A project report on

GAUSSIAN MIXTURE MODEL BASED CONTRAST ENHANCEMENT

Submitted in partial fulfilment of the Requirement for the award of degree of

Master of Technology

In

Information Systems

Submitted By:

MAHIMA DAYAL

(2K14/ISY/05)

Under the Guidance of:

Mr. Anil Singh Parihar

(Assistant Professor, Department of Computer Engineering, DTU)

2014-2016

Department of Computer Science and Engineering

Delhi Technological University

Bawana Road, Delhi – 1100422

CERTIFICATE

This is to certify that Ms. Mahima Dayal (2K14/ISY/05) has carried out the major project titled "Gaussian Mixture Model Based Contrast Enhancement" as a partial requirement for the award of Master of Technology degree in Information Systems by Delhi Technological University. The major project is a bonafide piece of work carried out and completed under my supervision and guidance during the academic session 2014-2016. The matter contained in this report has not been submitted elsewhere for the award of any other degree.

(Project Guide)

Mr. Anil Singh Parihar

Assistant Professor

Department of Computer Science Engineering

Delhi Technological University

ACKNOWLEDGEMENT

I express my gratitude to my major project guide Mr. Anil Singh Parihar, Assistant Professor Department of Computer Engineering, Delhi Technological University, for the valuable support and guidance he provided in making this major project. It is my pleasure to record my sincere thanks to my respected guide for his constructive criticism and insight without which the project would not have shaped as it has. I humbly extend my words of gratitude to other faculty members of this department for providing their valuable help and time whenever it was required.

Mahima Dayal

2K14/ISY/05

M.Tech (Information Systems)

ABSTRACT

Image enhancement is the process of applying transformation on a digital image to get a better picture. As such there is no way to measure the enhancement of an image except the human perception, however a certain characteristics are used t o determine whether the image is suitable for a particular application. Gaussian mixture model based contrast enhancement serves as a powerful algorithm for image enhancement. The main idea behind the algorithm is to estimate a Gaussian mixture model from the image histogram. . It consists of three phases- First to estimate the Gaussian parameters by using previously mentioned methods and obtain mean, Gaussian boundary , variance and scaling factor. In the second phase, the gamma is calculated using the these parameters for each Gaussian territory. Finally, the calculated gamma is applied through an intensity transformation.

TABLE OF CONTENTS

List Of Figures-

CHAPTER-1

Introduction

1.1Introduction

An image is a visual representation of a scene or a still capture. It can be captured using a camera or drawn manually. Images can be categorized as analog or digital. Nowadays, since digital cameras are used, mostly the images are digital. Analog images are as they are, no units for them, however digital images have pixels as their basic unit.

1.1.2 Pixel-

Also known as pel, dot or pixel element is the smallest possible unit of an image. An image can be considered as a two-dimensional grid of pixels such that each pixel has a unique intensity which has a strong correlation with the neighboring pixels since the transition of intensities in the image is generally gradual.

1.1.3 Gray scale and Color Images-

A gray scale image contains black white and various shades of gray only, these shades are referred to as Levels when speaking about digital images. A color image is a composite image containing three different components. These components can be modeled using two color models-RGB (Red Green Blue) and HSI (Hue Saturation Intensity).

1.1.4 Dynamic Range-

The dynamic range of a gray scale image is the difference between the lowest and highest grayintensity present in the image. This is generally referred to as contrast of the image the image as well. Gray level images generally have 256 (0-255) distinct gray levels, 0 being black and 255 being white, however a 256 gray level image may contain all these intensities is not always true, hence, all enhancement approaches basically work upon increasing this dynamic range to contrast and make the image visually better.

1.1.5 Resolution-

Resolution of an image can be categorized as Spatial and Intensity resolution. Spatial resolution is to the number of pixels in an image while, intensity resolution refers to the dynamic range of the image. An image having higher spatial and intensity resolution is visually better than low resolution images also, it’s bigger in size.

1.1.6 Image Enhancement-

Enhancement of an image is the process of applying transformations to make the image look better by increasing its dynamic range. The aim of image enhancement is to improve theinterpretability or perception of information in images for human viewers, or to provide better' input for other automated image processing techniques. Image enhancement techniques can be divided into two broad categories:

- Spatial Domain- When image enhancement is carried out in spatial domain, the transformation is applied directly to the pixel.

- Frequency Domain-The image is converted to frequency domain, after which transformation is carried out and then converted back to frequency domain.

There is no way to measure the enhancement of an image, it's only about human perception and interpretability that one image looks better than other. However if the image is being processed for any specific application, then a few parameters may be considered.

1.2 Basic image Transformations-

The basic image transformation is done using the following formulae-

$$S=T(r) \tag{1}$$

Where, r=input image

s=output image

T=Transformation function

Traditionally, the following transformations are used for images-

1.2.1 Linear Transformations-

There are basically two types of linear transformations, namely identity and invert.

- Identity- It is nothing but a simple plot of all pixels from levels 0 to L-1. The output is same as the input.

$$s=r$$

- Invert- Invert transformation is like a negative of the image. It is calculated as a difference of the current intensity of the pixel and the maximum level intensity (L-1).

$$s=L-1-r$$

For a 256 level image,

$$s=255-r$$

1.2.2 Logarithmic Transformations-

The Logarithmic transformation is defined by the following formula-

$$s=c \ \mathrm{Log}(r+1) \tag{2}$$

where, S=output image,

r=input image,

c=constant.

1.2.3 Power Law Transformation-

Also called gamma transformation, power law transformation is given as follows-

$$s=c \ r^{\wedge}Y \tag{3}$$

where, s=output image r=input image c=constant Y=power or gamma

The power law can be grouped into two categories, one where gamma is less than 1 and the other where gamma is greater than 1. However if gamma equals 1, the output would be the input image itself. Summing up all the transformations, they can be represented in a single graph as follows-

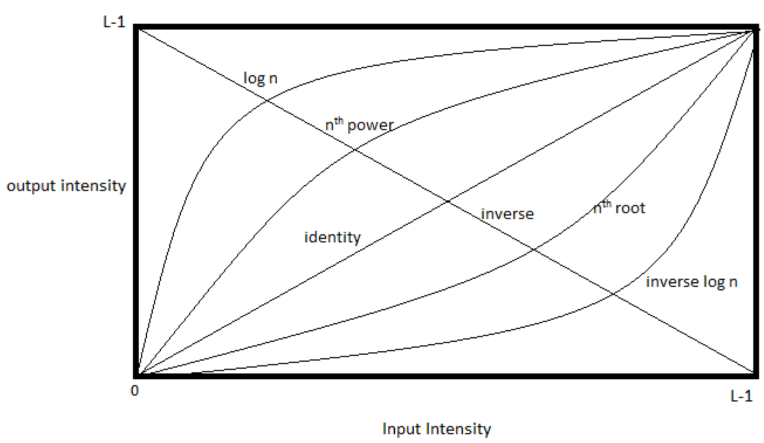


Fig. 1 Various Image Transformations

1.3 Histogram Equalization-

1.3.1 Histogram of an image-

A Histogram is a graphical representation of distribution of pixels throughout the intensities. It is plotted by having intensities on the x-axis and number of pixels on y-axis. The number of Pixels corresponding to each intensity is plotted in the graph. Numerically it can be expressed as follows-

$$h((k)=n(k) \qquad k=0,1,2,3,\ldots\ldots\ldots\ldots L-1 \qquad (4)$$

Where, h(k)=histogram at K^{th} intensity level,

n(k)=number of pixels having K^{th} intensity,

1.3.2 Normalized Histogram-

A normalized histogram is similar to a histogram i.e. it also shows the pixel distribution of .The image throughout the intensities however, it does represent the number of pixels corresponding to a given intensity but the probability density function of the pixels.

Numerically, it is formulated as follows-

$$p((k)=n(k)\,/N \qquad k=0,1,2,3,\ldots\ldots\ldots\ldots L-1 \qquad (5)$$

Where, p(k) is the pdf of K^{th} intensity and n(k) is same as above,

N-total number of pixels

1.3.3 Histogram Equalization-

Histogram equalization is the conventional and basic image enhancement technique. The Cumulative density function is alculated from the image pdf and then applied to calculate the equalized histogram. The original histogram is modified in a way such that, the dynamic range of the image increases making the image visually better. However simple histogram introduces artifacts in the image and therefore, new techniques are being devised to achieve better image enhancement. Numerically, histogram equalization is given as follows-

$$h_{eq}(k) = (L-1)\sum p(k) \qquad k=0,1,2,3\ldots\ldots\ldots\ldots\ldots L-1 \tag{6}$$

CHAPTER-2

Literature Survey

2.1 Brightness-Preserving Bi-Histogram Equalization (BBHE)-

The traditional histogram equalization had various drawbacks due to which, new algorithm were developed in which these limitations were considered and were tried to overcome. The histogram equalization technique introduces changes in the image brightness and degrades . The contrast. Also it treats all the images in the same way, and does not consider any of its parameters . The mean brightness of the input image is also not preserved and mean brightness preservation is important as it characterizes the image. Brightness preserving bi-histogram equalization or BBHE overcomes this limitation of Traditional histogram equalization and helps in preserving the mean brightness of the image. The main technique behind BBHE is to divide the histogram of the input image on the basis of the mean intensity into two halves and equalize each part independently constraining the output histogram that the new dynamic range after equalization should also be limited to their partitions in the input histogram.

The BBHE algorithm can be briefly explained as follows-

- The histogram of the input image is calculated.
- The mean brightness (X_m) is obtained from the histogram.
- The histogram is partitioned on the basis of X_m as follows-

$$X=X_L \cup X_U \tag{7}$$

$X_L=\{X(I,j)|X(I,j)<=X_m\}$ i.e intensities less than the mean

$X_U==\{X(I,j)|X(I,j)>X_m\}$ i.e intensities greater than mean

- Each partition is equalized independently.

- The equalized partitions are combined to form the resultant image.

2.2 Recursive Mean-Separate Histogram Equalization for Scalable Brightness Preservation-

To overcome the limitations of traditional histogram equalization, Brightness preserving bi histogram equalization is devised which preserves the mean brightness. While Histogram equalization always outputs the middle gray level as the mean intensity irrespective of the input mean intensity , BBHE preserves the mean intensity to some extent. However BBHE does not perform so well when image contrast is very low and requires higher degree of brightness preservation . Also the partitioning of histogram based on mean intensity is also done only once To overcome these limitations of BBHE and extent the concept of sub- histogram equalization to a more complex and efficient algorithms a new technique was developed namely Recursive Mean Separate Histogram Equalization or RMSHE . It is nothing but a generalization of Histogram Equalization and BBHE. In BBHE the histogram is partitioned only once on the mean intensity while, in RMSHE, the histogram is partitioned recursively until the output mean is closest to the input mean . The number of times the histogram is partitioned based on the mean depends on the image. This is known as recursion level and is expressed as ‘r’ therefore , if r=0 the RMSHE algorithm becomes histogram equalization as there is no partitioning at all and when r=1 it becomes BBHE i.e. only one time partitioning. If r>1 say 2 the means of each sub-histogram obtained by one partitioning are again divided on the basis means of the sub-histograms. In general if r=n the ouput mean

is given by-

$$E(Y) = ((2^n - 1)X_m + X_G) / 2^n \tag{8}$$

$$= X_m + [(X_G - X_m) / 2^n] \tag{9}$$

Therefore, RMSHE out performs both HE and BBHE as the number of recursion levels can be controlled according to the input image snd its mean intensity.

2.3 Minimum Mean Brightness Error Bi-Histogram Equalization (MMBEBHE)-

All the above algorithms can be used for image enhancement but each of them have their own drawbacks , HE does not provide brightness preservation at all while BBHE does to some extent. RMSHE is a generalization of both the algorithms where recursive sub- histograms are calculated to attain maximum brightness preservation . However RMSHE one does not know how many times it should be executed . There is a need to quantify as to when to stop the recursion for a given image. To overcome this limitation of RMSHE , MMBHE or Minimum Mean Brightness Error Bi-Histogram Equalization was developed where a parameter AMBE or absolute mean brightness is calculated to find out the most suited intensity for partitioning the sub-histogram . The algorithm for MMBEBHE can be explained as follows-

- Each intensity is considered as a threshold for partitioning and mean brightness error is calculated by applying BBHE on them.
- The threshold X_T is set to the intensity which yields the minimum mean brightness error.
- Sub-histograms are separated based on threshold X_T.
- Each of the sub-histogram is equalized.

Although the algorithm majorly enhances the image, the drawback here is the huge computation time as each AMBE calculation involves one full execution of BBHE.This can be overcome by approximation of output however the calculated value of the output may vary. Yet MMBEHE on a whole is one of the frequently used algorithms for image enhancement due to the quality of the output.

2.4 Weighted Threshold Histogram Equalization-

The above set of algorithms basically work upon selecting a threshold dividing the Histograms on the basis of that threshold and equalizing the sub-histograms. Besides these techniques, various other techniques are used for image enhancement, one of the major being global enhancement approach, which works on the histogram globally. Weighted Threshold Histogram equalization is one such algorithm. It offers less artifacts in the output image as compared to histogram equalization and less complexity as compared to sub-histogram methods. Histogram equalization is perfect for continuous images but not for discrete images. Intensity levels with high probability (which is generally the background) becomes over enhanced while the ones with less probability becomes less enhanced. WTHE performs HE based on modified histogram and each PDF is replaced by a weighted threshold PDF, P_{WT} The algorithm is as follows-

- The PDF of the image is calculated.
- The weighted threshold probability density function is calculated as follows-

$$P_{WT}(k)=\Omega P(k)=\begin{cases} Pu & P(k) > Pu \\ (\frac{P(k)-Pl}{Pu-Pl})\text{^}r.Pu & Pl < P(k) < Pu \\ 0 & P(k) < Pl \end{cases} \quad (10)$$

- P_u is calculated as the percentage cut off of the maximum pdf P_{max} as follows-

$$P_u=v.P_{max}$$

- Then the weighted CDF C_{WT} is calculated from P_{WT}
- Finally the level mapping is carried out as follows-

$$F`(I,j)=Wout \times C_{WT}(F(I,j))+M_{adj}. \quad (11)$$

CHAPTER-3

Gaussian Mixture Model Based Contrast Enhancement

3.1 Gaussian or normal distribution-

It is a function with a bell shaped curve with the following probability density function-

$$P(x,\mu,\sigma^2)=\frac{1}{\sqrt{2\pi\sigma^2}}\exp\left(-\frac{(x-\mu)^{\wedge}2}{2\sigma^{\wedge}2}\right) \tag{12}$$

where μ (mean) and σ^2 (variance) are the Gaussian parameters which are defined as follows-

- Mean(μ)- The mean of a Gaussian function is that point on the graph at which the function attains the maximum value.
- Variance(σ^2)- The variance of the Gaussian function controls the spreading of the bell shaped curve. Numerically it is the distance of the pdf from the mean where the curve attains 68% of the mean.

3.2 Gaussian Mixture Models-

A mixture model is basically a probabilistic model for representing the presence of sub-Populations in an overall population without requiring that an observed data set should identify the sub-population to which an individual population belongs. A Gaussian mixture model is a weighted sum of Gaussian component densities. Each of the Gaussian has a weight and is represented as a sub-population. A gaussian mixture model is formulated as follows-

$$P(x|\lambda)=\sum_{i=1}^{M} wig(x|\mu i,\sum i) \tag{13}$$

Where w_i are the weights and $\lambda=\{ w_i, \mu_i,\sum i\}$ therefore, λ is nothing but a collection of parameters.

3.3 Gaussian mixture model based contrast Enhancement-

In natural images, each homogeneous area is considered to be have a corresponding Gaussian shaped sun-histogram in the image histogram of the. Therefore each histogram can be approximated with a of Gaussian functions. Mean of Gaussian indicate corresponding average intensity while variance corresponds to texture details. So it can be concluded that a histogram can be considered as a Gaussian mixture model. However for the histogram of an image to be similar to a gaussian mixture model, the image should havean intensity distribution in way such that it has a few large regions of similar intensities so thatthe gaussians obtained are distinct and non-overlapping . In GMMCE, the gaussian parameters are approximated and a gaussian mixture model is obtained corresponding to the given image histogram. The estimation of parameters is the most crucial phase.

3.3.1 Parameter Estimation-

The parameters mean, variance and the weights (scaling factors) are approximated from the histogram of the image. Generally, parameters of a gaussian mixture model are approximated by applying EM or expectation maximization algorithm however here, low complexity greedy approach is used to estimate the parameters.

- Mean Parameter Estimation-

Mean can be calculated by finding the local maxima of the histogram but this not the most efficient way as the shape of the histogram is not smooth. So, another approach is employed for approximating the mean. In this technique, an intensity which satisfies the following objective function is found out-

$$\mu` = \text{argmax} \sum_{j=0}^{L-1} \mathrm{N}(\mathrm{I}|\ \mathrm{j}, 2\ \sigma 2), \mathrm{horg}(\mathrm{j}) \quad (14)$$

Where, h_{org} is the original histogram and $N(j|I, \sigma^2)$ is the aussian pdf. The variance σ^2 is randomly chosen.

The above optimization function basically approximates a mean around which the shape of the histogram is that of a gaussian function. For thi it takes each of the intensities as the mean and gives an optimal solution.

- Gaussian Territory Estimation-

After the mean is found out, the gaussian boundary is calculated, this is important as each point on the x-axis is actually affected by all the gaussians propotionally to their tail thickness at that point. These undesirable effects are unavoidable when a gaussian sub-histogram is to be estimated . Hence it is imporatant to find out the purest neighbourhood around the mean obtained. The neighborhood is estimated in the following manner-

a) H_{org} i.e. the original histogram is padded with ad/equate number of $h_{org}(0)$ and $h_{org}(L-1)$ in the beginning and end respectively.
b) A one-dimensional averaging filter of size 2 X n +1 is applied to replace each intensity with the average of its neighborhood.
c) Then the upper and lower bounds of the aussian are approximated by finding out the local minima in both the directions.
d) Hence lower bound i.e. Lb and upper bound i.e. Ub are obtained.

- Variance estimation-

For variance parameter estimation, mean, lower and upper bounds are used as inputs. Drop ratios R^d is calculated for both backward and forward direction. The variance is calculated as under-

$$R^{d}_{(fw/bw)}=e^{\wedge}d^2/2\sigma^2 \tag{15}$$

Therefore,

$$\sigma = \frac{d}{\sqrt{2.\ln(R(fw/bw))}} \qquad d=1,2,3\ldots\ldots \tag{16}$$

➢ Scaling Factor Estimation-

Once the mean and variance are estimated, the sub-histogram should be removed from global histogram, so that the next dominant histogram may appear and be identified. Therefore, on the basis of the height of ongoing sub-histogram the Gaussian PDF is scaled and thus subtracted from the original histogram

$$H^{t+1}{}_{s}(I)= h^{t}{}_{s}(I)-\dot{\omega}.N(I|\ \mu, 2\sigma^2) \tag{17}$$

Where, h_s^{t+1} and $h^t{}_s$ are smoothed histograms before and after subtracting the current estimated gaussian PDF. From this, $\dot{\omega}$ can be calculated considering that after subtraction h_s^{t+1} will be zero

$$-H^{t}{}_{s}(I)-\dot{\omega}.N(I|\ \mu, 2\ \sigma^2)=0 \tag{18}$$

Therefore from this we obtain-

$$\dot{\omega}=\sqrt{2\pi}\sigma^2\ .\ h^{t}{}_{s}(\mu) \tag{19}$$

Finally, the following transformation functions are applied on mean and variance to get the modified histogram with scattered mean and increased variances-

$$\tilde{\mu}=\ddot{\mu}_i\text{-}Lb/Ub\text{-}Lb \qquad i=1,2,\ldots\ldots\ldots\ldots\ldots,k \tag{20}$$

$$\tilde{\Sigma} = \ddot{\sigma} \times \frac{256}{\mathrm{Ub-Lb}} \tag{21}$$

CHAPTER-4

Adaptive Gamma Correction

4.1 Power Law-

The power law or gamma law on image works in a way that for positive integral powers, it shifts the histogram towards left thus making the image darker while, for positive powers less than 1, the histogram shifts towards the right side which introduces an increase in the brightness thus making the image brighter.

4.2 Adaptive Gamma-

The behavior of the histogram with power law can be used for contrast enhancement. Since it is observed that histogram shifts towards left for positive integers and left for decimal values this property can be used to increase the dynamic range of the image. The concept is known as Adaptive gamma, the gamma is applied according to the intensity of the image. For lower intensity values, larger integers are used while for higher intensity value smaller fractions are applied , however at the mean the value is tried to kept 1 for mean brightness preservation.

4.3 Contrast Enhancement Using Adaptive Gamma Correction-

The general form of gamma transformation is given by following equation-

$$T(l)=l_{max}(l/l_{max})^{y} \tag{22}$$

Where, l_{max} is the maximum intensity.

To attain the desired contrast enhancement, one needs a parameter that can change according to the image intensity. For this purpose, the cumulative density function is used since it changes according to the image intensity. Hence the following transformation is used-

$$T(l)=l_{max}(l/l_{max})^{(1-cdf)} \quad (23)$$

The cdf is subtracted from 1 since its very low for lower pdf and higher for high pdf, so get the desired effect, it is subtracted from1.

The above implementation of adaptive gamma using nomal cdf does not work so well. Hence to further increase the dynamic range the weighted cdf, cdf_w is calculated from weighted pdf, pdf_w as follows-

$$pdf_w(l)=pdf_{max}\left[\frac{pdf(l)-pdf_{min}}{pdf_{max}-pdf_{min}}\right] \quad (24)$$

and hence the cdf_w is calculated as under-

$$cdf_w=\sum_{l=0}^{l_{max}} pdf(l) \quad (25)$$

Therefore the y applied is-

$$Y`=1-cdf_w \quad (26)$$

CHAPTER-5

Proposed Approach

5.1 The Approach-

The proposed algorithm uses a mixture of previously mentioned Gaussian Mixture Model based contrast contrast enhancement and adaptive gamma correction with modifications made to calculate gamma by estimated Gaussian parameters. It consists of three phases- First to estimate the Gaussian parameters by using previously mentioned methods and obtain mean, Gaussian boundary , variance and scaling factor. In the second phase, the gamma is calculated using the these parameters for each Gaussian territory. Finally, the calculated gamma is applied through an intensity transformation. Gaussian parameters are use to calculate gamma because they serve as a very deterministic way to give information about the histogram. A Gaussian mixture model is a better way to implement and understand the characteristics of an image The algorithm works best for those images which have large regions with similar intensities a. In that case, the histogram is shaped in such a way that few distinct peaks and therefore the parameters of the corresponding Gaussian can be easily estimated. The number of times the algorithm for Gaussian parameter estimation will run is decided by the intensity distribution of the input image.Once the Gaussian histogram is obtained, the difference between the original and Gaussian histogram is optimized. The mean of means, maximum variance and upper and lower boundaries corresponding to the maximum variance are calculated and used for calculation of gamma as follows-

$$y` = PDF_{gaussian} \times \left(\frac{mean_m}{\max\_var}\right)^{0.5} \tag{27}$$

Finally, the following intensity transformation is used-

$$T(l)=\frac{Ub}{Lb}\times l^{(2-y`)} \tag{28}$$

4.2 Flowchart-

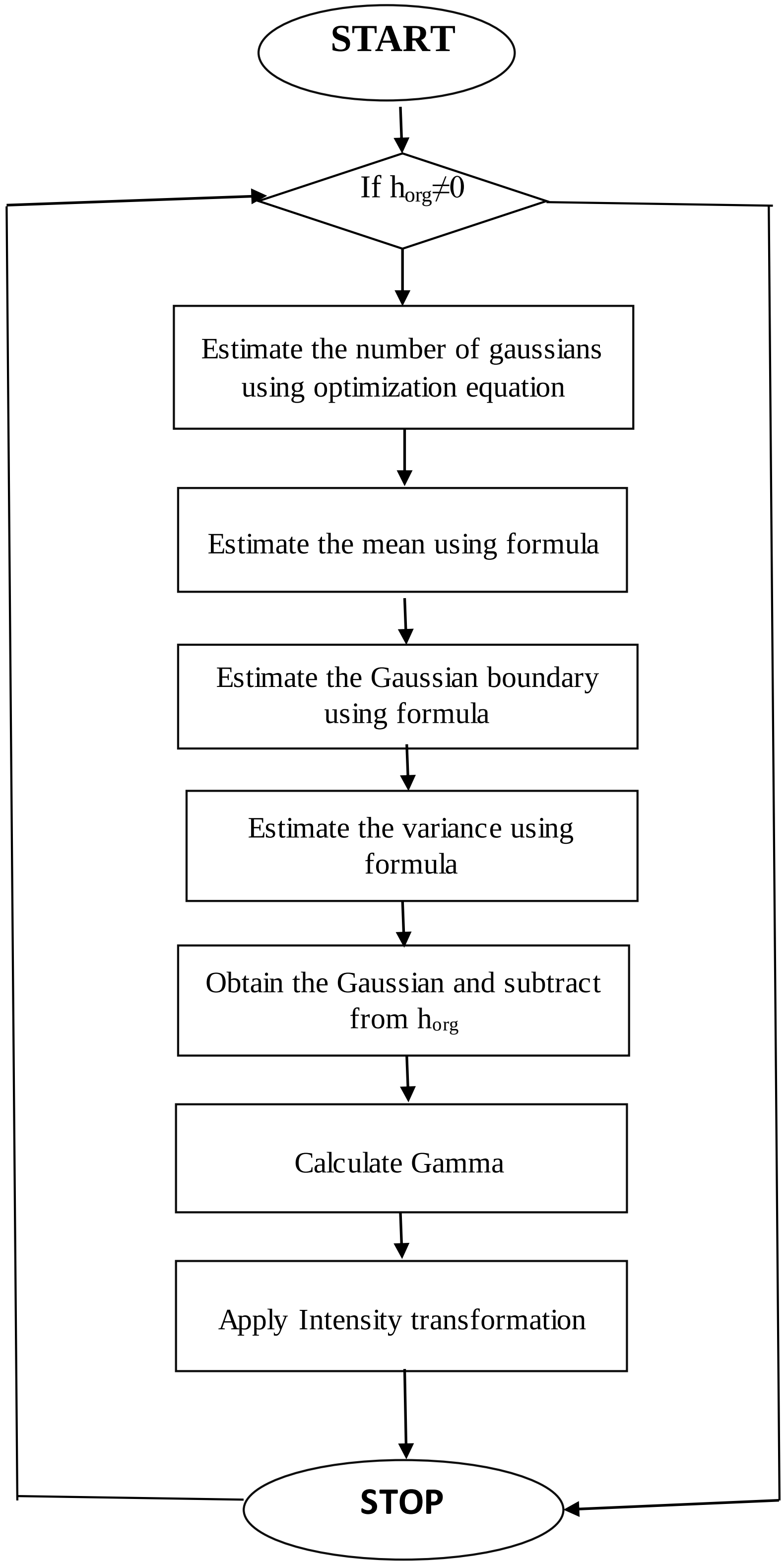


Fig.2 Flowchart of Proposed Approach

5.3 Pseudocode-

1. The mean parameter of the image is estimated at first. This is done by finding out the shape of the histogram around which is similar to that of a Gaussian.

2. After the mean is estimated, it is used as input for estimation of Gaussian territory. For which, first the histogram is padded with lowest and highest values on both side respectively then an averaging filter is used to smooth the histogram and finally the localminima around the mean are estimated in both the directions.

3. The mean and the Gaussian boundary are used as input for calculation of variance for which drop ratios are calculated in both forward as well as the backward directions. Then formula as in GMMCE is applied for estimation of variance.

4. Once one particular Gaussian is obtained, it is removed from the original histogram and the above process is repeated for rest of the Gaussian, the process terminates when all the gaussians have been estimated.

5. Once Gaussian histogram is obtained, mean of the means and the maximum variance is obtained, the values of lower and upper bound corresponding to the Gaussian with maximum variance are also taken and the gamma is calculated as follows-

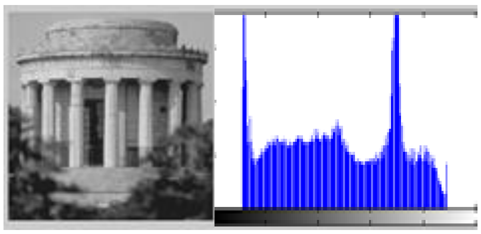
$$y` = PDF_{gaussian} \times \left(\frac{mean_m}{\max\_var}\right)^{0.5} \quad (29)$$

6. Finally, the intensity transformation function is applied as follows-

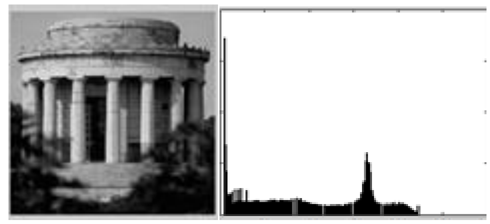
$$T(l) = \frac{Ub}{Lb} \times l^{(2-y`)} \quad (30)$$

CHAPTER-6

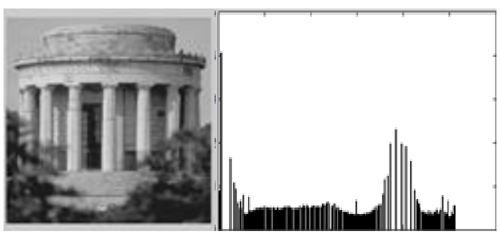
Results and Output



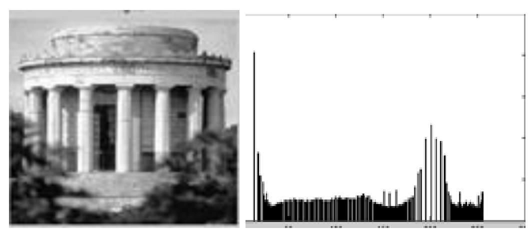
(a)



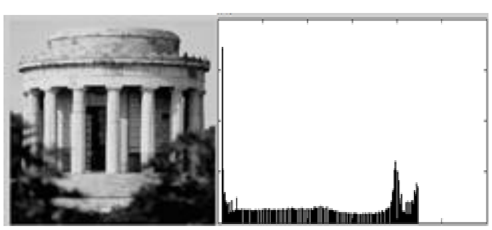
(b)



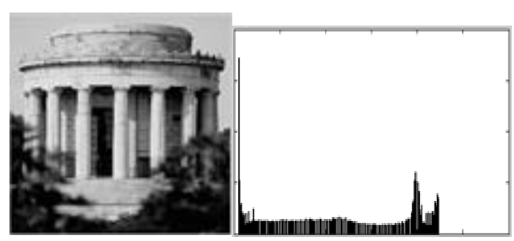
(c)



(d)

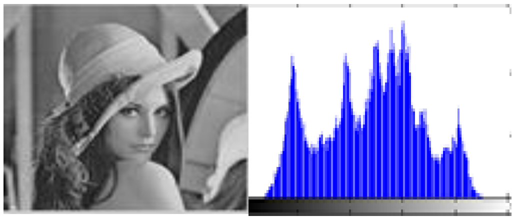


(e)

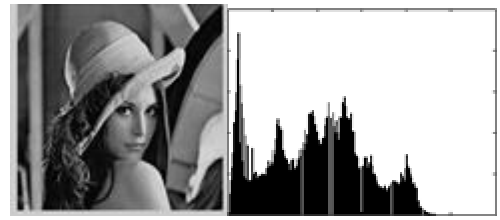


(f)

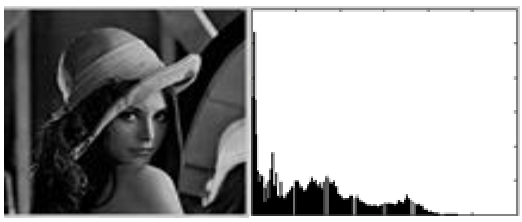
Fig.2 (a)Original image and its histogram (b)Histogram Equalization (c)BBHE (d)MMBEBHE (e)AGCWD (f)Proposed Method



(a)

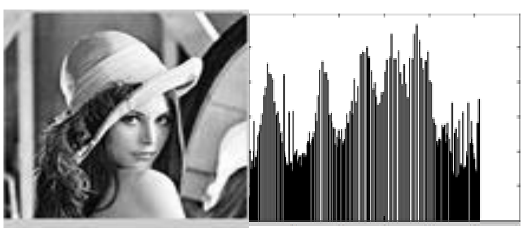


(b)

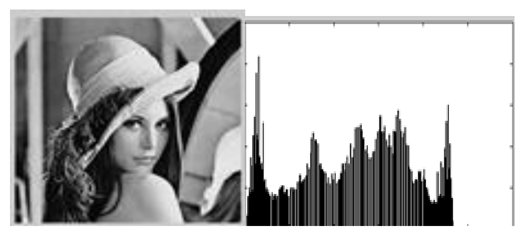


(c)

(d)

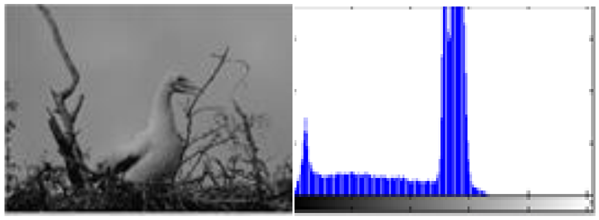


(e)



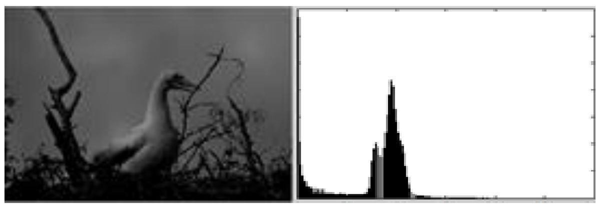
(f)

Fig.3 (a)Original image and its histogram (b)Histogram Equalization (c)BBHE (d)MMBEBHE (e)AGCWD (f)Proposed Method

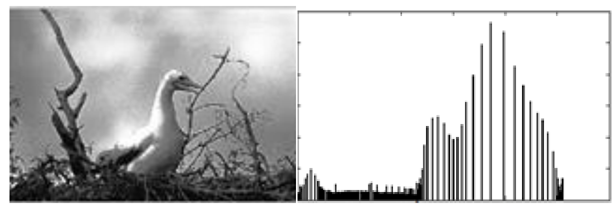


(a)

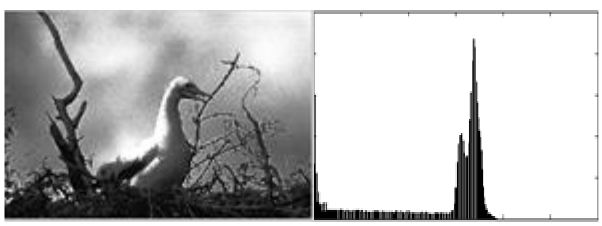
(b)



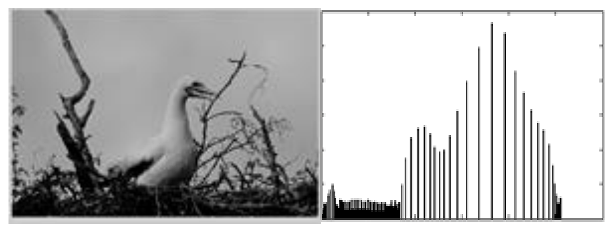
(c)



(d)

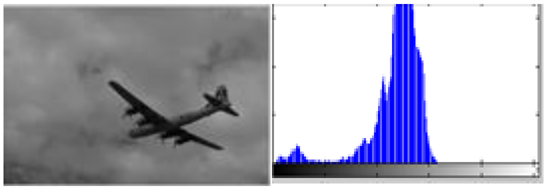


(e)

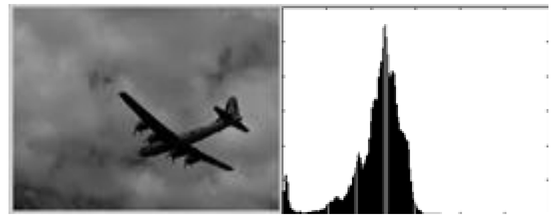


(f)

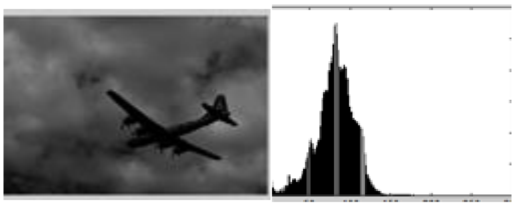
Fig.4 (a)Original image and its histogram (b)Histogram Equalization (c)BBHE (d)MMBEBHE (e)AGCWD (f)Proposed Method



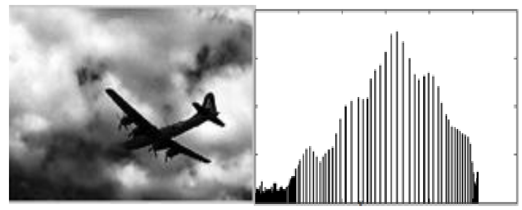
(a)



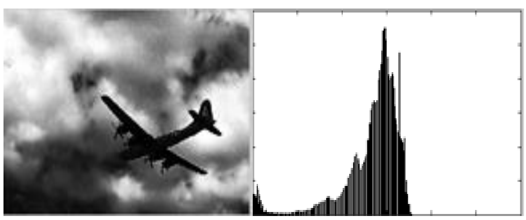
(b)



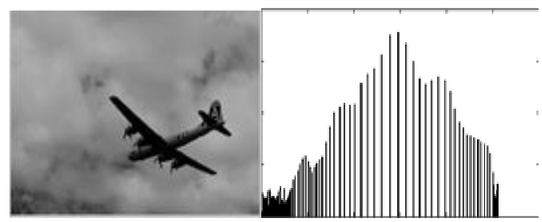
(c)



(d)

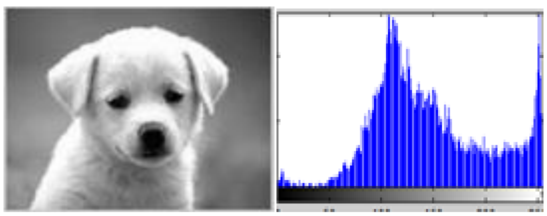


(e)

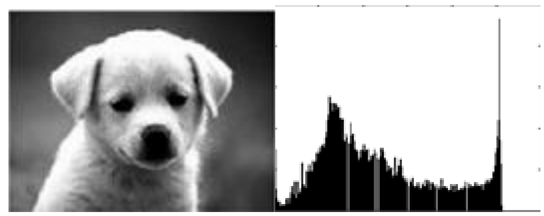


(f)

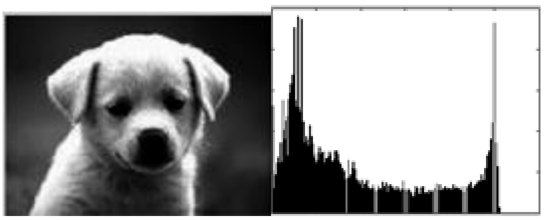
Fig.5 (a)Original image and its histogram (b)Histogram Equalization (c)BBHE (d)MMBEBHE (e)AGCWD (f)Proposed Method



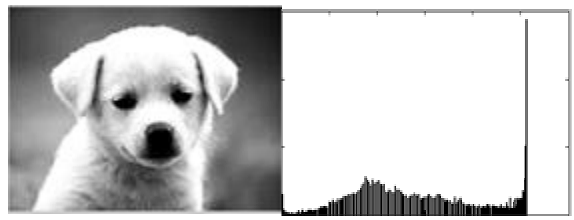
(a)



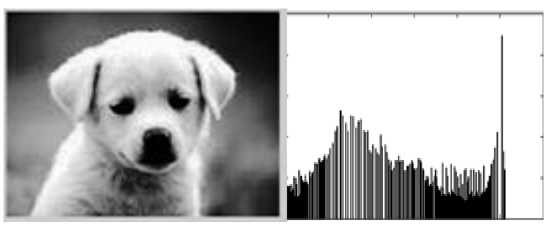
(b)



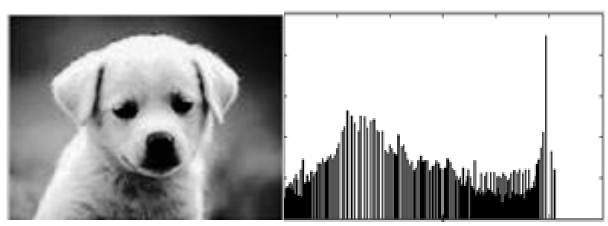
(c)



(d)



(e)



(f)

Fig.6 (a)Original image and its histogram (b)Histogram Equalization (c)BBHE (d)MMBEBHE (e)AGCWD (f)Proposed Method

CHAPTER-7

Conclusion

In the proposed method, the means , variances as well as the Gaussian territories were estimated Using which the adaptive gamma was calculated and an intensity transformation function was applied to the imput image pixel by pixel. It was observed that the proposed method showed considerable contrast enhancement of the input images. The dynamic range of the input images was increased keeping the mean brightness preserved. Therefore, it was concluded that Gaussian mixture model based contrast enhancement using adaptive gamma correction serves as a powerful algorithm for image enhancement.

CHAPTER-8

References

[1] A. Beghdadi and A. L. Negrate, "Contrast enhancement technique based on local detection of edges," Comput. Vis, Graph., Image Process., vol. 46, no. 2, pp. 162–174, May 1989.

[2] Yeong-Taeg Kim, "Contrast Enhancement Using Brightness Preserving Bi-Histogram Equalization," IEEE Trans Consumer Electronics, vol. 43, no. 1, pp. 1-8, Feb. 1997.

[3] Yu Wan, Qian Chen and Bao-Min Zhang., "Image Enhancement Based On Equal Area Dualistic Sub-Image Histogram Equalization Method," IEEE Trans Consumer Electronics, vol. 45, no. 1, pp. 68-75, Feb. 1999.

[4] Young-tack Kim and Yong-hun Cho, "Image Enhancing Method Using Men-Separate Histogram Equalization," United States Patent, Paten No. 5,963,665, Oct 5, 1999.

[5] H.-D. Cheng and H. J. Xu, "A novel fuzzy logic approach to contrast enhancement," Pattern Recognit., vol. 33, no. 5, pp. 809–819, May 2000.

[6] Soong-Der Chen, Abd. Rahman Ramli "Minimum Mean Brightness Error Bi-

Histogram Equalization in Contrast Enhancement" IEEE Trans on Consum. Electron., Vol. 49, No. 4, Nov. 2003

[7] C. Wang and Z. Ye, "Brightness preserving histogram equalization withmaximum entropy: A variational perspective," IEEE Trans. Consum. Electron., vol. 51, no. 4, pp. 1326–1334, Nov. 2005.

[8] M. Hanmandlu and D. Jha, "An optimal fuzzy system for color image enhancement," IEEE Trans. Image Process., vol. 15, no. 10, pp. 2956–2966, Oct. 2006.

[9] K. S. Sim, C. P. Tso, and Y. Tan, "Recursive sub-image histogram equalization applied to gray-scale images," Pattern Recognit. Lett., vol. 28, no. 10, pp. 1209–1221, Jul. 2007.

[10] M. Kim and M. G. Chung, "Recursively separated and weighted histogram equalization for brightness preservation and contrast enhancement," IEEE Trans. Consum. Electron., vol. 54, no. 3, pp. 1389–1397,Aug. 2008.

[11] M. Hanmandlu, O. P. Verma, N. K. Kumar, and M. Kulkarni, "A novel optimal fuzzy system for color image enhancement using bacterial foraging," IEEE Trans. Instrum. Meas., vol. 58, no. 8, pp. 2867–2879, Aug. 2009.

[12] 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.

[13] L. Zhang, L. Zhang, X. Mou, and D. Zhang, “FSIM: A feature similarity index for image quality assessment,” IEEE Trans. Image Process., vol. 20, no. 8, pp. 2378–2386, Aug. 2011.

[14] Y.-S. Chiu, F.-C. Cheng, and S.-C. Huang, “Efficient contrast enhancement using adaptive gamma correction and cumulative intensity distribution,” in Proc. IEEE Conf. Syst. Man Cybern., Oct. 2011, pp. 2946–2950.

[15] Soong-Der Chen and Abd. Rahman Ramli (2003) ‘Contrast enhancement using recursive mean separate histogram equalization for scalable brightness preservation’, IEEE Trans. Consumer Electron., vol. 49, no. 4, pp. 1301-1309.

[16] K. Wongsritong, K. Kittayaruasiriwat, F. Cheevasuvit, K. Dejhan and A. Somboonkaew (1998): ’Contrast enhancement using multi peak histogram equalization with brightness preserving’, IEEE Asia-Pacific Conference on Circuit and System, pp. 455-458, 24-27.

[17] M. Abdullah-Al-Wadud, Md. Hasanul Kabir, M. Ali Akber Dewan, and Oksam Chae(2007): ‘A dynamic histogram equalization for image contrast

enhancement', IEEE Trans. Consumer Electron., vol. 53, no. 2, pp. 593-600.

[18] Nicholas Sia Pik Kong and Haidi Ibrahim (2008): 'Color Image Enhancement Using Brightness Preserving Dynamic Histogram Equalization', IEEE Transactions on Consumer Electronics, Vol. 54, No. 4, pp.1962-1968.

[19] Renjie He, Sheng Luo, Zhanrong Jing and Yangyu Fan (2011): 'Adjustable Weighting Image Contrast Enhancement Algorithm and Its Implementation', IEEE Conference on Industrial Electronics and Applications, pp.1750-1754.

[20] J.-K. Song and S. B. Park, "Rendering distortion assessment of image quality degraded by tone," J. Disp. Technol., vol. 7, no. 7, pp. 365–372, Jul. 2011.

[21] Minyun Zhu, Feng, Wujing," Improved Multiscale Retinex Approaches for Color Image Enhancement," Applied Mechanics and Materials
Vol. 39, 2011.

[22] Chulwoo Lee, Chul Lee," Power-Constrained Contrast Enhancement for Emissive Displays Based on Histogram Equalization," IEEE Trans. on image processing, vol. 21, no. 1, Jan 2012

[23] Z. Wang, A.C. Bovik, "Modern Image Quality Assessment", Morgan and Claypool Publishing Company, New York, 2006.

[24] Z. Wang, A. C. Bovik, H. R. Sheikh, E. P. Simoncelli, 2004, "Image quality assessment: From error visibility to structural similarity", IEEE Transactios on Image Processing, Vol. 13, No. 4, 2002, pp.600-612.