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Contrast Enhancement based on Gaussian Mixture Modeling with Noise Adaptive Fuzzy Switching Median Filter

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***Abstract*— The proposed algorithm automatically enhances the contrast in an input image. The algorithm uses the Gaussian mixture model to model the image gray-level distribution. In a mixture distribution, its density function is just a convex combination (a linear combination in which all coefficients or weights sum to one) of other probability density functions. The Gaussian components with small variances are weighted with smaller values than the Gaussian components with larger variances By enhancing the contrast of an image in such a way might amplify noise if present and produce worse results. A noise adaptive fuzzy switching median filter is used for salt-and-pepper noise removal. It is able to suppress high-density of salt-and-pepper noise, at the same time preserving fine image details, edges and textures.**

***Keywords*. Gaussian Mixture Model (GMM), Noise Adaptive Fuzzy Switching Median (NAFSM), Bihistogram Equalization (BBHE), Minimum Mean Brightness Error Bi-Histogram Equalization (MMBEBHE). Recursive Mean Separate Histogram Equalization (RMSHE)**

I. INTRODUCTION

Generally, an image may have poor dynamic range or distortion due to the poor quality of the imaging devices or the adverse external conditions at the time of acquisition. Whenever an image is converted from one form to other such as digitizing the image some form of degradation occurs at output. The main goal of image enhancement technique is to improve the characteristics or quality of an image, such that the resulting image is better than the original image. There are two broad categories of image enhancement techniques: (1) spatial domain techniques and (2) frequency domain techniques.

Several image enhancement techniques were proposed in the past. Histogram equalization (he) [1] is a very popular technique for image enhancement. One problem of the histogram equalization is that the brightness of an image is changed after the histogram equalization, hence not suitable for consumer electronic products, where preserving the original brightness and enhancing contrast are essential to avoid annoying artifacts. . So bi-histogram equalization (bbhe) has been proposed which can preserve the original brightness to a certain extend. However, there are still cases that are not handled well by BBHE [2], as they require higher degree of preservation. The extension of BBHE is

Minimum Mean Brightness Error Bi-Histogram Equalization (MMBEBHE). The result of MMBEBHE [3] is bad for the image with a lot details. Recursive Mean-Separate Histogram Equalization (RMSHE) [3] is another improvement of BBHE. However, it also is not free from side effects.

Although these methods can achieve good contrast enhancement, they also generate annoying side effects depending on the variation in the gray-level distribution. may create problems when enhancing a sequence of images, when the histogram has spikes, or when a natural-looking enhanced image is required. In this paper a contrast enhance ment algorithm using GMM is proposed along with a noise adaptive fuzzy switching median filter. Images with low contrast are automatically improved in terms of an increase in the dynamic range. The proposed algorithm is free from parameter setting. The NAFSM filter is able to suppress high density salt-and-pepper noise,and at the same time it preserves fine image details, edges and textures well. Also, it does not require any further tuning or training of parameters once optimized.

The rest of the paper is organised as follows: Section II presents the proposed algorithm. Section III presents the results of algorithm. Section IV concludes this paper.

II. PROPOSED ALGORITHM

Let us consider an input image, $X = \{x(i, j) \mid 1 \leq i \leq H, 1 \leq j \leq W\}$, of size $H \times W$ pixels, where $x(i, j) \in R$. Assume that X has a dynamic range of $[x_d, x_u]$ where $x(i, j) \in [x_d, x_u]$. The main objective of the proposed algorithm is to generate an enhanced image, $Y = \{y(i, j) \mid 1 \leq i \leq H, 1 \leq j \leq W\}$, which has a better visual quality with respect to X. The dynamic range of Y can be stretched or tightened into the interval $[y_d, y_u]$, where $y(i, j) \in [y_d, y_u]$, $y_d < y_u$ and $y_d, y_u \in R$.

A.Denoising

A noise adaptive fuzzy switching median (NAFSM) filter for salt-and-pepper noise removal. It is a recursive double-stage filter. The NAFSM filter is a hybrid between the simple adaptive median filter and the fuzzy switching median filter. The adaptive behavior enables the NAFSM filter to expand the size of its filtering window according to the local noise density, making it possible to filter high-density of salt-and-pepper noise. Meanwhile, the inherited switching median behavior will speed up the filtering process at the same time preserving image details by selecting only “noise pixels” for processing. In addition, the resorted fuzzy reasoning deals with the uncertainty presence in the local information and helps to produce an accurate correction term when restoring detected “noise pixels”[4].

The detection stage starts by searching for two salt and- pepper noise intensities or local maximums L_{max} and L_{min} from both ends of the noisy image histogram. The search is directed towards the center of the histogram. Once these intensities were found the search is stopped. Based on these possible noise pixels of image are identified. A binary noise mask $N(i,j)$ will be created to mark the location of “noise pixels” by using

$$N(i,j) = \begin{cases} 0, X(i,j) = L_{salt} \text{ or } L_{pepper} \\ 1, \text{otherwise} \end{cases} \qquad (1)$$

where $N(i,j) = 1$ represents noise free pixels and $N(i,j) = 0$ represents noise pixels. When a “noise pixel” is detected, it is subjected to the next filtering stage. Otherwise, when a pixel is classified as “noise-free,” it will be retained and the filtering action is spared to avoid altering any fine details and textures that are contained in the original image.

In the filtering stage noise pixel marked with $N(i,j) = 0$ will be replaced by an estimated correction term. A square filtering window is used here. Then the number of noise free pixels in the window is counted. If the current filtering window does not have a minimum number of one noise-free pixel ,then the filtering window will be expanded by one pixel at each of its four sides . This procedure is repeated until the criterion of having a minimum one noise-free pixel is met. For each detected noise pixel, the size of the filtering window is initialized to 3×3. These “noise-free pixels” will all be used as candidates for selecting the median pixel, $N(i,j)$ given by

$$M(i,j) = median\{X(i+m, j+n)\} \qquad (2)$$

$$\text{with } N(i+m, j+n) = 1$$

where $m, n \in (-s, \cdots\cdots, o, \cdots\cdots s)$.

Fuzzy reasoning is applied to the extracted local information. Finally, the correction term to restore a detected noise pixel is a linear combination between the processing pixel $X(i,j)$ and median pixel $M(i,j)$.

B.Modeling

Gaussian mixture model is used for image modeling. Like K-Means, Gaussian Mixture Models (GMM) can be regarded as a type of unsupervised learning or clustering methods. They are among the most statistically mature methods for clustering. But unlike K-Means, GMMs are able to build soft clustering boundaries, i.e., points in space can belong to any class with a given probability. In statistics, a mixture model is a probabilistic model which assumes the underlying data to belong to a mixture distribution. In a mixture distribution, its density function is just a convex combination (a linear combination in which all coefficients or weights sum to one) of other probability density functions. Each of the Gaussian components has a different mean, standard deviation, and proportion (or weight) in the mixture model.

The human eye is not sensitive to small variations around dense data but is more sensitive to widely scattered fluctuations. Thus, in order to increase the contrast while retaining image details, dense data with low standard deviation should be dispersed, whereas scattered data with high standard deviation should be compacted. While doing this the gray-level distribution should be retained[5].

The grey-level distribution p (x), where $x \in X$, of the input image X can be modeled as a density function composed of a linear combination of N functions using the GMM, i.e.,

$$p(x) = \sum_{n=1}^{N} P(\omega_n) p(x|\omega_n) \qquad (3)$$

where (w_n) is the prior probability of the data points generated from component w_n of the mixture and $p(x|w_n)$ is the nth component density and is given by

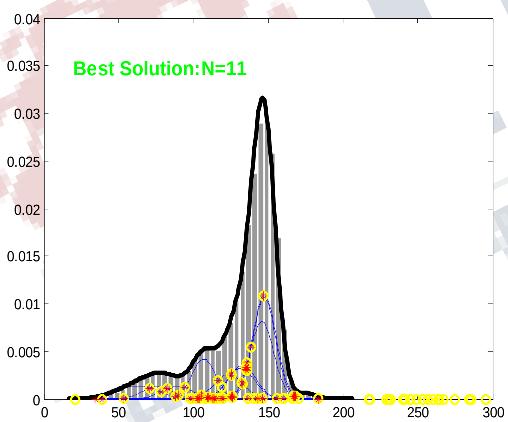
$$p(x|\omega_n) = \frac{1}{\sqrt{2\pi\sigma_{\omega_n}^2}} exp\left(-\frac{(x-\mu_{\omega_n})^2}{2\sigma_{\omega_n}^2}\right) \qquad (4)$$

Here μ_{Wn} and σ^2_{Wn} are respectively the mean and the variance of the nth component. Therefore a GMM is completely specified by its parameters

$$\theta = \{p(\omega_n), \mu_{\omega_n}, \sigma^2{}_{\omega_n}\}_{n=1}^{N} \quad (5)$$

The Figueiredo-Jain (FJ) algorithm [6] is used for parameter estimation which tries to overcome three major weaknesses of the basic EM algorithm. The EM algorithm requires the user to set the number of components and the number will be fixed during the estimation process. The FJ algorithm adjusts the number of components during the

(a)



(b)

Fig 1. (a) Gray-level image and (b) its histogram and GMM fit

estimation by annihilating components that are not supported by the data. This leads to the other EM failure point, the boundary of the parameter space. FJ avoids the boundary when it annihilates components that are becoming singular. FJ also allows to start with an arbitrarily large number of components, which tackles the initialization issue with the EM algorithm. The classical way to select the number of mixture components is to adopt the ”modelclass/ model” hierarchy, where some candidate models (mixture PDFs) are computed for each model-class (number of components), and then select the ”best” model. The idea behind the FJ algorithm is to abandon such hierarchy and to find the ”best” overall model directly by using the minimum message length criterion and applying it to mixture models.

Fig. 1(a) and (b) illustrates an input image and its histogram, together with its GMM fit, respectively. The histogram is modeled using eleven Gaussian components, i.e., N=11. The close match between the histogram (shown as rectangular vertical bars) and the GMM fit (shown as solid black line) is obtained using the FJ algorithm.

C.Partitioning

The goal of partion is to change the representation of an image into something that is easier to analyze. The result of image partion is a set of segments that collectively cover the entire image. For partioning the intersection points are selected from different Gaussian components. The intersection points between two Gaussian components w_m and w_n are found by solving

$$P(\omega_m)p\big((x|\omega_m)\big) = P(\omega_n)p\big((x|\omega_n)\big) \quad (6)$$

or equivalently

$$-\frac{(x-\mu_{\omega m})^2}{2\sigma_{\omega m}^2} + \frac{(x-\mu_{\omega n})^2}{2\sigma_{\omega n}^2} = ln\left(\frac{P(\omega_n)\sigma_{\omega m}}{P(\omega_m)\sigma_{\omega n}}\right) \quad (7)$$

The second order parametric equation has two roots, *i.e.*,

$$x_{m,n}^{(1)} = \frac{-b+\sqrt{b^2-4ac}}{2a} \text{ and } x_{m,n}^{(2)} = \frac{-b-\sqrt{b^2-4ac}}{2a} \quad (8)$$

On solving the above equation, we obtain the numerical values of intersection points. The total number of intersection points thus calculated is N(N-1). From this significant intersection points are selected to cover the entire dynamic range of the image. For a given intersection point $x_{m,n}^{(k)}$, where k={1,2}, between Gaussian components ω_m and ω_n , it is selected as a significant intersection point if and only if it is a real number in the dynamic range of the ·components ω_m and ω_n contain the maximum value in the mixture for point $x_{m,n}^{(k)}$, i.e.,

$$P(\omega_m)p\left(x_{m,n}^k|\omega_m\right) = P(\omega_n)p\left(x_{m,n}^k|\omega_n\right) \quad (9)$$

$$P(\omega_m)p\left(x_{m,n}^k \middle| \omega_m\right) > P(\omega_n)p\left(x_{m,n}^k \middle| \omega_n\right) \quad (10)$$

The significant intersection points are sorted in ascending order of their value and are partitioned into gray-level intervals to cover the entire dynamic range of X. The consecutive pairs of significant intersection points are used to partition the dynamic range of X into subintervals,

i.e., $[x_d, x_u] = [x_s^1, x_s^2]\ U\ [x_s^2, x_s^3]\ U \cdots \left[x_s^{(k-2)}, x_s^{(k-1)}\right]$ $U\left[x_s^{(k-1)}, x_s^k\right]$.

Thus the dynamic range of input image is represented by the union of all intervals where k is the maximum number of significant intersection points. For each input gray level interval there is only one Gaussian component that is dominant with respect to the others which represents the data within that interval. Subinterval $[x_s^{(k-1)}, x_s^{(k)}]$ is represented by a Gaussian component w_k, which is dominant with respect to the other Gaussian components in it. The dominant Gaussian component is found by considering the a posteriori probability of each component in specified interval.

D.Mapping

Enhanced image is obtained by mapping each input interval to corresponding output interval by adding weight which depends on the rate of the total number of pixels that fall into interval and the standard deviation of the dominant Gaussian component ω_k.

$$\alpha_k = \frac{\sigma_{\omega_k}^{\gamma}}{\sum_{i=1}^{N} \sigma_{\omega_i}^{\gamma}} \frac{F\left(x_s^{(k+1)}\right) - F\left(x_s^{(k)}\right)}{\sum_{is=1}^{k-1} F\left(x_s^{(i+1)}\right) - F\left(x_s^{(i)}\right)} \quad (11)$$

The first term adjusts the brightness of the equalized image,and γ €[0,1] is brightness constant. The lower the value of γ , the brighter the output image is. The second term in (19) is related to the gray-level distribution and is used to retain the overall content of the data in the interval. Equation (19) maintains a balance between the data distribution and the variance of the data in a certain interval. Since the human eye is more sensitive to sudden changes in widely scattered data and less sensitive to smooth changes in densely scattered data, larger weights are given to widely scattered data and vice versa.

Using , the input interval $[x_s^{(k-1)}, x_s^{(k)}]$ is mapped onto the output interval $[y^{(k-1)}, y^{(k)}]$ according to

$$y^{(k)} = y_d + (y_u - y_d)\sum_{i=1}^{k-1} \alpha_i$$

$$y^{(k+1)} = y^k + \alpha_k (y_u - y_d) \quad (12)$$

Where m=1, 2…….M – 1.

The gray levels of the pixels in each input interval are transformed according to the dominant Gaussian component and the CDF of the interval to obtain the contrast-equalized image. Let the Gaussian distribution with parameters $\mu_{\omega_{n'}}$ and $\sigma^2{}_{\omega_{n'}}$ represent the Gaussian component in range $[y^{(k-1)}, y^{(k)}]$ .The new parameters of the Gaussian distribution are computed as follows:

$$\mu_{\omega_{k'}} = \frac{\left(\frac{x_s^{(k)} - \mu_{\omega_k}}{x_s^{(k+1)} - \mu_{\omega_k}} y^{k+1} - y^{(k)}\right)}{\left(\frac{x_s^{(k)} - \mu_{\omega_k}}{x_s^{(k+1)} - \mu_{\omega_k}} - 1\right)} \quad (13)$$

$$\sigma_{\omega_{k'}} = \frac{\left(y^{(k)} - \mu_{\omega_{k'}}\right)}{\left(x_s^{(k)} - \mu_{\omega_k}\right)} \sigma_{\omega_k}$$

Thus final mapping is done by linearly transforming each input interval to corresponding output interval so as to get an equalized and contrast enhanced image. It is achieved by considering all Gaussian components in the GMM to retain the pixel distributions in input and output intervals equal by using the superposition of distributions i.e.,

$$y = \sum_{i=1}^{N} \left(\left(\frac{x - \mu_{\omega_{i'}}}{\sigma_{\omega_{i'}}} \right) \sigma_{\omega_{i'}} + \mu_{\omega_{i'}} \right) P_{\omega_{i'}} \quad (13)$$

As shown in Fig.1(b) all intersection points between Gaussian components that fall within the dynamic range of the input image are denoted by yellow circles, and significant intersection points that are used in dynamic range representation are denoted by orange points. The proposed method is extended to color images by applying the method to their luminance component only and preserve the chrominance components.

III. RESULTS AND DISCUSSION

A data set comprising of standard test images from [7] is used to evaluate the proposed algorithm. An output image is said to have been enhanced over the input image if it enables the image details to be better perceived. An assessment of image enhancement is not an easy task as an improved perception is difficult to quantify. Some contrast enhancement results on grayscale images are shown in Figs.

2-3. For comparison purpose techniques like histogram equalizationand Brightness Preserving Dynamic Fuzzy Histogram Equalization (BPDFHE) are used.

The input image in Fig. 2(a) shows an ariel view of a tank. There are three main gray tones in the input image corresponding to the tank, its shadow, and the image background. The other gray-level tones are distributed around the three main tones. By using the proposed algorithm, the dynamic range of the input image is modeled with the GMM, which makes it possible to model the intensity values of shadow, background and tank differently. Input gray-level values are assigned to output gray-level values according to their representative Gaussian components. The nonlinear mapping is designed to utilize the full dynamic range of the output image. Thus, the proposed algorithm improves the overall contrast while preserving image details. The HE method over enhances the image and destroys the natural appearance of the image.

The bright input image in Fig. 3(a) shows an aerial view of a junction in a city . Visual verification shows that natural look of the enhanced image is retained by the proposed algorithm in Fig. 3(c) by preserving the overall shape of the gray-level distribution and redistribution of the gray levels of the input image within the dynamic range. The BPDFHE does not darken the image as done by competing methods. But HE method produces sufficient contrast for the different objects to be recognized.

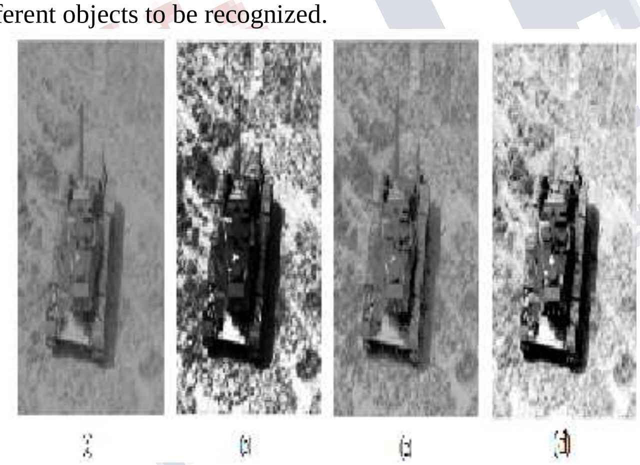


Fig 2. Contrast enhancement for grey image *tank*: (a) Original image, (b) Histogram Equalization (c) BPDFHE and (d) Enhanced output using proposed method.

Fig 3. Contrast enhancement for grey image *city* (a) Original image (b) Histogram Equalization (c) BPDFHE and (d) Enhanced output using proposed method

The PSNR (dB) evaluation scheme is used to assess the strength of the filtered image. Since image is subjective to the human eyes, visual inspection is carried out on the filtered images as to judge the effectiveness of the filters in removing salt-and-pepper noise.The performance of the NAFSM filter was evaluated on the basis of comparison of PSNR with existing techniques like aconventional median filter, hybrid median (HMF) filter.

Fig 4.(a), (b) and (c) shows the test image Elaine corrupted with 90%, 50% and 10% salt and pepper noise respectivley. Table I shows the PSNR values for the same image for a conventional median filter, hybrid media sameimage for a conventional median filter, hybrid median (HMF) filter and the NAFSM filter. It is clear that NAFSM has better noise filtering action compared to other filters like HMF and conventional median filter. From Fig. (d), (e) and (f) and the high PSNR values shows that the implemented filter (NAFSM) is capable of removing high density salt and pepper noise.

TABLE I PSNR VALUES OF TEST IMAGE ELAINE

Percentage Of Noise	Type Of Filter		
	Median	*HMF*	*NAFSM*
10%	22.92	34.27	39.10
50%	14.82	14.89	31.06
90%	6.65	6.61	22.66

TABLE II MSE VALUES OF TEST IMAGE ELAINE

Noise(%)	*Median*	*HMF*	*NAFSM*
10%	331.3	24.29	7.98
50%	0.0021	2.10	50.89
90%	0.00014	1.41	352.40

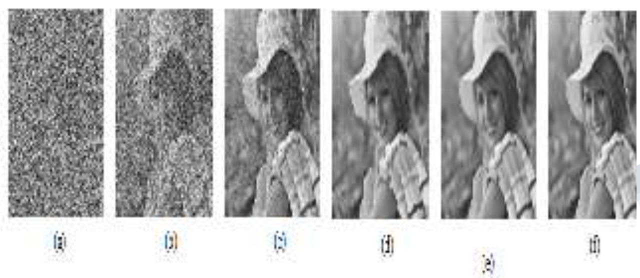


Fig 4. Test image *Elaine* corrupted with (a) 90% (b) 50% (c) 10% noise respectivley and (d),(e),(f) represents the corresponding images after NAFSM, filtering.

IV. CONCLUSION

The automatic image enhancement algorithm using Gaussian mixture modelling of an input image to perform non-linear data mapping generates visually pleasing enhancement on different types of images. A noise adapyive fuzzy median filtering was implemented to remove salt and pepper noises. It is able to suppress high-density of salt-and-pepper noise, at the same time preserving fine image details, edges and textures. This methodology can not only enhance the details, but also maintains the naturalness for the nonuniform illumination images. The images enhanced by this methodology are visually pleasing, artefact free and natural looking. It doesnt require parameter tuning. Future works focuses on applying the algorithm to color images and for rendering HDR images on conventional displays.

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