TEXTURE BASED CONTENT RETRIVAL FOR SATELLITE IMAGES USING FILTER TECHNIQUE

Y N Mamatha [(1)] and A.G Ananth [(2)]
[(1)] Lecturer, R V College of Engineering, Bangalore-59
[(2)] Professor, R V College of Engineering, Bangalore-59
mamatharaj_76@rediffmail.com

Abstract:

The purpose of this work is the study of urban and rural areas based on texture analysis methodology that may improve the investigation through remote sensing, dedicated to seismic vulnerability in correlation with the geometrical properties of building blocks and the vulnerability data, taken from field surveys. Most of the algorithms for urban classification in the image processing domain are based only on the use of spectral information, not taking into account the geometric characteristics given by the spatial distribution to roads, buildings and green areas on the image. The study of these local proprieties, as the texture, may enrich the available information on the image, providing a further information layer which may improve the differentiability among suburban areas originally belonging to homogeneous areas. In order to overcome those limitations, a new methodology, based on the analysis of connected regions, was studied. At first the image is threshold in order to detect built pixels. Then these pixels are connected into sub-regions and these sub-regions are investigated to extract features. Based on the gray thresh the level the appropriate filters have been used to retrieve the required features from the satellite images. The filters that have been used for this work are STD filter, Range filter, and Entropy filter. In this paper we are presenting that entropy filter is best filter for high resolution satellite imageries.

Keywords: *Feature Extraction, gray thresh,, spectral graph, STD filter, Range filter, entropy filter.*

Introduction:

The texture study is based on the analysis of the spatial distribution of ground radiance level variations, which is able to point out linear structures of a remotely sensed image, used to characterize urban morphology. To give a strict definition of texture in image processing and machine vision is not an easy task. In literature a large number of texture definitions can be found, depending on the application field. It has to be highlighting that most of methodology developed are strictly dependent on the texture definition.

This consideration was supported when we tried to apply classical texture analysis techniques on urban areas. Most of traditional methods are window based. In these methods local proprieties are extracted by computing different features within a fixed dimension window moved onto the image. These approaches strongly depend on the window dimension choice. Two limits were pointed out: bad results on texture boundaries and impossibility to define a unique window dimension over the whole image. In order to test classical techniques a synthetic texture sample of an urban centre was *ad hoc* created. The sample texture includes two different satellite images with different orientation, results are shown in figures.

The results obtained from the known methods weren't acceptable for our task, hence a new methodology was studied. At first a general and useful definition of texture analysis in remote sensing, in accordance with urban or rural texture definition, was given. *The analysis of the spatial distribution of grey level variations, which is able to point out geometrical structures of an image*[6].

In accordance with this texture definition, a window and orientation independent method was studied based on the detection of regions (or objects) surrounded by elements of separation and it is performed using the analysis of connected regions. In urban situation separator elements can be roads and connected objects can be building blocks. After having extracted all the connected regions, separator elements are assigned to the nearest connected region in order to organize the image into sub-regions. Then texture features are calculated within the detected regions to group regions with the same geometric structure. The main steps of the new algorithm can be resumed as follows.

- *image thresholding in order to detect pixels related to buildings;*
- *the pixels representing the buildings are connected (building blocks) and the image is divided into sub-regions;*
- *features are extracted within these sub-regions;*
- *the image is classified on the basis of extracted features.*

Feature extraction:

Although sub-regions are recognized within the bi-level image, the features are computed within the original one. At first a list of pixel positions on the bi-level image for each sub-region is compiled, then sub-regions are extracted on the grey level image on the base of this list. The feature extraction choice was not so immediate. A large number of different features are proposed in literature. Many features are computed within these regions based on first order and second order statistics as, for example, entropy, mean, contrast, dissimilarity. These are not considered satisfactory so *ad hoc* features based on the shape and dimension of the building block has been defined. These can be described as follows:

Built percentage: a ratio between sub-region area and built area is computed within each sub-region.

Shape descriptor: a ratio between built area and the area of the minimum rectangle including the block is computed within each sub-region;

Block dimension: area of the built block for each sub-region.

Image classification:

Although software applied in the previous steps has been developed in our laboratory, an IsoData clustering method to perform the texture classification provided by in a image processing tool, has been used. This choice was done to make the evaluation of the texture algorithm quicker. The classification is performed on the image obtained by the feature evaluation within each sub region. This process divides the urban area into different sub-urban zone having similar building blocks feature.

Brief Overview of Texture Analysis GLCM and GLDV:

Basic of GLCM Texture considers the relation between two neighboring pixels in one offset, as the second order texture. The grey value relationships in a target are transformed into the co-occurrence matrix space by a given kernel mask such as 3*3, 5*5,7*7and so forth. In the transformation from the image space into the co-occurrence matrix space, the neighboring pixels in one or some of the eight defined directions can be used; normally, four direction such as 0°, 45°, 90°, and 135° is initially regarded, and its reverse direction (negative direction) can be also counted into account.

Therefore, general GLCM texture measure is dependent upon kernel size and directionality, and known measures such as contrast, entropy, energy, dissimilarity, angular second moment (ASM) and homogeneity are expressed as follows:

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

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

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

Where i and j are coordinates of the co-occurrence matrix space, g(i,j) is element in the co-occurrence matrix at the coordinates i and j, Ng is dimension of the co-occurrence matrix, as grey value range of the input image. While, in GLCM texture measure, normalization of GLCM matrix, by each value dividing by the sum of element values, is applied, and then g(i,j) is replaced to the probability value. Furthermore, measures related to each texture variables also can use weights related to the distance from the GLCMdiagonal.

Texture measure in GLCM and GLDV needs to interpretation reference. Each measure contains different meaning for this. Homogeneity is measure for uniformity of co-occurrence matrix, and 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. The texture-augmented image analysis procedure is illustrated in Fig. 3. As mentioned before, after orthorectification and removal of non-vegetation areas texture analysis was carried out on the high resolution (panchromatic) image of the study site to collect texture features that might be helpful in the detection of target species. The collected texture features were Then sorted according to a principal component analysis (PCA). The first few principal component (PC) bands representing most of the variations were selected along with the original spectral band for a maximum likelihood classification and the classified result was verified against and evaluated by ground truth data. Although there are variants of texture analysis methods, among them, gray level co-occurrence matrix (GLCM) algorithm 1986 is probably the most commonly adopted for remote sensing. GLCM is very suitable for finding texture information in images of natural scenes and performs well in classification. Therefore GLCM should also be an appropriate method of texture analysis in this project.

GLCM quantifies texture by measuring the spatial frequency of co-occurrence of pixel gray levels in a user defined moving kernel (window) and forms a co-occurrence matrix of the kernel. After that, different statistical measures can be used to extract characteristics of the matrix that reflect spatial variations (textures features) of the window.

Co-occurrence matrix and *N* is the gray level of the texture image. As its name suggests, Contrast (also called sum of square variances) measures the weighted contrast of GLCM cells according to their distances to the matrix diagonal. The weighting of Contrast increases exponentially, so Contrast will result in a large number if there is great contrast in a window.

The above methodology was applied to a High resolution urban image as shown in Figure1. The texture analysis performed using built percentage.

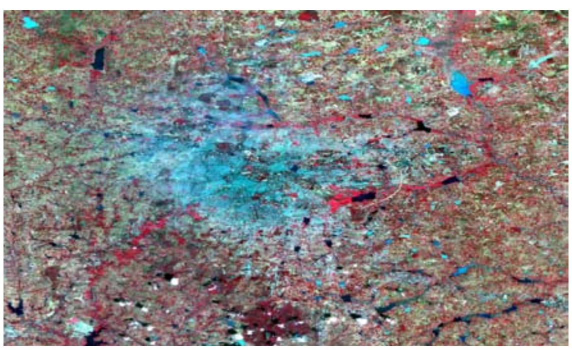

Figure1: Original Urban Satellite image

Then order to make a better estimation of the original image has been divided into exactly four quadrants. The sub images in Quadrants I have been selected for further image processing. Fig 2 shows the original two sub-images selected for detailed analysis.

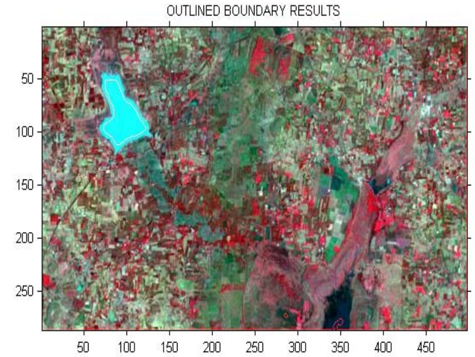

Figure 2: 1st quadrant of original image Urban Satellite image

The three statistical texture filtering functions are

STD filter: *Calculates the local standard deviation of an image*

Range filter: *Calculates the local range of an image*

Entropy filter: *Calculates the local entropy of a grayscale image*

The above filtering technique neighborhood around the pixel of interest and calculate the statistic for that neighborhood.

STD filter: The std filter technique specify defining a neighborhood around the pixel of interest and calculating the statistic for the neighborhood to determine the pixel value in the output image. The output of the std filter is as shown in figure3(a). The **stdfilt** function calculates the standard deviation of all the values in the neighborhood.

Range filter: Range filter technique specifies neighborhoods or different shapes and sizes. The **rangefilt** function uses a 3-by-3 neighborhood but you can specify neighborhoods or different shapes and sizes. Determining Pixel Values in Range Filtered Output Image. The output is as shown in figure 3(b).

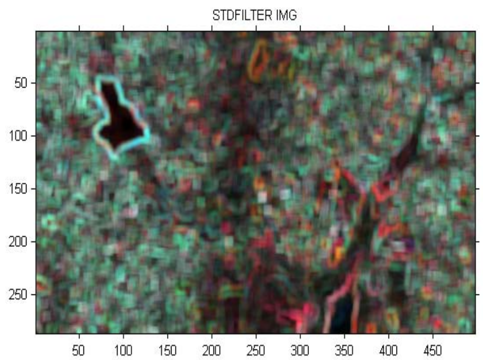

Figure 3(a): STD filter image

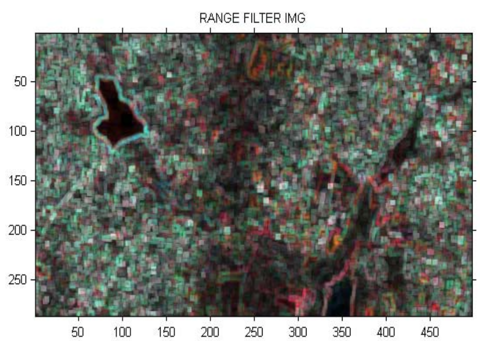

Figure 3(b): Range filter image

Entropy filter: The entropy filter technique specifies defining a neighborhood around the pixel of interest and calculating the statistic for the neighborhood to determine the pixel value in the output image. The **entropyfilt** function calculates the entropy of the neighborhood and assigns that value to the output pixel. Note that, by default, the **entropyfilt** function defines a 9-by-9 neighborhood around the pixel of interest. To calculate the entropy of an entire image, use the entropy function.

The images are tested with three different filter techniques are used to identify the different features. They are Range filter, STD filter and Entropy filter. There is an improvise result in the Range filter out put compared to the STD filter for the analysis and process. The output of the STD filter and Range filter is as shown in figure3(a) and 3(b).

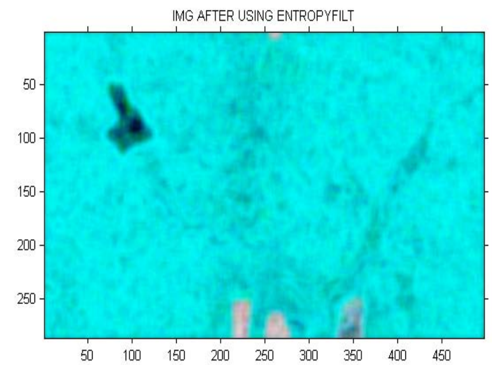

Figure 3(c): Entropy filter image

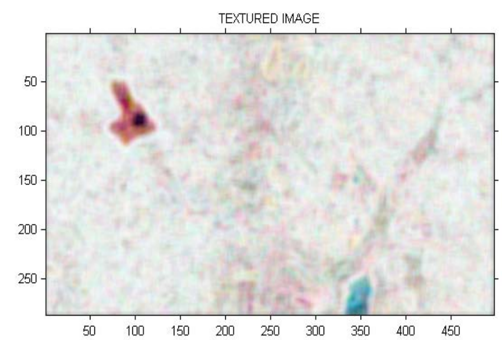

Figure 3(d): Textured image

The entropy of an entire image, the texture filter functions can detect regions of texture in an image. There is very little variation in the gray-level value. Foreground pixels have more variability and thus higher range values. Range filtering makes the edges and contours of the dense content is more visible.

Texture Segmentation is obtained by using Texture Filters with same image. Analyzing the Texture of an Image. Using Gray-Level Co-Occurrence main zones can be differentiated in relation n to the texture typology. In this case data related to similar urban areas are used to construct information layers related to analyze one. The similarity measure can be given by the texture analysis performed on both the known and unknown zone.

Conclusion:

Our purpose is based on the use of texture feature for urban typologies retrieval. Two possible ways are inquired: one is based on the construction of a texture image database and one in based on the features formalization in order to apply them in an expert system. Based on this textured analysis content based retrieval can be processed.

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