IMAGE ENHANCEMENT BY MULTI-HISTOGRAM EQUALIZATION USING ERROR BACK PROPAGATION NETWORK

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ABSTRACT: *Histogram Equalization Is A Simple And Working Well Expert Way Of Art And So On For Image Comparison Thing Giving Greater Value To But In Does Not Special Field The Brightness. Bi-Histogram Equalization Has Been Offered And Got Broken Up (Into Simpler parts) mathematically that it can special field the uncommon, noted brightness to a certain gets stretched out. image Dependent brightness keeping safe histogram Equalization expert way of art and so on is a better way of doing for comparison thing giving greater value to but it's not always giving best unlimited middle, half way between brightness Error.*
more than one or histogram using error back propagation network provides not only better comparison but also it gives better scalable brightness process of making safe. First the image is decomposed into equal part sub-images based on how probable measure of space between parts purpose, use .curvet make great change is used to make out the bright field, range. separating of histogram on the base of board forming floor of doorway level which give the least possible or recorded AMBE value. Error Back propagation network (EBPA) is used to support the right Euclidean distance which gives the better value of PSNR. experiment 6results shows that offered careful way gives the better AMBE and PSNR results made a comparison with other ways of doing.

KEYWORDS: Histogram Equalization, EBPA, PDF and CDF

I. INTORDUCTION

The field of digital image processing refers to processing digital images by means of a digital computer. Vision is the most advanced of our senses, so it is not surprising that images play the single most important role in human perception. One useful way of thinking is to think about three types of computerized: low, mid and high-level processes. Low-level processes involve (very simple/from a time very long ago) operations such as image pre-processing to reduce noise, contrast improvement, and image sharpening.

A low-level process is seen as the fact that both its inputs and outputs are images .Mid level processing on images involve tasks such as Mid- as (division of something into smaller parts). (Separating (with a wall) an image into areas or objects), description of those objects to reduce them to a form good for computer processing, and classification (recognition) of individual objects .

The goal of image improvement is to improve the quality of the image such that the (pulled out or taken from something else) image is better than input image. Histogram Equalization (HE) is a very popular and simple way of doing things of improving the contrast [1]. Based on the image's original gray level distribution, the image's histogram is reshaped into a different one with uniform distribution property in order to increase the contrast [2]. The HE way of doing thing is a world wide operation because of this; it does not preserve the image brightness. To overcome this issue local-HE [3] and brightness preserving local HE [4]-[14] ways of doing things have been proposed .

HE are not always the best brightness preserving ones, their resulting brightness is always very closeto the brightness of the original images. In order to improve contrast, brightness and produce natural looking image, this article propose a Multi Resolution Histogram Self Organizing Map Filter (MHEBPN). In MHEBPN we first rot the input image into (more than two, but not a lot of) sub-images. The curvlet change and histogram matching way of doing things using Error Back Spread Set of computer instructions (EBPA) is used. The proposed MHEBPN method goes through two steps. Are identification using the curvelet changes. Training of image pixels using Error Back Spread Set of computer instructions (EBPA).Computation of a histogram of original image pixels and image pixels after training Change ofa image histogram with respect to a histogram of the identified area.

II. RELATED WORK

According to H.D. Cheng and X.J. Shi in "A simple a nd effective histogram equalization approach to image enhancement" mostly, improvement methods can be divide into two classes: global and local methods. In this paper, the multi-peak generalized histogram equalization (multi-peak GHE) is projected. In this method, the global histogram equalization is better by using multi-peak histogram equalization shared with local information. In our experiments, different local information is employed. This method adopts the behavior of existing methods. It also makes the degree of the enrichment entirely controllable. Experimental outcome show that it is very useful in enhancing images with low contrast, regardless of their brightness. Multi-peak GHE method is very effective to enhance different kinds of images when the right features (local information) can be extracted.

According to Joug-Youn Kim,Lee-Sup Kim and Seung-Ho Hwang "An Advance contrast Enhancement

Using Partially Overlapped Sub-Blok Histogram Equalization" They offered an advanced Histogram Equalization algorithm for contrast Enhancement. Global Histogram Equalization is easy and high-speed but its contrast enhancement power is comparatively low. Local histogram enhancement is on the other hand, can enhance overall contrast more efficiently. For High contrast and simple calculation a low pass filter type mask is proposed. The low pass filter type mask is realized by partially overlapped sub-block histogram equalization (POSHE). POSHE is derived from local histogram equalization but it is much effective and much faster. The most significant feature of POSHE is Low-pass filter shaped mask.

According to Byoung-Woo Yoon and Woo-Jin Song in "I mage contrast enhancement based on the generalized histogram" present an adaptive contrast improvement method based on the generalized histogram, which is obtained by relaxing the limit of using the integer count. For every pixel, the integer count 1 allocated to a pixel is split into the partial count and the remains count. The generalized histogram is generated by accumulating the fractional

count for each intensity level and distributing the remainder count regularly throughout the intensity levels. The intensity mapping function, which determines the contrast gain for each intensity level, is derived from the generalized histogram. Since only the partial part of the count allocated to every pixel is used for growing the contrast gain of its intensity level, the amount of contrast enhancement is adjusted by varying the fractional count according to regional characteristics. By adjusting the partial count for each pixel according to user's condition and its spatial movement, the amount of contrast enhancement is controlled appropriately to the human observers. Therefore, the proposed method can achieve visually more pleasing contrast enhancement than the conventional histogram equalization methods.

According to P. Rajavel in "Image Dependent Bright ness Preserving Histogram Equalization" They proposes image-dependent brightness preserving histogram equalization (IDBPHE) method to improve image contrast while preserving image brightness. The curvelet transform and histogram matching method are used to enhance image. The proposed IDBPHE technique undergoes two steps. (i) The curvelet transform is used to identify bright regions of the original image. (ii) Histogram of the original image is customized with respect to a histogram of the identified regions. Histogram of the actual image is modified using a histogram of portion of the same image hence, it improves image contrast while preserving image brightness without any undesired artifacts. A subjective assessment to compare the visual quality of the images is carried out. Absolute mean brightness error (AMBE) and peak signal to noise ratio (PSNR) are used to calculate the effectiveness of the proposed method in the objective sense.

III. PROPOSED WORK

The proposed Multi Histogram using Error Back Propagation Network(MHEBPN) method use the packaging discrete curvelet transforms (WDCvT), Error Back Propagation Algorithm (EBPA) as a filter and the histogram matching method.

A. Curvelet Transforms

Motivated by the require of image analysis, Candes and Donohol developed curvelet transform in 2000 [Candes and Donoho 2000]. Curvelet transform has a extremely redundant dictionary which can offer sparse representation of signals that have edges along regular curve. Initial structure of curvelet was redesigned later and was re-introduced as Fast Digital Curvelet Transform (FDCT) [Candes et al. 2006]. This subsequent generation curvelet transform is meant to be simpler to understand and use. It is also more rapidly and less redundant compared to its first generation version. Curvelet transform is defined in both continuous and digital domain and for higher dimensions. Since image-based feature extraction requires only 2D FDCT, we'll restrict our discussion to the same.

In order to implement curvelet transform, first 2D Fast Fourier Transform (FFT) of the image is taken. Then the 2D Fourier frequency plane is divided into wedges. The parabolic shape of wedges is the result of partitioning the Fourier plane into radial (concentric circles) and angular divisions.The concentric circles are responsible for the decomposition of an image into multiple scales (used for band-passing the image at different scale) and the angular divisions partition the band-passed image into different angles or orientations. Thus if we want to deal with a particular wedge we'll need to define its scale j and angle. When the image is of the correct type, curvelets provide a demonstration that is considerably sparser than other wavelet transforms. This can be quantified by considering the most excellent approximation of a geometrical test image that can be represented using only n wavelets, and analysing the approximation error as a function of n. For a Fourier transform, the error decreases only as $O(1 / n^{1/2})$. For a wide variety of wavelet transforms, including both directional and non-directional variants, the error decreases as $O(1 / n)$. The extra assumption underlying the curvelet transform allows it to achieve $O((log(n))^3 / n^2)$.

Multi-Histogram Equalization Using Error Back Propagation Network (MHEBPN)

Efficient numerical algorithms exist for computing the curvlet transform of discrete data. The computational cost of a curvlet transform is approximately 10–20 times that of an FFT, and has the same dependence of $O(n^2 log(n))$ for an

image of size $n \times n$.

B. Error Back Propagation Algorithm (EBPA)

Lack of suitable training methods for multilayer perceptions (MLP)s led to a waning of interest in NN in 1960s and 1970s. This was changed by the reformulation of the back Propagation training method for MLPs in the mid-1980s by Rumelhart et al. Back propagation was created by generalizing the Windrow-Hoff learning rule to multiple-layer networks and nonlinear differentiable transfer functions. Standard back propagation is a gradient descent algorithm, as is the Windrow-Hoff learning rule, in which the network weights are moved along the negative of the gradient of the performance function. The term back propagation refers to the manner in which the gradient is computed for nonlinear multilayer networks.

As in simple cases of the delta learning rule training studied before, input patterns are submitted during the back-propagation training sequentially. If a pattern is submitted and its classification or association is determined to be erroneous, the synaptic weights as well as the thresholds are adjusted so that the current least mean square classification error is reduced. The input /output mapping, comparison of target and actual values, and adjustment, if needed, continue until all mapping examples from the training set are learned within an acceptable overall error. Usually, mapping error is cumulative and computed over the full training set.

Basic EBPA Algorithm Can Be Described As Follows

· First apply the inputs to the network and work out the output – remember this initial output could be anything, as the initial weights were random numbers.

· Next work out the error for neuron B. The error is What you want – What you actually get, in other wor ds:

$Error_b = Output_b\ (1-Output_b)\ (Target_b - Output_b)$

The "Output(1-Output)" term is necessary in the equ ation because of the Sigmoid Function – if we were only using a threshold neuron it would just be (Target – Output).

· Change the weight. Let W^+_{AB} be the new (trained) weight and W_{AB} be the initial weight.

$W^+_{AB} = W_{AB} + (Error_b \ X \ Output_a)$

Notice that it is the output of the connecting neuron (neuron A) we use (not B). We update all the weights in the output layer in this way.

Calculate the Errors for the hidden layer neurons. Unlike the output layer we can't calculate these directly (because we don't have a Target), so we Back Propagate them from the output layer (hence the name of the algorithm). This is done by taking the Errors from the output neurons and running them back through the weights to get the hidden layer errors. For example if neuron A is connected as shown to B and C then we take the errors from B and C to generate an error for A.

$$\mathbf{Error_a = Output_A\ (1 - Output_A)\ (Error_b\ W_{AB} + Error_c\ W_{AC})}$$

Again, the factor "Output (1 - Output)" is present because of the sigmoid squashing function.

· Having obtained the Error for the hidden layer neurons now proceed as in stage 3 to change the hidden layer weights. By repeating this method we can train a network of any number of layers.

Here all the calculations for a full sized network with 2inputs, 3 hidden layer neurons and 2 output neurons as shown in figure 3.4. W^+ represents the new, recalculated, weight, whereas W (without the superscript) represents the old weight.

C. MOULTI Histogram Error Back Propagation Network (MHEBPN):

Proposed multi resolution histogram equalization technique use the wrapping discrete curvlet transforms (WDCvT), Error Back Propagation Network (EBPN) and histogram matching technique. Corresponding steps in flow chart of proposed technique are as follows:

· ***Region Identification and Separation:*** Curvlet transformation is used to identify bright regions of an original image.

· ***Histogram Computation:*** A histogram of original image and histogram of pixels after training using Error Back Propagation Algorithm (EBPA) are computed.

· Modify original image histogram with respect to a histogram of image pixels after training with EBPA

In proposed paper the flow chart of the process is as follows:

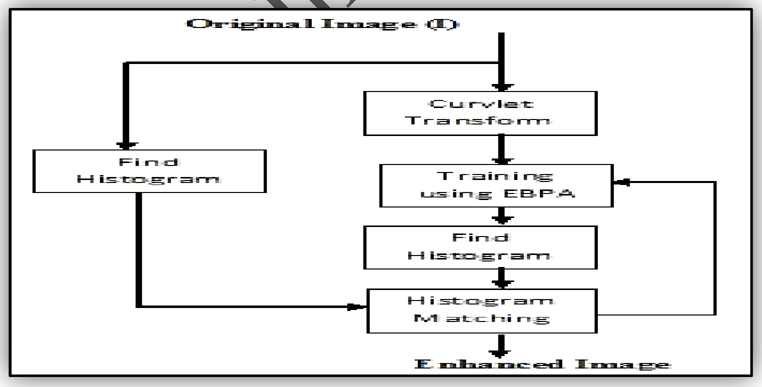

Figure 3: Flow Chart of Proposed Method

· **A. Region Identification and Separation Process use the Following Steps:**

· Take the curvlet transform of original image (I) and obtain the curvlet coefficient $C_{i,j}$, where $C_{i,j}$ represent ith directional sub-band at scale j.

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 Scale the curvlet coefficients $C_{i,j}$, by scaling constants and obtain the modified curvlet coefficients $C_{i,j}$

· Fine the Euclidean distance between points. Create distance vector.
· Create the weight matrix with the help of distance vector.
· Perform the training of the image co-ordinate with weight matrix W_{ij}.

IV. EXPERIMENTAL RESULTS

The proposed method was tested with several gray scale images and has been compared with histogram equalization methods HE, MHE, IDBPHE Figure 11 show a comparison among our proposed method and other methods for two different images. The input images used in the experiments were the ones previously used in [2]-[5], [7]. They are named as Einstein and barbara.

To start our analysis, for each image, we computed the PSNR and AMBE.

Table 1: AMBE and PSNR Values for Eintein and Barbara Image

Methods	AMBE		PSNR	
	papperes	**cameraman**	**papperes**	**cameraman**
HE	62.55	54.3578	17.95	15.602
MHE	60.41	52.4957	20.08	17.4501
IDBPHE	36.62	31.8267	20.08	21.492
Proposed	15.81	13.7406	39.38	34.2266

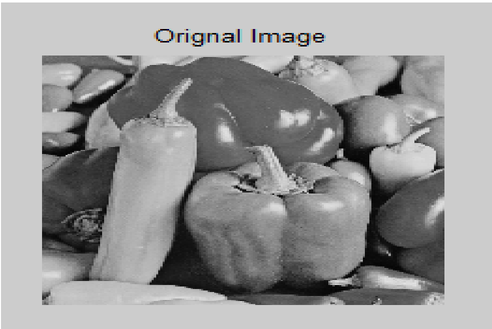

Figure 4: Original Image of papperes

Figure 5: Result of HE on Image papperes

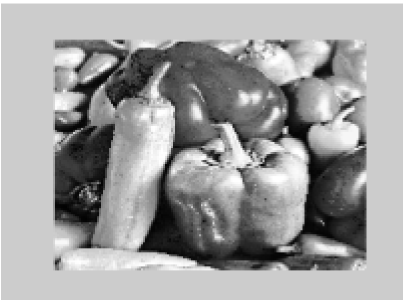

Figure 6: Result of MHE of Image papperes

Figure 7: Result of IDBPHE of Image papperes

Figure 8: Result of papperes

To evaluate effectiveness of the proposed method absolute mean brightness error(AMBE) and peak signal to noise ratio(PSNR) are used.

AMBE is used to access the degree of brightness preservation. Smaller AMBE is better. Smaller AMBE indicates that mean value of the original and result images are almost same. AMBE is given by,

$$AMBE(X, Y) = |M_X - M_Y|$$

Where M_x, M_y represent mean values of the input image X and output image Y, respectively.

PSNR is used to assess the degree of contrast enhancement. Greater the PSNR is better. Greater PSNR indicates better image quality.

PNSR is given by,

$$PSNR = 10 \cdot \log_{10}\left(\frac{MAX_I^2}{MSE}\right) = 20 \cdot \log_{10}\left(\frac{MAX_I}{\sqrt{MSE}}\right)$$

Figure 9: Original Image or Camera Man

Figure 10: HE Result of Image Camera Man

Figure 11: Result of MHE of Image Camera Man

Figure 12: Result of IDBPHE of Image Camera Man

Figure 13: Result of MHEBPN of Image Camera Man

Table 1 shows the AMBE and PSNR values for image 1(Papperes) and image 2(Camera Man). From table and figure 8 and figure 13 it's clearly shows that the proposed method is better compared to other method for gray image contrast enhancement. Even though the proposed method is not always give the better results for any image.

V. CONCLUSIONS

In this paper Multiple Histogram using Error Back Propagation Algorithm (MHEBPN) technique is proposed for image contrast enhancement and brightness preserving. Curvlet transform, Error Back Propagation Algorithm (EBPA) and histogram matching techniques enhance the original image contrast level and also preserve the brightness. Proposed method is checked on standard image such as Papperes and cameraman image. Proposed method enhance the contrast and improve the image visualization more effectively.

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