

Image Analysis Technique to Enhance Low Contrast Regions of Regenerated Satellite Image Texture

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Abstract— Image Enhancement refers to attenuation or sharpening of image features such as boundaries, edges or contrast to make the processed image more useful for analysis. It is one of the most important and vital techniques in the field of image processing. The aim of image enhancement is to improve the visual appearances of images or to provide a better transform representation for future automated image processing. Many images like medical images, satellite images, aerial images and even real life photographs suffer from poor contrast and noise. It is necessary to enhance the contrast and remove the noise to increase image quality. In this regard, this paper presents an image analysis technique to enhance the low contrast regions in any satellite image. Four different set of parameters (Contrast, Correlation, Energy and Homogeneity) are studied and analyzed. While analyzing and comparing the original satellite image and the processed image, the results have shown significant improvements especially under low contrast regions of satellite image.

Keywords— Satellite image, low contrast region, colors gradient co-occurrence matrix, homogeneity, histogram, energy, correlation.

I. INTRODUCTION

Image Enhancement transforms images to provide better representation of the hidden details. It is a vital tool for researchers in a wide variety of fields including (but not limited to) remote sensing, forensics, medical imaging, atmospheric sciences, art studies, etc. Textures of an image are very essential for the analysis of the image. It gives information about the spatial arrangement of the intensities in the region of interest. Texture analysis is frequently used in image processing techniques especially while classifying their methods. However, there is no universally recognized definition of texture. The texture can be assumed as comprehensive pattern arising from the recurrence of confined sub-patterns or as a region where a set of the confinement properties are either constant or slowly varying [1-3]. Several different techniques for organizing texture have been developed that are based on their characteristics. Some of the important methods that are reported by several researchers include methods like Scale-Invariant Feature transform (SIFT), Speeded Up Robust Feature (SURF), Histogram of Oriented Gradients (HOG), Gradient Location and Orientation Histogram (GLOH), Region Covariance Matrix (RCM), Edgelet, Gray Level Co-occurrence Matrix (GLCM), local Binary Patterns (LBP), Color Correlograms (CCG), Color Coherence Vectors (CCV), Color Indexing, Steerable filters and Gabor filters [4-17]. These techniques may be useful for enhancing satellite images. Image Enhancement techniques are used for making satellite images more informative and so that it is readily interpreted by human eye [18]. Enhancement techniques aim to alter the appearance of an image in such a way that the information contained in that image is more readily interpreted visually. However, to enhance specifically the low contrast areas, all these methods referred are not

significant in use. To enhance the specific regions of low contrast in satellite images, the method must be designed to handle the levels of background energy. Due to large variations in spectral response, no standard radiometric correction could optimally account for and display the optimum brightness range and contrast for all targets [19]. Thus, for each application and each image, a custom adjustment of the range and distribution of brightness values is usually necessary.

Recently, the addition of color information has been evaluated for co-occurrence matrices [20]. A major difficulty encountered when analyzing texture is that results strongly depend on image resolution and scale, an effect that is especially problematic with edge-based approaches. Hence, there is a necessity to improve the visual appearance of the image using automated image processing techniques that can perform analysis, detection, segmentation, recognition, etc. [21]. Moreover, this technique should be capable of processing background information that is essential to understand the object's behaviour without requiring expensive human visual inspection. However, there are occasions when we cannot clearly extract objects from the dark background due to low contrast.

In this paper, a novel application for texture analysis using the Gray Level Co-occurrence Matrix (GLCM) is discussed. The proposed technique in this paper verified that the information contained in the low contrast regions can be enhanced considerably by the proposed method.

II. METHODOLOGY

The image texture presents visual patterns that have properties of homogeneity that do not result from the presence of only a single color or intensity. Texture determination is ideally suitable to retrieve the satellite and medical images.

The correlation function of any image is used to quantify the regularity and the coarseness of a texture. For any image I , The co-occurrence function $\rho(x, y)$ function can be defined as

$$\rho(x, y) = \frac{\sum_{u=0}^N \sum_{v=0}^N I(u, v) I(u+x, (v+y))}{\sum_{u=0}^N \sum_{v=0}^N I^2(u, v)} \quad (i)$$

A texture is characterized by a set of values called energy, contrast and homogeneity. The following formulas are used to calculate the features and are shown in equations (ii), (iii) and (iv) respectively [22].

$$\text{Energy} = \sum_i \sum_j P_d^2(i, j) \quad (ii)$$

$$\text{Contrast} = \sum_i \sum_j P_d(i, j) \log P_d(i, j) \quad (iii)$$

$$\text{Homogeneity} = \sum_i \sum_j \frac{P_d(i, j)}{1+|i-j|} \quad (iv)$$

The performance of the texture features are tested using input image as shown in Fig. 1 that acts as a test image for the experiment in our work.

In this work, a very simple algorithm has been developed to identify the minute details that cannot be seen in the original input satellite images from our naked eyes. The process flow is as shown in Fig. 2. Four different image features (Contrast, Correlation, Energy and Homogeneity) are extracted from the selected 1-dimensional image for three color channels, i.e., red, green and blue. The above four parameters are independent of image size and orientation. It is one of the most straight forward features utilized by humans for visual recognition and discrimination. The algorithm will only identify the masses with some distinguishing features to ease further investigation.

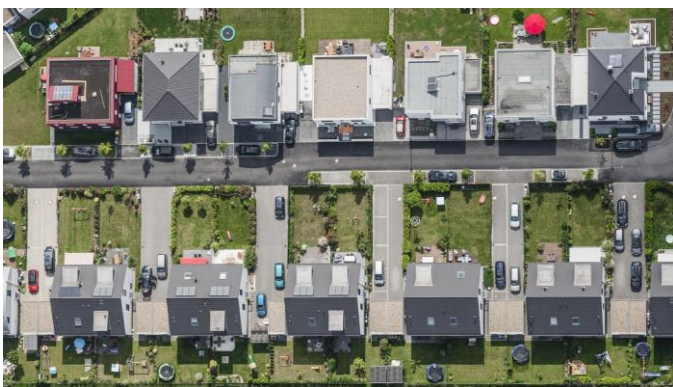


Fig. 1. Input image taken for the proposed work.

The input image used in this experiment is taken from the internet source. The original image has been resized and reduced so that every image is 1400 pixels x 788 pixels. All images are held as 8-bit gray level scale images with 256 different gray levels (0-255) and physically in .jpeg format. The image is separated into 3 basic color components i.e.,

Red, Green and blue, thus, generating 3 new images having red, green and blue channels respectively.

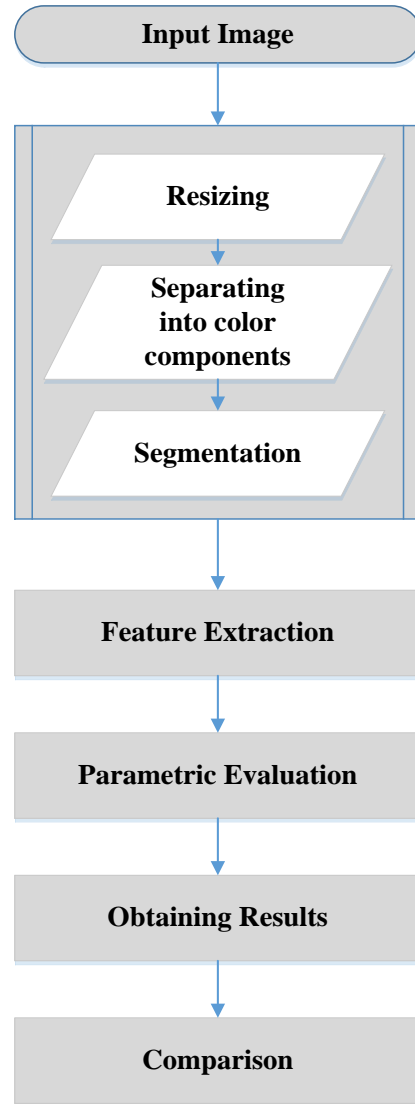


Fig. 2. Flow chart showing procedural steps.

For each color component image we segmented the entire image into 8 x 8 blocks. To each block of Red component image, Gray Level Co-occurrence Matrix (GLCM) is applied and the image having red channel is finally reconstructed. The matrix of newly reconstructed image is multiplied with the matrix of input image so as to get an image in which the pixels having low contrast are highlighted. The four features (Contrast, Correlation, Energy and Homogeneity) are obtained for Red component of image. The same process is done for Green and Blue components of image. The processed image is the resultant of the sum of individual primary color component images. Mean and standard deviation are calculated for the proposed features in overall processed image.

III. RESULTS & DISCUSSIONS

This experiment is done to evaluate four different features

which are contrast, energy, homogeneity and correlation from the color components of an input image. Table I shows the mean and standard deviation (S.D.) obtained from the study of input image, while Table II shows the values for processed image related to the features evaluated.

TABLE I. Mean and standard deviation calculated for the proposed features in input image.

Parameters	Mean for individual color components			Standard Deviation for individual color components		
	Red	Green	Blue	Red	Green	Blue
Contrast	122.97	124.66	110.77	5.8624	5.5214	6.4852
Correlation	122.97	124.66	110.77	5.8624	5.5214	6.4852
Energy	122.97	124.66	110.77	5.8624	5.5214	6.4852
Homogeneity	122.97	124.66	110.77	5.8624	5.5214	6.4852

TABLE II. Mean and standard deviation calculated for the proposed features in processed image.

Parameters	Mean for individual color components			Standard Deviation for individual color components		
	Red	Green	Blue	Red	Green	Blue
Contrast	0.678	0.662	0.668	0.315	0.315	0.315
Correlation	NaN	NaN	NaN	NaN	NaN	NaN
Energy	0.576	0.579	0.570	0.019	0.019	0.019
Homogeneity	0.827	0.828	0.823	0.013	0.013	0.013

It is important to mention that the processed image is the resultant of the sum of individual primary color component images. Mathematically,

$$I=I(R) + I(G) + I(B) \quad (v)$$

where, I is the resultant Image, I(R) is the red component image, I(G) is the green component image and I(B) is the blue component image.

Statistically, it denotes the joint probability of the intensities of the three color channels. Hence, the major statistical data that are extracted are histogram mean, standard deviation, and median for each color channel i.e. Red, Green, and Blue. Fig. 3 shows the resultant image obtained after processing.



Fig. 3. Processed image obtained after experiment.

Finally, the histograms for color components of input and processed output image are studied and compared. Fig. 4

shows the histogram for input image while Fig. 5 shows the obtained histograms of the processed image. Fig. 5(a) shows the contrast counts with respect to the intensity of the processed resultant image. Similarly, for resultant image, Fig. 5(b), Fig. 5(c) and Fig. 5(d) shows the counts for correlation, Energy and homogeneity evaluated after experiment.

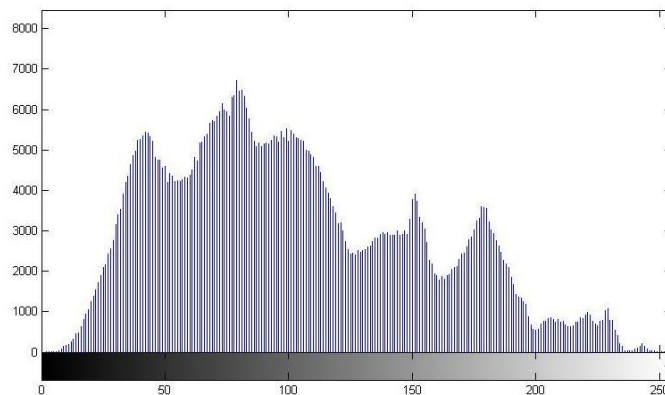


Fig. 4. Histogram obtained for input satellite image.

From Fig. 5, it is clear that contrast for low intensities are higher and it decreases exponentially with increase in intensity of an image. Hence, it is also verified from the resultant image that textures of low intensities shows better information than the input original image. However, correlation is constant throughout the image, while the energy and homogeneity shows random changes with change in intensities. Overall, for low intense textures (dark areas) response is much better than the input image.

IV. CONCLUSION & FUTURE SCOPE

This paper describes the enhancement technique for low contrast portions of a satellite image. Colored picture has been taken as input image and the enhancement of low contrast portions has been observed after processing of input image. Gray Level Co-occurrence Matrix (GLCM) based technique is applied and results are evaluated after decomposition of the colored image into their primary components. Parameters such as, contrast, energy, correlation and homogeneity are evaluated and these parameters are compared for both input image and processed image. Histograms revealed that these parameters help in enhancing the low contrast regions of the input image.

The future scope will be to further enhance the proposed algorithm in order to study the texture pattern of diseases in dermatology images.

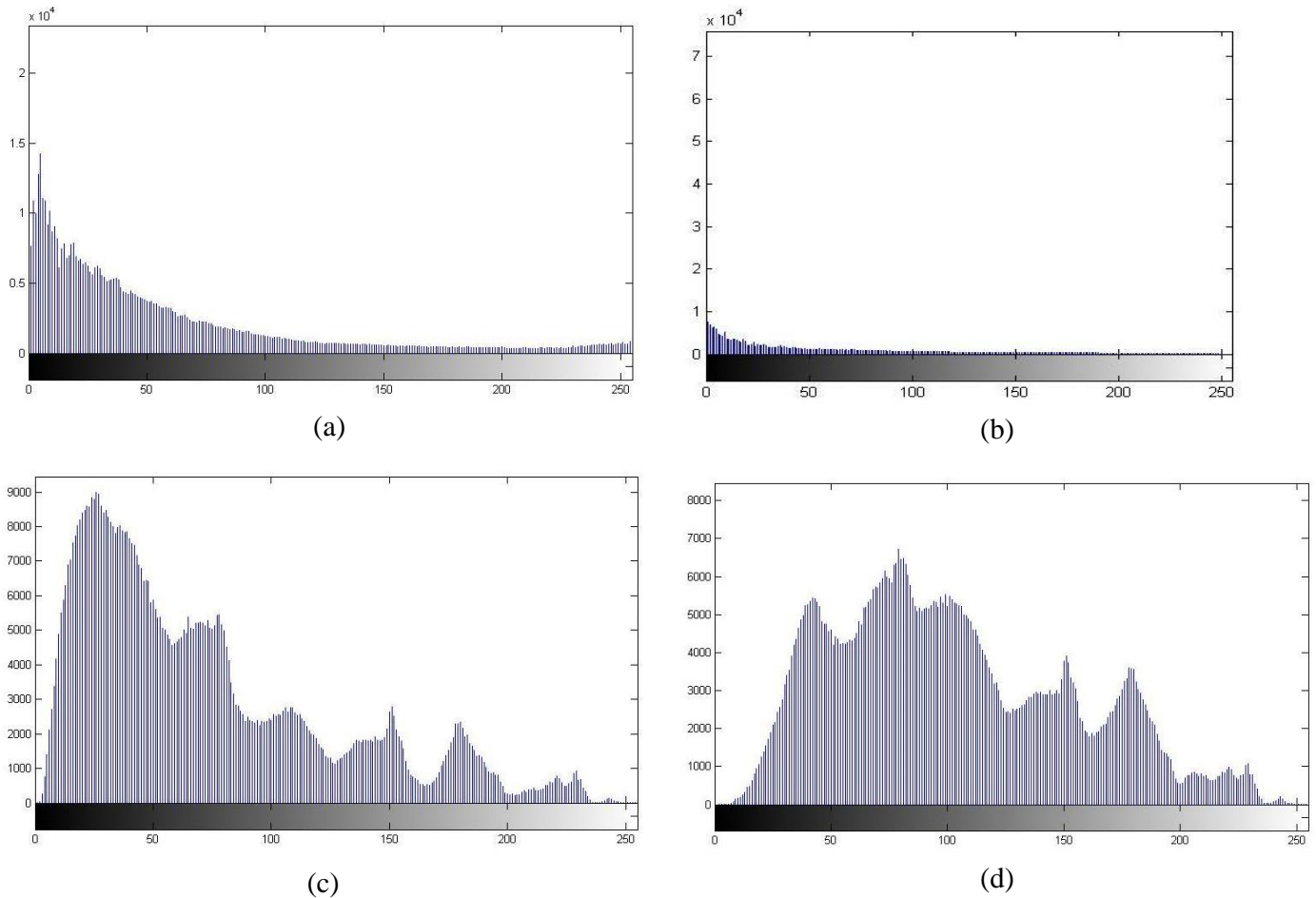


Fig. 5. Histograms obtained for processed satellite image.

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