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Haralick Parameters for Texture feature Extraction

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Abstract— Texture, the pattern of information or arrangement of the structure found in an image, is an important feature of many image types. In a general sense, texture refers to surface characteristics and appearance of an object given by the size, shape, density, arrangement, proportion of its elementary parts. Due to the signification of texture information, texture feature extraction is a key function in various image processing applications, remote sensing and content based image retrieval. Texture features can be extracted in several methods, using statistical, structural, model-based and transform information, in which the most common way is using the Gray Level Co-occurrence Matrix (GLCM). GLCM contains the second-order statistical information of spatial relationship of pixels of an image. From GLCM, many useful textural properties can be calculated to expose details about the image content.

Keywords: *Gray Level Co-occurrence Matrix, Angular Second Moment, Inverse Difference Moment*

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I. INTRODUCTION

Texture classification is a fundamental problem in computer vision with a wide variety of Applications. Two fundamental issues in texture classification are how to characterize textures using derived features and how to define a robust distance/similarity measure between textures, which remain elusive despite considerable efforts in the literature. Because images of the same underlying texture can vary significantly, textural features must be invariant to (large) image variations and at the same time sensitive to intrinsic spatial structures that define textures.

Texture is an important feature of objects in an image. The perception of texture is believed to play an important role in the human visual system for recognition and interpretation. There has been a great interest in the development of texture based pattern recognition methods in many different areas, especially in the areas of industrial automation, remote sensing and medical diagnosis. Texture classification passes through the difficult step of texture representation or description. What is seen as a relatively easy task to the human observer becomes a difficult challenge when the analysis is made by a computational algorithm. How can we copy the human brain in its capability to analyze, classify and recognize textures? Putting aside these questions about human brain workings, and focusing mainly on the necessity of how to describe a texture from its content, different approaches and models have been proposed.

The extraction of texture features from high resolution remote sensing imagery provides a complementary source of data for those applications in which the spectral information is not sufficient for identification or classification of spectrally heterogeneous landscape units. However, there is a wide range of texture analysis techniques that are used with different criteria for feature extraction: statistical methods (grey level co-occurrence matrix, semivariogram analysis); filter techniques (energy filters, Gabor filters); or the most recent techniques based on wavelet decomposition. The combination of parameters that optimize a method for am specific application should be decided when these techniques are used. These parameters include the neighborhood size, the distance between pixels, the type of filter or mother wavelet used, the frequency or the standard deviation used to create the Gabor filters, etc. The combination of parameters and the texture method used is expected to be key in the success and efficiency of these techniques for a particular application.

Multispectral information provided by airborne and satellite sensors are successfully used for creating and updating cartography for forest and agriculture uses, as well as for monitoring urban sprawl. This information is valuable as a complement to the field data and the more traditional manual interpretation of aerial photographs, allowing for an increase in the efficiency of the processes by partially automatizing certain tasks, thus reducing costs of field data collection and improving the updating frequency due to the regularity of quality imagery data.

Texture is an innate property of virtually all surfaces the grain of wood, the weave of a fabric, the pattern of crops in a field, etc. It contains important information about the structural arrangement of surfaces and their relationship to the surrounding environment. Although it is quite easy for human observers to recognize and describe in empirical terms, texture has been extremely refractory to precise definition and to analysis by digital computers. Since the textural properties of images appear to carry useful information for discrimination purposes, it is important to develop features for texture. We present in this paper a computationally quick procedure for extracting textural features of images and discuss the usefulness of these features for discriminating between different kinds of image data.

Our initial perspective of texture and tone is based on the concept that texture and tone bear an inextricable relationship to one another. Tone and texture are always present in an image, although one property can dominate the other at times. The basic intuitively perceived relationships between tone and texture are the following. When a small-area patch of an image has little variation-i.e., little variation of features of discrete gray tone-the dominant property of that area is tone. When a small-area patch has a wide variation of features of discrete gray tone, the dominant property of that area is texture. Crucial to this distinction are the size of the small-area patch, the relative sizes of the discrete features, and the number of distinguishable discrete features.

As the number of distinguishable tonal discrete features decreases, the tonal properties will predominate.
In fact, when the small-area patch is only the size of one resolution cell, so that there is only one discrete feature, the only property present is tone. As the number of distinguishable features of discrete gray tone increases within the small-area patch, the texture property will dominate.

One important property of tone-texture is the spatial pattern of the resolution cells composing each discrete tonal feature. When there is no spatial pattern and the gray-tone variation between features is wide, a fine texture results. As the spatial pattern becomes more definite and involves more and more resolution cells, a coarser texture results.The preceding description of texture is, of course, a gross simplification and idealization of what actually occurs. Discrete tonal features are really quite fuzzy in that they do not necessarily stand out as entities by themselves. Therefore the texture analysis we suggest is concerned with more general or macroscopic concepts than discrete tonal features.

II. Extraction of GLCM

A GLCM is a matrix where the number of rows and columns is equal to the number of gray levels, G, in the image. The matrix element P (i, j | Δx, Δy) is the relative frequency with which two pixels, separated by a pixel distance (Δx, Δy), occur within a given neighborhood, one with intensity 'i' and the other with intensity 'j'. The matrix element P (i, j | d, θ) contains the second order statistical probability values for changes between gray levels 'i' and 'j' at a particular displacement distance d and at a particular angle (θ). Using a large number of intensity levels G implies storing a lot of temporary data, i.e. a G × G matrix for each combination of (Δx, Δy) or (d, θ). Due to their large dimensionality, the GLCM's are very sensitive to the size of the texture samples on which they are estimated. Thus, the number of gray levels is often reduced. GLCM matrix formulation can be explained with the example illustrated in fig 2.1 for four different gray levels. Here one pixel offset is used (a reference pixel and its immediate neighbour). If the window is large enough, using a larger offset is possible. The top left cell will be filled with the number of times the combination 0,0 occurs, i.e. how many time within the image area a pixel with grey level 0 (neighbour pixel) falls to the right of another pixel with grey level 0(reference pixel).

neighbour pixel value ---> ref pixel value:	0	1	2	3
0	0,0	0,1	0,2	0,3
1	1,0	1,1	1,2	1,3
2	2,0	2,1	2,2	2,3
3	3,0	3,1	3,2	3,3

III. EXTRACTION OF TEXTURE FEATURES OF IMAGE

Gray Level Co-Occurrence Matrix (GLCM) has proved to be a popular statistical method of extracting textural feature from images. According to co-occurrence matrix, Haralick defines fourteen textural features measured from the probability matrix to extract the characteristics of texture statistics of remote sensing images. In this paper various important features, namely Angular Second Moment (energy), (inertia moment), Correlation, Entropy, Inverse

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Difference Moment, Contrast, Homogeneity, Variance, Sum Average, Sum Variance, Sum Entropy, Sum Of Squres Variance, Diffrence Variance, Diffrence Entropy, Information Correlation are selected for implementation using MATLAB

1. **Angular second moment (ASM):**

The ASM is known as uniformity or energy. It measures the uniformity of an image.
When pixels are very similar, the ASM value will be large.

$$f_1 = \sum_{i=0}^{N_g-1} \sum_{j=0}^{N_g-1} p_{d,\theta}(i,j)^2$$

2. **Contrast:**

Contrast is a measure of intensity or gray-level variations between the reference pixel and its neighbor. In the visual perception of the real world, contrast is determined by the difference in the color and brightness of the object and other objects within the of
same field of view.

$$f_2 = \sum_{n=0}^{N_g-1} n^2 \left\{ \sum_{i=0}^{N_g-1} \sum_{j=0}^{N_g-1} p_{d,\theta}(i,j) \right\} \text{, where } n = |i-j|$$

When i and j are equal, the cell is on the diagonal and i- j = 0. These values represent pixels entirely similar to their neighbor, so they are given a weight of 0. If i and j differ by 1, there is a small contrast, and the weight is 1. If i and j differ by 2, the contrast is increasing and the weight is 4. The weights continue to increase exponentially as (i,j) increases.

3. **Entropy:**

Entropy is a difficult term to define. The concept comes from thermodynamics; it refers to the quantity of energy that is permanently lost to heat every time a reaction or a physical transformation occurs. Entropy cannot be recovered to do useful work. Because of this, the term can be understood as amount of irremediable chaos or disorder. The equation of entropy is:

$$f_3 = \sum_{i=0}^{N_g-1} \sum_{j=0}^{N_g-1} p_{d,\theta}(i,j) log\left(p_{d,\theta}(i,j)\right)$$

4. **Variance:**

Variance is a measure of the dispersion of the values around the mean of combinations of reference and neighbor pixels.

$$f_4 = \sum_{i=0}^{N_g-1} \sum_{j=0}^{N_g-1} (i-\mu)^2 p_{d,\theta}(i,j)$$

5. **Inverse Difference Moment (IDM):**

IDM is usually called homogeneity that measures the local homogeneity of an image. IDM feature obtains the measures of the closeness of the distribution of the GLCM elements to the GLCM diagonal.

$$f_6 = \sum_{i=0}^{N_g-1} \sum_{j=0}^{N_g-1} \frac{1}{1+(i-j)^2} p_{d,\theta}(i,j)$$

IDM weight value is the inverse of the Contrast weight, with weights decreasing exponentially away from the diagonal.

6. **Correlation:**

Correlation feature shows the linear dependency of gray level values in the co-occurrence matrix. It presents how a reference pixel is related to its neighbor, 0 is uncorrelated, 1 perfectly correlated.

$$f_5 = \sum_{i=0}^{N_g-1} \sum_{j=0}^{N_g-1} p_{d,\theta}(i,j) \frac{(i-\mu_x)(j-\mu_y)}{\sigma_x \sigma_y}$$

7. **Sum Average:**

$$f_7 = \sum_{i=0}^{2(N_g-1)} i.p_{x+y}(i)$$

Where,

$$p_{x+y}(k) = \sum_{i=0}^{N_g-1} \sum_{j=0}^{N_g-1} p_{d,\theta}(i,j) \quad ,k = i+j = \{0,1,2,...,2(N_g-1)\}$$

8. **Sum Variance:**

$$f_8 = \sum_{i=0}^{2(N_g-1)} (i-f_7)^2 p_{x+y}(i)$$

9. **Sum Entropy:**

$$f_9 = -\sum_{i=0}^{2(N_g-1)} p_{x+y}(i) log p_{x+y}(i)$$

10. **Difference Variance:**

$$f_{10} = \sum_{i=0}^{N_g-1} \left(i - f'_{10}\right)^2 p_{x-y}(i)$$

Where,

$$p_{x-y}(k) = \sum_{i=0}^{N_g-1} \sum_{j=0}^{N_g-1} p_{d,\theta}(i,j) \quad ,k = |i-j| = \{0,1,2,...,(N_g-1)\}$$

11. **Difference Entropy:**

$$f_{11} = -\sum_{i=0}^{N_g-1} p_{(x-y)}(i) log p_{x-y}(i)$$

12. **Homogeneity:**

Homogeneity measures the similarity of pixels. A diagonal gray level co-occurrence matrix gives homogeneity of 1. It becomes large if local textures only have minimal changes.

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$$Homogeneity = \sum_{i=1}^{N_g}\sum_{j=1}^{N_g}\frac{P_d(i,j)}{1+|i-j|}$$

13. Energy:

Energy also means uniformity, or angular second moment (ASM). The more homogeneous the image is, the larger the value. When energy equals to 1, the image is believed to be a constant image.

$$Energy = \sum_{i=1}^{N_g}\sum_{j=1}^{N_g}P_d^2(i,j)$$

IV. RESULTS & OBSERVATION

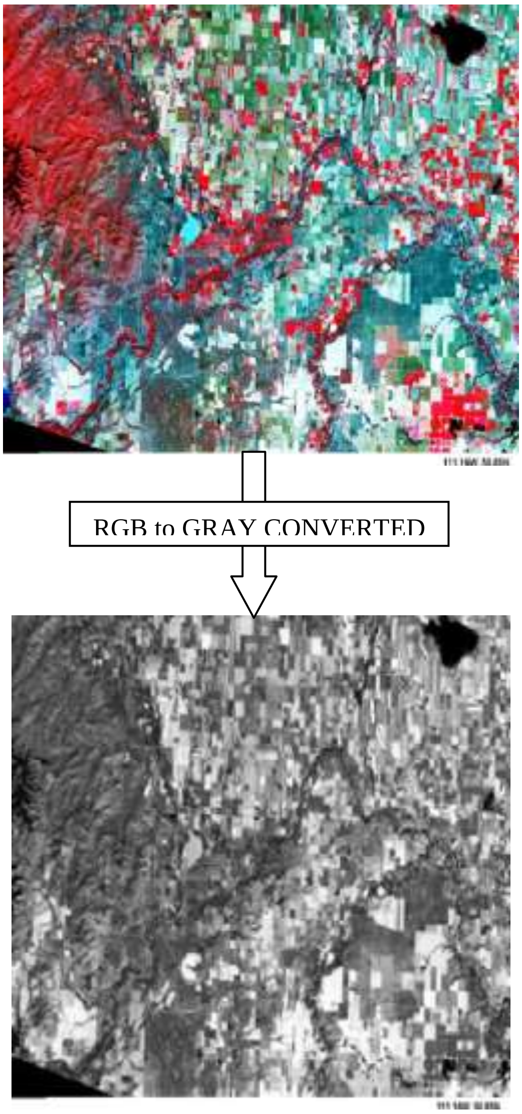

Fig 4.1. Input image & Converted output sample Image

4.2. Grey Level Co-occurrence Matrix

$$\begin{pmatrix} 817 & 111 & 32 & 5 & 1 & 1 & 0 & 0 \\ 82 & 689 & 902 & 197 & 60 & 22 & 10 & 2 \\ 19 & 846 & 8683 & 3765 & 750 & 203 & 71 & 29 \\ 5 & 184 & 3638 & 8044 & 3087 & 828 & 263 & 47 \\ 4 & 49 & 756 & 2970 & 4753 & 2083 & 619 & 121 \\ 1 & 24 & 248 & 805 & 2038 & 3488 & 1332 & 226 \\ 0 & 14 & 60 & 283 & 611 & 1364 & 2815 & 559 \\ 0 & 4 & 11 & 26 & 110 & 218 & 608 & 5687 \end{pmatrix}$$

Texture Features Extraction for satellite Image

		IMAGE SIZE				
Sr. No.	TEXTURE FEATURES PARAMETERS	256X256	128X128	64X64	256X128	128X64
1.	Correlation	0.8389	0.7969	0.7716	0.7812	0.7520
2.	Contrast	0.95642	1.0527	0.9998	1.1977	1.1589
3.	Energy	0.0657	0.0631	0.0644	0.0593	0.0611
4.	Homogeneity	0.7478	0.7157	0.7061	0.7016	0.6911
5.	Variances	3.3888e+006	1.9907e+005	1.2579e+004	7.3350e+005	4.6918e+004
6.	Entropy	3.0701	3.0712	3.0040	3.1397	3.0638
7.	Sum Average	9.5466	9.5495	9.5513	9.5547	9.5601
8.	Sum of Variance	61.4200	60.5939	59.8330	60.9084	60.4643
9.	Sum of Entropy	2.4403	2.3884	2.3344	2.4023	2.3293
10.	Sum of square Variance	25.5781	25.1863	24.7405	25.3598	24.9330
11.	Difference Variance	0.0425	0.0387	0.0394	0.0363	0.0363
12.	Difference Entropy	1.0142	1.0545	1.0283	1.1033	1.0876
13.	Angular Second Moment	0.0657	0.0613	0.0644	0.0593	0.0611
14.	Inverse Difference Moment	0.7333	0.6986	0.6903	0.6814	0.6710
15.	Information Measures of Correlation	0.8498	0.8074	0.7874	0.7952	0.7720

As the size of the image for which Texture features are extracted increases the values of all the features are also increased proportionally. So the optimum size to be used for extraction is 128x128 for better resolution and minimum loss of information.

V. CONCLUSION

The Gray Level Co-ocurrence Matrix (GLCM) method is used for extracting various Statistical Texture Parameters i.e Angular Second Moment (energy), (inertia moment), Correlation, Entropy, Inverse Difference Moment, Contrast, Homogeneity, Variance, Sum Average, Sum Variance, Sum

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Entropy, Sum Of Squres Variance, Diffrence Variance, Diffrence Entropy, Information Correlation are selected for implementation using MATLAB. By extracting the features of an image by GLCM approach, the image compression time can be greatly reduced in the process of converting RGB to Gray level image when compared to other Techniques.

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