A Comparative Study of Different Histogram Equalization Algorithm for Contrast Enhancement

Abhishek Chandra Gangwar
PG Student
Department of Communication System
L.D College of Engineering

Prof. Suresh L. Bharvad
Assistant Professor
Department of Communication System
L.D College of Engineering

Abstract

One of the common method used for contrast enhancement (CE) is histogram equalization (HE).this method is used for maximised the contrast of images and to get more information. By this adjustment, the intensities can be better distributed on the histogram. The basic disadvantage of HE is that it can change the mean values of the image which affect the brightness of the image, sometimes it also introduces over enhancement and saturation effect. To overcome this various HE algorithm have been introduce to overcome these drawbacks. In this paper, we present different methods for image enhancement that is constructed to minimized the intensity saturation effects that are introduced by standard contrast enhancement (CE) methods based on histogram equalization. Like Brightness Preserving Bi-Histogram Equalization (BBHE), Minimum Mean Brightness Error Bi-Histogram Equalization (MMBEBHE), Texture Enhanced He Using TV L1 Image Decomposition.

Keywords: BBHE, Histogram Equalization, Image Decomposition, MMBEBHE, TV L1

I. INTRODUCTION

To increase the visibility of the images many method have been emphasizing the different parts or different component or part of the image. Contrast enhancement is one of the methods for image enhancement in image processing. Where histogram equalization is one of the most common and popular method. HE can change the image so that the histogram of that image becomes flat, where the probability of all the level is equal. In this method it will be assumed that the information is in the image is in form of probability of occurrence of gray level. To extract the more information we distribute the probability of gray level occurrence in a uniform manner. Contrast enhancement (CE) is mainly seen as global histogram wrapping process and global histogram equalization (GHE) is common, as we get more information but by this it also introduces over enhancement and intensity saturation effect. So to overcome these type of drawback we introduce some different algorithm i.e. BBHE, MMBEBHE, TV L1 algorithm. And we also get more information with respect to entropy.

II. LITERATURE REVIEW

A. Contrast Enhancement Using Brightness Preserving Bi-Histogram Equalization:

This method is the extension of the standard histogram equalization, which can preserve the brightness of image by preserving the mean of the bi-histogram equalization [4]. By this method we can overcome the problem of standard histogram equalization.

In this method we can divide or we can say decomposed the image in two parts taking mean as a threshold. One part have the set of sample values which is greater than the value of mean and one part which have set of values lesser than mean. Then BBHE equalize the image which is decomposing in to two sub images independently on the bases of their respective histogram. The mapping is done within the range from minimum gray level to mean. Now let input image is decomposed into two sub-images X_L and X_U by using the input mean Xm. Next, define the respective probability density function (pdf) of the sub-image X_L and X_U. And by pdf we clearly find out the cdf of the respective sub images

Now defining transformation function defined in histogram equalization for both the sub image-

$$F_L(X_L) = X_0 + (X_M - X_0)\, cdf_L(X_i) \quad (1)$$

$$F_U(X_U) = X_{m+1} + (X_{L-1} - X_M)\, cdf_M(X_i) \quad (2)$$

Based on both the above transform functions, sub images are equalized independently and the output of BBHE is composition of equalized sub images. Now the output of BBHE, Y can be shown as-

$$Y = F_L(X_L) \cup F_U(X_U) \quad (3)$$

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B. Minimum Mean Brightness Error Bi-Histogram Equalization in Contrast Enhancement(MMBEBHE)

This method proposes the novel extension of BBHE referred to as minimum mean brightness error bi-histogram equalization. It performs the separation based on the threshold level which would return minimum absolute mean brightness error (AMBE). MMBEBHE [1] works in these three steps defined by the following-

1) First it calculates the AMBE for each of the threshold level.
2) Then it finds the minimum threshold level, X_T that yield minimum MBE.
3) Finally it separates the input histogram based on the X_T found in step 2 and applies histogram equalization each of the separated histograms as in BBHE.

AMBE will define as:-

$$\text{AMBE}(X, Y) = |X_M - Y_M|$$

Where, X_M is mean of the input image X = {x (i,j) }
And, Y_M is mean of the output image Y = {y (i,j) }

C. Texture Enhanced Histogram Equalization using TV L1 Image Decomposition

To decomposed the image into cartoon and texture we used the total vibrational [8] model which can be used for data denoising, like decomposing noisy image into correct image and noise here we use this method to decompose the image(I) into cartoon(c) and texture(t) (part other than texture is defined as cartoon).

$$I = c + t \tag{4}$$

The cartoon image can we determined by minimizing the following expression:

$$\min \int \Omega \quad |\nabla c| + \lambda \left| |I - C| \right| L1 \; d\Omega \tag{5}$$

Where $\Omega \subset Z^2$ denotes the image domain and the symbol $\| \cdot \| L1$ defines the L1 norm. The TV-L1 [2] vibrational model is controlled by the Lagrange multiplier $\lambda \epsilon R^+$, which is inversely proportional to the strength of the data smoothing process. Using the calculus of variation we can derive the Euler-Lagrange equation [2]of above equation.

$$c_t = \nabla . \left(\frac{\nabla c}{|\nabla c|}\right) + \lambda \frac{I-c}{|I-c|}, c(t=0) = I \tag{6}$$

Where c_t is the partial derivative of c with respect to the time variable t, $\nabla .$ Is the divergence and ∇ denotes the gradient operator. The implementation of above equation in the discrete image domain requires the approximation of the partial derivatives with central differences where the solution is done by the steepest gradient descent as indicated in below.

$$c_{ij}^{n+1} = c_{ij}^{n} + \frac{\Delta t}{\Delta x \Delta y}\left(\nabla_x^- \left(\frac{\nabla_x^+ c_{ij}^n}{|\nabla c_{ij}^n| + \beta}\right) + \nabla_y^- \left(\frac{\nabla_y^+ c_{ij}^n}{|\nabla c_{ij}^n|}\right)\right) + \Delta t \left(\lambda \frac{I_{ij} - c_{ij}^n}{\left(I_{ij} - c_{ij}^n\right)^2}\right) \tag{7}$$

Where (i, j) denotes the position of the pixel in the image, ∇^+ and ∇^- are the forward and backward discrete gradients, respectively, $|\nabla c_{i,j}|$ is the magnitude of the gradient, Δt is the time step, n is the iteration index, and Δx and Δy are the discrete spatial distances of the image grid. When we got the cartoon of the image by applying the above equation on the image the texture of the image is:

$$t_\lambda = I - c_\lambda \tag{8}$$

By this information we have to calculate the histogram transform for the contrast enhancement. The main concept of this is to implement a local intensity mapping process which can change the histogram the cartoon image by the help of the information content in the texture. Once we get the texture pixel we show the evaluation of the neighborhood around each texture pixel. Now we have to find out the neighbor pixels which have the extreme intensity values. By the help of these local texture pixels we can alter the histogram of cartoon image Hc.

After the calculation of the texture-enhanced distribution Hc the next step involves the construction of the cumulative distribution. That will be used as a look up table [10] in HE process:

$$f(s) = \frac{L}{\int_0^N w(s)ds} \int_0^s w(r)dr \tag{9}$$

Where N is the right bound of K and L is the number of levels, if w(s) can be replaced by the histogram of the input image then the histogram mapping function is reduced to histogram equalization.

$$\text{ENTROPY, E } (H_N) = \sum_{s \in M} Hn(s) \log 2(Hn(s))$$

Where Hn is the normalized version of histogram H.

$$Hn = \frac{H(s)}{\sum_{r \in M} H(r)} \tag{10}$$

D. Numerical Results Obtained By Different Histogram Equalisation Based Contrast Enhancement Startegies[2]

Table - 1

Image	*Method*	*Entropy*
Cameraman	*GHE*	*6.76*
	BPBHE	*6.79*
	MMBEBHE	*6.75*
	TV L1	*6.86*

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COUPLE IMAGE	*GHE*	*6.35*
	BPBHE	*6.37*
	MMBEBHE	*6.29*
	TV L1	*6.47*

A B C

D E

Fig. 1: Contrast enhancement results - 'Cameraman' image. (a) Input image. (b) GHE. (c) BP-BHE. (d) MMBE-BHE. (E) TV-L1 TE-HE. [2]

III. SUMMARY

This paper presents comparative study of different histogram equalization based image enhancement methods. In this we show the different approaches to avoid the occurrence of undesired artefacts such as intensity saturation and over-enhancement that are characteristic for conventional histogram equalisation methods. And also On the basis of the entropy we also see that by using the TV L1 algorithm we get the maximum information as comparison to others.

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