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EVALUATION OF IMAGE TEXTURE PARAMETERS FOR URBAN LAND COVER CLASSIFICATION

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ABSTRACT

Remote sensing technology is paving its own way with remarkable advantages in various fields. Feature extraction from satellite imagery is one of the challenging tasks in image processing. As far as low resolution images were concerned, per pixel analysis and sub-pixel analysis were gaining its importance. Now with the advancements in technology, high resolution imageries are acquired easily and made used in various applications. When speaking about high resolution imageries, it is made known that an object or feature in the imagery is made up of several pixels which is contrary to the low resolution imageries. Thus, an alternative technique for feature retrieval is necessary to extract features from high resolution imagery. Spatial relationships between the pixels were taken into consideration along with its spectral characteristics. Texture is one of the spatial parameter which is of much importance. The texture of an image gives us the information about the spatial arrangement of colours or intensities and it is a function of the texture surface, its albedo, the illumination and the camera and its viewing position. There are various parameters to characterize the texture of an image. Haralick's texture parameters were found to be of much importance compared to the other texture parameters. Thus Haralick's texture parameters were considered in the study. There are about thirteen Haralick's texture parameters. In urban feature extraction, it is not necessary that all these thirteen parameters have to be imposed because certain parameters have no influence in extracting the urban features. So based on this aspect, statistical analysis was made so as to examine and quantify the influence of each Haralick's texture parameter.

Out of thirteen, six were found to be of considerable importance. Using these six textural characteristics, classification was carried out and 88% accuracy was obtained in urban feature extraction.

Keywords: *texture; satellite imagery; haralick's texture parameters; statistical analysis; urban feature extraction; classification*

INTRODUCTION

The texture of an image gives us the information about the spatial arrangement of colours or intensities. It contains the important information about the structural arrangement of surfaces and their relationship to the surrounding environment. The analysis of these spatial distributions of grey level variations which is able to point out the geometrical structures of an image is called as texture analysis. The textural information is the one which defines the contrast, uniformity, rugosity or regularity of the image. The texture of an image is a function of the texture surface, its albedo, the illumination and the camera and its viewing position. There are several computations of computing texture. The Haralick's texture computation has been taken into consideration in this study.

The criteria which are to be considered in calculating Haralick's texture parameters are directions, displacement and kernel size. Kernel sizes of 3x3, 5x5 and 7x7 were chosen and texture parameters were computed. For direction criteria, 0º, 45º, 90º and 135º were taken into consideration and one pixel is the displacement applied. The optimal criteria necessary for the urban feature retrieval were statistically analyzed and used in this project.

BACKGROUND CONCEPT

Satellite imagery is a raster image which is composed of pixels. Each pixel has a specific spectral value based on the radiation acquired by the sensor from the object at the time of acquisition.

The textural parameters are computed from the Gray Level Co-occurrence Matrices (GLCM). A co-occurrence matrix is a two-dimensional array in which both the rows and the columns represent a set of possible image values. For example, for gray-tone images, the image values can be the set of possible gray tones and for color images, it can be the set of possible colors.

The value of each cell in the array, say (i, j) indicates how many times value i co-occurs with value j in some designated spatial relationship. Let d be a displacement vector (dr, dc) where dr is a displacement in rows (downward) and dc is a displacement in columns (to the right). Let V be a set of gray tones. The gray-tone co-occurrence matrix Cd for image I is defined by

$$Cd\,(i, j) = |\{(r, c) \mid I\,(r, c) = i \text{ and } I(r + dr, c + dc) = j\}| \quad (1)$$

The Fig. 1 illustrates this concept with a 4 x 4 image I and three different co-occurrence matrices for I: C(0,

1), C(1, 0), and C(1, 1).

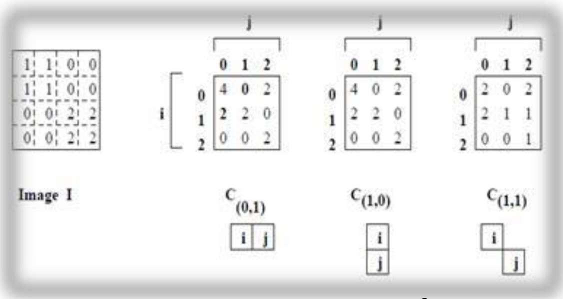

Figure 1. Computation of Co-occurance Matrices.

From the GLCM, the thirteen Haralick's texture features were computed. They are:

Homogeneity, Contrast, Dissimilarity, Mean, Standard Deviation, Entropy, Angular 2nd moment, Correlation, GLDV Angular 2nd moment, GLDV Entropy, GLDV Mean, GLDV Contrast and Inverse Difference.

MATERIALS

High resolution imagery of a dense urban region is the primary data used for the project. IKONOS image of SanDiego city, California, USA is used for the project which has spatial resolution of 1m. SanDiego is the most important city in California which has a dense urban region. Software such as PCI Geomatica and ERDAS Imagine were used for computation of texture parameters and other processes. Microsoft Excel worksheet was used for statistical computation and analysis. Fig. 2 is the true colour IKONOS image of a part of SanDiego city.

Figure 2. IKONOS image of SanDiego city.

METHODOLOGY

Texture analysis is computed for the IKONOS imagery considering the two criteria such as direction and kernel size. The statistical computations are made for each Area of Interest (i.e.) each urban feature, so as to examine the optimal criteria which are best suited for urban feature retrieval. The texture parameters thus chosen are layer stacked and unsupervised classification is carried out to classify the urban features based on the texture parameters.

The image classification based on texture involves a series of procedures which is given in a flow chart in figure 3. Each layer of Haralick's texture parameter were computed and analyzed individually for each kernel size, each direction and each area of interests. Nearly about 936 images were analyzed individually so as to conclude with the optimal texture layers required for the urban feature extraction.

Statistical methods were adopted in the texture analysis of each layer. The separability analysis proved the variation between the various areas of interest provided

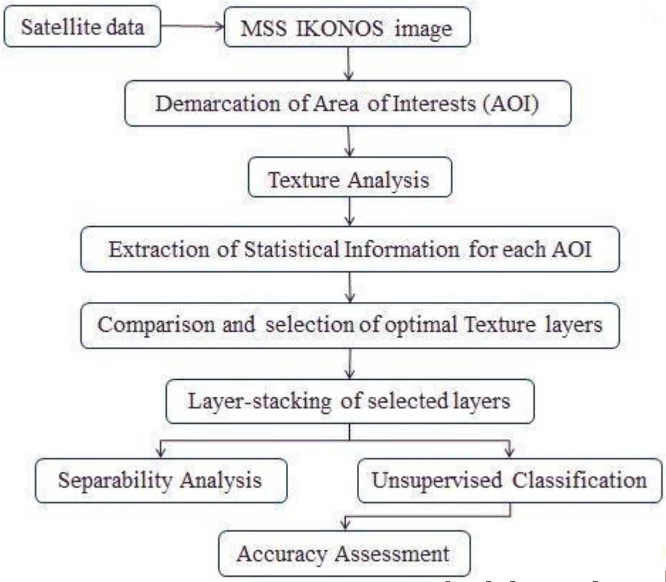

Figure 3. Methodology Flow Chart.

RESULTS AND DISCUSSION

A. Texture Analysis

The texture analysis was carried out over the imagery and all thirteen Haralick's texture parameters were computed for directions such as 0^o, 45^o, 90^o and 135^o and for kernel sizes 3x3, 5x5, 7x7.

B. Statistical Analysis

Statistical mean for each layer obtained from texture analysis were computed and were compared. Results based on direction criteria displayed in the charts in the following Fig. 4 shows that all the four directions are of considerable importance in urban feature extraction. Thus all directions are taken into consideration in the further procedures. In case of the kernel sizes, it was observed that there was not much variation in the statistical analysis based on kernel size criteria, thus kernel size of 5x5 is chosen as the optimal.

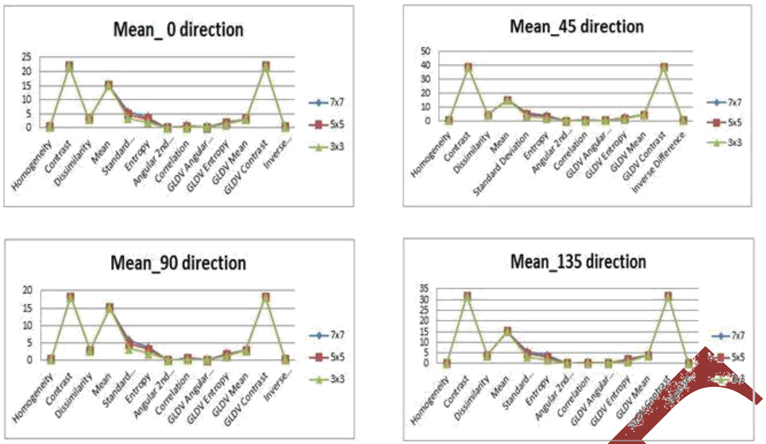

Figure 4. Statistical Mean for three Kernels and thirteen Texture Layers.

Statistical mean was also computed for each urban feature (AOI) in each layer of texture parameter so as to choose the layers which are of considerable importance in classifying the urban features. Concrete buildings, Red tiled buildings, Dense and sparse vegetation, Roads and Barren land were the various AOI’s.

From the statistical analysis based on these urban features the six texture parameters were found to be of considerable importance in urban feature extraction. They are: Contrast, Mean, Dissimilarity, GLDV Entropy, Standard Deviation, GLDV Angular 2nd moment. The chosen layers of 5 x 5 kernel and 45º direction is shown in the following Fig. 5. These texture parameter layers are layer-stacked and used for the further procedures.

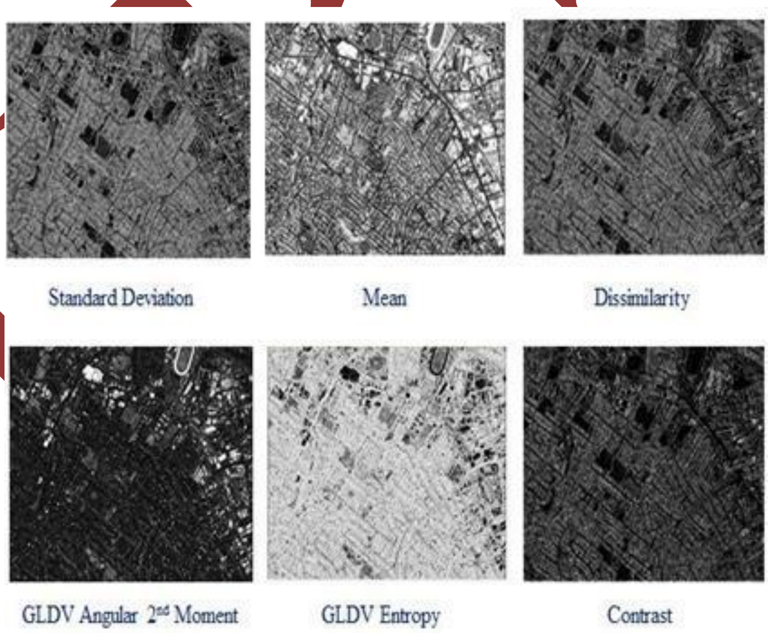

Figure 5. Selected Texture Layers.

*C. **Separability Analysis***

The separabilty analysis determines that how far each class varies from each other. This difference helps us to understand the distinguishable nature of each class in the image. The separability matrix was computed using Jefferies Matusita distance computation.

Distance measure: Jefferies-Matusita
Using Layers: 1 2 3 4 5 6
Combination: 1 2 3 4 5 6
Taken 6 at a time

5x5_0_separability
Best Average Separability: 863.815

Signature name	Pure urban	Mixed urban	MU with med_size build	Slum	Urban with little veg	Urban with med_veg	Urban with dense veg	Vegetation
Pure urban	0	310.162	972.935	692.131	738.673	727.588	968.615	1406.36
Mixed urban	310.162	0	902.328	713.926	812.367	594.934	881.014	1390.65
Mixed urban with medium size buildi	972.935	902.328	0	1002.24	810.968	531.816	625.209	1250
Slum	692.131	713.926	1002.24	0	819.312	818.911	929.019	1387.27
Urban with little veg	738.673	812.367	810.968	819.312	0	502.276	555.245	1288.45
Urban with medium veg	727.588	594.934	531.816	818.911	502.276	0	498.245	1291.11
Urban with dense veg	968.615	881.014	625.209	929.019	555.245	498.245	0	1111.07
Vegetation	1406.36	1390.65	1250	1387.27	1288.45	1291.11	1111.07	0

5x5_45_separability
Best Average Separability: 805.18

Signature name	Pure urban	Mixed urban	MU with med_size build	Slum	Urban with little veg	Urban with med_veg	Urban with dense veg	Vegetation
Pure urban	0	400.092	982.708	855.321	855.321	753.451	973.436	1403.84
Mixed urban	400.091	0	896.791	590.412	590.412	553.851	791.448	1384.88
Mixed urban with medium size buildi	982.708	896.791	0	845.677	845.677	570.475	661.053	1239.63
Slum	855.321	590.412	845.677	0	0	[illegible]	511.989	1268.98
Urban with little veg	855.321	590.412	845.677	0	0	[illegible]	511.989	1268.98
Urban with medium veg	753.451	553.851	570.475	480.887	480.887	0	646.442	1267.7
Urban with dense veg	973.436	791.448	661.053	511.989	511.989	[illegible]	0	1313.05
Vegetation	1403.84	1384.88	1239.63	1268.98	1268.98	1267.7	1313.05	0

5x5_90_separability
Best Average Separability: 843.884

Signature name	Pure urban	Mixed urban	MU with med_size build	Slum	Urban with little veg	Urban with med_veg	Urban with dense veg	Vegetation
Pure urban	0	371.404	975.178	636.679	[illegible]	[illegible]	905.032	1405.75
Mixed urban	371.404	0	840.38	659.134	515.173	[illegible]	780.69	1392.96
Mixed urban with medium size buildi	975.178	840.38	0	981.791	748.081	[illegible]	616.24	1271.81
Slum	636.679	659.134	981.791	0	850.902	[illegible]	951.016	1386.64
Urban with little veg	685.884	515.173	748.081	850.902	0	389.62	543.284	1295.94
Urban with medium veg	747.488	538.224	589.985	825.022	389.62	0	439.948	1304.25
Urban with dense veg	905.032	780.69	616.24	[illegible]	543.284	439.948	0	1380.46
Vegetation	1405.75	1392.96	1271.81	[illegible]	1295.94	1304.25	[illegible]	0

5x5_135_separability
Best Average Separability:823.856

Signature name	Pure urban	Mixed urban	MU with med_size build	Slum	Urban with little veg	Urban with med_veg	Urban with dense veg	Vegetation
Pure urban	0	489.764	[illegible]	614.738	658.1	713.427	[illegible]	1399.43
Mixed urban	489.764	0	[illegible]	615.732	537.344	481.121	[illegible]	1388.33
Mixed urban with medium size buildi	912.921	848.46	0	969.75	[illegible]	590.248	[illegible]	1225.89
Slum	614.738	615.732	[illegible]	0	[illegible]	745.152	894.224	1384.48
Urban with little veg	658.1	537.344	[illegible]	[illegible]	0	395.402	513.132	1280.94
Urban with medium veg	713.427	481.121	[illegible]	[illegible]	[illegible]	0	408.006	1281.97
Urban with dense veg	889.282	756.96	[illegible]	[illegible]	[illegible]	[illegible]	0	1128.47
Vegetation	1399.43	1388.33	[illegible]	[illegible]	1280.94	[illegible]	1128.47	0

Figure 6. Separability Matrix by Jefferies-Matusita Algorithm.

The JM distance values range between 0 and 1414. The distances closer to the higher limit specifies that those classes are of high separability and ones which have the values closer to the lower limit indicate that the classes are inseparable. Fig. 6 shows the JM separability matrix.

D. Classification and Accuracy Assessment

The layer-stacked imagery is made to undergo unsupervised classification by K-means algorithm. Based on the texture parameters, the image was classified as Roads, Trees, Concrete Buildings, Red-tiled Buildings, Barren Land and Wooden Buildings. The classified imagery is shown in Fig. 7.

The accuracy assessment was carried out for the classified imagery and it was examined that 88% accuracy was obtained.

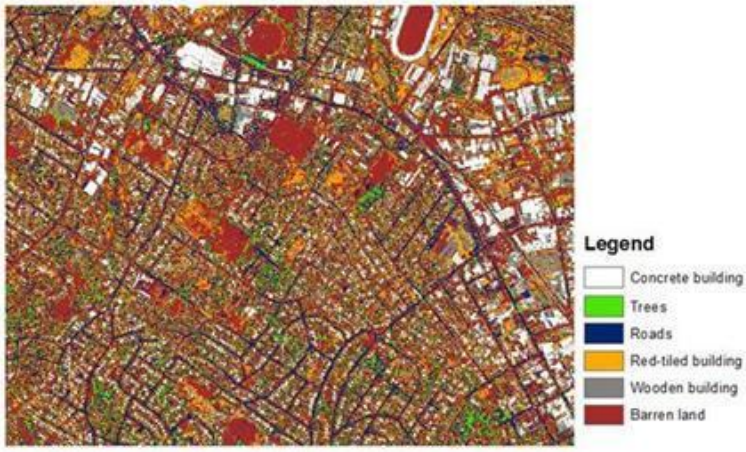

Figure 7. Separability Matrix by Jefferies-Matusita Algorithm.

CONCLUSION

Texture analysis over an urban area was found to be of good advantage in extraction of urban features. 88% accuracy which was obtained has proved that texture is a good parameter for classifying urban features in high resolution imagery. The separability between the different classes proved to be of good significance in order to distinguish the different urban and sub-urban classes. Incorporating the spatial relationships in the classification of images along with the spectral relationships brings out best classification results. The statistically chosen six parameters have also proved valid structurally too.

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