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Comparison of Automatic Image Contrast Enhancement Using Gaussian Mixture Model and Global Histogram Equalization

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ABSTRACT

In this project, we have implemented Image Contrast Enhancement algorithm that automatically enhances the contrast in an input image. The algorithm uses the Gaussian mixture model to model the image gray-level distribution and the intersection points of the Gaussian components in the model are used to partition the dynamic range of the image into input gray-level intervals. The contrast equalized image is generated by transforming the pixels' gray levels in each input interval to the appropriate output gray-level interval according to the dominant Gaussian component and the cumulative distribution function of the input interval. To take account of the hypothesis that homogeneous regions in the image represent homogeneous silences (or set of Gaussian components) in the image histogram, the Gaussian components with small variances are weighted with smaller values than the Gaussian components with larger variances, and the gray-level distribution is also used to weight the components in the mapping of the input interval to the output interval. Experimental results show that the proposed algorithm produces better or comparable enhanced images than state-of-the-art algorithms like GHE. Unlike the other algorithms, the proposed algorithm is free of parameter setting for a given dynamic range of the enhanced image and can be applied to a wide range of image types.

Keywords:- Image enhancement system, Gaussian mixture model. Histogram specific enhancement, brightness-preserving histogram equalization with maximum entropy, minimum mean brightness error bi-histogram equalization

I. INTRODUCTION

Digital image processing is the use of computer algorithms to perform image processing on digital images. As a subcategory or field of digital signal processing, digital image processing has many advantages over analog image processing. It allows a much wider range of algorithms to be applied to the input data and can avoid problems such as the build-up of noise and signal distortion during processing. Since images are defined over two dimensions (perhaps more) digital image processing may be modelled in the form of multidimensional systems.

In imaging science, image processing is any form of signal processing for which the input is an image, such as a photograph or video frame; the output of image processing may be either an image or a set of characteristics or parameters related to the image. Most image-processing techniques involve treating the image as a two-dimensional signal and applying standard signal-processing techniques to it. Image processing usually refers to digital image processing, but optical and analog image processing also are possible. This article is about general techniques that apply to all of them. The acquisition of images (producing the input image in the first place) is referred to as imaging.

Image enhancement is refers to accentuation, or sharpening, of image features such as boundaries, or contrast to make a graphic display more useful for display & analysis. This process does not increase the inherent information content in data. It includes gray level & contrast manipulation, noise reduction, edge christenings and sharpening, filtering, interpolation and magnification, pseudo colouring, and so on.

Image enhancement is designed to emphasize features of the image that make the image more pleasing to the observer. It is the process of improving the quality of a digitally stored image by manipulating it. Image enhancement is used in various important fields such as medical image diagnosis, finger print recognition, photography enhancement, satellite imagery. Image enhancement is mainly used for improving visibility of pictures and for feature recognition. Contrast enhancement is a common operation in image processing. It's a useful method for processing scientific images such as X-Ray images or satellite images. And it is also useful to improve detail in photographs that are over or under-exposed.

Image enhancement system:

The enhancement system could be a spatial domain where manipulation with direct image pixels or could be frequency domain where manipulation of Fourier transform of an input image or wavelet transform of an input image. The reason for enhancement is to attenuate the effects of sub-sampling, to attenuate quantization effects, to remove noise and simultaneously preserve edges and image details, and to avoid aliasing effects, to attenuate the blackness effect and to enhancement special features to be more easily detected by a machine or a human observer.

The brief introduction of GMM:

Image modelling is one of the important phases in image enhancement. For image modelling, Gaussian Mixture Model (GMM) is the standard methodology. Gaussian mixture model has been widely used in fields of pattern recognition, information processing and data mining. If the number of the Gaussians in the mixture is pre-known, the well-known Expectation-Maximization (EM) algorithm could be used to estimate the parameters in the Gaussian mixture model.

Image contrast enhancement using Gaussian mixture modelling is an effective in terms of improving the visual quality of different types of input images. Images with low contrast are automatically improved in terms of an increase in the dynamic range. Images with sufficiently high contrast are also improved but not as much. Firstly the pixel values of an input image are modelled using the Gaussian mixture model (GMM).The intersection points of the Gaussian components are used in partitioning the dynamic range of the input image into different intervals. The pixels in each input interval are transformed to the output interval according to the dominant Gaussian component and the CDF of the input interval.

The objective of the project:

The main objective of an image enhancement technique is

- To bring out hidden image details
- To increase the gray level differences among objects and background
- To increase the dynamic range of an image with a low dynamic range.
- To generate an enhanced image, which has a better visual quality with respect to input image.

II. LITERATURE SURVEY

Image enhancement is required mostly for better visualization or rendering of images to aid our visual perception. There are various reasons, why a raw image data requires processing before display. The dynamic range of the intensity values may be small due to the presence of strong background illumination, as well as due to the insufficient lighting. It may be the other way also. The dynamic range of the original image may be too large to be accommodated by limited number of bit-planes of a display device. The problem gets more complicated when the illumination of the scene widely varies in the space focused on the enhancement of gray-level images in the spatial domain. These methods include adaptive histogram equalization, unsharp masking, constant variance enhancement, homomorphic filtering, high-pass, and low-pass filtering, etc.

Enhancement techniques:

Numerous enhancement techniques have been introduced and these can be divided into three groups:

1) Techniques that decompose an image into high and low frequency signals for manipulation [3], [4];

2) Transform-based techniques [5]; and

3) Histogram modification techniques [6]–[17].

Techniques in the first two groups often use multiscale analysis to decompose the image into different frequency bands and enhance its desired global and local frequencies. These techniques are computationally complex but enable global and local contrast enhancement simultaneously by transforming the signals in the appropriate bands or scales. Furthermore, they require appropriate parameter settings that might otherwise result in image degradations. For example, the centre-surround Retinex [2] algorithm was developed to attain lightness and colour constancy for machine vision applications. The constancy refers to the resilience of perceived colour and lightness to spatial and spectral illumination variations. The benefits of the Retinex algorithm include dynamic range compression and colour independence from the spatial distribution of the scene illumination. However, this algorithm can result in “halo” artefacts, particularly in boundaries between large uniform regions. Moreover, “greying out” can occur, in which the scene tends to change to middle gray.

Among the three groups, the third group received the most attention due to their straightforward and intuitive implementation qualities. Linear contrast stretching (LCS) and global histogram equalization (GHE) are two widely utilized methods for global image enhancement. The former linearly adjusts the dynamic range of an image, and the latter uses an input to output mapping obtained from the cumulative distribution function (CDF), which is the integral of the image histogram. Since the contrast gain is proportional to the height of the histogram, gray levels with large pixel populations are expanded to a larger range of gray levels, whereas other gray-level ranges with fewer pixels are compressed to smaller ranges. Although GHE can efficiently utilize display intensities, it tends to over enhance the image contrast if there are high peaks in the histogram, often resulting in a harsh and noisy appearance of the output image. LCS and GHE are simple transformations, but they do not always produce good results, particularly for images with large spatial variation in contrast. In addition, GHE has the undesired effect of overemphasizing any noise in an image.

In order to overcome the aforementioned problems, local histogram-equalization (LHE)-based enhancement techniques have been proposed, e,g.,[6] and [7]. For example, the LHE method [7] uses a small window that slides through every image pixel sequentially, and only pixels within the current position of the window are histogram equalized; the gray-level mapping for enhancement is done only for the centre pixel of the window. Thus, it utilizes local information. However, LHE sometimes causes over enhancement in some portion of the image and enhances any noise in the input image, along with the image features. Furthermore, LHE-based methods produce undesirable checkerboard effects.

Histogram specification (HS) [2] is a method that uses a desired histogram to modify the expected output-image histogram. However, specifying the output histogram is not a straightforward task as it varies from image to image. The dynamic HS (DHS) [8] generates the specified histogram dynamically from the input image. In order to retain the original histogram features, DHS extracts the differential information from the input histogram and incorporates extra parameters to control the enhancement such as the image original value and the resultant gain control value. However, the degree of enhancement achievable is not significant.

Some research works have also focused on improving histogram-equalization-based contrast enhancement such as mean preserving bihistogram equalization (BBHE) [9], equal-area dualistic sub image histogram equalization (DSIHE), and minimum mean-brightness (MB) error bihistogram equalization (MMBEBHE) [11]. BBHE first divides the image histogram into two parts with the average gray level of the input-image pixels as the separation intensity. The two histograms are then independently equalized. The method attempts to solve the brightness preservation problem. DSIHE uses entropy for histogram separation. MMBEBHE is the extension of BBHE, which provides maximal brightness preservation. Although these methods can achieve good contrast enhancement, they also generate annoying side effects depending on the variation in the gray-level distribution [8]. Recursive mean-separate histogram equalization [11] is another improvement of BBHE. However, it is also not free from side effects. Dynamic histogram equalization (DHE) [13] first smoothens the input histogram by using a 1-D smoothing filter. The smoothed histogram is partitioned into sub histograms based on the local minima. Prior to equalizing the sub histograms, each sub histogram is mapped into a new dynamic range. The mapping is a function of the number of pixels in each sub histogram; thus, a sub histogram with a larger number of pixels will occupy a bigger portion of the dynamic range. However, DHE does not place any constraint on maintaining the MB of the image. Furthermore, several parameters are used, which require appropriate setting for different images.

Optimization techniques have been also employed for contrast enhancement. The target histogram of the method, i.e., brightness-preserving histogram equalization with maximum entropy (BPHEME) [13], has the maximum differential entropy obtained using a vibrational approach under the MB constraint. Although entropy maximization corresponds to contrast stretching to some extent, it does not always result in contrast enhancement [15]. In the flattest HS with accurate brightness preservation (FHSABP) [15], convex optimization is used to transform the image histogram into the flattest histogram, subject to a MB constraint. An exact HS method is used to preserve the image brightness. However, when the gray levels of the input image are equally distributed, FHSABP behaves very similar to GHE. Furthermore, it is designed to preserve the average brightness, which may produce low contrast results when the average brightness is either too low or too high. In histogram modification framework (HMF), which is based on histogram equalization, contrast enhancement is treated as an optimization problem that minimizes a cost function [16]. Penalty terms are introduced in the optimization in order to handle noise and black/white stretching. HMF can achieve different levels of contrast enhancement through the use of different adaptive parameters. These parameters have to be manually tuned according to the image content to achieve high contrast. In order to design a parameter-free contrast enhancement method, genetic algorithm (GA) is employed to find a target histogram that maximizes a contrast measure based on edge information [17]. We call this method contrast enhancement based on GA (CEBGA). CEBGA suffers from the drawbacks of GA-based methods, namely, dependence on initialization and convergence to a local optimum. Furthermore, the mapping to the target histogram is scored by only maximum contrast, which is measured according to average edge strength estimated from the gradient information. Thus, CEBGA may produce results that are not spatially smooth. Finally, the convergence time is proportional to the number of distinct gray levels of the input image.

Brief review on related ieee papers:

[12] M. Abdullah-Al-Wadud, M. Kabir, M. Dewan, and O. Chae, “A dynamic histogram equalization for image contrast

enhancement," *IEEE Trans. Consum.Electron.*, vol. 53, no. 2, pp. 593–600, May 2007.

In this paper, a novel contrast enhancement algorithm is proposed. The proposed approach enhances the contrast without losing the original histogram characteristics, which is based on the histogram specification technique. It is expected to eliminate the annoying side effects effectively by using the differential information from the input histogram. The experimental results show that the proposed dynamic histogram specification (DHS) algorithm not only keeps the original histogram shape features but also enhances the contrast effectively. Moreover, the DHS algorithm can be applied by simple hardware and processed in real-time system due to its simplicity.

[14] C. Wang, J. Peng, and Z. Ye, "Flattest histogram specification with accurate brightness preservation," *IET Image Process.*, vol. 2, no. 5, pp. 249–262, Oct. 2008.

This method uses convex optimization to transform the image histogram into the flattest histogram, subject to a MB constraint. An exact HS method is used to preserve the image brightness. It is also designed to preserve the average brightness, which may produce low contrast results when the average brightness is either too low or too high.

[15] T. Arici, S. Dikbas, and Y. Altunbasak, "A histogram modification framework and its application for image contrast enhancement," *IEEE Trans. Image Process.*, vol. 18, no. 9, pp. 1921–1935, Sep. 2009.

In this, contrast enhancement is posed as an optimization problem that minimizes a cost function. It is used to handle noise and black/white stretching. This method can achieve different levels of contrast enhancement through the use of different adaptive parameters. The parameters have to be manually tuned according to the image content to achieve high contrast which is a disadvantage.

The aforementioned techniques 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, an image contrast enhancement algorithm is implemented that automatically enhances the contrast of image in an effective manner. The first step of algorithm is to model the image and for this, EM clustering algorithm is used to model the image which is faster and effective. After modelling, intersection points of Gaussian components are used to partition the image into different intervals. Then the image is generated by transforming the pixels in each input interval to the appropriate output interval according to the dominant Gaussian component and the cumulative distribution function of the input interval. The Gaussian components with small variances are weighted with smaller values than the Gaussian components with larger variances, and the gray-level distribution is also used to weight the components in the mapping of the input interval to the output interval.

Advantages:

- Simple and more effective.
- Provide better enhancement.

Disadvantages:

Require appropriate parameter settings that might otherwise result in image degradations.

III. GAUSSIAN MIXTURE MODELING

An image enhancement algorithm using GMM automatically enhances the contrast in an input image. The algorithm uses the Gaussian mixture model to model the image gray-level distribution, and the intersection points of the Gaussian components in the model are used to partition the dynamic range of the image into input gray-level intervals. The contrast equalized image is generated by transforming the pixels' gray levels in each input interval to the appropriate output gray-level interval according to the dominant Gaussian component and the cumulative distribution function of the input interval. To take account of the hypothesis that homogeneous regions in the image represent homogeneous silences (or set of Gaussian components) in the image histogram, the Gaussian components with small variances are weighted with smaller values than the Gaussian components with larger variances, and the gray-level distribution is also used to weight the components in the mapping of the input interval to the output interval.

While using Gaussian mixture modelling EM algorithm is used to partition or cluster the image for grouping objects, clustering. Again all objects need to be represented as a set of numerical features. In addition the user has to specify the number of groups (referred to as *k*) he wishes to identify. Each object can be thought of as being represented by some feature vector in an *n* dimensional space, *n* being the number of all features used to describe the objects to cluster. The algorithm then randomly chooses *k* points in that vector space, these point serve as the initial centres of the clusters. Afterwards all objects are each assigned to centre they are closest to. Usually the distance measure is chosen by the user and determined by the learning task. After that, for each cluster a new centre is computed by averaging the feature vectors of all objects assigned to it. The process of assigning objects and recomposing centres is repeated until the process converges. The EM algorithm can be proven to converge after a finite number of iterations.

Several tweaks concerning distance measure, initial centre choice and computation of new average centres have been explored, as well as the estimation of the number of clusters *k*. Yet the main principle always remains the same.

The GMM algorithm have three steps.

Modelling*:* Here GMM is using to partition the distribution of the input image into a mixture of different Gaussian components. The data within each interval are represented by a single Gaussian component that is dominant with respect to the other components.

Partitioning*:* The numerical values of the intersection points between GMM components are determined using an equation. The consecutive pairs of significant intersection points are used to partition the dynamic range of the input image.

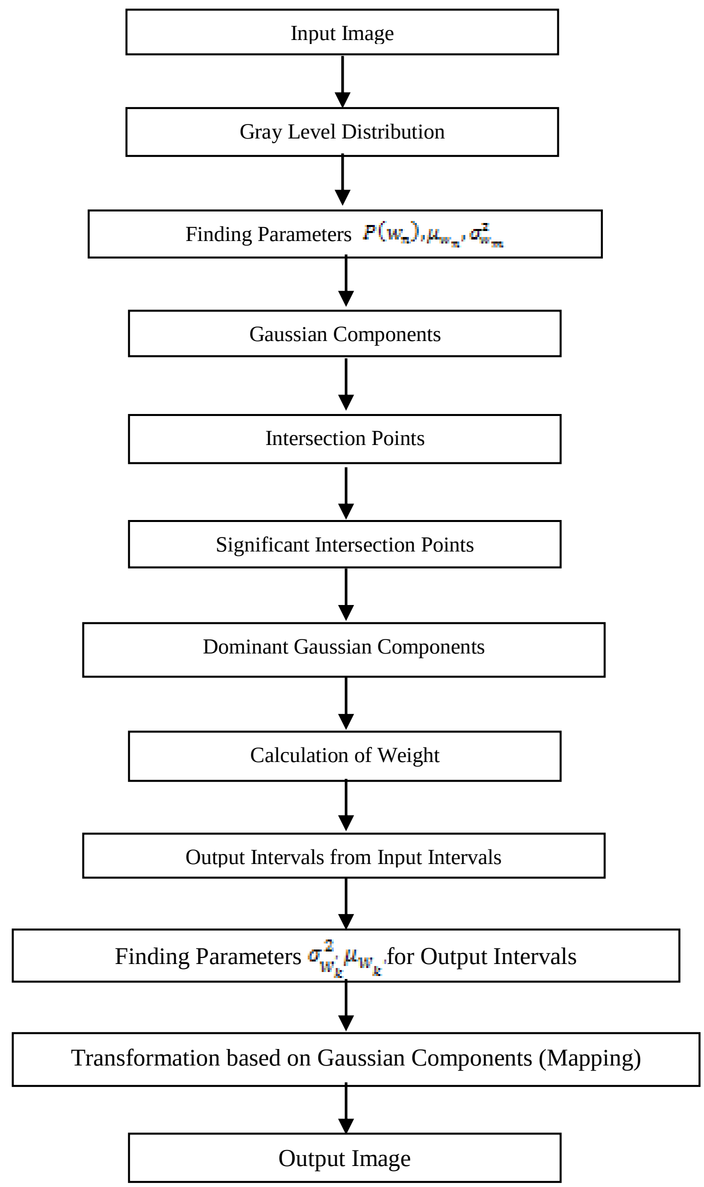
Mapping*:* In mapping, each interval covers a certain range, which is proportional to weight. In the final mapping of pixel values from the input interval onto the output interval, the CDF of the distribution in the output interval is preserved.

The flow chart of the proposed paper

In this project, the GMM technique includes three steps namely: a) Image modelling, b) partitioning and c) mapping. For image modelling, GMM is used to partition the distribution of the input image into a mixture of different Gaussian components. The data within each interval are represented by a single Gaussian component that is dominant with respect to the other components. In the second step, partitioning the numerical values of the intersection points between GMM components are determined using an equation. The consecutive pairs of significant intersection points are used to partition the dynamic range of the input image. At last in mapping, each interval covers a certain range, which is proportional to weight. In the final mapping of pixel values from the input interval onto the output interval, the CDF of the distribution in the output interval is preserved.

Modelling:

A GMM can model any data distribution in terms of a linear mixture of different Gaussian distributions with different parameters. Each of the Gaussian components has a different mean, standard deviation, and proportion (or weight) in the mixture model. A Gaussian component with low standard deviation and large weight represents compact data with a dense distribution around the mean value of the component. When the standard deviation becomes larger, the data is dispersed about its mean value. 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. This operation should be done so that the gray-level distribution is retained. In order to achieve this, we use the GMM to partition the distribution of the input image into a mixture of different Gaussian components.



The grey level distribution $p(x)$, where $x \in \mathbf{X}$, of the input image $\mathbf{X}$can be modelled as a density function composed of a linear combination of N functions using the GMM [18], i.e.,

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

Where p(x | w_n) is the nth component density and P(w_n) is the prior probability of the data points generated from component w_n of the mixture. The component density functions constrained to be Gaussian distribution functions, given in equation (2)

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

where μ_{w_n} and $\sigma_{w_n}^2$ are the mean and the variance of the nth component, respectively. Each of the Gaussian distribution functions satisfies the following constraint:

$$\int_{-\infty}^{\infty} p(x|w_n)\, dx = 1 \qquad (3)$$

The prior probabilities are chosen to satisfy the following Constraints:

$$\sum_{n=1}^{N} P(w_n) = 1 \qquad (0 \le P(w_n) \le 1) \qquad (4)$$

A GMM is completely specified by its parameters $\{(P(w_n), \mu_{w_n}, \sigma_{w_n}^2\}$. The estimation of the probability distribution function of an input-image data x reduces to finding the appropriate values of $\boldsymbol{\theta}$. In order to estimate, maximum-likelihood-estimation techniques such as the Expectation Maximization (EM) algorithm have been widely used.

The EM algorithm starts from an initial guess for the distribution parameters and the log-likelihood is guaranteed to increase on each iteration until it converges.

EM algorithm:

EM algorithm is based on the interpretation of X as incomplete data pixels i.e., $X = \{x^{(1)}, x^{(2)}, \ldots \ldots x^{(HW)}\}$. For Gaussian Mixtures, the missing part is a set of HW labels $Z = \{z^{(1)}, z^{(2)}, \ldots \ldots z^{(HW)}\}$ associated with the HW pixels, indicating which component produced each pixel.

$z^{(i)}$ is the group label of data point $x^{(i)}$. Where each label is $z^{(i)} = \{z_1^{(i)}, \ldots \ldots z_k^{(i)}\}$, where $z_m^{(i)} = 1$ and $z_p^{(i)} = 0$ for $p \neq m$ means that data pixel $x^{(i)}$ was produced by m^{th} component.

Example: $z_m^{(1)} = \{1, 0, 0, 0\} \rightarrow$ data pixel $x^{(1)}$ is in group1

$z_m^{(9)} = \{0, 0, 0, 1\} \rightarrow$ data pixel $x^{(9)}$ is in group4 and so on.

As we are in clustering setting X is given and Z is unknown, now the complete log likelihood corresponding to a k-component mixture is

$$\log p(Y, Z|\theta) = \sum_{i=1}^{HW} \sum_{n=1}^{N} z_n^{(i)} \log[P(w_n) p(x^{(i)}|\theta_n)] \qquad (5)$$

Each $x^{(i)}$ was generated by randomly choosing $z^{(i)}$ from $\{1, 2 \ldots k\}$, and then $x^{(i)}$ was drawn from one of k Gaussians. The parameters of our model are $\theta = (P(w_n), \mu_{w_n}, \sigma_{w_n}^2)$.

The EM algorithm produces a sequence of estimates $\theta(t), t = 0, 1, 2..$ by alternating applying two steps (until some convergence criterion is met)

E-step: Computes the conditional expectation of the complete log-likelihood, given Y and the current estimate $\hat{\theta}(t)$ .Since $\log p(Y, Z/\theta)$ is linear with respect to the missing, we simply have to compute the conditional expectation $\gamma = E[Z/Y, \hat{\theta}(t)$, and plug it into $\log p(Y, Z/\theta)$. The result is so called Q-function. Expectation and maximization to improve our estimates of $P(w_n), \mu_{w_n}, \sigma_{w_m}^2$, Z continue iterating until converged.

Now we have parameters $\theta = (P(w_n), \mu_{w_n}, \sigma_{w_n}^2)$ for all Gaussian components (here we have N=4 no. of groups/ Gaussian components)

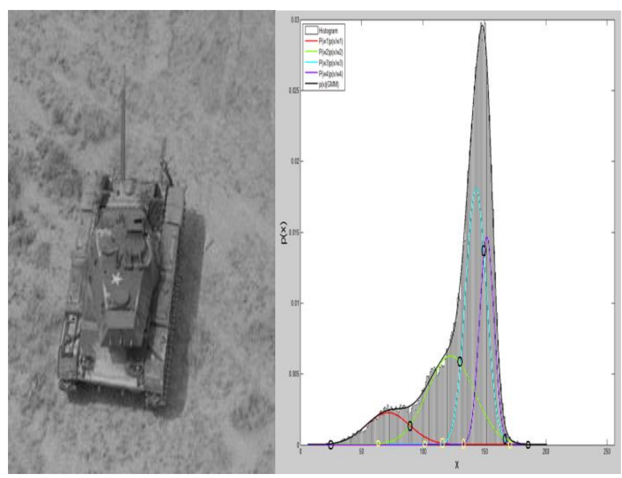


Figure 3.1: Gray Level Image Figure 3.2: Gray level Image histogram for figure 3.1 and its GMM fit

The selection of (partly) determines where the algorithm converges or hits the boundary of the parameter space to produce singular results. Furthermore, the EM algorithm requires the user to set the number of components, and the number is fixed during the estimation process.

Fig. 3.1 and Fig 3.2 illustrates an input image and its histogram, together with its GMM fit, respectively The histogram is modeled using four Gaussian components, i.e., $N = 4$. The close match between the histogram (shown as rectangular vertical bars) and GMM fit (shown as solid black line) is obtained using EM algorithm. There are three main grey tones in the input image corresponding to the tank, its shadow and the image background. The other grey-level tones are distributed around the three main tones. However, EM algorithm results in four Gaussian components $(N = 4)$ for the mixture model. This is because the grey tone with the highest average grey value corresponding to the image background has a deviation too large for a single Gaussian component to represent it. Thus it is represented by two Gaussian components, *i.e.*, w_3 and w_4 as shown in Fig. 3.2.

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 black circles. There is only one dominant Gaussian component between two intersection points, which adequately represents the data within this grey-level interval. For instance, the range of the input data within the interval of [41, 89] is represented by Gaussian component w_1 (shown as solid blue line). Thus the data within each interval is represented by a single Gaussian component which is dominant with respect to the other components. The dynamic range of the input image is represented by the union of all intervals.

Partitioning:

In computer vision, **image partition** is the process of partitioning a digital image into multiple segments (sets of pixels, also known as super pixels). The goal of partition is to simplify and/or change the representation of an image into something that is more meaningful and easier to analyze. Image partition is typically used to locate objects and boundaries (lines, curves, etc.) in images. More precisely, image partition is the process of assigning a label to every pixel in an image such that pixels with the same label share certain visual characteristics. The result of image partition is a set of segments that collectively cover the entire image, or a set of contours extracted from the image (see edge detection). Each of the pixels in a region are similar with respect to some characteristic or computed property, such as colour, intensity, or texture. Adjacent regions are significantly different with respect to the same characteristic. For partitioning the significant intersection points are selected from all the possible intersections between the Gaussian components. The intersection points of two components are independent of the order of the components. All possible intersection points that are within the dynamic range of the image are detected.

In Fig. 3.2 all intersection points between GMM components are denoted by yellow circles. The numerical values of the intersection points determined using Eq. (9) are shown in Table I. Table I is symmetric, *i.e.*, the intersection points between the components w_1 and w_2 are the same as the intersection points between components w_2 and w_1. The intersection points of two components are independent of the order of the components. All possible intersection points that are within the dynamic range of the image are detected. The leftmost intersection point between components w_1 and w_2 is at −652.04 which is not within the dynamic range of the input image, thus it could not be considered. In order to allow combination of intersection points to cover only the entire dynamic range of the input image a further process is needed.

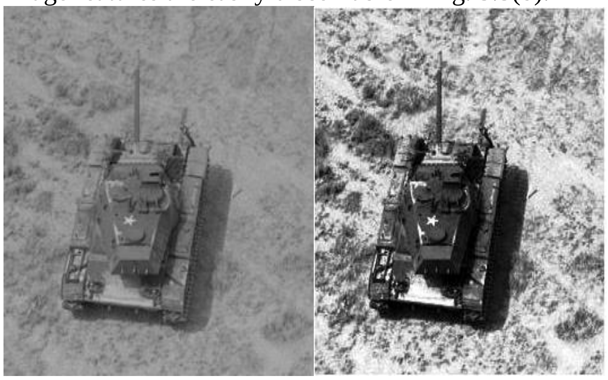
	GMM Components			
	w_1	w_2	w_3	w_4
w_1	-	-652.04, 89.4	116.04, 212.79	129.91, 193.85
w_2	-652.04, 89.4	-	130.51, 166.51	142.52, 167.87
w_3	116.04, 212.79	130.51, 166.51	-	150.21, 169.97
w_4	129.91, 193.85	142.52, 167.87	150.21, 169.97	-

Table I: Numerical Values of Intersection Points Denoted By Yellow circles in Figure 3.2 Between Components of the GMM fit to the Gray level Image shown in Figure 3.1

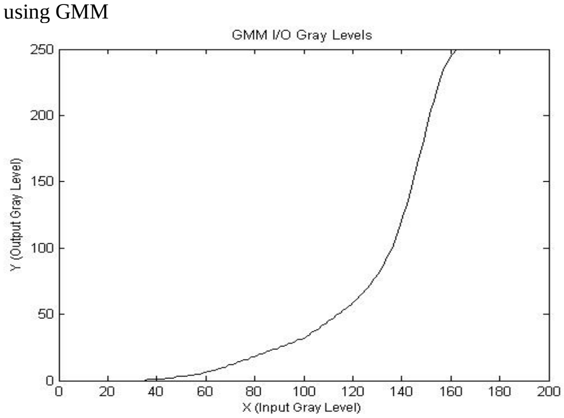
***Mapping*:**

The interval $[x_s^{(k)}, x_x^{(k+1)}]$, where $k = 1,2,\ldots..K-1$, in x_s is mapped onto the dynamic range of the output image Y. In the mapping, each interval covers a certain range, which is proportional to a weight α_k where $\alpha_k \in [0,1]$ which is calculated by considering two figure of merits simultaneously: 1) the rate of the total number of pixels that fall into the interval $[x_s^{(k)}, x_x^{(k+1)}]$ and the standard deviation of the dominant Gaussian component w_k, i.e.,

Fig. 3.3(a), (b) and (c) shows the input images and the equalized images using the GMM algorithm, respectively, where the dynamic range of the output image is $[y_d, y_u] = [0, 255]$, and the mappings between input image data points x and equalized output image data points y are according to Eq. (31). Fig. 3.3(c) shows that a different mapping is applied to a different input gray level interval. Fig. 3.3(b) shows that the GMM algorithm increases the brightness of the input image while keeping the high contrast between object boundaries. The proposed algorithm linearly transforms the gray levels as shown in Fig. 3.3(c), so that the image features are easily discernable in Fig. 3.3(b).



(a)Gray Level Input Image (b) Equalized Output Image Y using GMM



(c) Data mapping between the input and output images.

Figure 3.3

IV. EXPERIMENTAL RESULTS

A dataset comprising standard test images from [21]–[24] is used to evaluate and compare the GMM algorithm with our implementations of GHE [2]. The test images show wide variations in terms of average image intensity and contrast. Thus, they are suitable for measuring the strength of a contrast enhancement algorithm under different circumstances. An output image is considered 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. Thus, it is desirable to have both quantitative and subjective assessments. It is also necessary to establish measures for defining good enhancement. We use absolute mean brightness error (*AMBE*) [10], discrete entropy (*DE*) [25], and edge based contrast measure (*EBCM*) [26] as quantitative measures. AMBE is the absolute difference between the mean values of an input image $\mathbf{X}$ and output image $\mathbf{Y}$, i.e.,

$$\mathrm{AMBE}(\mathbf{X},\mathbf{Y}) = |\mathrm{MB}(\mathbf{X}) - \mathrm{MB}(\mathbf{Y})|$$

Where $\mathrm{MB}(\mathbf{X})$ and $\mathrm{MB}(\mathbf{Y})$ are the mean brightness values of $\mathbf{X}$ and $\mathbf{Y}$, respectively. The lower the value of AMBE, the better is the brightness preservation. The discrete entropy DE of an image $\mathbf{X}$ measures its content, where a higher value indicates an image with richer details. The edge based contrast measure *EBCM* is based on the observation that the human perception mechanisms are very sensitive to contours (or edges) [26]. The gray level corresponding to object frontiers is obtained by computing the average value of the pixel grey levels weighted by their edge values. *EBCM* for image $\mathbf{X}$ is thus computed as the average contrast value, i.e.,

$$\mathrm{EBCM}(\mathbf{X}) = \sum_{i=1}^{H}\sum_{j=1}^{W} c(i,j)/HW$$

It is expected that, for an output image $\mathbf{Y}$ of an input image $\mathbf{X}$, the contrast is improved when EBCM ($\mathbf{Y}$) ≥ EBCM ($\mathbf{X}$)..

		Image Contrast Enhancement Comparisons for GHE & GMM					
		AMBE		DE		EBCM	
Sl. No.	Image Name	GHE	GMM	GHE	GMM	GHE	GMM
1	Woman_ darkhair	20.12	4.599	1.747	2.147	0.01868	0.0404
2	Lena	31.88	14.29	1.791	2.137	0.03418	0.08234
3	Flower	51.62	17.23	1.791	2.239	0.02978	0.03708
4	Tower	12.7	2.046	1.791	2.277	0.103	0.135
5	Pepper	7.041	0.932	1.797	2.239	0.03592	0.05909

Table II: Image Contrast Enhancement Comparisons for GHE and GMM with AMBE, DE and EBCM numerical values calculated for standard images given in above table.

The simulation result shows that the Gaussian Mixture Modelling is much better than the GHE. Some standard images are taken for modelling in both GHE and GMM. We used 256 X 256 images with N=4 no. of groups/ clusters/ Gaussian components.

The output images of image contrast enhancement using GMM is given in following figures:

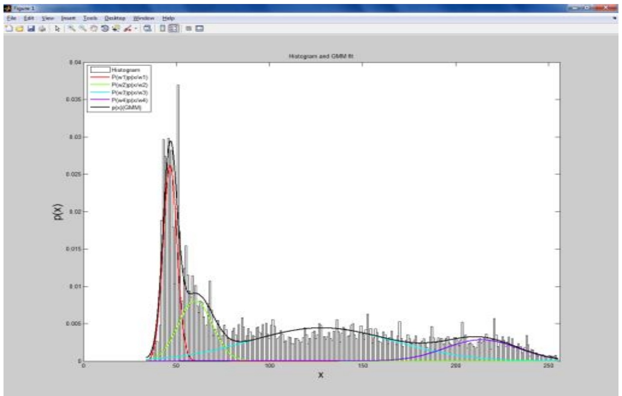


Figure 5.1: Histogram and its GMM fit for the image *Woman_darkhair*:

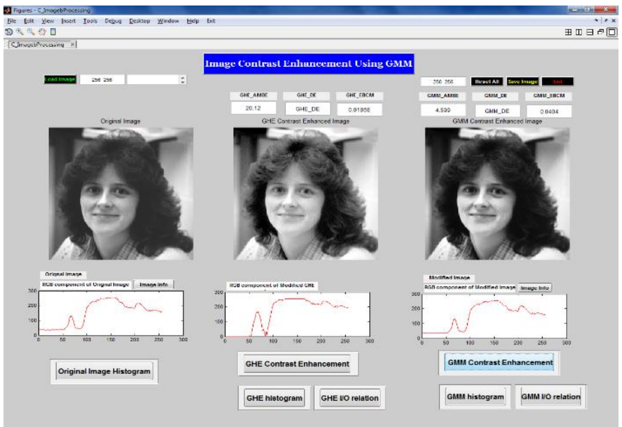


Figure 5.2: Contrast Enhancement Results for the image *Woman_darkhair* :Original Image, GHE and GMM method

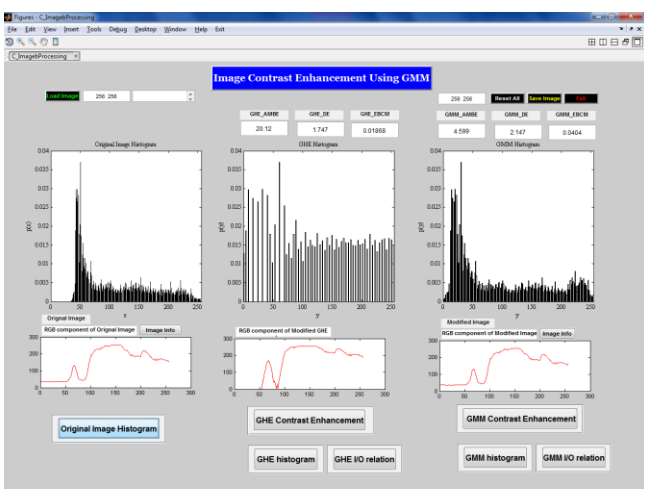


Figure 5.3: Histogram of original Image and enhanced Images using GHE and GMM method for the image *Woman_darkhair*

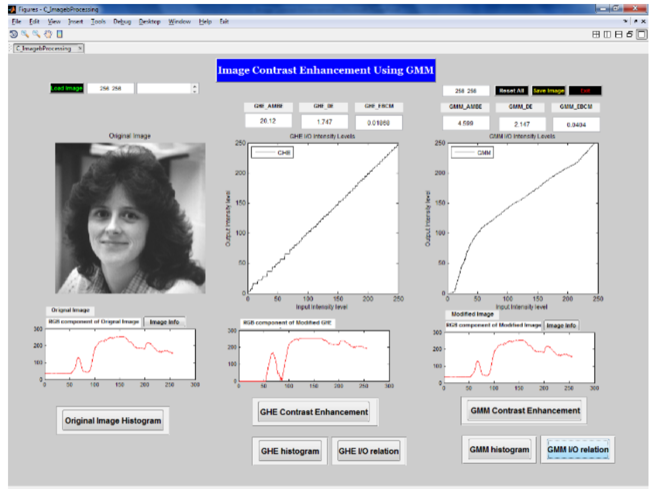


Figure 5.4: Mapping functions of enhanced Image for *Woman_darkhair* using GHE and GMM method

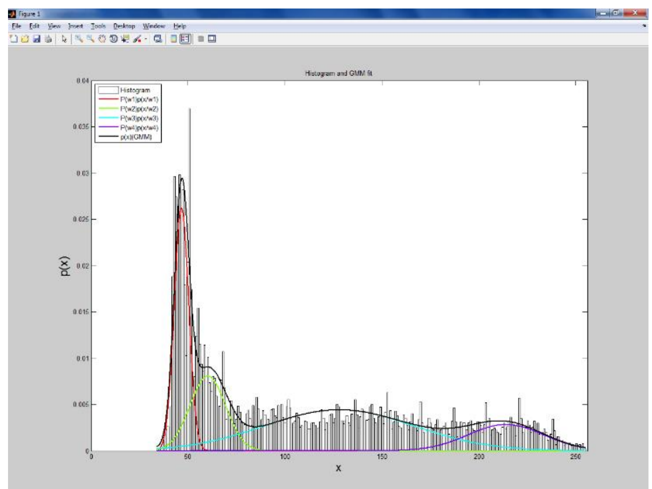


Figure 5.5: Histogram and its GMM fit for the image *Lena*

Figure 5.6: Contrast Enhancement Results for the image *Lena:* Original Image, GHE and GMM method

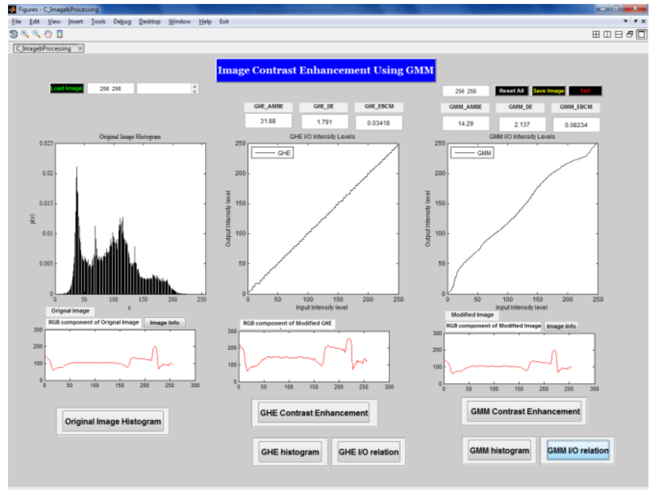


Figure 5.8: Mapping functions of enhanced Image for *Lena* using GHE and GMM method

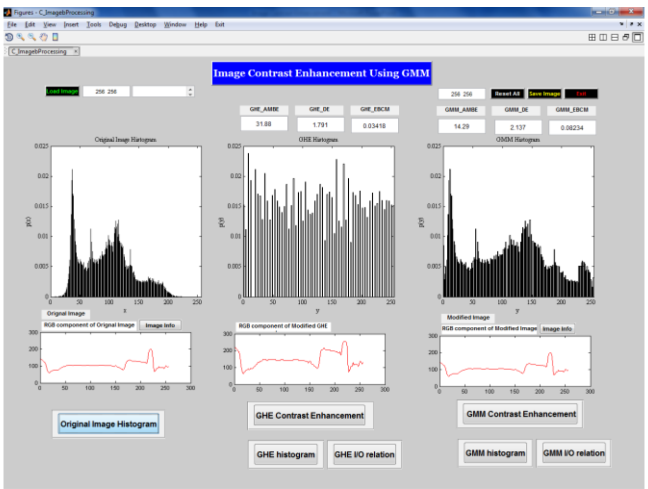


Figure 5.7: Histogram of original Image and enhanced Images using GHE and GMM method for the image *Lena*

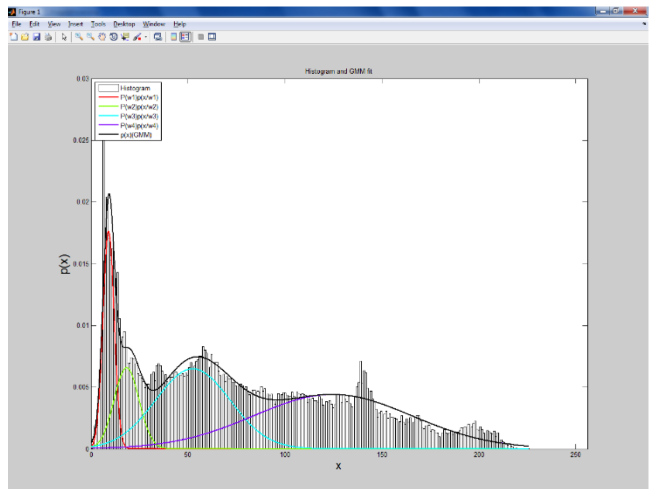


Figure 5.9: Histogram and its GMM fit for the image *Flower*

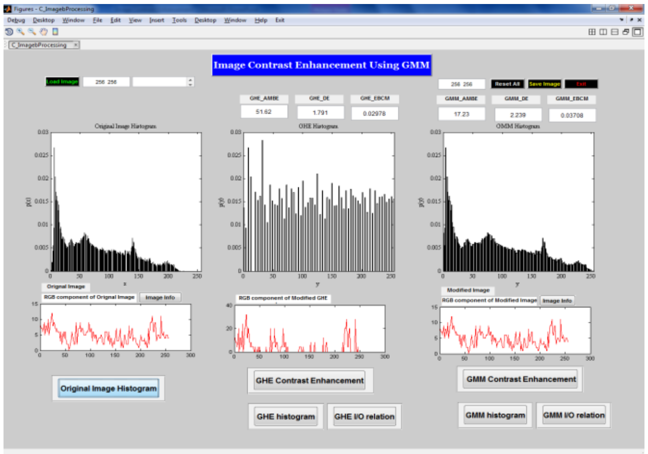


Figure 5.10: Histogram of original Image and enhanced Images using GHE and GMM method for the image *Flower*

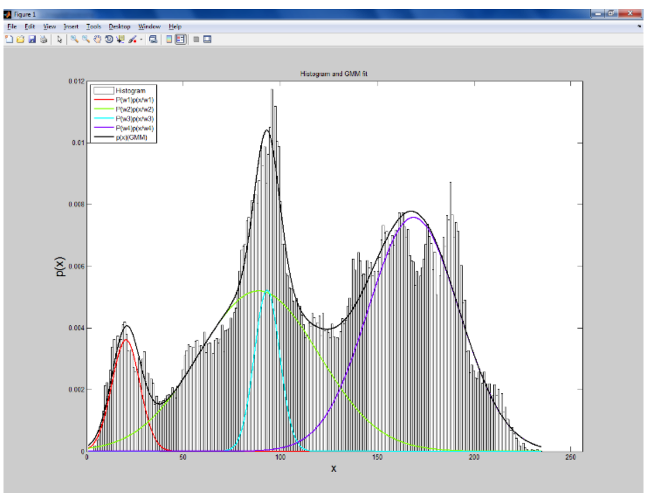


Figure 5.11: Histogram and its GMM fit for the image *Pepper*

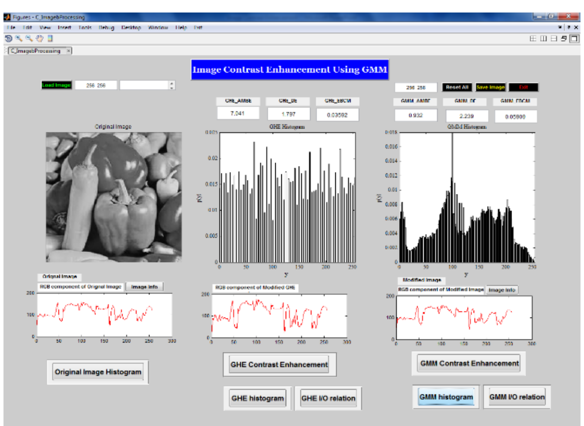


Figure 5.12: Histogram of original Image and enhanced Images using GHE and GMM method for the image *Pepper*

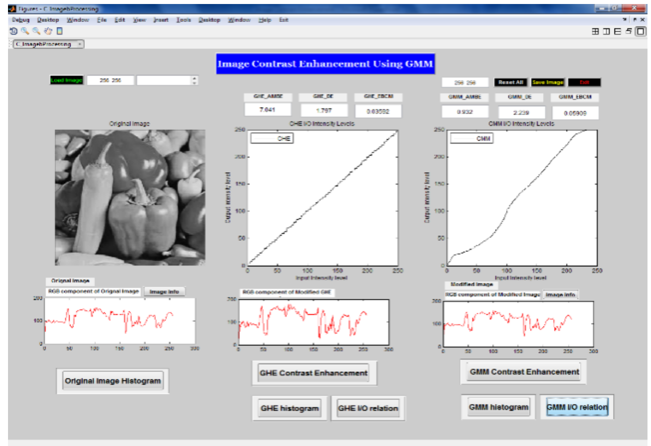


Figure 5.13: Mapping functions of enhanced Image for *Pepper* using GHE and GMM method

V. CONCLUSION

Image Contrast Enhancement using Gaussian Mixture Modelling (GMM) has been Implemented and analyzed mathematically. A performance comparison with state-of-the-art techniques like GHE shows that the implemented algorithm gives good results in terms of AMBE, DE and EBCM. The comparison table has given below

		Image Contrast Enhancement Comparisons for GHE & GMM					
		AMBE		DE		EBCM	
Sl. No.	Image Name	GHE	GMM	GHE	GMM	GHE	GMM
1	Woman darkhair	20.12	4.599	1.747	2.147	0.01868	0.0404
2	Lena	31.88	14.29	1.791	2.137	0.03418	0.08234
3	Flower	51.62	17.23	1.791	2.239	0.02978	0.03708
4	Tower	12.7	2.046	1.791	2.277	0.103	0.135
5	Pepper	7.041	0.932	1.797	2.239	0.03592	0.05909

AMBE means Absolute Mean Bit Error, a lower value indicates the better brightness preservation.

DE means Discrete Entropy, a higher value indicates an image with richer details.

EBCM means Edge Based Contrast Measure, a higher value indicates the contrast is improved

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