Digital Trimulus Color Image Enhancing and Quantitative Information Measuring

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Abstract– **Target detection via digital image processing is crucial to biomedical diagnosis and homeland security. Both image contrast enhancement and image segmentation are among the most practical approaches of image processing. Under conditions of improper illumination and unpleasant disturbances, adaptive image enhancement can be conducted, which adapts to the intensity distribution within an image. In trimulus color systems, each of three color components takes an independent role along with image processing procedures. To evaluate actual effects of image enhancement, some quantity measures should be taken into account instead of on a basis of intuition exclusively. In this article, new quantitative measures for trimulus color systems are proposed instead of the existing gray level ones so as to evaluate color image enhancement. Rather than the gray level measures, the corresponding three color component energy, entropy and relative entropy are employed to measure the effectiveness of adaptive image enhancement techniques. Images are selected such that the obscure essential objects will be identified within the image scope.**

Key-Words: - **Image Enhancement, Trimulus Color, Adaptive Equalization, Entropy, Relative Entropy, Energy**

1 Introduction

In most cases, the image enhancement technology plays an important role in pattern recognition. Matrix functions of certain image correspond to the energy at each image pixel. Apart from the illumination conditions, quality of images is also affected by noises and environmental disturbances such as atmosphere pressure and temperature fluctuations. Thus, image enhancement is necessary. Image enhancement is a critical technique for different areas of pattern recognition such as biometric verification, medical diagnosis and face detection. However, under some unconstrained illumination conditions, unsuitable enhancement increases the detection failure rate by amplifying noises. As a result, approaches of contrast limited image enhancement via stretching histograms over a reasonable dynamic range and multi-scale adaptive histogram equalizations have been developed. An adaptive image enhancement algorithm is adapted to the image intensity distribution either globally or locally, subject to actual applications. Effective image contrast enhancement for medical diagnosis can also be achieved by including the basic human visual properties. By separating smooth and detail areas of an image, the algorithm treats them individually so as to avoid excessive enhancement of noises. Consequently, those original images will be enhanced to certain degree of satisfaction.

Arisen from gray level image histograms and the associated probability distribution function, grey level energy, discrete entropy and relative entropy, the corresponding terms can be extended to three color component image processing. To quantify the effects of image enhancement, quantify measures should be introduced. With literature surveys, there are some valuable results being shown. For example, the entropy of a fuzzy set is viewed as a global measure of the fuzziness of the fuzzy set while the energy of a fuzzy set is viewed as a local measure, where the trade relationship exists between the entropy of a fuzzy set and information energy. In another case, the concept of relative entropy is employed to be the fitness function of genetic algorithms in optimal segmentation approaches. As a result, the concepts of gray level quantity measures of energy, discrete entropy and relative entropy are expanded to the evaluation of the digital trimulus color enhancement, which have been proposed to measure effects of adaptive image enhancement techniques in this research [1-15].

Basically, the actual value of the histogram energy is different from intuition, that is, a simple image has more histogram energy than a complex image. On the other hand, the discrete entropy of color component images is a statistical measure of randomness that used to characterize the original images and enhanced images. The entropy of an event is the summation of all those possible outcomes, represented by the product of the probability of outcome times the log of the inverse of the probability. In addition, the measure of proximity between probability density functions of original images and enhanced images is described as the relative entropy. All the measures are proposed to further study the effects of image enhancement. At the same time, by comparing with the values of potential maximum energy and maximum discrete entropy using Principal of Maximum Entropy, the resulting enhancement for several different types of images can be investigated from another point of view. These measures in terms of three color components will quantify the role of image enhancement in practical implementations for a wide variety of applications, such as medical diagnosis decision making, biometric identification, national defense and space program. These methodologies can also be used for other signal and image processing technologies.

2 Image Enhancement via Adaptive Histogram Equalization

In this article, adaptive image contrast enhancement schemes based on the histogram equalization are conducted. The idea is similar to the processing of gray level images. That is, the image contrast enhancement can be achieved by means of histogram equalization algorithms. The same as gray level images, a trimulus color image can be separated into a number of small regions. Within each small region, the histogram is obtained under the contrast limit and then the exponential distribution is applied as a basis to create the contrast transform function. For any color component, the assignments of pixels in each small local region can be specified from the contrast transformation. Each color component mapping from each local histogram is then generated. In order to avoid the occurrence of boundary artifacts stem from different neighborhoods of small regions and to obtain an evenly distributed enhancement overall effect throughout the entire regions, bilinear interpolations between four different mappings are used together so that the contrast saturation problem is solved via contrast constraints, until results from the adaptive equalization are satisfactory. Consequently, excessive enhancement of noises will be avoided. This approach has been applied to a set of RGB images with certain critical objects to be identified, namely, the volcano crater image, giant panda picture on top of the tree. For these RGB images, the histogram of each color component (Red, Green and Blue) contains 256 bins and the percentage of counts for each bin over its total value will give rise to its probability distribution. The parameter for exponential functions, the factor for contrast limiting and weights for bilinear interpolation can be adjusted to achieve quality outcomes. From Fig. 1 to Fig. 4, several cases of original and enhanced color images are shown using the adaptive image enhancement methodology.

Fig. 1 Original Image of Volcano Crater

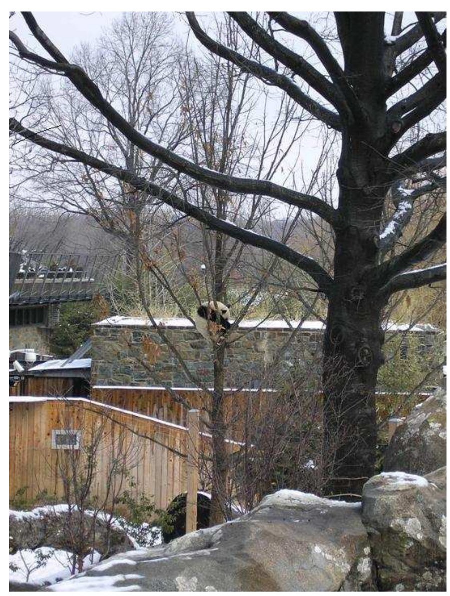

Fig. 2 Original Giant Panda Image at DC Zoo

Fig. 3 Enhanced Image of Volcano Crater

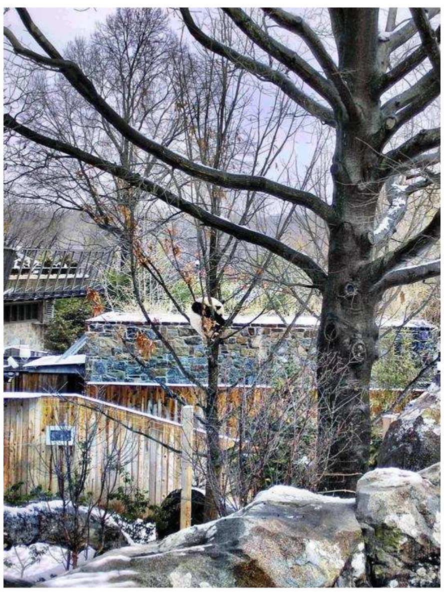

Fig. 4 Enhanced Giant Panda Image at DC Zoo

3 RGB Trimulus Color Model

In RGB color systems, each color appears as its primary spectral components (Red, Green and Blue) in the Cartesian coordinate system. All three intensity components (Red-Green-Blue) of the trimulus color systems can be computed and analyzed individually. In the color subspace, each color component is mapped into a cube in which RGB values are at three corners; black is at the origin and white is at the corner opposite to the origin; while other three colors (cyan, magenta, yellow) locate at three remaining corners. On the other hand, the gray scale color lies along with the diagonal line joining the black to white points. Each color is a vector on or inside the cube from the origin. The amounts of red, green and blue needed to form any particular color are referred to as trimulus values. The intensity component is the composite color image from 3D image planes.

4 Histogram and Probability Function

The histogram is used to display the brightness of each color component of RGB images, showing the occurrence of pixel counts for each of 256 intensity levels. Similar to that of gray level images, the occurrence of the trimulus color components is described as the co-occurrence matrices of relative frequencies as well. Classification is based on features being derived from co-occurrence matrices of images. The occurrence probability function of trimulus color components can be estimated from its histogram, which is formulated in (1), where p(k) is the probability distribution function and h(k) is the histogram function. In Figs. 5-8, histograms of original and enhanced images are plotted.

$$p(k)=\frac{h(k)}{\sum h(k)} \tag{1}$$

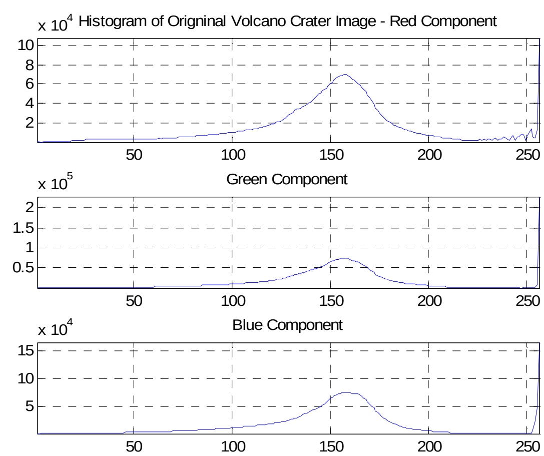

Fig. 5 Histogram of Volcano Crater Image

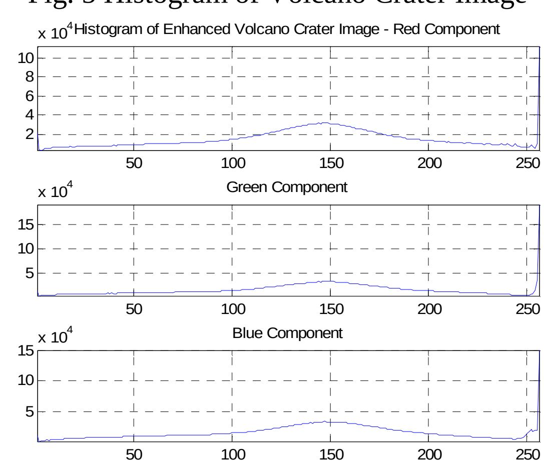

Fig. 6 Histogram of Enhanced Volcano Crater Image

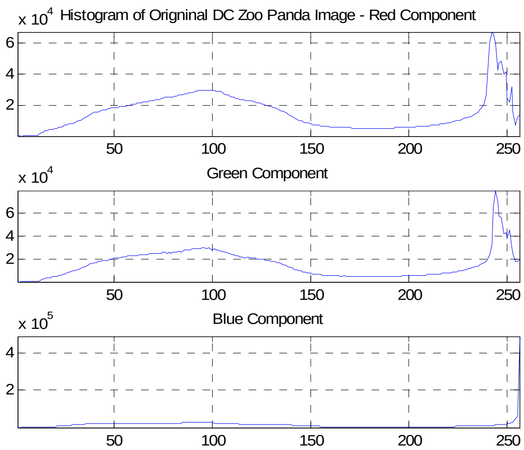

Fig. 7 Histogram Plot of Giant Panda Image

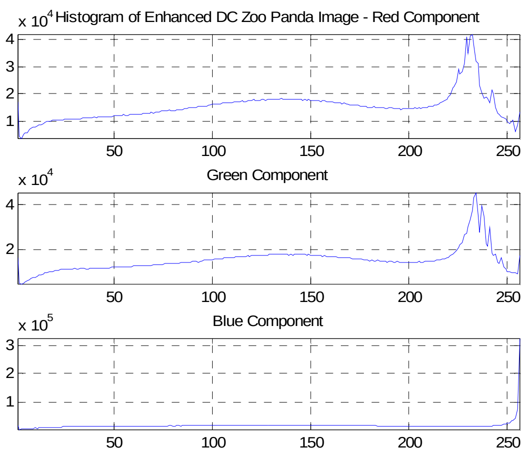

Fig. 8 Histogram Plot of Enhanced Giant Panda Image

5 Discrete Energy Analysis of Trimulus Color Components

The energy measure of three color component in trimulus systems indicates how the trimulus color components are distributed. The formulation is shown in (2), where E(x) represents the three color component energy with 256 bins and p(i) refers to the probability distribution functions under each color component, which contains the histogram counts. For a special case when an image has a constant value, the energy measure reaches its maximum value of 1, as shown in (3). An image with the larger energy can be compressed much easier than one with the smaller energy. The larger energy corresponds to a lower color component value and the smaller energy corresponds to a higher value.

$$E(x)=\sum_{i=1}^{k} p(i)^2 \quad (2)$$

$$\max\{E(x)\}=\max\{\sum_{i=1}^{k} p(i)^2\}=1 \quad (3)$$

Table 1. RGB Component Energy of Original & Enhanced Images

Original Image	Energy	Enhanced Image	Energy
Volcano Crater and Hikers Image			
Red	0.0102	Red	0.0055
Green	0.0136	Green	0.0071
Blue	0.0124	Blue	0.0064
Giant Panda Image at DC Zoo			
Red	0.0061	Red	0.0044
Green	0.0062	Green	0.0044
Blue	0.0199	Blue	0.0107

In Table 1, it can be seen that the enhanced images using the adaptive histogram equalization algorithms have the low levels of energy for each of three components to certain extent, which means enhanced images are relatively complex at all three cases, whose individual probability functions decrease through nonlinear transformation and interpolation.

6 Discrete Entropy Analysis

Entropy is the measure of the image information content, which can be interpreted as the average uncertainty of the information source. Discrete entropy is the summation of the products of the probability of outcome multiplied by the log of the inverse of probability of outcome, taking into considerations of all possible outcomes {1, 2, …, n} in the event $\{x_1, x_2, \ldots, x_n\}$, where n is the color component level; p is the probability distribution of each of the trimulus color components, considering all the histogram counts. Discrete entropy is formulated as (4-5).

$$H(x)=\sum_{i=1}^{k} p(i)\log_2 \frac{1}{p(i)} = -\sum_{i=1}^{k} p(i)\log_2 p(i) \quad (4)$$

$$\sum_{i=1}^{k} p(i)=1 \quad (5)$$

Discrete entropy is in fact a statistical measure of randomness. Maximal entropy occurs when all potential outcomes are equal. When the outcome is a certainty, minimal entropy occurs which is equal to zero. For image processing, the discrete entropy is a measure how many bits needed for coding the image data. Discrete entropy of different original images and enhanced images are shown in Table 2. It represents an average amount of information conveyed from each image. The results have shown that the entropy of the enhanced image is slightly higher using the adaptive histogram equalization algorithms and bilinear interpolation. From another aspect, it shows that the enhanced images are relatively complex. A relatively complex image has higher entropy than a relatively simple image. When the pixels in the image are distributed among more color levels, the values of the corresponding discrete entropy increase.

Table 2. RGB Component Entropy of Original & Enhanced Images

Original Image	Entropy	Enhanced Image	Entropy
Volcano Crater and Hikers Image			
Red	7.0977	Red	7.7817
Green	6.8195	Green	7.6712
Blue	6.8271	Blue	7.6894
Giant Panda Image at DC Zoo			
Red	7.6231	Red	7.9236
Green	7.6080	Green	7.9256
Blue	7.2472	Blue	7.6696

Principle of Maximum Entropy can be applied as well to analyze the potential of image enhancement and compression, assuming that mutually exclusive propositions have individual discrete probability distributions. The minimum information entropy of an image is equal to zero when one of the distributions is definitely true, representing the most informative distribution case. On the other hand, when the distribution is uniform, the maximum discrete entropy occurs with the discrete entropy value of $\log_2 n = 8$ bits (n=256). In this case, no proposition is superior to any other existing propositions, as a result, the least informative distribution occurs. The discrete entropy provides a numerical measure between zero and $\log_2 n$, from the most informative case to the totally uninformative case. All quantities of discrete entropy in these examples are within a range between 0 and 8, the latter of which is the maximum entropy possible.

7 Relative Entropy Analysis

Suppose two discrete probability distributions of the processing images have the probability functions of p and q. Relative entropy of p with respect to q is then defined as the summation of all possible states of the system, which is formulated as (6).

$$d=\sum_{i=1}^{k} p(i)\log_2 \frac{p(i)}{q(i)} \qquad (6)$$

Relative entropy is a convex function which is sometimes also referred to as the Kullback-Leibler distance. The effect of image enhancement can be evaluated by the measure of the relative entropy. In Table 3, the relative entropy of enhanced images with respect to original images is given.

Table 3. Relative Entropy of Enhanced w.r.t Original

Enhanced w.r.t. Original	Red	Green	Blue
Volcano Crater	0.3737	0.4857	0.5432
Giant Panda	0.4437	0.4668	0.2892

From Table 1 to Table 3, it has been shown that the color component energy, discrete entropy and relative entropy can be treated as quantity measures to indicate the quality of image enhancement. These quantity measures are useful to improve decision making in target detection.

8 Conclusions

RGB intensity components of the trimulus color systems have been used to determine the quantitative measures of image enhancement for some potential engineering applications. At first the adaptive image enhancement methodology is proposed and applied to processing of digital images with ambiguous objects, where the image contrast has been stretched to avoid feature ambiguity. To eliminate artifacts generated by noises throughout image enhancement, then the local adaptive histogram equalization is applied which is followed by interpolations so as to eliminate artificial boundaries. The enhancement effect is evaluated quantitatively using several quantity measures. Based on two groups of original and enhanced images with three color components, histograms and probability distributions are calculated. Therefore, the three color component quantities of the discrete energy, discrete entropy and relative entropy in the trimulus system are determined to evaluate the image enhancement. The results are also compared with those of the maximum energy and maximum entropy to examine the potential benefit using image enhancement schemes. The results are valuable for the key object identification in pattern recognition and decision making.

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