ON THE CAPABILITY OF APPLYING WAVELET TRANSFORM FOR TEXTURE ANALYSIS IN REMOTELY SENSED IMAGES

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ABSTRACT

This paper describes the capability of wavelets transform to extract textural patterns in remotely sensed images. In remote sensing field, edges are one of useful textural patterns to discriminate from other land covers and many filters using a matrix, in which a spatial relationship is considered and quantified, have been developed. But most of them are not robust against noise. On the other hand, wavelet transform has been used as a powerful tool for analysis in image processing, and a lot of researches have reported that it can detect edges more easily and efficiently than other conventional methods, because it can be applied with change of a scale parameter, which makes it possible to grasp a whole of an image on a large scale and, on the other hand, to examine details on a local scale.

In this research, we developed a system to extract crop fields, which comprises main three parts: segmentation, edge detection and line extraction. Firstly, the areas are remained where crop fields seem to be included by automatic threshold technique because edges are easily detected in other land covers, like forests, except crop fields. Then, wavelet transform approach is involved in the process of edge detection. In the last process, as a characteristic of crop fields, lines are extracted by using detected edges. The experiment was aimed to extract cropping patterns in an agricultural field in the northern part of Thailand, using Landsat Thematic Mapper (TM) 5 image. Wavelet's utilities was compared with a conventional edge detection filter, Sobel, and it was proved that Wavelet is a more appropriate and efficient method to extract textural patterns like crop fields than conventional filters.

1. INTRODUCTION

Remotely sensed images are widely used to extract some geological, meteorological and other characteristics. One of common methods to extract characteristic is texture analysis. Most of algorithms for texture analysis aim to quantify a part of an image under some statistical criteria: gray level co-occurrence matrices [1], [2], gray-level-run-length statistics [3], gray level difference [2], second-order moment [2], [4], Gauss-Markov random fields [5].

Edges of a targeted object in an image can be thought as one of textural information and many spatial filters have been developed: gradient (Sobel[6], Prewitt[7], and Roberts[8]) template (Robinson[9], Prewitt[7] and Kirsh [10]) and laplacian. Those are useful to pick up local characters, but are not so robust against noise and not suitable to comprehend a whole of an image's structure unlike human interpretation of an image.

Wavelet transform has been used as a powerful tool for analysis in image processing, and one of its advantages is that it can be used for multi-resolution analysis by changing a scale parameter, which makes it possible to grasp a whole of an image on a large scale and, on the other hand, to examine details on a local scale. A lot of researches have reported that it can detect edges more easily and efficiently than other conventional methods.

This paper describes the use of wavelet transform for remotely sensed image, Landsat TM, for the purpose of textural analysis. Edge detection approach by wavelet transform was applied to extract crop field in South East Asia.

2. METHODOLOGY

In terms of edges, it should be concerned that there are some land covers like forests, which show edges in the targeted image. And huge area of crop fields can be found in Landsat TM images detected during dry season and some characteristics of them are 1) the boundaries are almost linear edges, and 2) its shapes are not always rectangular. Considering these characteristics, linear patterns seem to be a clue to discriminate crop fields and three steps below can be considered as one of efficient approaches of crop field extraction.

1) Segmentation to roughly separate from other land covers
2) Edge detection
3) Line extraction using edges

One of the simplest methods for segmentation is level-slicing using thresholds against histogram of pixel values of an image. Scale-space filtering can find an appropriate and objective threshold automatically with change of scale parameter as long as how many thresholds should be determined.

A line can be recognized as a series of connected edges. Once edges are detected in an image, a line can be extracted by template matching.

2.1 Scale-space filtering [11], [12]

Scale-space filtering can embed the original image in a one-parameter, the current level of scale resolution, family of derived images. Scale-space function $F(x,\sigma)$ is defined by convolution of input signal $f(x)$ with Gaussian kernel $g(x,\sigma)$

$$F(x,\sigma) = f(x) * g(x,\sigma)$$
$$= \int_{-\infty}^{\infty} f(u) \frac{1}{\sigma\sqrt{2\pi}} \exp\left(-\frac{(x-u)^2}{2\sigma^2}\right) du \tag{1}$$

with an initial condition $F(x,0) = f(x)$.

2.2 Wavelet [13], [14]

Most multi-scale edge detectors smooth the signal at various scales and detect sharp variation points from their first- or second-order derivative. The extrema of the first derivative correspond to the zero crossings of the second derivative and to the inflection points of the smoothed signal.

We call a smoothing function any function $\theta(x)$ whose integral is equal to 1 and that converges to 0 at infinity. We suppose that $\theta(x)$ is twice differentiable and define, respectively, $\psi^a(x)$ and $\psi^b(x)$ as the first- and second-order derivative of $\theta(x)$

$$\psi^a(x) = \frac{d\theta(x)}{dx}, \psi^b(x) = \frac{d^2\theta(x)}{dx^2} \tag{2}$$

By definition, the functions $\psi^a(x)$ and $\psi^b(x)$ can be considered to be wavelets because their integral is equal to 0.

$$\int_{-\infty}^{\infty} \psi^a(x)dx = 0, \int_{-\infty}^{\infty} \psi^b(x)dx = 0 \tag{3}$$

A wavelet transform is computed by convolving the signal with a dilated wavelet. The wavelet transform of $f(x)$ at the scale s and position x, computed with respect to the wavelet $\psi^a(x)$ and $\psi^b(x)$, are defined by

$$W_s^a f(x) = f * \psi_s^a(x), W_s^b f(x) = f * \psi_s^b(x) \tag{4}$$

Then,

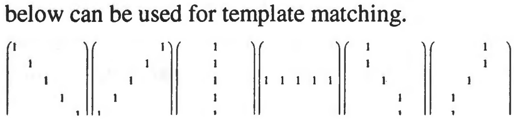
$$W_s^a f(x) = f * \left(s\frac{d\theta_s}{dx}\right)(x) = s\frac{d}{dx}(f * \theta_s)(x) \tag{5}$$

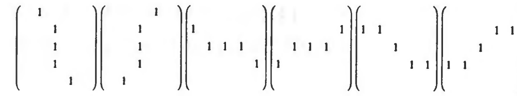
$$W_s^b f(x) = f * \left(s^2\frac{d^2\theta_s}{dx^2}\right)(x) = s^2\frac{d^2}{dx^2}(f * \theta_s)(x) \tag{6}$$

When the scale s is large, the convolution with $\theta_s(x)$ removes small signal fluctuations; therefore only sharp variations of large structures can be detected.

2.3 Template for line extraction

For extracting linear connection of edges, 12 matrices (5×5) below can be used for template matching.





2.4 System of crop field extraction

In our research, the data process for extraction of crop fields was set as follows (Figure 1).

1) Scale-space filtering (level-slicing) to separate and produce layers with crop fields
2) Wavelet transform for edge detection
3) Thinning of a mass of edges
4) Matching with linear template for line extraction
5) Overlaying of some crop field layers, in which lines are detected

Using thresholds found as a result of scale-space filtering, a few layers can be produced and layers with areas where crop fields seem to be included are selected by visual interpretation. Layers, which show lines after template matching, are overlaid through a weighted function

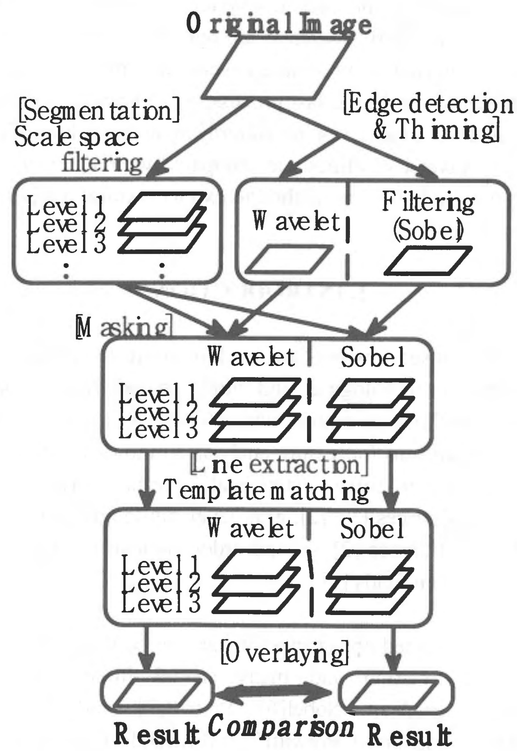


Figure 1 Process of crop extraction

3. EXPERIMENT & RESULTS

Landsat TM image (path 129, row 049; date Jan. 20, 1989) was used for an experiment. The test area in the image is in the northern part of Thailand and mixed with some land covers, mainly crop fields (sugarcane, maize), paddy field and grassland (Figure 2). Input data is NDVI transformed into 0-255, and several layers were produced by thresholds found through scale-space filtering. Among those, four layers were selected by simple visual interpretation. The results of crop field extraction

Figure 2 NDVI image (transformed 0-255)

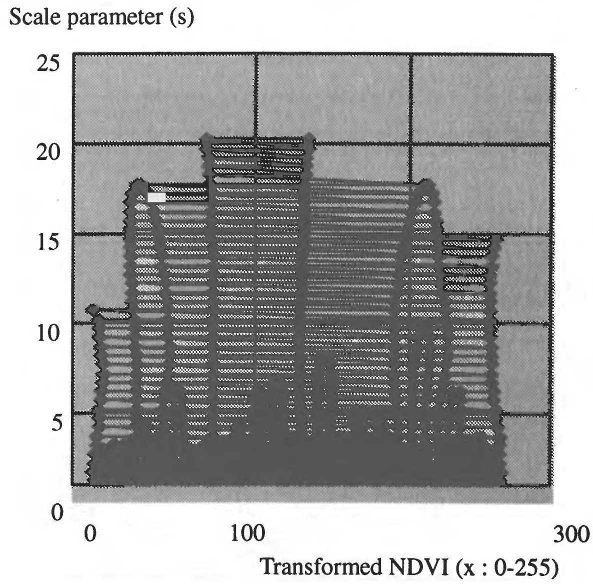


Figure 3 $\frac{dF}{dx} = 0$ in Scale-space

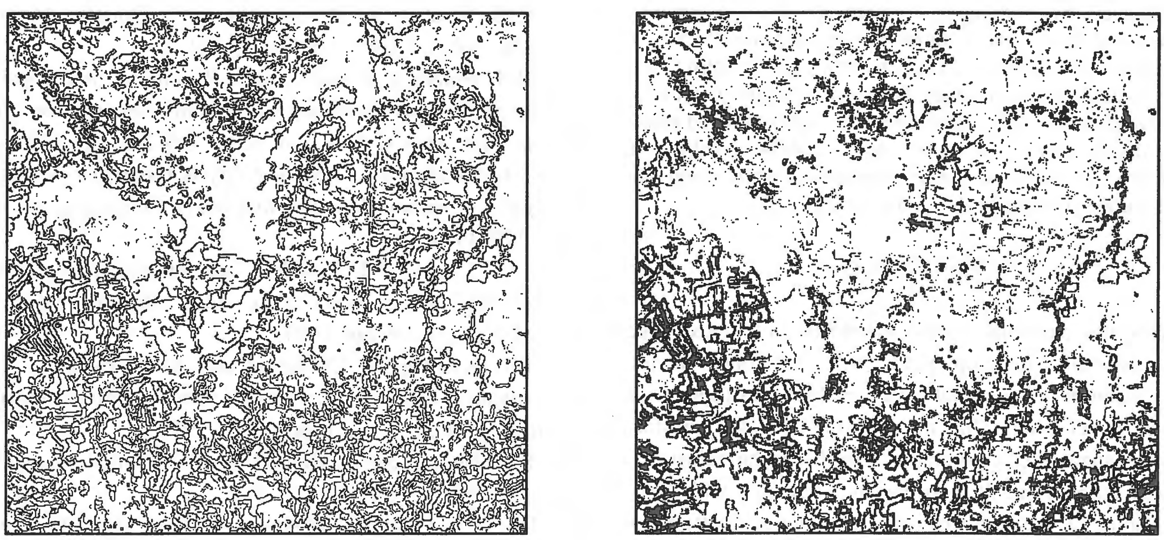


Figure 4 Edge detected images (Left : Wavelet, Right : Sobel)

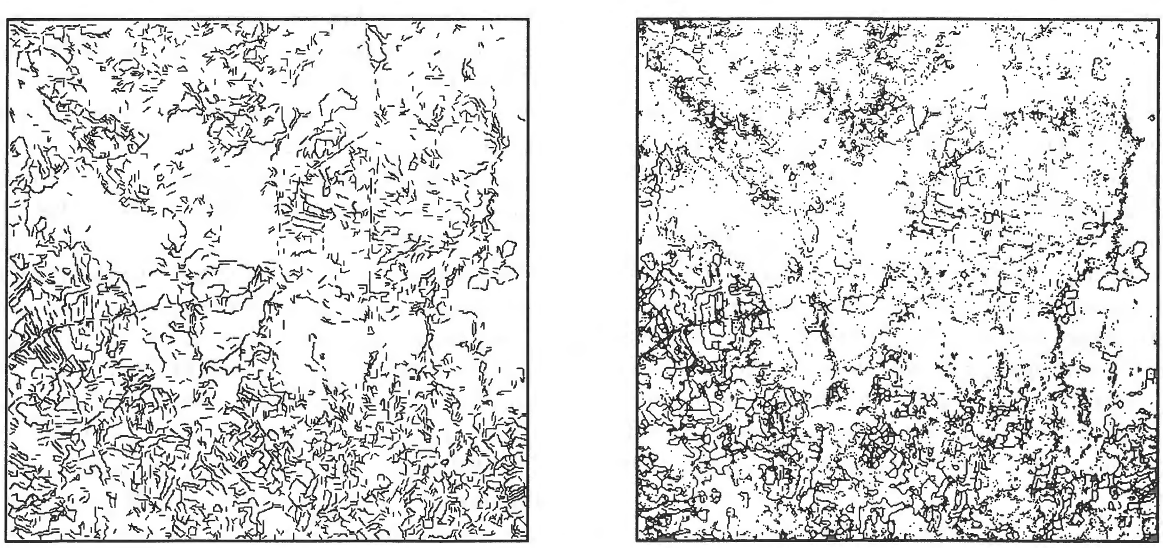


Figure 5 Line extracted images without masking (Left : Wavelet, Right : Sobel)

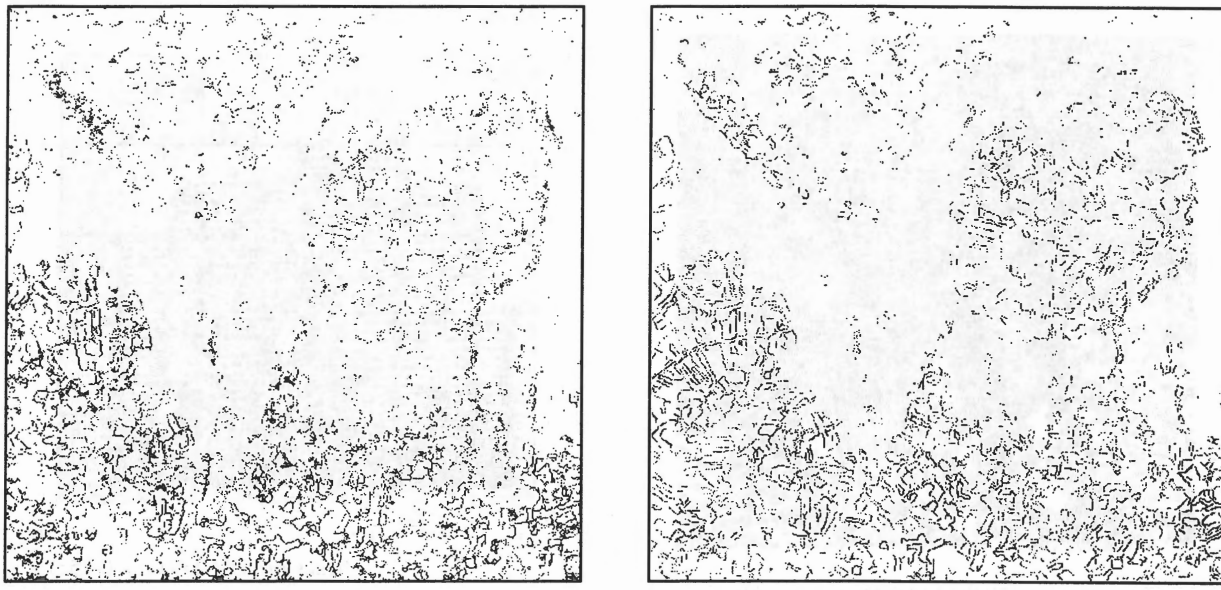


Figure 6 Result images of crop field extraction (Left : Wavelet, Right : Sobel)

were produced by overlaying through a weighted function, which weighed 4, 3, 2 and 1 for four layers as a simple case. To compare Wavelet's utilities, a conventional edge detection filter, Sobel, was used to detect edges. Space-scale figure (Figure 3), edge detected images (Figure 4), and crop field extracted results (Figure 6) are shown. As an example to show capability to extract lines, line extracted images were produced by using edge detected images without masking (Figure 5) .

4. DISCUSSION

In Figure 4, it is clear that wavelet transform could detect edges more successfully in crop fields with not only obvious boundaries (lower left part) but a little unclear ones (upper right part) than Sobel filter. That owes to the Wavelet transform ability to change a scale parameter, which can be adjusted so that scaled wavelet can fit input signal. Compared with NDVI image (Figure 2), the result by wavelet (Figure 6:Left) shows that the system for crop field extraction in this research function as mentioned of Figure 4 above.

5. CONCLUSION

We succeeded to develop a system to extract crop fields, which comprises main three parts: segmentation, edge detection and line extraction. Firstly, the areas are remained where crop fields seem to be included by automatic threshold. Then, wavelet transform is done for the purpose of edge detection. Finally, as a characteristic of crop fields, lines are extracted by using detected edges. Wavelet's utilities was compared with a conventional edge detection filter, Sobel. It was proved that Wavelet is a more appropriate and efficient method to extract textural patterns like crop fields than conventional filters, because of Wavelet transform ability to change a scale parameter, which can be adjusted so that scaled wavelet can fit input signal.

[1] R.M. Haralick, K. Shanmugam, and I. Dinstein, "Texxtural *Cybern.*, vol. 3, pp. 610-621, Nov. 1973.

[2] J.S. Weszka, C.R. Dyer, and A. Rosenfeld, "A Comparative Study of Texture Measures for Terrain Classification," *IEEE Trans. Syst., Man, Cybern.*, vol. 6, pp. 269-285, Apr. 1976.

[3] M.M. Galloway, "Texture Analysis Using Gray Lebel Run Lengths," *Computer Graphics and Image Processing*, vol. 4, pp. 172-179, 1975.

[4] P.C. Chen and T. Pavlidis, "Segmentation b texture using correlation," *IEEE Trans. Patt. Anal. Machine Intell.*, vol. PAMI-5, pp. 64-69, Jan. 1983.

[5] R.L. Kashyap, R. Chellappa, and A. Khotanzad, "Texture classification using features derived from random field models," *Patt. Recogn. Lett.*, vol. 1, pp. 43-50, 1982.

[6] R.O. Duda and P. E. Hart, *Pattern Classification and Scene Analysis*, Wiley, 1971, pp. 267-272

[7] J. M. S. Prewitt, "Object enhancement and extraction", in *Picture Processing and Psycho-pictorics*, New York: Academic Press, 1970, pp. 75-149

[8] L. G. Roberts, "Machine perception of three-dimensional solids", in *Optical Electro-Optical Processing of Information*, MIT Press, 1970, pp. 75-149

[9] G. S. Robinson, "Edge detection by compass gradient masks", *CGIP*, vol. 6, pp. 492-501, 1977

[10] R. Kirsh, "Computer determination of the constituent structure of biological images", *Comput. Biomed. Res.*, vol. 4, pp. 315-328, 1971

[11] T. Lindberg, "Scale-space for discrete signals", *IEEE Trans.*

[12] B. Zuerndorfer and G. H. Wakefield, "Extensions of scale-space filtering to machine-sensing systems", *IEEE Trans. Patt. Anal. Machine Intell.*, vol. 12, pp. 868-882, Sep. 1990

[13] S. Mallat, "Zero-crossings of a wavelet transform", *IEEE Trans. Info. Theory*, vol. 37, pp. 1019-1033, Jul. 1991

[14] S. Mallat and S. Zhong, "Characterization of signals from multiscale edges", *IEEE Trans. Patt. Anal. Machine Intell.*, vol. 14, pp. 710-732, Jul. 1992