VARIOGRAPHIC ANALYSIS OF MULTI-SOURCE REMOTELY SENSED IMAGERIES BY WAVELET-BASED APPROACHES

Hee-Young Yoo [a, *], Kiwon Lee [b]

[a] Dept. of Earth Science Education, Seoul National University, Seoul, Korea (ROK), skyblue1@snu.ac.kr
[b] Dept. of Information System Engineering, Hansung University, Seoul, Korea (ROK), kilee@hansung.ac.kr

ABSTRACT:

In the times of wide uses of commercialized high resolution satellite imageries, urban remote sensing is regarded as one of the important application fields. Currently, the main subjects and issues in urban remote sensing focus on the various attempts and approaches for these types of image data sets, distinguished from conventional image processing in remote sensing. Three types of different spatial resolution images were taken into account in this study: IKONOS 1 m, KOMPSAT 6.6 m and Landsat 15 m panchromatic imagery. Using these, we tried to investigate the pattern of spatial distribution of images using the variogram analysis. We used both theoretical variogram modelling, which is typically used, and wavelet analysis, which is composed of wavelet decomposition for approximation and detail components. Wavelet transform is profitable for analyzing individual image. However, it is difficult to compare every wavelet decomposition data to grasp similarity of a certain image with respect to other image. So, we used variogram modelling coefficient. For the variogram modelling, we tried to compound model which composed with logarithm model and nugget effect model. Results of the variography analysis reveal the spatial characteristics of each image. And Euclidean distance method using the variogram modelling coefficient was useful to search similarity characteristics of applied images. With this result, variographic analysis based on continuity computation can be considered as the effective method for characterization of urban features.

KEY WORDS: High resolution, Variogram, Urban, Wavelet transform

1. INTRODUCTION

The traditional image analysis or classification methods are mostly based on spectral information. However, the spatial information is more important according as resolution is higher and urban areas are more complex. The variogram has been used in geostatistics widely to presume the value of the needed location making use of the correlation of separated data in a specific distance. Curran (1998) and Woodcock et al. (1988a,b) provide readable introductions to the variogram while Dungan (1998) reviews geostatistical techniques for estimation and simulation in a remote sensing context. The variogram in remote sensing should be different from typical variogram on form and analysis method. In this study, we tried to analyze the spatial distribution of images using variogram. We used not only theoretical variogram modelling, which is typically used, but also wavelet to analyze variogram.

2. METHODOLOGY

2.1 Variogram

The variogram is a two-point statistical function that describes the increasing differences or decreasing correlation, or continuity, between sample values as separation between them increases. Traditionally, the variograms has been used for modelling spatial variability rather than the covariance although kriging systems are more easily solved with covariance matrices. In this study, we analyzed spatial distribution property of each image through variogram. The typical variogram exhibits a rise that gradually slows to form a straight horizontal line (sill) due to the fact that increasing the distance between their values. In many cases, the lag increase does not result in any more difference because the spatial autocorrelation between image values normally drops beyond a certain distance. The height of the sill is normally proportional to the global image variance while the lag at which the sill is attained, called the "range," is generally a very good indicator of texture coarseness. The variogram can be calculated along transects(Atkinson and Danson, 1988; Curran, 1988;Ramstein and Raffy,1989) but gives a better representation when calculated in more than one direction(Cohen et al., 1990;Woodcock et al., 1988) because texture is in many cases anisotropic (Davis, 1981).

A theoretical variogram model is then adjusted to the experimental variogram by least square fitting. We used logarithm and nugget model.

$$2\gamma(h) = \frac{1}{m}\sum_{i=1}^{m}[z(x_i) - z(x_i + h)]^2 \tag{1}$$

$$M(h) = C * \ln(h) + nugget \tag{2}$$

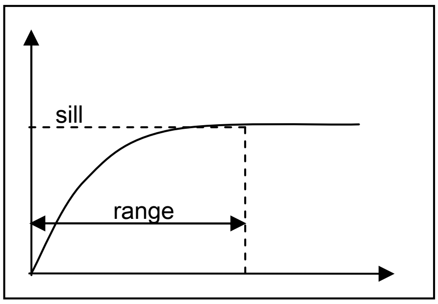


Figure 1. The typical variogram.

* Corresponding author: Hee-Young Yoo, E-mail: skyblue1@snu.ac.kr

2.2 Wavelet transform

Wavelets are functions satisfying a linear combination of different scaling and translation of a wave function. As well, a wavelet is used as a basis function in representing and analyzing target functions given, like sinusoidal functions in Fourier analysis. The basic of the wavelet scheme is to represent an arbitrary signal or image as a superposition of wavelets. By this superposition process, it can be decomposed the given function into different quad-scale levels (Antonini *et al*., 1992). One-dimensional signals are represented by translations and dilations of the wavelet, $\psi(\frac{x-b}{a})$,

$$f(a,b) = \frac{1}{|a|^{1/2}} \int \psi(\frac{x-b}{a}) f(x)dx \qquad (3)$$

One major advantage afforded by wavelets is the ability to perform local analysis. Wavelet analysis is capable of revealing aspects of data that other signal analysis techniques miss, aspects like trends, breakdown points, discontinuities in high derivatives and self-similarity.

However, calculating wavelet coefficients at every possible scale is a fair amount of work, and it generates an awful lot of data. If scales and positions based on powers of two are selected, wavelet analysis will be much more efficient and just as accurate. We obtain such an analysis from the discrete wavelet transform (DWT). The discrete wavelet transform can be implemented 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 frequency at the upper level. By repeating this procedure or down leveling, it is possible to perform the wavelet transformation of any level. The down-sampling procedure preserves the scaling parameter constant (n = 1/2) throughout successive wavelet transformation so that it enables a relatively simple computation. In this study, DAUB4, as the wavelet basis, was applied and it is known to one of basis functions for the wavelet processing (Huang and Dai, 2004).

3. RESULTS & DISCUSSION

3.1 Understanding the variogram

The variogram is various according to sensor type, spatial resolution, location, feature type, direction, the amount of noise. So, it is important data that shows the property of spatial information. Especially, it is more important in case of high resolution imagery and complex urban area.

As stated above, we can get totally different variogram according to resolution even though the images are obtained in same location. In case that resolution are different, the number of feature, feature size, a kind of obtainable information are changed. Three types of different spatial resolution images were used at the experiments in this study: IKONOS 1 m, KOMPSAT 6.6 m and Landsat 15m panchromatic imagery. IKONOS and KOMPSAT image are covered with regions around Namyangju-city bordered with Seoul, Gyeonggi-do, Korea. As we can see in fig. 2, every building can be divided correctly in IKONOS imagery. Meanwhile, KOMPSAT imagery has vague outlines and only large playground can be distinguished in Landsat imagery. As we can see in fig. 2, every building can be divided correctly in IKONOS imagery. Meanwhile, KOMPSAT imagery has vague outlines and only large playground can be distinguished in Landsat imagery.

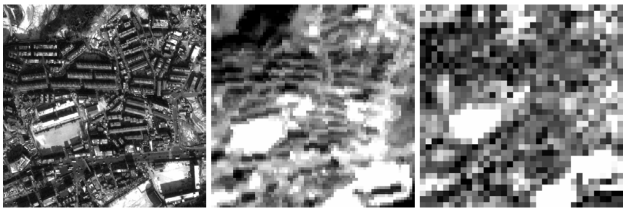

IKONOS KOMPSAT LANDSAT
Figure 2. Three images, which have different spatial resolution.

Fig.3 shows the variograms of three images. Sill is not existed unlike classical variogram. Though the slant of variogram decrease, variogram increase according as lag is longer. In the early part, the variogram of IKONOS imagery increase dramatically. Afterward, slope decrease quickly, it has the smallest value in the closing part. Meanwhile, the variogram of LANDSAT imagery is larger than KOMPSAT imagery

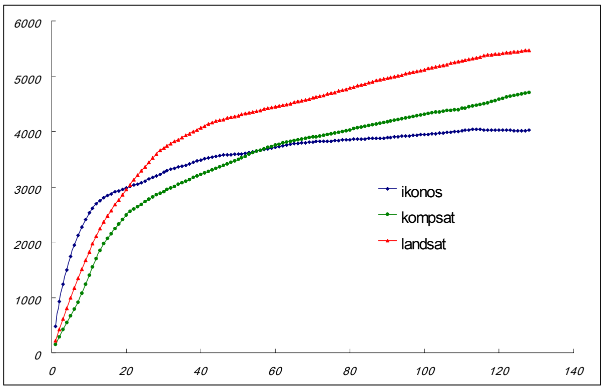
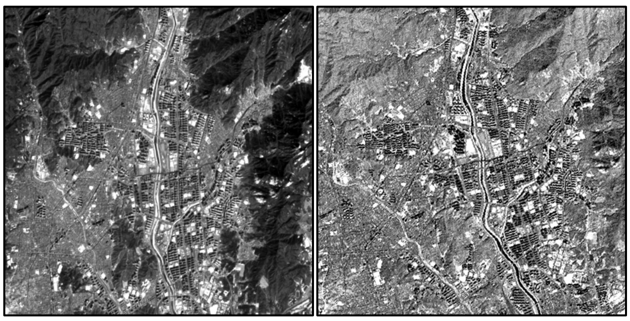


Figure 3. The variograms of three images in Fig. 2.

Fig. 4 shows KOMPSAT and LANDSAT imagery are covered with regions around Guri-city bordered with Seoul, Gyeonggi-do, Korea. These images have dense buildings in middle part and forest area on the border. The variogram of KOMPSAT imagery in this area has distinctive variogram shape. This has periodicity and looks like a sum of periodic function (Fig. 5).

If the periodicity of variogram analyze, we can get feature size, redundancy, some patterns. Fourier transform and wavelet transform can be used for periodicity analysis. Meanwhile, we can not identify building boundaries in LANDSAT imagery. Forest area is seldom noticed because they blend well with their surroundings. The variogram of LANDSAT imagery has totally different that of KOMPSAT Imagery.


LANDSAT
Figure 4. KOMPSAT and LANDSAT images in the Guri-city.

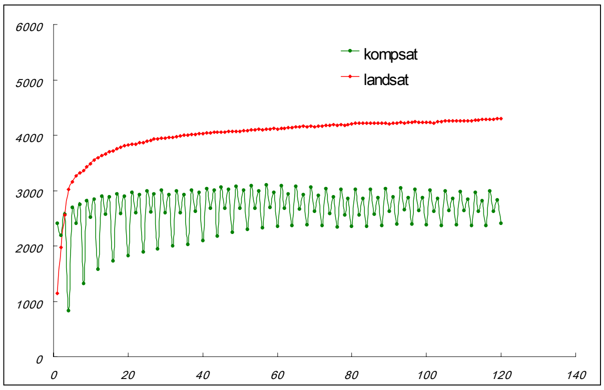


Figure 5. The variograms of two images in Fig. 4.

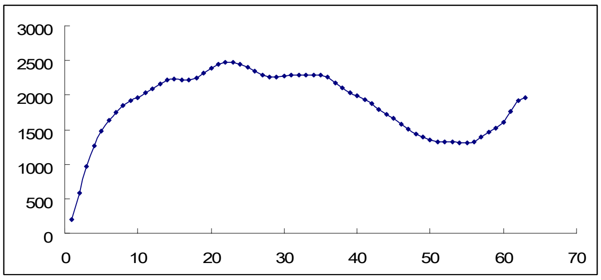


Figure 6. Periodic variogram.

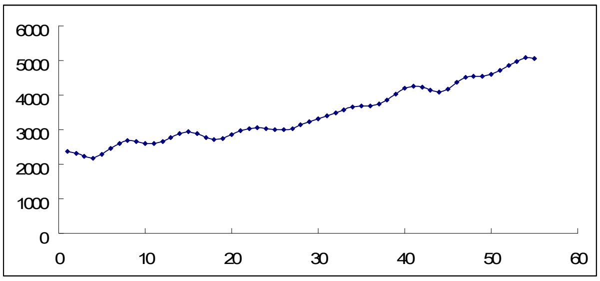


Figure 7. Aspatial variogram.

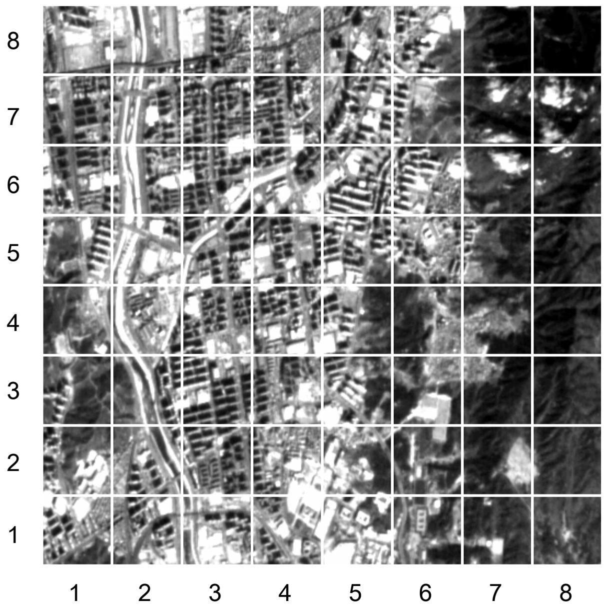


Figure 8. 64 sub images of KOMPSAT imagery.

We divided KOMPSAT imagery into 64 sub image and analyzed the spatial property of each image this time. Sub images, which have similar patterns, will be expected to have similar variogram, because every sub-image has same resolution.

In urban landscapes, semi-variograms are often of man-modified surfaces with a repetitive spatial pattern, and as a result this “classic” semivariogram is relatively unusual. The two very common forms are the ‘periodic’ semivariogram (Fig. 6) recorded across a repetitive pattern and the ‘aspatial’ semivariogram (Fig. 7) recorded either along such a repetitive pattern, randomly on a homogeneous surface, or when using a support that is larger than the range. Among several images, two images each, which have broad ways, dense building and forest area were selected and analyzed in detail. We tried to use wavelet transform form variogram analysis. The data set was composed of series of 64 by 64 pixel individual image (Fig. 8).

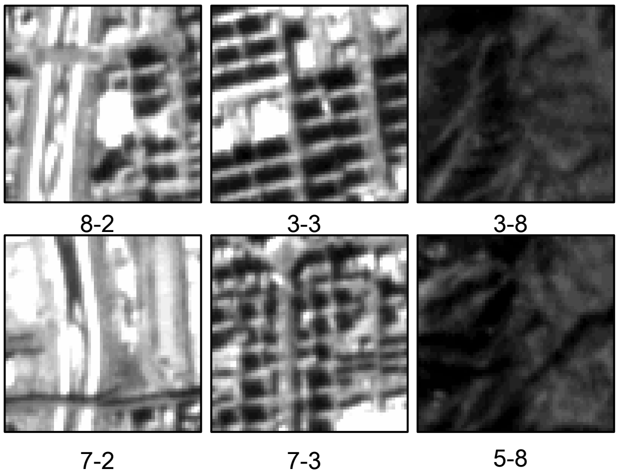


Figure 9. The tested subset.

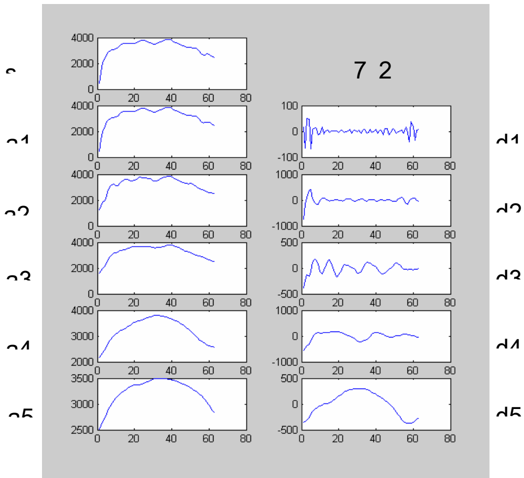


Figure 10. The example of wavelet analysis of variogram.

One major advantage afforded by wavelets is the ability to perform local analysis. If we use wavelet decomposition, we can get approximation and detail component easily. We were concerned how analysis by wavelets can effectively perform what is thought of as a Fourier-type function-that is, resolving a signal into constituent sinusoids of different frequencies. As a result of wavelet analysis, the optimum decomposition level of image 7_2 and 8_2 is 4. Approximation component, which shows whole trend, is different each other. Detail component is very alike. However Peak shows up before in 7_2 imagery (Fig. 9).

The optimum decomposition level of image 3_3 and 7_3 is 5. a5 shows whole trend and d5 has two ridge and flat d4 are analogous. But a1, a2 and a3 show difference (Fig. 10). The optimum decomposition level of image 3_8 and 5_8 is also 5. a5 in this variogram is very analogous. 3_3 has many low frequency components. Meanwhile, 5_8 has high frequency.

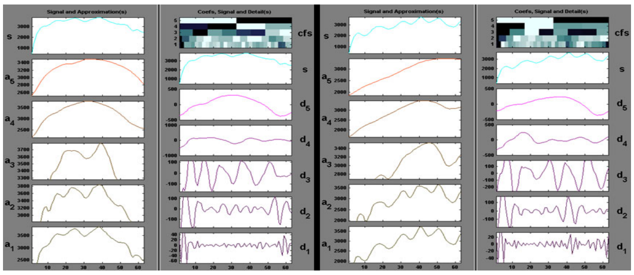


Figure 11. The wavelet analysis of 8_2 and 7_2.

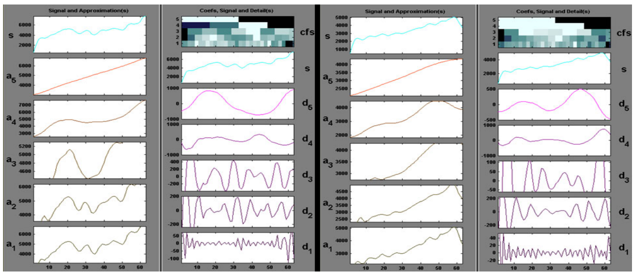


Figure 12. The wavelet analysis of 3_3 and 7_3.

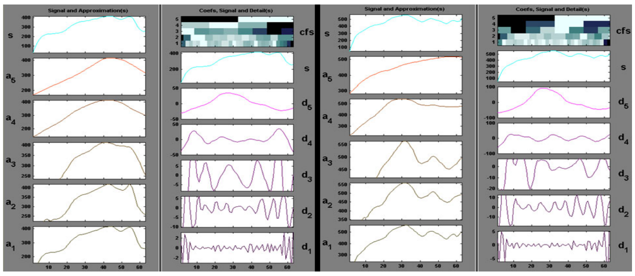


Figure 13. The wavelet analysis of 3_8 and 5_8.

Wavelet transform is profitable for analyzing each image. However, it is difficult to compare every wavelet decomposition data to grasp which image is similar to one image. So, we used variogram-modelling coefficient. For modelling, we tried to compound model that composed with logarithm model and nugget effect model. We calculated Euclidean distance between two images using each coefficient of logarithm model and nugget effect model and average of imagery on assumption that the most similar image pair is the nearest distance. Euclidean distance means the straight line distance between two points. In a plane with p_1 at (x_1, y_1, z_1) and p_2 at (x_2, y_2, z_2), equation (4) is Euclidean distance.

$$\sqrt{(x_1 - x_2)^2 + (y_1 - y_2)^2 + (z_1 - z_2)^2} \qquad (4)$$

Every value was normalized before distance calculation. 8_1 and 6_4, 6_1and 3_2, 5_1 and 5_3, 2_3 and 1_6, 8_5 and 6_5, 7_2 and 1_7, 3_8 and 5_8 imagery are similar each other in result (Fig. 11, Fig. 12 and Fig. 13). These results will be extended retrieval system or spatial pattern based classification later.

4. CONCLUSIONS

In this study, we tried to consider how to extract new information from imagery with the interest of spatial information.We analyzed the spatial distribution of images using variogram. Not only theoretical variogram modelling, which is typically used, but also wavelet to analyze variogram were applied this research. The variogram is various according to sensor type, spatial resolution, location, feature type and so on. Variogram showed well the spatial characteristics of each image. And Wavelet decomposition is effective method to extract some information from variogram, because wavelet decomposition helps us to get approximation and detail component easily. Meanwhile Euclidean distance method using variogram modelling coefficient was useful to search images have similar characteristics. With this result, variographic analysis based on continuity computation was performed for characterization of urban features.

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