CLASSIFICAION ACCURACY OF WAVELET-BASED FUSION IMAGE WITH TEXTURE FILTERING USING HIGH RESOLUTION SATELLITE IMAGES

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ABSTRACT:

Second-order statistical texture image is regarded as one of useful images which can be produced from original data images, and wavelet scheme is also multi-resolution image analysis, as one of current issues in remote sensing image processing. Though texture image and wavelet decomposed image can be applied for remote sensing image, there are rare cases in quantitative interpretation with the combined images. In this study, we attempted the classification application of texture image in wavelet scheme; in other words, this was concerned classification of wavelet-based texture image. Our approach consists in several cases: conventional multi-spectral classification with original image sets, classification with texture images, and classification with wavelet-based texture image. In addition, we studied different types of texture parameters and wavelet basis functions, considering the affect of classification accuracy. In conclusion, it is thought that we can provide some criteria to choose appropriate wavelet basis function and texture parameter in classification.

KEY WORDS: wavelet-based texture fusion imagery, classification accuracy

1. INTRODUCTION

Since there are various analysing methods of optical satellite imagery in these days, many kinds of techniques have been developed to extract the new information, which were not expressed in the imagery. Especially, Zhang(1999) and Liu (2005) have studied for the improvement of classification accuracy, which were about the texture techniques to calculate the stat among the neighbour pixels or the wavelet techniques to disassemble to the partial bands using horizontal and vertical filters. The motivation of this study is to investigate classification accuracy between the texture fusion image based on the wavelet and the creation technique of texture image and wavelet technique which have been frequently used recently.

2. APPILED METHODS AND DATA

In this study, the several experiments by using wavelet scheme and texture imaging process were performed (Yoo and Lee, 2005). We also extracted edge-component image from original image and then superimposed IDWT resultant image with edge image. The basic theory and methodology, which was implemented in this study, are overviewed briefly: Wavelet scheme, Texture image by Gray Level Co-occurrence Matrix (GLCM).

2.1 The wavelet scheme

The discrete wavelet transform (DWT) is known to one of the most useful techniques for multi resolution image analysis.

The wavelet scheme provides a powerful and flexible set of tools for handling problems in noise removal, signal or image compression, object detection, image enhancement and so on. Wavelets are functions satisfying a linear combination of different scaling and translation of wave function. In this process, wavelet is used as a basis function in representing target functions, like sinusoidal functions in Fourier analysis. The basic of the wavelet scheme is to represent an arbitrary function or image as a superposition of wavelets. By this superposition process, it can be decomposed the given function into different quad-scale levels.

One-dimensional signals are represented by translations and dilations of the wavelet, $\psi\left(\frac{x-b}{a}\right)$,

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

where a and b represent translation and dilation parameter, respectively.

The wavelet decomposition can be implemented by using two channel filter banks composed of a low-pass and a high-pass filter and each filter bank is then sampled at a half rate of the previous frequency. By repeating this procedure, it is possible to obtain wavelet transforms of any order. The down-sampling procedure preserves the scaling parameter constant (n = 1/2) throughout successive wavelet transforms so that it enables a relatively simple computing. In the case of a given image, the filtering is implemented by filtering the line-direction and column-direction, separately.

As a consequence, an original image can be decomposed into four sub-images,

- *LL: Both horizontal and vertical directions have low-frequencies.*
- *LH: The horizontal direction has low-frequencies and the vertical one has high-frequencies.*
- *HL: The horizontal direction has high-frequencies and the vertical one has low-frequencies.*
- *HH: Both horizontal and vertical directions have high-frequencies.*

In this study, DAUB4, as the wavelet basis, was applied.

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2.2 Texture

In the image analysis and interpretation, texture terms the variability or uniformity of image tone or color. It can be characterized by the spatial distribution of gray levels in a neighborhood. Only one pixel value is not sufficient to capture the spatial variability of an urban environment, because urban land cover features are composed of various materials.

Texture image processing based on second order statistics contains the initial step for grouping of neighborhood pixels instead of individual spectral values may be useful in complex urban area. For this purpose, the GLCM (Gray Level Co-occurrence Matrix) uses a tabulation of how often different combinations of pixel brightness values occur in an image.

GLCM texture needs considerations 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 stored as the probability form. When one want to transform the gray image space into the co-occurrence matrix space, the neighboring pixels can be counted; six types of directions such as 0°, 45°, 90°, 135° and circular direction, omni direction (Yoo and Lee, 2005). 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:

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

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

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

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

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

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

where i, j are coordinates of the co-occurrence matrix space, g(i, j) is the element of the i and j coordinates, and Ng is dimension of the co-occurrence matrix, which has gray value range of the original image. Prior to GLCM texture measuring, 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.

2.3 Applied Scheme and Data

The subset of high-resolution satellite imagery with less 1 m resolution of urban area was used for this research (Fig. 1). There are four bands, and the channel of this subset was red, green, and blue areas of visible ray and the infrared rays.

The generation of texture image carried out by calculation the second-order statistics among the neighbour pixels. We used GLCM (Grey Level Co-occurrence Matrix) method for creation of texture imagery. In GLCM method, there are six kinds of statistics calculation methods – Contrast, Homogeneity, ASM (Angular Second Moment), Dissimilarity, Energy, and Entropy.

While, the wavelet scheme can be used to interpret and measure 1D/2D signal to a given base function. It is a method of separating a image as 4 partial bands (LL, LH, HL, and HH) by using the horizontal and vertical filters such as low pass filter and high Pass filter. We used 2D-DWT(2-Dimension Discrete Wavelet Transform) method, which is one of the representative creation technique of wavelet imagery. There are vertical information in the LH band, horizontal information in the HL band, diagonal information in the HH band, and the entire information roughly in the LL band of the raw imagery (Fig. 2).

These methods were known to very effective image analysing methods on the discernment of spatial properties and on abstraction of the information and results which are not visible to the original images.

The classification were progressed by using wavelet based texture fusion imagery which unite to IDWT(Inverse Discrete Wavelet Transform) algorithm after inserting the texture imagery on LL spot among the 4 partial bands of wavelet imagery. So, in the wavelet based texture fusion imagery, there are roughly entire information of texture imagery by LL band, and characteristic information of wavelet imagery by LH, HL, HH band (Fig. 3).

Figure 1. Study Area.

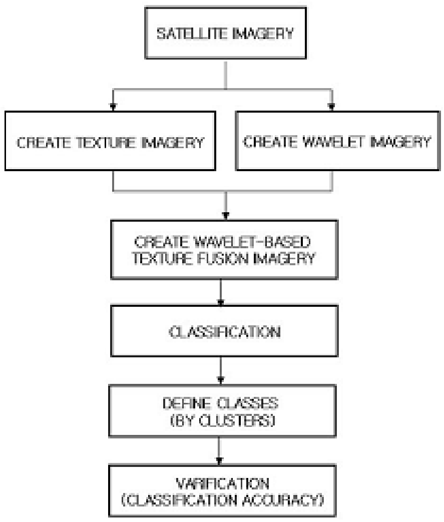

Figure 2. Workflow of this study.

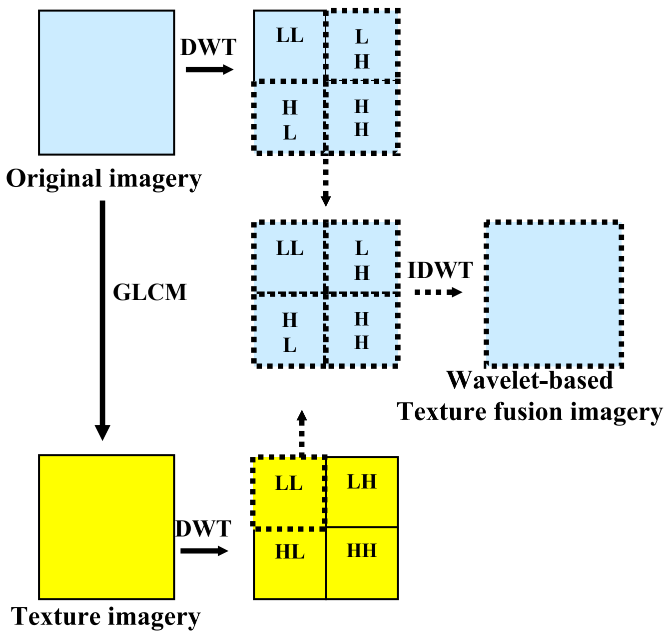

Figure 3. 4 bands of wavelet based texture imagery.

Because there are 6 statistical calculation method of texture imagery, there are 6 wavelet based texture fusion imagery method. Classification process was carried out according these cases.

Case 1. Raw data + Texture Imagery

Case 2. Raw data + Wavelet-based texture fusion imagery

Case 3. Raw data + Texture Imagery + Wavelet-based texture fusion imagery

And classification accuracy of the case studies was compared with results of conventional multi-spectral classification with original image sets. To carry out this classification, each texture imagery and wavelet-based texture fusion imagery was added as a new band of raw imagery.

In this study, total 19 imageries were used in the classification process including raw imagery.

2.4 Classification

In the classification using high-resolution satellite imagery, there are few mixed pixel problem and too much shade zones by tall buildings, trees and so on, to analysis these imagery.

In this study, ISODATA unsupervised classification was carried out. Clusters which are necessary to perform unsupervised classification process were used in class definition process. In this study, we defined 6 classes (Table 1).

Table 1. Class Definition

Class	Definition
A	Apartment (4~5floors) Complex
B	Apartment (Building Size)
C	Road(Aspalt)
D	Play Ground(Soil)
E	Housing Complex
F	Shadow

In this study, to calculate classification accuracy, we used omission error. And to classification accuracy, checking sites was used. It was independent of training data set which was used in definition process of classes by clusters.

3. RESULT

In this study, ISODATA unsupervised classification was carried out using 19 imageries and each classification accuracy was shown in Table 2, Table 3, and Table 4.

The result of classification accuracy by comparison of each case, the accuracy of case 3(raw data + texture imagery + wavelet-based texture fusion imagery) was the best. Especially, class A at Energy imagery, class B at Homogeneity and class E at homogeneity and ASM imagery were improved by using texture imagery and wavelet-based texture imagery with raw data. Moreover, Even if there was not a special technique like a texture technique or a fusion technique, it's possible to extract class F by class definition process. It considered a good method which can be extract useful information by accurate shade extracting.

Table 2. The classification accuracy – case 1. raw data + texture imagery

	Classes					
	A	B	C	D	E	F
Raw Data	46.05	60.24	96.77	90.94	19.95	100.00
Contrast	46.05	45.61	96.77	91.29	19.95	100.00
Dissimilarity	47.20	47.12	96.55	90.59	20.00	100.00
Homogeneity	50.66	61.05	96.77	58.89	20.60	100.00
ASM	60.69	56.31	64.01	93.38	20.60	100.00
Energy	60.86	42.99	65.73	100.00	19.85	100.00
Entropy	59.38	55.00	68.53	98.95	18.14	100.00

Table 3. The classification accuracy – case 2. raw data + wavelet-based texture fusion imagery

	Classes					
	A	B	C	D	E	F
Raw Data	46.05	60.24	96.77	90.94	19.95	100.00
Contrast	46.05	60.24	96.77	91.29	19.95	100.00
Dissimilarity	46.22	60.44	96.77	91.64	19.95	100.00
Homogeneity	48.03	45.91	96.77	95.82	20.25	100.00
ASM	55.26	56.81	96.12	93.38	20.40	100.00
Energy	48.52	59.94	96.12	90.24	20.40	100.00
Entropy	49.18	46.72	96.55	96.86	19.90	100.00

Table 3. The classification Accuracy – case 3. raw data + texture imagery + wavelet-based texture fusion imagery

	Classes					
	A	B	C	D	E	F
Raw Data	46.05	60.24	96.77	90.94	19.95	100.00
Contrast	46.22	60.34	96.77	91.64	19.95	100.00
Dissimilarity	46.71	51.06	96.55	97.56	19.60	100.00
Homogeneity	50.99	69.02	95.26	54.01	20.86	100.00
ASM	62.66	56.21	59.48	93.03	20.86	100.00
Energy	63.16	43.59	62.72	100.00	19.70	100.00
Entropy	60.36	55.40	68.10	99.30	17.33	100.00

4. CONCLUSION

Classification and its accuracy analysis were carried out with understanding characteristics of each classes using high-resolution downtown area imagery. For classification, texture imagery, wavelet-based texture imagery was added as a new band of a raw data respectively. Among applied cases, the best method of image classification was the third case: raw data + texture imagery + wavelet based texture fusion imagery. Especially, the largest increase of classification accuracy was shown in a low apartment complex. And 100% extraction of a shadow was shown, in the class definition process. It is possible that evaluated numerical value has a little difference by characteristics of each image.

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