Image Contrast Enhancement and Quantitative Measuring of Information Flow

ZHENGMAO YE[1], HABIB MOHAMADIAN[1], SU-SENG PANG[2], SITHARAMA IYENGAR[2]
[1]Southern University, Baton Rouge, LA 70813, USA

[2]Louisiana State University, Baton Rouge, Louisiana 70803

Abstract– **Contrast enhancement is an effective approach for image processing and pattern recognition under conditions of improper illumination. It has a wide variety of applications, such as on object identification, fingerprint verification and face detection. At the same time, unpleasant results might occur when certain types of noises are amplified at the same time. Thus, adaptive image enhancement can be conducted to avoid this drawback, which is used to adapt to the intensity distribution within an image. To evaluate the actual effects of image enhancement, some quantity measures should be taken into account instead of on a basis of intuition exclusively. In this study, a set of quantitative measures is proposed to evaluate the information flow between original and enhanced images. Concepts of the gray level energy, discrete entropy and relative entropy are employed to measure the goodness of the adaptive image enhancement techniques. The images being selected are the scenery picture, architecture picture, static object picture and living creature picture.**

Key-Words: - **Contrast Enhancement, Gray Level, Adaptive Equalization, Entropy, Relative Entropy, Energy**

1 Introduction

Image enhancement technology takes an important role in pattern recognition. Matrix functions of any image correspond to energy at each image pixel. Except for 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 unconstrained illumination conditions, unsuitable enhancement increases the detection failure rate by amplifying noises. As a result, approaches of contrast limited image enhancement via stretching the 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 handle each of them to avoid excessive enhancement of noises. Thus, original images are enhanced to certain degree of satisfaction.

To quantify the effects of image enhancement, quantify measures should be introduced. Stem from thermodynamics, concepts of thermodynamic entropy, relative entropy and energy have been expanded to a number of other areas like information theory, signal processing and image processing as quantity measures. From literatures, interesting results have been documented. For instance, the entropy of a fuzzy set is viewed as a global measure of the fuzziness of the fuzzy set and 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 treated as the fitness function of Genetic Algorithms for the optimal segmentation thresholding methods. Accordingly, the quantity measures of gray level energy, discrete entropy and relative entropy are proposed to evaluate effects of locally adaptive image enhancement techniques in this research.

On a basis of gray level image histograms and associated probability distribution functions, gray level energy, discrete entropy and relative entropy of original images and enhanced images can be compared to indicate information flow throughout the image enhancement process. In general, the histogram energy is opposite to imagination, that is, a simple image has more histogram energy than a complex image. On the other hand, the discrete entropy of gray level images is a statistical measure of randomness that used to characterize the original images and enhanced images. The entropy of an event is the sum of all those possible outcomes, represented by 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 measures are proposed to further study the effects of image enhancement. In another case, in comparison with the potential maximum energy and maximum discrete entropy from Principal of Maximum Entropy, the resulting enhancement for several different types of images can be investigated from another point of view. These measures are selected to quantify the role of image enhancement in practical implementations, like image compression [1-14].

2 Adaptive Histogram Equalization for Image Enhancement

Image contrast enhancement can be achieved by means of histogram equalization algorithms. It is inevitable that the noises could be amplified or induced simultaneously. For this reason, adaptive image contrast enhancement schemes based on histogram equalization are conducted in this study. The images are separated into a number of small regions. Within every small region, the histogram is obtained under contrast limit and then the exponential distribution is applied as a basis to create the contrast transform function. The new gray level assignments of pixels in each small local region will be specified by this contrast transformation for image enhancement. The gray level mapping from each local histogram is then generated. In order to avoid the occurrence of boundary artifacts arisen from different neighborhoods of small regions and to obtain an evenly distributed enhancement overall effect across the entire regions, bilinear interpolations between four different mappings are used together so that contrast saturation problem is solved via contrast limit, until results from the adaptive equalization are satisfactory. Through this approach, excessive enhancement of noises will be easily prevented.

As a general approach, this method has been applied to a group of gray scale images, namely, the scenery image of Mount Hollywood, Capitol architecture image, static South Point image and dramatic deer image on summit of Grouse Mountain. For these gray scale images, histogram contains 256 bins and the percentage of counts for each bin over the summation will give rise to its probability distribution. The parameter for exponential functions, the factor for contrast limiting and weights for bilinear interpolation may be adjusted to achieve quality outcomes. Using this adaptive image enhancement methodology, from Fig. 1 to Fig. 4, two types of original and enhanced scenery and architecture images are listed; From Fig. 5 to Fig. 8, another two types of original and enhanced static object and living creature images are listed.

Fig. 1 Original Image of Mount Hollywood

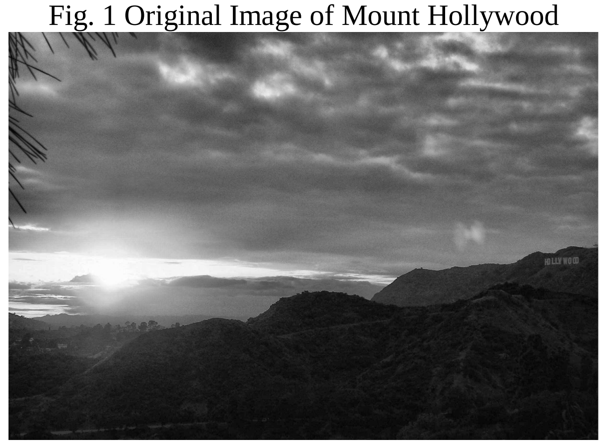

Fig. 2 Enhanced Image of Mount Hollywood

Fig. 3 Original Image of US Capitol

Fig. 4 Enhanced Image of US Capitol

Fig. 5 Original Image of US South Point

Fig. 6 Enhanced Image of US South Point

Fig. 7 Original Deer Image on Grouse Mountain

Fig. 8 Enhanced Deer Image on Grouse Mountain

3 Histogram and Probability Function

The histogram is used to display the brightness of the gray scale image, showing the occurrence of pixel counts for each of 256 intensity levels. Occurrence of the gray level configuration may be described as co-occurrence matrices of relative frequencies. Then the classification is based on features being derived from co-occurrence matrices of images. The occurrence probability function of the gray level can be simply estimated from the histogram, which is formulated in (1), where p(k) is the probability distribution function and h(k) is the histogram function.

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

In Figs 9-12, probability distributions of different types of original and enhanced images are plotted, which are used as quantity measures.

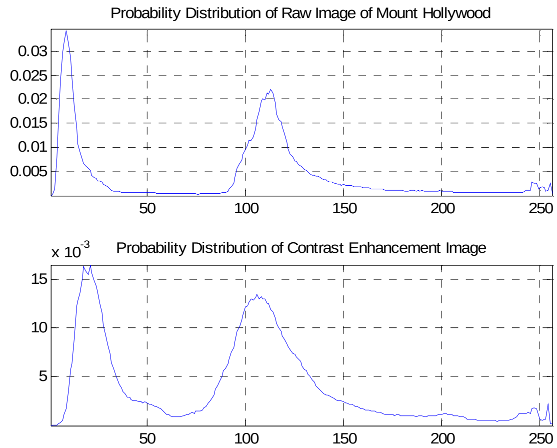

Fig. 9 Probability Distribution of Mount Hollywood Image

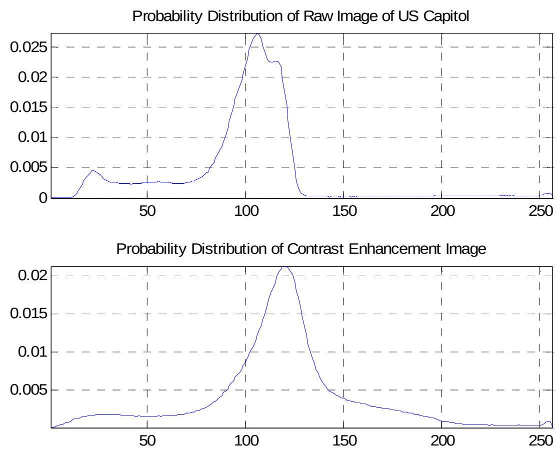

Fig. 10 Probability Distribution of US Capitol Image

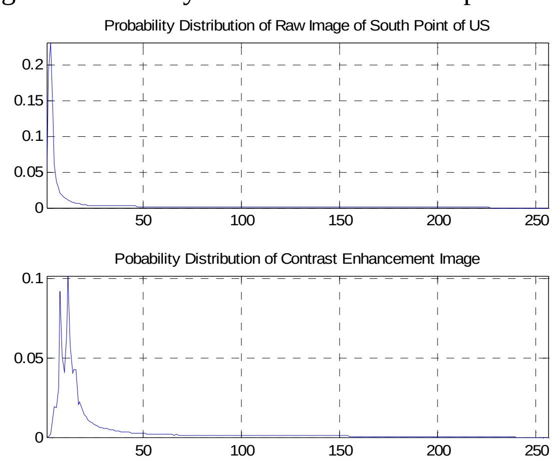

Fig. 11 Probability Distribution of US South Point

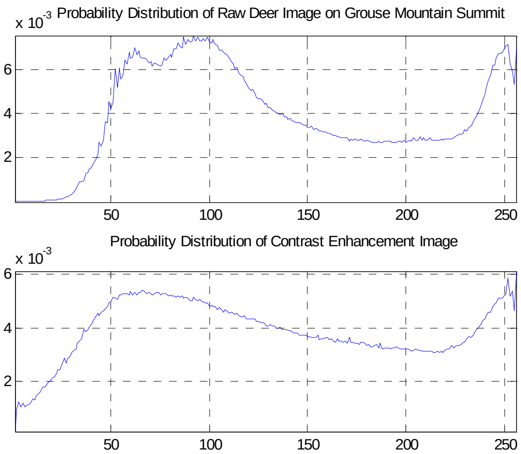

Fig. 12 Probability Distribution of Deer Image

4. Discrete Gray Level Energy

The gray level energy measure indicates how the gray levels are distributed. The formulation of the gray level energy is shown in (2), where E(x) represents the gray level energy with 256 bins and p(i) refers to the probability distribution functions under different gray levels, which contains the histogram counts. For a special case when an image has a constant value of gray level, 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 lower gray level values and the smaller one corresponds to higher gray level values.

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

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

Table 1. Energy of Original and Enhanced Images

Original Image	Energy	Enhanced Image	Energy
Hollywood	0.0144	Hollywood	0.0086
South Point	0.1185	South	0.0400
US Capitol	0.0052	US Capitol	0.0042
Mount	0.0161	Mount	0.0107

In Table 1, it can be seen that the enhanced images using the adaptive histogram equalization algorithms have the smaller gray level energy to some extent, which means the enhanced images are relatively complex for all four cases whose individual probability functions decrease through nonlinear transformation and bilinear interpolation.

5 Discrete Entropy

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, …, x_n}, where n is the gray level; p(i) is the probability at the gray level of i, which contains all the histogram counts. Discrete entropy is written as (4-5).

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

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

Discrete entropy is a statistical measure of randomness. Maximal entropy occurs when the probabilities of 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 gray levels, values of the corresponding discrete entropy increase.

Table 2. Entropy of Original and Enhanced Images

Original Image	Entropy	Enhanced Image	Entropy
Hollywood	6.7456	Hollywood	7.2698
South Point	4.3094	South	5.7259
US Capitol	7.7024	US Capitol	7.9365
Mount	6.4975	Mount	7.1024

Principle of maximum entropy can also be applied to analyze the potential of image enhancement and image compression. Assume 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 propositions, thus, the least informative distribution occurs. The discrete entropy provides a numerical measure between zero and $\log_2$ (n), from 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.

6 Relative Entropy

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 sometimes referred to as the Kullback Leibler distance. The effect of image enhancement can also be quantified by the measure of relative entropy. In Table 3, the relative entropy of enhanced images with respect to original images has been shown.

Table 3. Relative Entropy of Images

Enhanced v.s. Raw	Relative Entropy	Enhanced v.s. Raw	Relative Entropy
Mount Hollywood	0.6898	US Capitol	0.2567
US South Point	1.7372	Deer on Summit	1.1539

From Table 1 to Table 3, it has been shown that gray level energy, discrete entropy and relative entropy can all be treated as quantity measures to evaluate the quality of image enhancement. These quantity measures are in fact useful to improve the decision making process in pattern recognition and medical diagnosis.

7 Conclusions

The adaptive contrast enhancement methodology has been applied to processing of various types of images using histogram equalization algorithms, where the image contrast has been stretched. Then useful information is extracted and enhanced to avoid feature ambiguity. To eliminate artifacts generated by noises throughout the image enhancement, the local adaptive histogram equalization is applied which is followed by the interpolations among neighborhoods in order to eliminate artificial boundaries. The enhancement effect should be evaluated quantitatively rather than qualitatively. Thus several quantity measures are introduced to investigate the effectiveness of image enhancing techniques. Based on a group of original and enhanced grayscale images, histograms and corresponding probability distributions have been computed. Therefore quantities of the gray level energy, discrete entropy and relative entropy are derived to characterize original images and enhanced images. The results are also compared with those of the maximum gray level energy and maximum entropy to indicate the potential of image enhancing schemes. It also provides valuable examples to other useful image processing and pattern recognition techniques, such as image compression and image clustering.

References

[1] S. Hykin, “Neural Networks - A Comprehensive Foundation”, 2nd Edition, 1999, Prentice Hall

[2] R. Duda, P. Hart and D. Stork, “Pattern Classification,” 2nd Edition, John Wiley & Sons, 2000

[3] R. Gonzalez and R. Woods, “Digital Image Processing,” 2nd Edition, Prentice-Hall, 2002

[4] Y. Ye, Z. Ye, J. Luo, P. Bhattacharya, H. Majlesein, R. Smith, "On Linear and Nonlinear Processing of Underwater, Ground, Aerial and Satellite Images", Proceedings of the 2005 IEEE International Conference on Systems, Man and Cybernetics (SMC 2005), pp. 3364-3368, Oct. 10-12, 2005, Hawaii, USA

[5] Z. Ye, J. Luo and P. Bhattacharya, "Optimal Approach for Enhancement of Large and Small Scale Near-Infrared and Infrared Imaging", Proceedings of the 2005 IEEE International Conference on Industrial Electronics and Control Applications, Nov.29-Dec.2, 2005, Quito, Ecuador

[6] P. Refregier and F. Goudail, “Kullback Relative Entropy and Characterization of Partially Polarizes Optical Waves”, Journal of the Optical Society of America A, v 23, n 3, March 2006, p 671-8

[7] J. Wang, Y. Du, C. Chang; “Relative Entropy-Based Methods for Image Thresholding”, Proceedings of 2002 IEEE International Symposium on Circuits and Systems, May 26-9, 2002, Phoenix, USA

[8] Fotinos, G. Economou, E. Zigouris, “The Use of Entropy for Color Edge Detection”, Proceedings of 6th IEEE International Conference on Electronics, Circuits and Systems, pt.1, pp. 437-40 vol.1, 1999

[9] W. Wanga, C. Chiu, “Entropy and information energy for fuzzy sets”, Fuzzy Sets and Systems, 108 (1999) 333 - 339

[10] Z. Yang, Z. Pu, Z. Qi, “RELATIVE Entropy Multilevel Thresholding Method Based on Genetic Optimization”, IEEE International. Conference Neural Networks & Signal Processing, Nanjing, China, Dec. 14-17, 2003

[11] E. Pantin, J. Starck, “Deconvolution of Astronomical Images using Multiscale Maximum Entropy Method”, Astronomy and Astrophysics, Supplement Series, 118, 575-585, 1996

[12] J. Stark, “Adaptive Image Contrast Enhancement using Generalizations of Histogram Equalization”, IEEE Transactions on Image Processing 9(5): 889-896, May 2000.

[13] T. Ji, M. Sundareshan, H. Roehrig, “Adaptive image contrast enhancement based on human visual properties”, IEEE Transactions on Medical Imaging, pp. 573 - 586, Volume 13, Issue 4, Dec. 1994

[14] E. Chiut, J. Vaiseyt and S. Atkins, “Joint Space-Frequency Segmentation, Entropy Coding and the Compression of Ultrasound Images”, IEEE International Conference on Image Processing, pp. 411-414, Volume 2, 2000