Implementation for Texture Imaging Algorithm based on GLCM/GLDV and Use Case Experiments with High Resolution Imagery

So Hee Jeon
Dept. of Earth Sciences Education
Seoul National University, Seoul, 152-792, Korea
Jsh1118@snu.ac.kr

Kiwon Lee
Dept. of Information Systems
Hansung University, Seoul, 136-792, Korea
kilee@hansung.ac.kr

Byung-Doo Kwon
Dept. of Earth Sciences Education
Seoul National University, Seoul, 152-792, Korea
bdkwon@mantle.snu.ac.kr

Abstract: Texture imaging, which means texture image creation by co-occurrence relation, has been known as one of useful image analysis methodologies. For this purpose, most commercial remote sensing software provides texture analysis function named GLCM (Grey Level Co-occurrence Matrix). In this study, texture-imaging program for GLCM algorithm is newly implemented in the MS Visual IDE environment. While, additional texture imaging modules based on GLDV (Grey Level Difference Vector) are contained in this program. As for GLCM/GLDV texture variables, it composed of six types of second order texture function in the several quantization levels of 2(binary image), 8, and 16: Homogeneity, Dissimilarity, Energy, Entropy, Angular Second Moment, and Contrast. As for co-occurrence directionality, four directions are provided as E-W (0°), N-E (45°), S-W (135°), and N-S (90°), and W-E direction is also considered in the negative direction of E-W direction. While, two direction modes are provided in this program: Omni-mode and Circular mode. Omni-mode is to compute all direction to avoid directionality problem, and circular direction is to compute texture variables by circular direction surrounding target pixel. At the second phase of this study, some examples with artificial image and actual satellite imagery are carried out to demonstrate effectiveness of texture imaging or to help texture image interpretation. As the reference, most previous studies related to texture image analysis have been used for the classification purpose, but this study aims at the creation and general uses of texture image for urban remote sensing.

Keywords: Circular-direction, GLCM/GLDV, Texture, Omni-direction

1. Introduction

Object detection and analysis in the diverse images or photography give new information to human as well as the information, which is very useful to a lot of fields. Especially, satellite image is one of the images really important sources in interpretation and provides the useful information periodically at low cost. For that reason, as remotely sensed images are widely used, diverse methods of image analysis are developed continuously.

The texture imaging, which means creation by co-occurrence relation, has been known as one of useful image analysis methodologies. In this study, texture analysis functions such as GLCM, GLDV are provided for texture imaging. There are some previous researches, which compared texture analysis methods; Dulyakarn et al. (2000) compared each texture image from GLCM and Fourier spectra, in the classification. Maillard (2003) performed comparison works between GLCM, semi-variogram, and Fourier spectra at the same purpose. Bharati et al. (2004) studied comparison work of GLCM, wavelet texture analysis, and multivariate statistical analysis based on PCA (Principle Component Analysis). In those works, GLCM scheme can be provided as the effective texture analysis schemes.

In this study, texture-imaging program for GLCM and GLDV-based algorithm is implemented on MS Visual environments. This study and implementation is based on the original concept of GLCM (Grey Level Co-occurrence Matrix) and GLDV (Grey Level Difference Vector), which are the most popular texture image generation and analysis scheme, summarized by Haralick et al. (1973), Parker (1997) and Hall-Beyer (2004). A GLDV is similar to a GLCM, but GLDV deals with the sum component of the diagonals of the GLCM. So sometimes texture measures use the GLDV instead of the GLCM. Especially, Omni direction and circular direction are newly implemented. Omni direction is created by conventional computation of 8 directions. And circular direction can create result image consideration on circular neighboring pixels.

2. GLCM/GLDV: Rationale

GLCM (Gray Level Co-occurrence Matrix) texture has basically consideration for the relationship between two neighboring pixels in one offset, as the second order texture. But GLCM is different from other using second order texture, because GLCM considers relationship between pairs of pixels in the kernel after transformed to gray image. There are 4 kernel masks in this study; 3*3, 5*5, 7*7, 11*11. 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 we transform 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 newly implemented two directions are omni and circular in this study. The directions, if user chooses, count its original direction and also its reverse direction. 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:

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

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

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

$$\text{Entropy} = \sum_{i=0}^{Ng-1}\sum_{j=0}^{Ng-1}g(i,j)(-\ln(g(i,j))) \tag{4}$$

$$\text{Dissimilarity} = \sum_{i=0}^{Ng-1}\sum_{j=0}^{Ng-1}g(i,j)\,|\,i-j\,| \tag{5}$$

$$\text{Energy} = \sqrt{\sum_{i=0}^{Ng-1}\sum_{j=0}^{Ng-1}g^2(i,j)} \tag{6}$$

where i, j are coordinates of the co-occurrence matrix space, g (i, j) is the element of the i and j coordinates, and N_g 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 matrix. As for GLDV texture measure, it is the sum of the diagonals of the GLCM. GLDV is related to the distance from the GLCM diagonal. In GLDV, these types of texture measures are also possible by Hall-Beyer (2004).

Homogeneity can inform us about uniformity of co-occurrence matrix. For example, if most elements lie on the main diagonal, its value will be large, compared to other case. Dissimilarity measures how different elements of the co-occurrence matrix are from each other. Contrast measures how most elements do not lie on the main diagonal. Entropy is to measure randomness, and it will be the maximum when the all elements of the co-occurrence matrix are same. In case of Energy and ASM, they measure extent of pixel pair repetitions and pixel orderliness, respectively.

3. Texture Imaging by GLCM/GLDV

The GLCM/GLDV texture images can be created by using program newly implemented in this study (Fig.1). In this program, the main frame contains 3 menus: Set_Depth_Level for grey level quantization, GLCM, and GLDV for 6 types texture measures of Homogeneity Dissimilarity, Contrast, Entropy, Energy, ASM (Angular Second Moment). And a user can determine two texture parameters such as window kernel size, direction, after transforming to gray image. After the grey value relationships in a target are transformed into the co-occurrence matrix space by a given kernel masks such as 3*3, 5*5, 7*7 and 11*11, the neighboring pixels as one of the four directions as East-West of 0°, NorthEast-SouthWest of 45°, North-South of 90°, NorthWest-SouthEast of 135°, circular-direction and omni-direction will be computed in the co-occurrence matrix space. Among them, omni-direction and circular-direction represent the average value with those of four directions and value by neighboring pixels of target pixel lie on the perimeter of circles of different radii (Cooper, 2004), respectively.

4. GLCM/GLDV Texture imaging: Results

Fig.2 shows direction dependency of texture measures, and Texture Scheme. In Fig.2, notation of (16, GLCM, 5*5, N-S, HOM) means gray level (one of 2, 8, or 16),

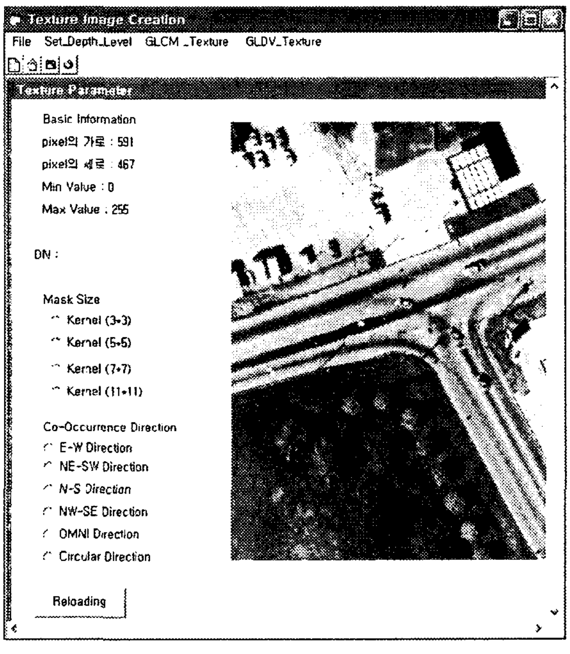


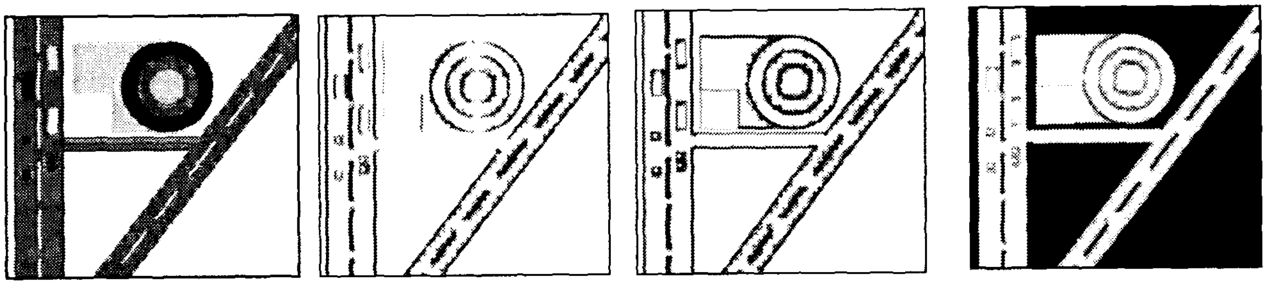
Fig. 1 GLCM and GLDV texture imaging program, implemented in this study.

application scheme (one of GLCM or GLDV), kernel size (one of 3,5,7, or 11), direction(one of E-W, NE-SW, NW-SE, N-S, OMNI, or Circular), texture type, respectively. While, HOM and ENT represent homogeneity and entropy, respectively.

As shown in Fig.2, two results, (b) and (c) images are only different direction with other same parameter. As we interpret this case, (b) image considers only two directions including reverse direction. So this image has some problems. For example, some lines are not detected. It visually appeared well comparing (c) image. Because (b) image considers just two directions, north and south, that image can't show horizontal direction lines well. Therefore, considered direction is presented well, but we can know that some else directions can't be presented in the image. Therefore direction dependency for texture measure is problematic, although it's useful to detect objects of different direction. So we implement omni-direction to solve this direction problem. As for Fig. 2 (c) image, it is created as computing the average value, which is considered 8 directions.

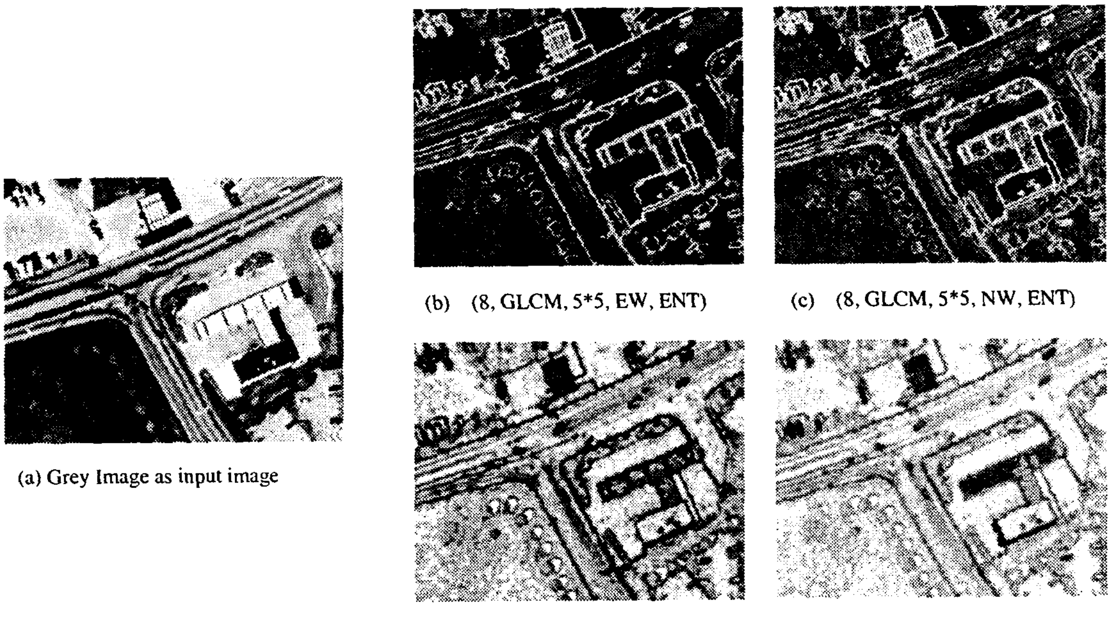
The (c) image presents every direction lines and makes us detect object well. Although omni-direction method has more time consuming comparing to other methods, its result image is more useful. So omni- direction method can help interpretation of complicated urban image, because the image includes all kinds of lines such as straight line, curved line and round shape without considering of directions. Through two images (b) and (c) in Fig.3, we can also analysis of difference of direction dependency.

And Fig. 2(d) image is created using GLDV texture scheme. The (d) image is compared to (c) image, and both of them are transformed with same gray level, kernel size, direction, and texture type. Their results are different each other. The GLCM image is more useful to analysis pavement state and detection of cars comparing to GLDV image. And (d), (e) images in Fig.3 are also different. The (d) image is more obvious than (e) image, in total. But (e) image of GLDV is presented well some parts such as detail of building, small object.



(a) Artificial image (b) (16, GLCM, 5*5, N-S, HOM) (c) (16, GLCM, 5*5, OMNI, HOM) (d) (16, GLDV, 5*5, OMNI, HOM)

Fig. 2. Texture images using artificial image showing urban environments. Notation of (16, GLCM, 5*5, NS, HOM) represents (Grey Level, Texture Scheme, Kernel size, Direction, Texture Variable).

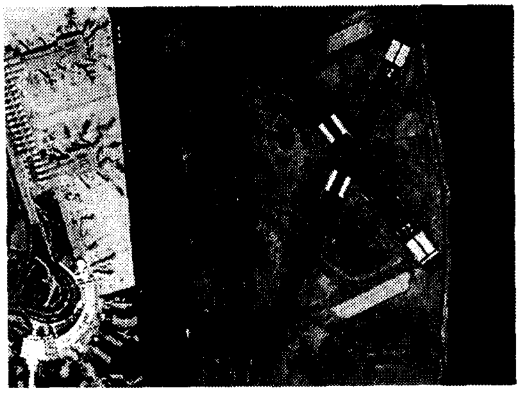


(a) Grey Image as input image

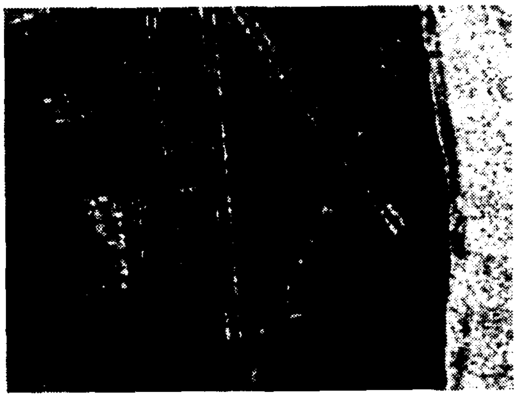
(b) (8, GLCM, 5*5, EW, ENT) (c) (8, GLCM, 5*5, NW, ENT)

(d) (16, GLCM, 7*7, OMNI, HOM) (e) (16, GLDV, 7*7, OMNI, HOM)

Fig. 3. Texture images using air-borne photo image data. Data is excerpted from Demin(2000).



(a) Applied Image (http://www.isprs.org/data/ikonos/)



(b) Texture Image (16, 7*7, GLDV, Circular, ASM)

Fig. 4. Results of texture imaging with ISPRS sample image.

The Fig. 4(b) image is created considering circular-direction. This method considers relationship between target pixel and circular neighboring pixels. The image result is good recognizing pavement condition. Because of using ASM texture type, the result image is a little dark. ASM texture measures pixel orderliness. And it spends less time creating this image comparing to omni-direction image. Some further works are needed to analysis.

5. Conclusions and Further works

This study is a little different from most previous studies, which have been toward the improvement of classification accuracy. In this study, application program for texture measures based on GLCM and GLDV is newly implemented.

By using this program, GLCM and GLDV-based texture images by different gray level, kernel size, and texture type are created with the high-resolution satellite image covering urban area. And also omni-direction method and circular-direction method are attempted to detect and analyze objects. In this study, omni-direction texture measures help to reduce directional dependency which causes difficulty in texture images interpretation. Also circular- direction texture measure helps to detect shadow zones, classify building types, and interpret pavement condition. So GLCM and GLDV program is useful to apply urban remote sensing, and use as guide of proper type among texture measures to characterize complicated urban features. Further works are needed to make out correlations among each texture measure images and analysis complicated urban satellite image more accuracy.

References

[1] Bharati, M. H, J. J. Liu and J. F. MacGregor, 2004. Image texture analysis: methods and comparisons, *Chemometrics and Intelligent Systems*, 72: 57-71.

[2] Demin X., 2002. Remote Sense and GIS-based Evacuation Analysis, ORNL presentation material, NCRST 2002.

[3] Dulyakarn, P, Y. Rangsanseri, and P. Thitimajshima, 2000. Comparison of Two Features for Multispectral Imagery Analysis, Proceeding of Asian Conference of Remote Sensing.

[4] Franklin, S. E., M. A. Wulder and G. R. Gerylo, 2001. Texture analysis of IKONOS panchromatic data for Douglas-fir forest age class separability in British Columbia, *Int. Jour. of Remote Sensing*, 22: 2676-2632.

[5] Cooper, 2004. The texture analysis of gravity data using co-occurrence matrices, Computer & Geosciences, 30: 107-115

[6] **URL** : Hall-Beyer,M.,2004. GLCM Texture: A Tutorial v.2.7.1,http://www.ucalgary.ca/~mhallbey/texture/texture_tutorial.html.

[7] Haralick, R. M., K. Shanmugam and I. Dinstein, 1973. Textural features for image classification, *IEEE Trans. Sys. Man. Cybern.*, SMC-3: 610-621.

[8] Herold, M. H, X. Liu and K. C. Clake, 2003. Spatial Metrics and Image Texture for Mapping Urban Land Use, *Photogrammetry Engineering & Remote Sensing*, 69: 991-1001.

[9] Maillard, P., 2003. Comparing Texture Analysis Methods through Classification, *Photogrammetry Engineering & Remote Sensing*, 69(4): 357-367.

[10] Mari Partio, Bogdan Cramariuc, Moncef Gabbouj, and Ari Visa. ROCK TEXTURE RETRIEVAL USING GRAY LEVEL CO-OCCURRENCE MATRIX

[11] Kiema, J. B. K., 2002. Texture analysis and data fusion in the extraction of topographic object from satellite imagery, *Int. Jour. of Remote Sensing*, 23(4): 767-776.

[12] Parker, J. R., 1997. *Algorithms for Image Processing and Computer Vision*, John Wiley & Sons: 150-175.

[13] Wang, X. and A. R. Hanson, 2001. Surface texture and microstructure extraction from multiple aerial images, *Computer Vision and Image Understanding*, 83: 1-37.

[14] Zhang, Y, 1999, Optimisation of building detection in satellite images by combining multispectral classification and texture filtering, *ISPRS Journal of Photogrammetry & Remote Sensing*, 54: 50-60.