except LL band. Wavelet sub-bands are very complicated and have many speckles like salt and pepper effect, especially HL band. Most of the wavelet sub-bands are blurred. The details, which were not appeared on occasion of using original pixel values, are seen vividly. We thought this is characterized because texture images using original pixel values contain all information.

Sometimes, too much information makes image be complicated. Texture images using wavelet coefficients are more effective in case of higher resolution imagery. It also can detect large feature and shadow well. Meanwhile, we thought that texture images using original pixel values have very detailed lines are suited to middle resolution imagery like KOMPSAT.

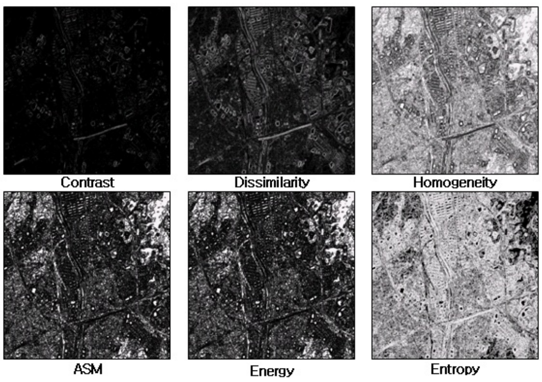


Figure 6. Texture images of KOMPSAT image by the space domain.

Fig. 8 shows the texture images of IKONOS image. Texture measures such as contrast, entropy, energy, dissimilarity, angular second moment (ASM) and homogeneity are computed from GLCM. The first row shows texture results of original pixel values. The texture images in the first row are more complex than wavelet-based texture image and have a lot of fine lines. In case of LL band, homogeneity, ASM and energy images are the brightest. Entropy image is the darkest. LL band can not show details, but the difference of intensity is remarkable. These characteristics coincide with the property that LL band contains approximation components. And shadow parts are divided with LL band. LH band shows vertical components well, but horizontal details are not revealed well. Meanwhile, horizontal components can be extracted with HL band. For example, apartments' edges are seen clearly in the lower-middle part of HL band. HH band shows diagonal road in the direction of lower right well.

In this study, a fusion scheme of texture images is proposed in Fig. 9. Though this scheme is using GLCM and wavelet transformation and inverse wavelet transformation in the several steps, it is an experiment case and other alternatives are also possible to apply actual data sets.

Fig. 10 represents some resultant images by this proposed scheme. One case is texture image of Dissimiliarity measure into HH, and other is Homogeneity into LL, and the further experiment results are not presented in this paper.

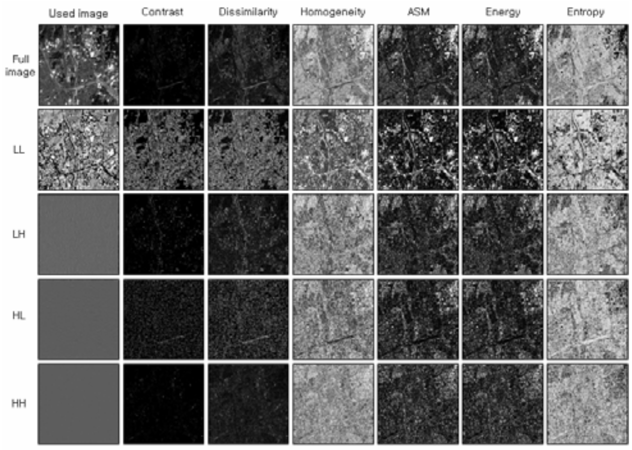


Figure 7. Texture images of KOMPSAT image (Fig. 5(A)) by the wavelet scheme: LL, LH, HL, and HH.

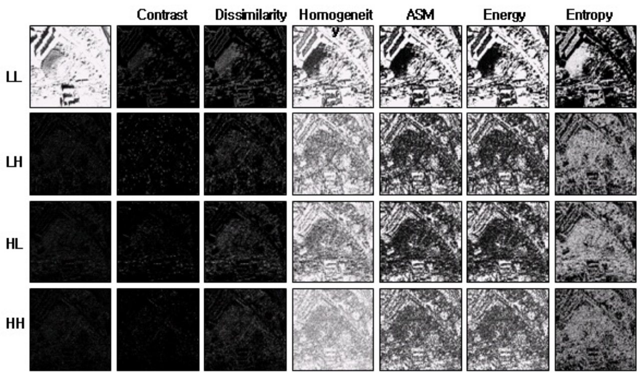


Figure 8. Texture images of IKONOS image (Fig. 5(B)) by the wavelet scheme: LL, LH, HL, and HH.

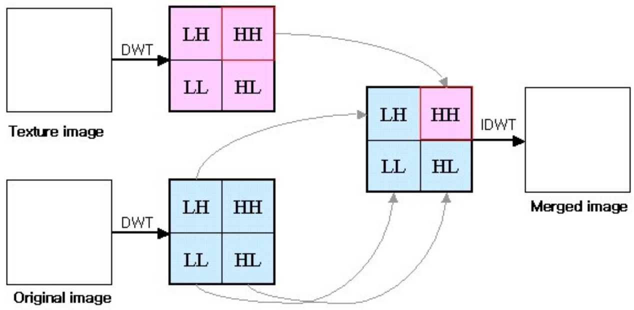


Figure 9. A proposed scheme for texture image fusion for complex feature analysis.

Original (LL, LH, HL)+ Dissimilarity (HH) Homogeneity (LL) + Original (LH, HL, HH)

Figure 10. The case results of texture image fusion with IKONOS image.

4. CONCLUDING REMARKS

To study a certain urban area, it is hard to get sufficient information with each pixel value. So texture analysis, which considers neighborhood pixels, is essential. Many previous studies already attempted texture analysis using GLCM and Wavelet transform and used to classification or retrieval system. But, these studies didn't treat investigations about the properties of texture image is fundamental data for classification and retrieval. In this study, we performed texture imaging using wavelet coefficients and compared these results with the outputs are obtained using original pixel values. In result, the texture images using original pixel values are more complex than wavelet-based texture image and have plenty of fine lines. In case of wavelet-based texture analysis, LL band can not represent details, but the difference of intensity is remarkable. These characteristics coincide with the property that LL band contains approximation components. And shadow parts can be distinguished from the other part. LH band shows vertical components well, but horizontal details aren't revealed well. Meanwhile, horizontal components can be extracted with HL band.

Almost all the wavelet sub-bands are blurred. In case of KOMPSAT image, systematic buildings' edges are revealed well at Homogeneity, ASM, Energy and Entropy of the full image. But, wavelet sub-bands are very complicated and have a lot of speckles like salt and pepper effect, especially HL band. The details, which weren't appeared on occasion of using original pixel values, are seen vividly.

Texture images using original pixel values include all of information in one image. So, it looks complicated and Information can be offset each other. But, to contain all kinds of information in one image means we use just one variable for retrieval. It makes retrieval simple. This method may be more effective low or middle resolution imagery than high resolution imagery such as KOMPSAT imagery, we thought. Meanwhile, wavelet-based texture analysis divides one image into 4 sub-bands and represents information in each sub-band. So we can subdivide information according to frequency and direction. The complex information can be expressed simply. And it is effective for the extracting shadows. Therefore, this approach is expected to be suited to high resolution imagery like IKONOS, which include complex and large features. Because 4 texture values are computed from one image (If image decomposes higher level than one level, we can get more texture values.), let's assume these values to be a kind of vector value. In that case, these values will be useful to retrieval and classification system using Euclidean distance.

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