International Journal of Engineering Research & Technology (IJERT)
ISSN: 2278-0181
Vol. 2 Issue 3, March - 2013

"Survey On Image Equalization Using Gaussian Mixture Modeling With Contrast As An Enhancement Feature"

Girish N
M.Tech Student, VTU
Computer Networking, EWIT

Bangalore.

Smitha P.
Assistant Professor,
Department Of ISE, EWIT

Bangalore.

Abstract - In this paper we propose the Image Equalization for the contrast enhancement feature. The image equalization is carried out in terms of histogram equalization. Histogram equalization is a common technique for enhancing the appearance of images. The main objective of this paper is to concentrate on the contrast enhancement which would be handled by the image equalization algorithm which continues with the different models for different possibilities of work within the enhancement feature for the images. The algorithm uses the GMM (Gaussian Mixture Modeling) for modeling the grey level input image.

***Key terms*– Image Equalization, Contrast Enhancement, GMM.**

I. Introduction

The major concept of image equalization is applied to the image enhancement in the field of digital image processing. Digital image enhancement technique broadly classified into two categories. They are spatial domain enhancement technique and frequency domain enhancement technique. Image equalization is one among the two groups which falls under the spatial domain enhancement techniques. In which the enhancement technique directly deals with the pixel's value of the image, where as the frequency domain enhancement technique deals the transformation functions. Enhancement techniques based on various combinations of methods from these two categories are not unusual. There is no general theory of image enchantment. When an image is processed for visual interpretation, the viewer is the ultimate judge of how well a particular method works. The working of image enhancements also comprises of linear contrast stretching (LCS) and global histogram equalization (GHE) which are widely used [1]. LCS linearly adjusts the dynamic range of an image and latter uses an input-to-output mapping obtained from cumulative distribution function (CDF) which is integral part of the histogram. Since the contrast gain is proportional to height of the histogram, gray levels with large pixel populations are expanded to a larger range of gray levels, where as other gray-level ranges with fewer pixels are compressed to smaller ranges. GHE also have same concerns but suffer with disadvantages, it tends to over enhance the image contrast if there are high peaks in the histogram, often resulting in harsh and noisy appearance of the output image. Thus in order to overcome the fore mentioned problem, local histogram equalization (LHE) [10] method has been proposed. The LHE method uses a small window that slides through every image sequentially, and only pixels within the current position of the window are histogram equalized; the gray level mapping for enhancement is done for image enhancement is done. However sometimes LHE causes over enhancement in some portion of the image and enhances noise in the input image, along with the image features. Thus Histogram specification (HS) [1] is a method used to modify the expected output-image histogram. However specifying the histogram, is not a direct task. It will be carried out the dynamic histogram specification (DHS) [11]. The DHS generates the specified histogram dynamically from the input image. DHS extracts the differential information from input histogram and incorporates extra parameters to control the enhancement such as the original value and resultant control gain. However, the degree of enhancement was achievable is not sufficient. Thus some research work based on Histogram Equalization (HE) is discussed in the related work. The working of GMM as follows Gaussian mixtures are the combination of a finite number of Gaussian distributions. They are used to model complex multi-dimensional distributions. The parameters of the Gaussian mixtures (i.e. mean and standard deviation) are computed by the maximization likelihood concept that is expectation maximization (EM) algorithm. The Gaussian mixture model (GMM) is a parametric probability density function represented as weighted sum of Gaussian component densities. GMM's are commonly used as a parametric model of the probability distribution of continuous measurements or features in a biometric system, such as vocal-tract related spectral features in speaker identification [2].

II. Related Work

Image enhancement techniques are broadly classified into two group's namely spatial domain and frequency domain enhancement techniques. Spatial domain image enhancement technique is based on direct manipulation of pixel's values in the image. And frequency domain image enhancement technique involves some transformation functions for the enhancements. In the proposed algorithm we just concentrate on the Histogram Equalization which falls in the first category called spatial domain image enhancement technique. Although histogram equalization is a better work for enhancement of the images, the histogram equalization also suffers from the disadvantages. Thus the disadvantages of histogram equalization can be overcome by the improvement in the working of the histogram equalization they all are as follows mean preserving bihistogram equalization (BBHE) [4], in which 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 independently equalized, but this method suffers from brightness preservation problem. Thus the minimum mean brightness error bihistogram equalization is proposed (MMBEBHE) [5], is the extension of BBHE, which provides maximal brightness preservation although these methods provide good contrast enhancement also they generate annoying side effects depending on the gray-level distribution. Dynamic Histogram Equalization (DHE) [6] is proposed as an extension to the histogram equalization in which it first smoothens the input histogram by using a 1-D smoothing filter. The smoothed histogram is partitioned into subhistograms based on the local minima. Prior to equalizing the subhistograms, 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 pixel occupies a bigger portion of the dynamic range. However DHE does not concentrate on maintaining the minimum brightness (MB) of the image. Optimization techniques have been also employed for contrast enhancement; that is brightness preserving histogram equalization with maximum entropy (BPHEME) [7]. BPHEME has the maximum differential entropy obtained using a variational approach under the MB constraint. Although entropy maximization corresponds to contrast stretching to some extent, it does not always result in contrast enhancement. In the flattest histogram specification with accurate brightness preservation (FHSABP) [8] convex optimization is used to transform the image histogram into flattest histogram, subject to a MB constraint. However histogram specification is used to preserve image brightness. However it is designed to preserve the average brightness, which may produce the low contrast results when average brightness is either too low or too high. The histogram modification framework as also being proposed in which the contrast enhancement is treated as an optimization problem that minimizes a cost function (HMF) [9]. 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 parameters. These parameters have to be tuned manually according to the image content to achieve high contrast. Although the output achieved was not sufficient. Hence the genetic algorithm (GA) was introduced which was parameter free that maximizes a contrast measure on edge information [12]. Thus this algorithm is called as Contrast based enhancement on GA (CEBGA). CEBGA also suffered from following disadvantages they are initialization dependence and convergence. Hence finally the concept of histogram equalization with contrast as an enhancement feature is proposed. As this concept of the algorithm, the GMM is introduced, the parameters for the GMM [2] (i.e., mean and standard deviation) are selected by the expectation maximization algorithm (EM). Then the algorithm followed with the modeling partitioning and mapping. The partitioning part of the algorithm is used to concentrate on the division of the dynamic range of the input image. In the partition process the intersection points of the Gaussian component is searched. The searching function would be carried by the binary search focusing on the respective parameters of the Gaussian mixture model. The mapping would be carried out within the specified range of the input image. The gray levels of the pixels in input interval are transformed according to the dominant Gaussian component. And the cumulative distribution function (CDF). The final step of the proposed algorithm results in the better contrast enhanced image.

Fig 1: on the left half low contrast, and on the right half high contrast image

III. PROPOSED ALGORITHM

The input to the algorithm is $X = \{x (i, j) \mid 1 \leq i \leq H, 1 \leq j \leq W\}$ of size H x W pixels, 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 algorithm concentrates on the following important steps they are:

A. Modeling
B. Partitioning
C. Mapping.

A. Modeling

A GMM can model any data distribution in terms of 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 [2]. The parameters for the GMM would be provided by the finite mixture models which have maximum likelihood for finite mixture models. That is EM algorithm is used for estimating the parameters for the GMM. Different Gaussian components have different parameters and also different parameters deal with different results. 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. 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 [2]. The cost function is used for estimating the number of Gaussian components required for the algorithm [3]. After estimating the number of Gaussian components the further step is followed with the partitioning of the histograms into number of subhistogram.

B. Partitioning

The intersection points of the Gaussian components are used as in partitioning the dynamic range of the input image into input gray-level intervals. The intersection points that are within the dynamic range of the image are detected. The partition part of the algorithm also involves the searching the intersection points of the different Gaussian components. The searching work in the algorithm is handled by the binary search concept to search the intersection points.

C. Mapping

In the mapping, each interval covers a certain range, which is proportional to weight. The contrast enhancement image is obtained by mapping input to output intervals in the given image. In the final mapping of pixel values from input interval onto the output interval, the cumulative distribution function (CDF) of the distribution in the output interval is preserved. 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.

IV. CONCLUSION

The proposed algorithm which enhances the image that employs GMM for the input image, which in turn GMM uses the expectation maximization (EM) for providing the inputs to the GMM. The algorithm can achieve image equalization that is good enough even under diverse illumination condition. The proposed algorithm produces good contrast enhancement results by utilizing the concept of histogram equalization. The proposed algorithm is applied only for gray scale images. It does not distract the overall content of an input image with high contrast.

V. FUTURE ENHANCEMENTS

Since the EM algorithm is proposed for providing the input for GMM in the algorithm which suffers from choosing the initial parameters. Thus in the future enhancement work parameter free algorithm would be proposed. The current work is focused only on grey scale images; in the future this would be enhanced for other color images.

ISSN: 2278-0181
Vol. 2 Issue 3, March - 2013

REFERENCES

[1] R. C. Gonzalez and R. E. Woods, *Digital Image Processing*. Upper Saddle River, NJ: Prentice-Hall, 2006.

[2] "Automatic Image Equalization and Contrast Enhancement Using Gaussian Mixture Modeling" Turgay Celik, Tardi Tjahjadi

[3] "Gaussian Mixture Modeling of Histograms for Contrast Enhancement", Yu-Ren Lai, Kuo-Liang Chung Guei-Yin Lin, Chyou-Hwa Chen.

[4] Y.-T. Kim, "Contrast enhancement using brightness preserving bi-histogram equalization," *IEEE Trans. Consum. Electron.*, vol. 43, no. 1, pp. 1–8, Feb. 1997.

[5] S.-D. Chen and A. Ramli, "Minimum mean brightness error bi-histogram equalization in contrast enhancement," *IEEE Trans. Consum. Electron.*, vol. 49, no. 4, pp. 1310–1319, Nov. 2003.

[6] 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.

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

[8] 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.

[9] 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.

[10] T. K. Kim, J. K. Paik, and B. S. Kang, "Contrast enhancement system using spatially adaptive histogram equalization with temporal filtering," *IEEE Trans. Consum. Electron.*, vol. 44, no. 1, pp. 82–87, Feb. 1998.

[11] C.-C. Sun, S.-J. Ruan, M.-C. Shie, and T.-W. Pai, "Dynamic contrast enhancement based on histogram specification," *IEEE Trans. Consum. Electron.*, vol. 51, no. 4, pp. 1300–1305, Nov. 2005.

[12] S. Hashemi, S. Kiani, N. Noroozi, and M. E. Moghaddam, "An image contrast enhancement method based on genetic algorithm," *Pattern Recognit. Lett.*, vol. 31, no. 13, pp. 1816–1824, Oct. 2010.