Practical Approaches on Enhancement and Segmentation of Trimulus Color Image with Information Theory Based Quantitative Measuring

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Abstract– Image enhancement and image clustering are two practical implementation approaches for pattern recognition with a variety of engineering applications. In most cases, the actual outcomes of some advanced image processing approaches will directly affect the decision making, such as in target detection and medical diagnosis. Among these approaches, image adaptive contrast stretching is a typical enhancement approach under conditions of improper illumination and unpleasant disturbances, which adapts to the intensity distribution of an image. K-means clustering is a typical segmentation approach to minimize the medium dispersing impact, which produces the distinctive clusters or layers for representing different components of the information being detected. 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 and image segmentation, quantitative measures should be taken into account rather than qualitative evaluations exclusively. In this article, quantitative measures for trimulus color systems are proposed instead of the existing gray level ones. Considering the gray level image measures, the corresponding true color RGB component energy, discrete entropy, relative entropy and mutual information are proposed to measure the effectiveness of color image enhancement and segmentation techniques.

Key-Words: - Image Enhancement, Image Segmentation, Trimulus Color, Energy, Discrete Entropy, Relative Entropy, Mutual Information, Contrast Stretching, K-means Clustering

1 Introduction

In most cases, image enhancing technologies play an important role in pattern recognition. Apart from the illumination conditions, the quality of images is also affected by noises and environmental disturbances like atmosphere pressure and temperature fluctuations. Image enhancement is thus critical for different areas of pattern recognition such as biometric verification, medical diagnosis and face detection. However, under 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 suitable dynamic range and multi-scale adaptive histogram equalizations have been developed. An adaptive algorithm is adapted to the image intensity distribution either globally or locally, subject to actual applications. By separating smooth and detail areas of an image, the algorithm treats them individually so as to avoid excessive enhancement of noises [1-5]. To minimize medium dispersing impact and to improve the decision making, image segmentation can be used to accumulate similar pixels together and form a set of coherent image layers from individual images. Matrix functions of images correspond to energy at each image pixel. Quality of images can be affected by atmosphere, water, pressure and temperature. Thus, image segmentation needs to be conducted, which is to categorize an image into various parts that have strong correlations with objects in order to reflect the actual information collected from the real world [6-11].

Arisen from gray level image histograms and the associated probability distribution functions, concepts of the energy, discrete entropy, relative entropy and mutual information can be extended to the trimulus color systems. To quantify image enhancement, some quantitative measures should be introduced. Form literature surveys, 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. The indices for image assessment can be proposed, based on notion of discrimination information between two fuzzy sets. Fuzzy C-Means algorithm initialized by fixed threshold clustering is presented to give more accurate results. Also the concept of relative entropy can be employed to be the fitness function of genetic algorithms in segmentation approaches [12-20]. In this study, the concepts of gray level quantity measures of energy, discrete entropy and relative entropy are extended to evaluate trimulus color image processing, which is proposed to evaluate image enhancement and segmentation techniques.

2 Image Enhancement Using Adaptive Histogram Equalization

The 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 a 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 overall enhancement 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, the Manhattan skyline of NYC. 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 lead 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. 6, several cases of original and enhanced color images are shown using the adaptive image enhancement methodology.

Fig. 1 Original Image of Volcano Crater

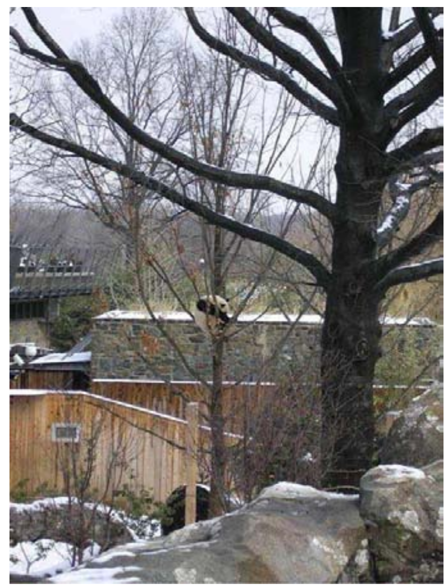

Fig. 2 Original Giant Panda Image at DC Zoo

Fig. 3 Original Manhattan Skyline Image

Fig. 4 Enhanced Image of Volcano Crater

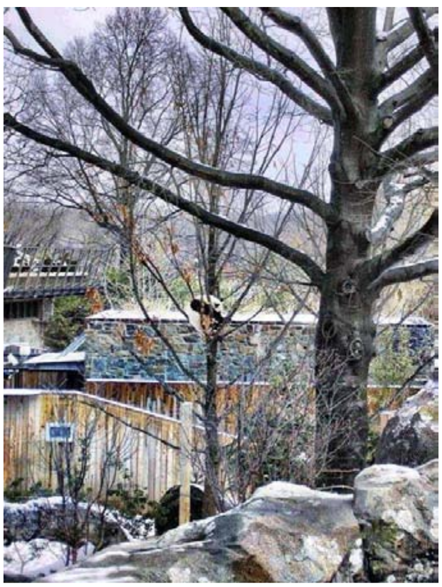

Fig. 5 Enhanced Giant Panda Image at DC Zoo

Fig. 6 Enhanced Manhattan Skyline Image

3 Image Segmentation Using K-Means Clustering

Image segmentation is an effective approach to identify object contents for data analysis. It requires the number of clusters be specified for partitioning. Centers of each cluster are defined at first which represent mean values of all those data points in that cluster. Three-layer color space is selected on a basis of the trimulus values into the K-means clustering algorithm. This color space consists of red-green chromaticity layer, blue-yellow chromaticity layer and luminosity layer. For all three layers, partition is conducted in such a way that objects within each cluster are as close as possible to each other, and vice versa, as far as possible from objects in other clusters.

A distance metric must be defined to quantify the relative distances of objects. Both the Euclidean and Mahalanobis distances are two typical distance metrics. The distance measure is based on spatial color histograms of the original images. The Mahalanobis metric distance has been used, which is formulated as:

$$d=(s-X_A)^T K_A^{-1} (s- X_A) \quad (1)$$

where X_A is the cluster center of any layer A, s is any point, d is the Mahalanobis distance, K_A^{-1} is inverse of covariance matrix.

Clustering is the approach that separates groups of objects. K-means clustering assigns each object a space location. K-means clustering classifies data sets through K number of clusters. Optimal statistical algorithms are generally selected for classification, which can be threshold based, region based, edge based or surface based. The distances of any data point to different cluster centers are compared. Images will then be decomposed into three recognized physical entities. Clustering depends on partition of images into a set of layers. To minimize the distortion, the K-means clustering algorithm iterates between the cluster point labeling and cluster center reassigning. Point labeling groups data points belong to the same cluster. At each iteration, points are reassigned to the winning center. Center reassigning recalculates centers for all clusters. This algorithm iterates between point labeling and center reassigning procedures until convergence to local stationary is made. In Figs. 7-10, original ocean floor images near the Maui Island and all three clusters after K-means segmentation have been shown.

Fig. 7 Maui Ocean Floor Image

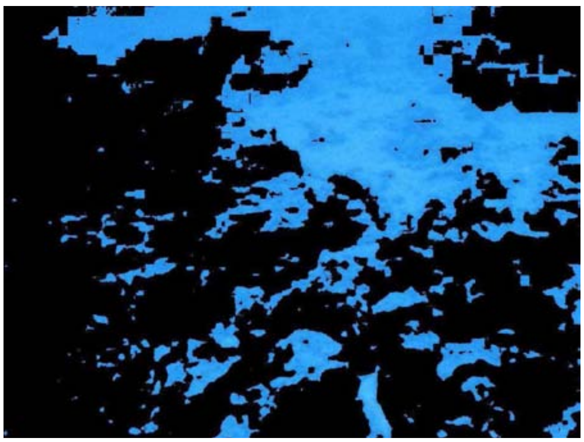

Fig. 8 Maui Ocean Floor Image (Cluster 1)

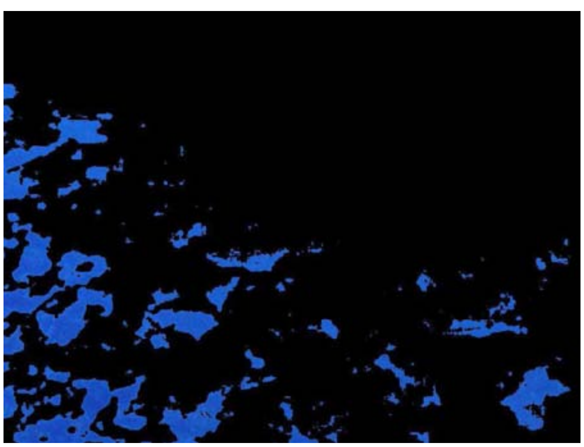

Fig. 9 Maui Ocean Floor Image (Cluster 2)

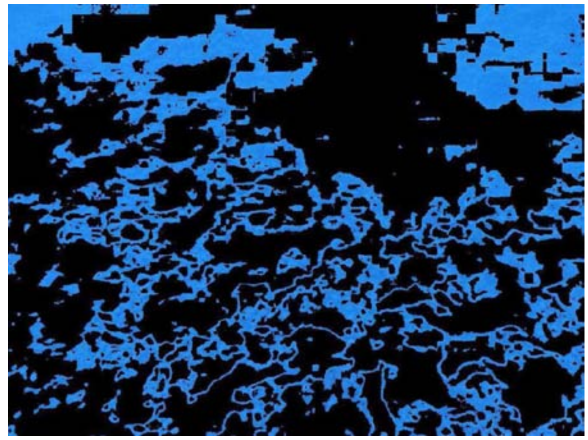

Fig. 10 Maui Ocean Floor Image (Cluster 3)

4 RGB - Trimulus Color Model

In trimulus 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 system 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 the 3D image planes.

5 Histogram and Probability Function

The histogram plot 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 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 is estimated from its histogram, which is formulated as,

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

where p(k) is a probability distribution function and h(k) is a histogram function. Histograms of original and processed images are plotted in Figs. 11-17.

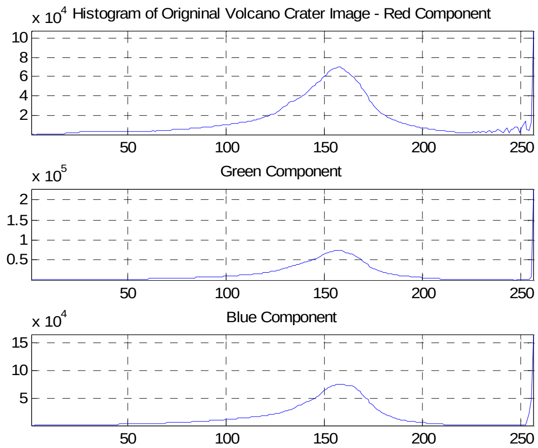

Fig. 11 Histogram of Volcano Crater Image

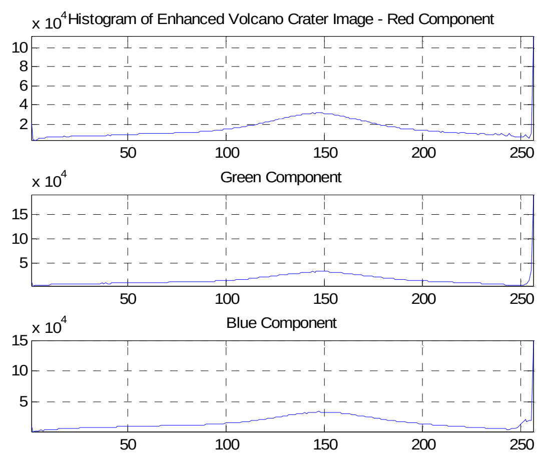

Fig. 12 Histogram of Enhanced Volcano Crater Image

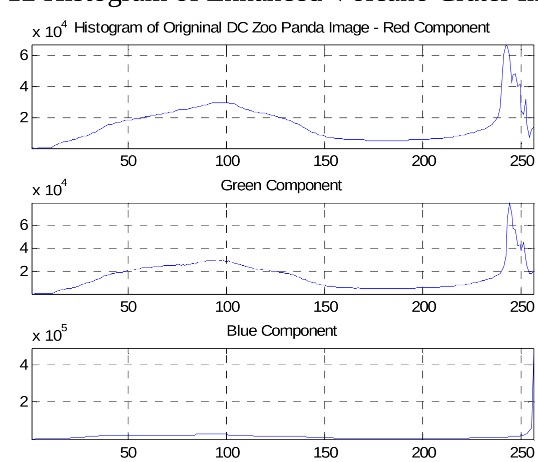

Fig. 13 Histogram Plot of Panda Image

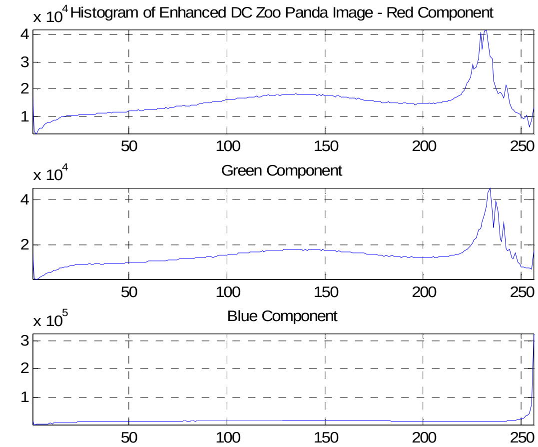

Fig. 14 Histogram Plot of Enhanced Panda Image

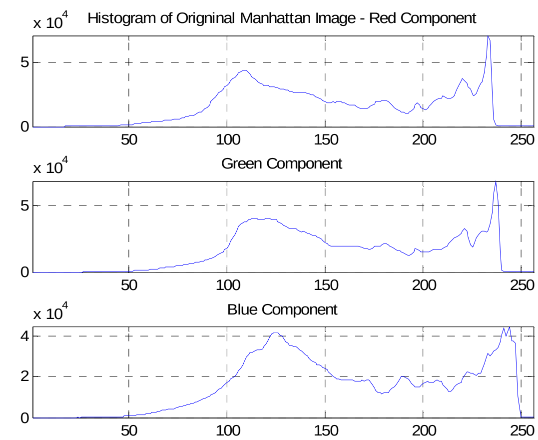

Fig. 15 Histogram Plot of Manhattan Image

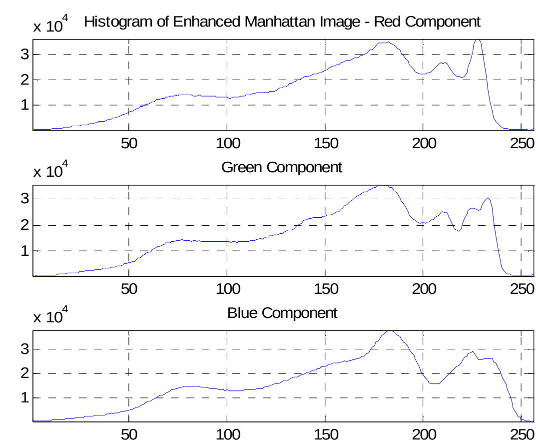

Fig. 16 Histogram Plot of Enhanced Manhattan Image

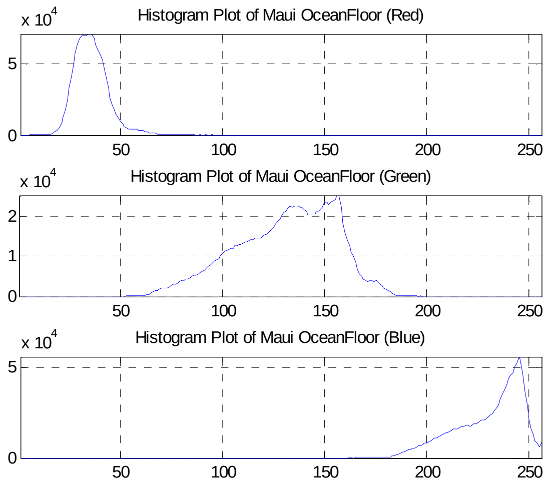

Fig. 17 Histogram Plot of 3 Clusters of Ocean Floor

6 Energy of RGB Component

The energy measure of three color component in trimulus systems indicates how the trimulus color components are distributed. It is formulated as in (2),

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

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

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 in (3). The larger energy corresponds to a lower number of color component levels. The smaller one corresponds to a higher number of color component levels.

Table 1. RGB Component Energy in Image Processing

Original Image	Energy	Enhanced Image	Energy
Volcano Crater			
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
Manhattan Image			
Red	0.0072	Red	0.0057
Green	0.0073	Green	0.0058
Blue	0.0067	Blue	0.0056
Energy in Maui Ocean Floor Image Segmentation			
Images	Red	Green	Blue
Raw	0.0377	0.0120	0.0211
Cluster 1	0.4354	0.4065	0.3946
Cluster 2	0.4354	0.4065	0.3946
Cluster 3	0.4354	0.4065	0.3946

In Table 1, it is indicated that the enhanced images using the adaptive histogram equalization algorithms have the low energy for each of three components, which means enhanced images are relatively complex at all three cases, whose probability functions decrease through nonlinear transformation and interpolation. For K-means clustering, all individual clusters are much simpler than the raw image (high energy). As the current K-means segmentation is color based, thus different clusters have shown the same energy level. Image processing can be partially evaluation by the energy level. Other quantitative measures can also be used to analyze image processing techniques.

7 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).

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

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

Discrete entropy is in fact a statistical measure of randomness. The 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. 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. In a similar way, for K-means clustering, individual clusters are simpler than the raw image, thus smaller entropy values are obtained than that of the raw image. Due to the color based image segmentation, different clusters have the same entropy values as well.

Table 2. RGB Component Entropy

Original Image	Entropy	Enhanced Image	Entropy
Volcano Crater			
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
Manhattan Image			
Red	7.3012	Red	7.5958
Green	7.2734	Green	7.5828
Blue	7.3819	Blue	7.6285
Entropy in Maui Ocean Floor Image Segmentation			
Images	Red	Green	Blue
Raw	4.9883	6.5659	5.8386
Cluster 1	2.8725	3.0595	3.1849
Cluster 2	2.8725	3.0595	3.1849
Cluster 3	2.8725	3.0595	3.1849

Principle of Maximum Entropy can be applied as well to analyze the potential of image processing, 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 proposition, 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.

8 Relative Entropy Analysis

Suppose two discrete probability distributions of the processing trimulus color 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).

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

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

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
Manhattan	0.4080	0.3998	0.3934
Cluster w.r.t. Original	Red	Green	Blue
Cluster 1	0.0391	0.0391	0.0391
Cluster 2	0.1689	0.1689	0.1689
Cluster 3	0.3133	0.3133	0.3133

9 Mutual Information Analysis

Another concept can be applied as the quantitative measure to evaluation the image processing as well. It is mutual information I(X; Y), which describes how much information one variable tells about the other.

$$\begin{aligned} I(X;Y) &= \sum_{X,Y} p_{XY}(X, Y)\log_2 \frac{p_{XY}(X, Y)}{p_X(X)p_Y(Y)} \\ &= -\sum_{X} p_X(X)\log_2 p_X(X) + \sum_{X,Y} p_{XY}(X, Y)\log_2 \frac{p_{XY}(X, Y)}{p_Y(Y)} \qquad (7) \\ &= H(X) - H(X|Y) \end{aligned}$$

where H(X) and H(X|Y) are values of the entropy and conditional entropy; p_{XY} is the joint probability density function; p_X and p_Y are marginal probability density functions. It can be interpreted as information that Y can tell about X is the reduction in uncertainty of X due to the existence of Y. It also shows the relative entropy between the joint distribution and product distribution. The results are shown in Table 4.

Table 4. Mutual Information between Images

I(X; Y)	Volcano Crater	Giant Panda	Skyline Manhattan
Raw and Enhancement	0.6840	0.3005	0.2947
Cluster w.r.t. Original	Red	Green	Blue
Cluster 1	2.1158	3.5065	2.6538
Cluster 2	2.1158	3.5065	2.6538
Cluster 3	2.1158	3.5065	2.6538

From Table 1 to Table 5, it has been shown clearly that the color component energy, discrete entropy and relative entropy can be treated as quantity measures to indicate quality of trimulus color image enhancement. The quantity measures are useful to enhance decision making in various fields of pattern recognition.

10 Conclusions

The RGB component intensity of trimulus color systems have been used to determine the quantitative measures of image enhancement and segmentation for some potential engineering applications. The adaptive image enhancement methodology is proposed and applied to image processing with ambiguous objects, where the image contrast has been stretched to avoid feature ambiguity. To eliminate artifacts generated by noises throughout image enhancement, local adaptive histogram equalization is applied which is followed by interpolations so as to eliminate artificial boundaries. Nonlinear K-means clustering of the trimulus color images has also been applied for image segmentation, which is to classify an image into parts that have strong correlations with the objects in order to reflect actual information. To evaluate image enhancement and image segmentation, the three color component quantities of the discrete energy, discrete entropy and relative entropy and mutual information in the trimulus system are employed. Results are also compared with those of the maximum energy and maximum entropy to examine the potential of image processing. These methodologies can be applied to most types of image processing techniques.

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