RESEARCH ARTICLE OPEN ACCESS

Gaussian Mixture Model Based Contrast Enhancement with the Reversible Data Hiding (RDH) Algorithm

[1] K. Appasamy, [2] A. Bathsheba Parimala, [3] B. Jefferson
Assistant professor, Department of BCA & M.SC(NT&IT) , St . Johns College ,Palayamkottai.

Abstract:

In this paper, a reversible data hiding (RDH) algorithm with contrast enhancement is proposed for images. Here, to improve the image quality we need a contrast enhancement; the proposed algorithm for contrast enhancement is called Gaussian Mixture Model based Contrast Enhancement (GMMCE), which enhances the contrast of a image to improve its visual quality. It brings into play the Gaussian mixture modeling of histograms to model the content of the images. From the histogram, the highest two bins are selected for data embedding hence histogram equalization can be performed by repeating the process. The side data is inserted alongside the message bits into the host image with the goal that the original image is totally recoverable. Based on this, that each homogeneous area in natural images has a Gaussian-shaped histogram, it decomposes the narrow histogram of low contrast images into a set of scaled and shifted Gaussians. The individual histograms are then stretched by increasing their variance parameters, and are diffused on the entire histogram by scattering their mean parameters, to build a broad version of the histogram. Contrasted with the current histogram-based strategies, the experimental results demonstrates that the nature of GMMCE improved pictures are for the most part steady and beat other benchmark techniques.

Keywords — **Reversible data hiding, Gaussian Mixture Model based Contrast Enhancement, Histogram equalization.**

I. INTRODUCTION

Reversible data hiding (RDH) has been studied in the community of signal processing. It is also known as invertible or lossless data hiding, RDH is used to embed a piece of information into a host signal to generate the marked one, from which the original signal can be completely recovered after extracting the embedded data. The technique of RDH is useful in some sensitive applications where no permanent change is allowed on the host signal. In the literature, most of the proposed algorithms are for digital images to embed invisible data (e.g. [1]–[8]) or a visible watermark (e.g. [9]). To evaluate the performance of a RDH algorithm, the hiding rate and the marked image quality are important metrics. Increasing the hiding rate often causes more distortion in image content. The peak signal-to-noise ratio (PSNR) value of the marked image is determined to measure the distortion. Generally speaking, direct modification of image histogram [2] provides less embedding capacity. In contrast, the more recent algorithms (e.g. [5]–[8]) manipulate the more centrally distributed prediction errors by exploiting the correlations between neighboring pixels so that less distortion is caused by data hiding. One of the leading works on contrast enhancement is Histogram Equalization (HE) [8], where it tries to spread out the intensity values of the histogram on the entire intensity range. In other words, it effectively broadens out the narrow histogram of a low contrast image and generates its broadened version in such a way that the visual quality is improved.

In this paper, Gaussian Mixture Model based Contrast Enhancement enhances the contrast of a image to improve its visual quality. It brings into play the Gaussian mixture modeling of histograms to model the content of the images. The highest two bins in the histogram are selected for data embedding so that histogram equalization can be performed by repeating the process. The side information is set alongside the message bits into the host image so that the original image is totally recoverable. Based on the fact that each homogeneous area in natural images has a Gaussian-shaped histogram, it decomposes the narrow histogram of low contrast images into a set of scaled and shifted Gaussians.

The rest of the paper is organized as follows. Section II discusses the related work. Section III discusses the proposed GMMCE. Section IV discusses the simulation results for histogram equalization to contrast the image enhancement. Conclusions are drawn in the last section.

II. RELATED WORKS

D. Coltuc and J.-M. Chassery[4] proposed that a spatial domain reversible watermarking scheme that achieves high-capacity data embedding without any additional data compression stage. The scheme is based on the reversible contrast mapping (RCM), a simple integer transform defined on pairs of pixels. Even if the least significant bits of the transformed pixels are lost RCM is inverted perfectly.. Hao-Tian Wu, Jean-Luc Dugelay and Yun-Qing [9] Shi proposed that reversible data hiding (RDH) algorithm is proposed for digital images. Enhance the contrast of a host image to improve its visual quality inorder to keep PSNR high. The highest two bins in the histogram are selected for data embedding such that histogram equalization can be performed by repeating the process. The side information is set along with the message bits into the host image so that the original image is recoverable. Jun Tian[1] proposed that a high-capacity, high visual quality, reversible data-embedding method for digital images. This method can be applied to digital audio and video as well. Both the payload capacity limit and the visual quality of embedded images , exhibits a low computational complexity. X. Li, B. Yang, and T. Zeng[6] proposed reversible watermarking scheme inaccordance with PEE two new strategies namely, adaptive embedding and pixel selection . Z. Ni, Y. Q. Shi, et al.,[2] proposed that Reversible data hiding algorithm recovers the original image without any distortion from the marked image after the hidden data have been extracted. It is applied to a wide range of images, including commonly used images, medical images, texture images, aerial images and all of the 1096 images in CorelDraw database. D.M. Thodi [3]proposed that a histogram shifting technique as an alternative to embedding the location map. It improves the distortion performance at low embedding capacities and mitigates the capacity control problem. The DE embedding technique involves pairing the pixels of the host image and transforming them into a low-pass image containing the integer averages and a high-pass image containing the pixel differences. H. T.Wu and J. Huang[8] proposed that PEE technique embeds data consistently, using Embedded Zero tree Wavelet (EZW), Bit-plan Complexity Segmentation (BPCS) based embedding is applied to embed on natural images. This avoids expanding pixels with huge prediction errors likewise it also reduces embedding impact by diminishing the maximum modification to pixel values. Z. Zhao,H.Luo,Z.-et al[7]., proposed that the inverse "S" order is adopted to scan the image pixels for difference generation. The secret data are binary sequences produced by pseudo random number generator. In the data embedding stage, a multilevel histogram modification strategy is utilized. An integer parameter called embedding level EL (EL $\geq$ 0) is involved to control the hiding capacity.

III. PROPOSED SYSTEM

As the use of digital images grows in different applications, the need for more efficient methods of image enhancement to be applied on degraded images is perceived. One of the common degradations on images is the lack of contrast which can be due to the poor lighting conditions, such as extremely dark or bright environment. The interpretation of low contrast in terms of histogram representation of digital images is that in images with low contrast content, the distribution of intensity values has low variance and consequently, their histograms have narrow shapes. The solutions to this problem, called contrast enhancement methods, have several applications in medical imaging, remote sensing, machine vision applications, consumer electronics and so forth. Though diverse classes of approaches have been proposed for this problem, they can be classified into two general categories: histogram based and non-histogram based methods. Regarding different applications and their restrictions, one category may be preferred to the other. One of the leading works on contrast enhancement is Histogram Equalization (HE), where it tries to spread out the intensity values of the histogram on the entire intensity range. In other words, it effectively broadens out the narrow histogram of a low contrast image and generates its broadened version in such a way that the visual quality is improved. Despite its simplicity, this straightforward method suffers from major drawbacks such as inability to preserve overall brightness of the image when the raw image is too dark or too bright or overenhancing the histogram when there are large peaks in the histogram. To overcome these well known drawbacks some extensions to HE have been proposed.

The first generation of extensions to HE are the brightness-preserving methods. They choose a specific intensity value from the dynamic range of the histogram to be fixed during the process of broadening the histogram. This intensity value acts as a separation point and consequently, the output histogram would consist of two sub-histograms, independently equalized with HE and shared a joint intensity value at their separation point. Preserving a single intensity value of the histogram is not necessarily adequate to generate a high contrast and at the same time a visually fine image. Hence, the next generation of extensions aimed at preserving more than one intensity value of the histogram so that the histogram is separated more than once. These methods, called recursive brightness-preserving methods, perform similarly to the brightness-preserving methods except that they use a parameter named "Recursion Level (RL)" which indicates the number of separation points at which the current sub-histogram is split in two. All abovementioned derivatives of HE can be considered as "static" methods, since the number of selected separation points and their positions on the histogram before and after enhancement remain unchanged. As an alternative idea, two other sub-categories named "semi-dynamic" and "dynamic" methods have been introduced where the separation points and their positions are no longer predetermined. In the semi-dynamic methods, either the number of separation points is fixed, yet their positions might change during the contrast enhancement, or the positions of the separation points are fixed but their numbers is variable. In the dynamic methods both the number of separation points and their positions can change depending on the characteristics of the image. As mentioned, there are also non-histogram based methods which improve the visual quality of images by taking advantage of features other than histogram characteristics. Generally, these methods need to have access to spatial attributes instead of global histogram characteristics. For instance, in order to enhance the contrast, a non-histogram based method might exploit over and under exposure versions of a low contrast image, statistical features of image related to stochastic resonance or a genetic algorithm with non-histogram based chromosome structure. Actually, there are several research works fitting in the non-histogram based category, but they are out of the scope of this study as they do not concern the proposed method in this paper.

GAUSSIAN MIXTURE MODEL BASED CONTRAST ENHANCEMENT (GMMCE)

In this section, first the idea behind using the Gaussian Mixture Modeling (GMM) to model the structure of a histogram is clarified and then the details of the proposed Gaussian mixture model based contrast enhancement method are explained.

Histogram Modeling by Gaussians

Any arbitrary image can be assumed to be composed of individual meaningful regions occupying near- homogeneous areas of the image. Each region in natural images has a Gaussian-shaped histogram where the means of the Gaussian histograms indicate their corresponding average intensity levels and the variance corresponding to their texture details. These Gaussians are separated by their mean values and spread out with their variances, thus forming the global histogram. Based on the fact that low contrast images have narrow histograms, if one departs the important means from each other, the contrasts of individual areas are enhanced and the visual quality of the image is improved. In other words, the structure of an image is directly reflected in its histogram in a manner that any significant peak in the histogram is actually the mean intensity value corresponding either to a vast near homogeneous zone of the image, or to several zones which together occupy a major portion of the area. In either case, these intensity levels are particularly important to the global visual quality of the image and should be carefully treated during any enhancement process.

GMM Formulation

Each arbitrary histogram can be formulated as a weighted sum of k Gaussians which requires to estimate three vectors of k parameters, namely mean μ, variance σ2 and scaling factor ω. Thus the continuous GMM of the histogram can be expressed as:

$$h^{k}_{GMM}(I/\mu\,,\sigma^2,\omega) = \sum_{j=1}^{k}\omega_j N(I/\mu_{j,}\sigma_j^2)$$

I=0,1,…..L-1

where 2 ($N(I|\mu_j,\sigma_j^2)$) is the jth Gaussian probability density function (PDF) at intensity level I ϵ [0, L-1] with variance σ_j^2 and mean μ_j. According to (3.4), the height of each Gaussian is scaled by ω_j which is proportional to the area is occupied by its corresponding region in the image. In other terms, the larger is a region, the more dominant is its corresponding Gaussian in the histogram, by having the highest peak in the global histogram.

However, increasing the number of Gaussians can be interpreted as increasing the number of dominant intensity levels. This has the drawback of having many Gaussians, as well as Gaussians with minor peaks, which represent a small fraction of the global intensity. The ultimate effect is that the increased number of Gaussians not only increases the complexity of image enhancement, but also has a negative effect on its quality. To decrease the absolute residual error, since it consists of many gaussians would cause considering non-dominant regions as important as the actual dominant regions. Therefore, there should be a balance between, using not too few Gaussians to miss the dominant intensity levels and not too many Gaussians to include the non-dominant intensity levels. This is considered in the proposed model by limiting the number of Gaussians to a value where the area under their resultant GMM is no more than α percent of the area under the original histogram. In GMMCE, given a histogram, it searches for an optimal composition of Gaussians to construct the histogram. As an objective function, the optimality of a composition is measured by its similarity to the original histogram. The difference between a GMM and the original histogram is optimized, in a least square sense, as:

$$\operatorname{argmin}_{\mu,\sigma,\omega} \sum_{I=0}^{L-1} \left(h_{org}(I) - h_{GMM}^{k}(I / \mu,\sigma^2,\omega)\right)^2$$

where h_{org} is the original histogram of the image. As discussed earlier, μ, σ and ω are the unknown parameters of the GMM to be estimated. For optimization one might use the Expectation Maximization (EM) algorithm (like almost all other GMM based optimization problems) which is an iterative approach to estimate the latent variables of a statistical model. In GMMCE the statistical model is a combination of a specific number of Gaussians and the latent variables include the means and the variances of the Gaussians as well as their scaling factors (i.e. vectors μ, σ and ω, respectively). Although EM has proven to be a very accurate solution for GMM-based problems, it has short falls that make it "not the best approach" for some conditions.

IV. RESULTS AND DISCUISSIONS

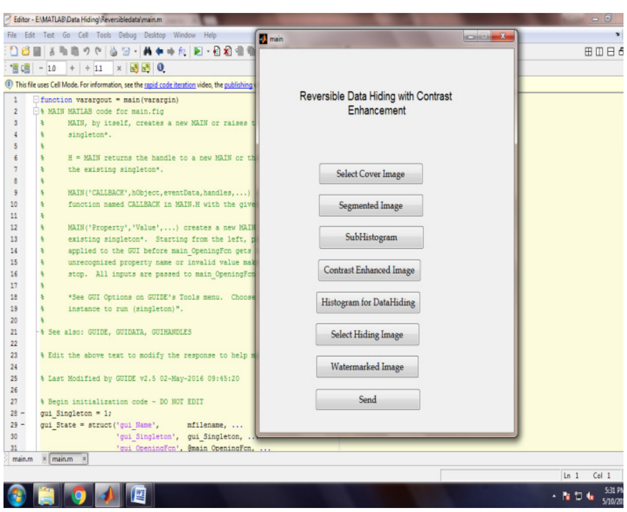

Fig 1 Home page

Fig .1 shows the home page of reversible data hiding with contrast enhancement. In this the sender will send an image with following process like calculating the segmented image, sub-histogram, contrast enhanced image, calculating the histogram for hiding data in which place and then calculate the watermarked image. After sending the image the receiver will extract the images by giving histogram values and received watermarked image.

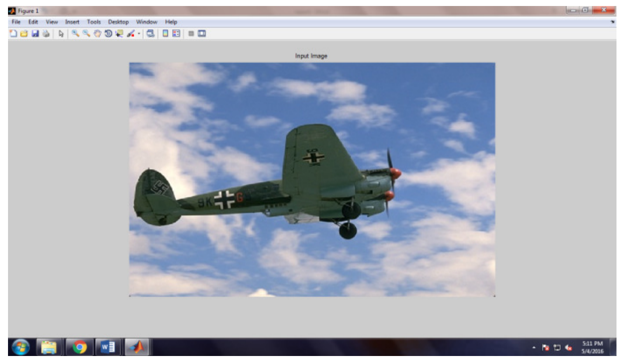

Fig 2 Input Cover Image

Fig 2 shows that input cover image. This cover image is further segmented and enhanced by Gaussian mixture model. The contrast enhanced image is given to calculate the histogram for data hiding. The image to be hided is selected and hided on that histogram of contrast enhanced image.

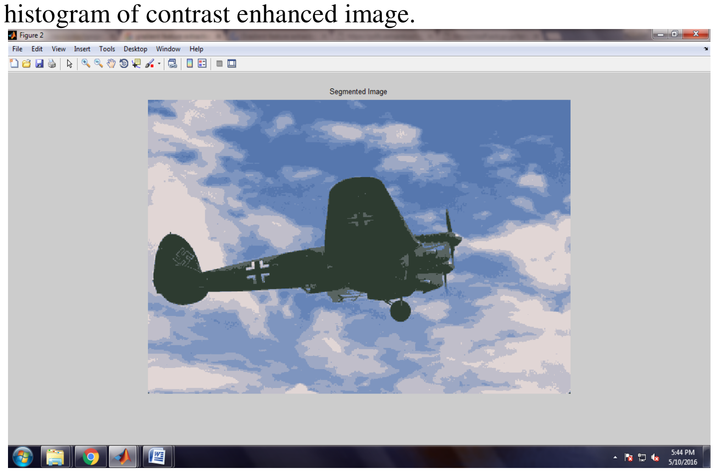

Fig 3 Segmented image of input

Fig.3 shows that the segmented image of input. Here gradient based segmentation is used. After segmentation sub-histogram is calculated for enhancing the contrast of the input image.

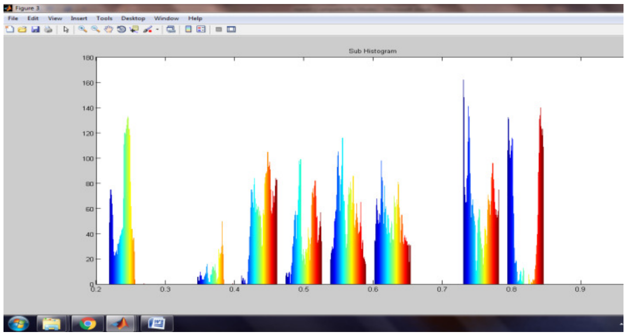

Fig 4 Sub-histogram

Fig.4 shows that sub-histogram of the segmented image. The segmented image is further enhanced to improve the data hiding rate. For enhancing the contrast of the segmented image sub-histogram is calculated using Gaussian mixer model.

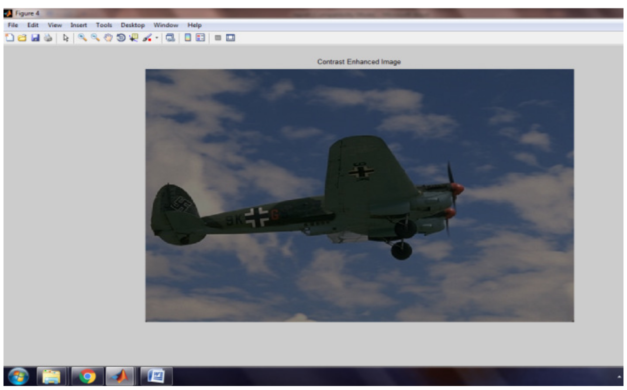

Fig 5 Contrast Extracted Image

Fig 5 shows that contrast enhanced image. The contrast of segmented image is enhanced by calculating sub-histogram values.

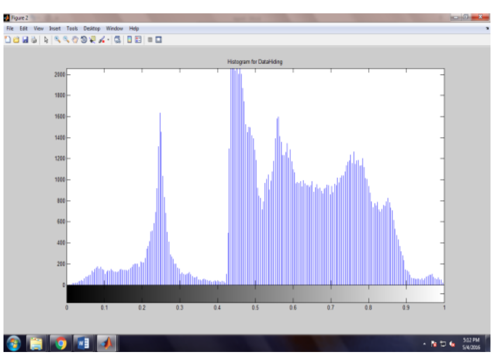

Fig 6 Histogram of Data Hiding

Fig 6 shows that histogram values for data hiding. From this histogram peak values the image is hided. The image to be hided is hyperspectral image.

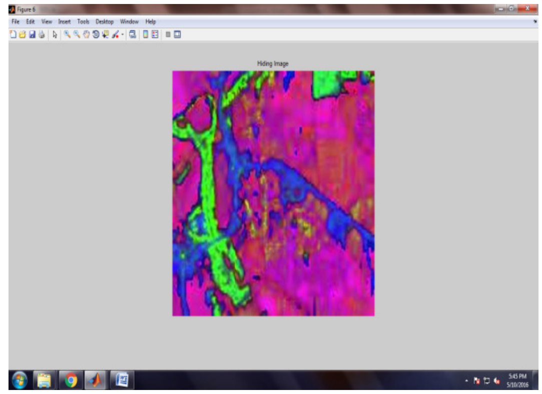

Fig 7 Hiding Image

Fig 7 shows that hiding image. This image is hided on histogram peak values which are calculated from the previous step. The hackers did not know the place of image to be hided because it is difficult to know the histogram values of contrast enhanced image.

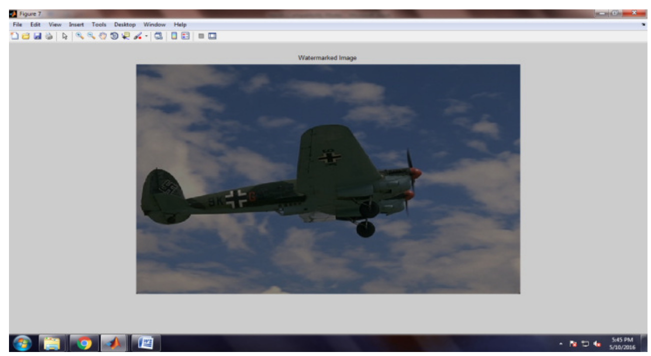

Fig 8 Watermarked image

Fig 8 shows that watermarked image. The watermarked image is obtained by hiding the image with histogram values.

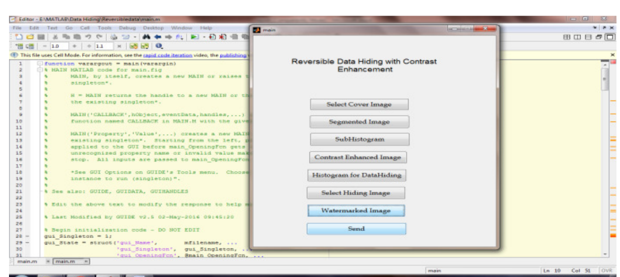

Fig 9 Send to receiver.

Fig 9 shows the send to receiver. Finally the watermarked image is transferred to receiver side.

The receiver extracts the image by giving the histogram values.

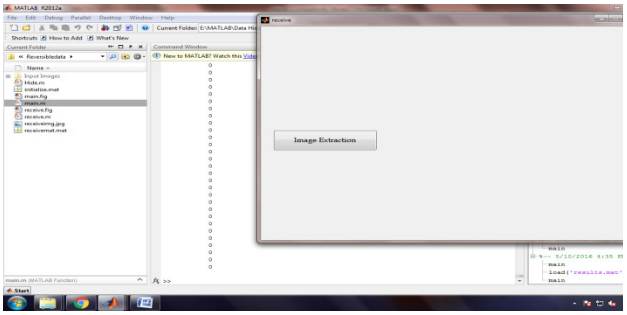

Fig 10 Image Extraction

Fig 10 Image Extraction. The receiver will extract the image by giving received watermark image as well as histogram values.

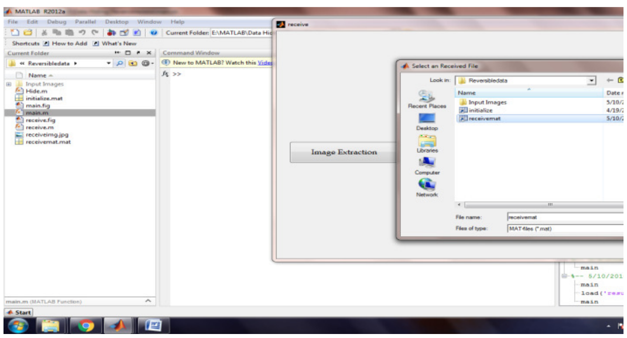

Fig 11 Received histogram value

Fig 11 shows the received image. The received histogram values will be given and after that the receiver will extract the information one by one.

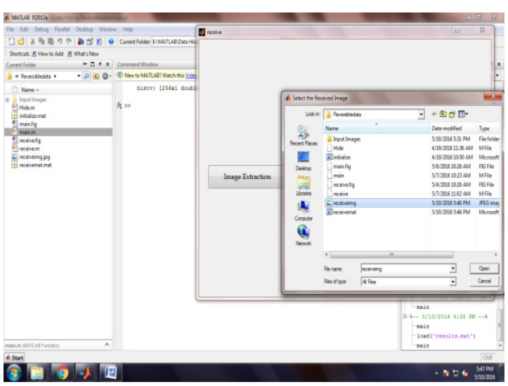

Fig 12 Received Watermarked Image

Fig 12 shows that received watermark image. The watermarked image will be given after that only the receiver will decode the image.

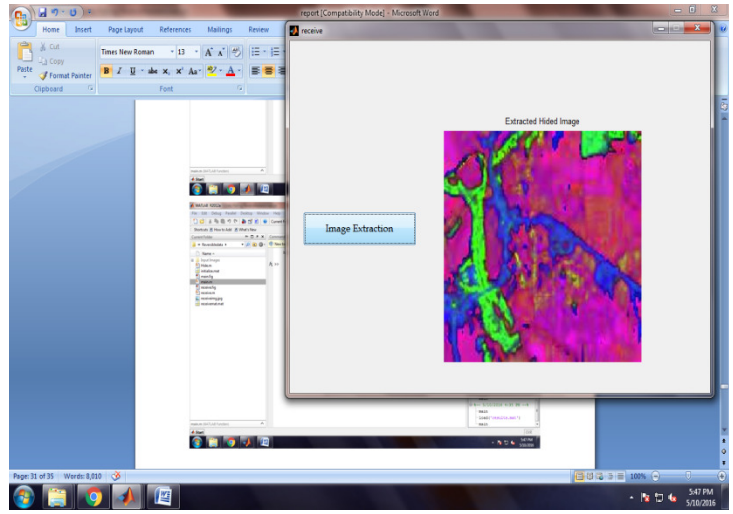

Fig 13 Image Extraction

Fig 13 shows the extracted hided image. This image is hided with that cover image. This image is decoded by giving the histogram values of contrast enhanced image.

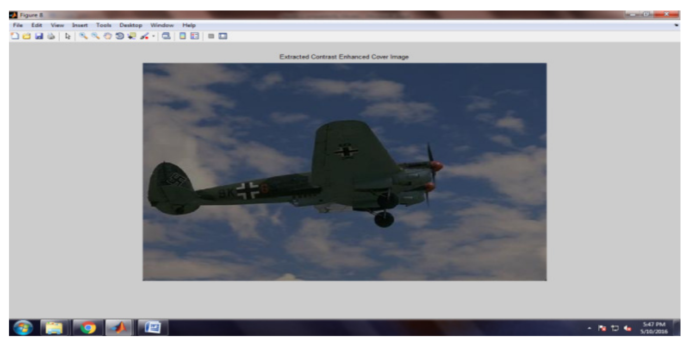

Fig14 Extracted Contrast Enhanced image

Fig14 shows that the Extracted Contrast Enhanced image. After extracting the hided image the original contrast enhanced image will be extracted.

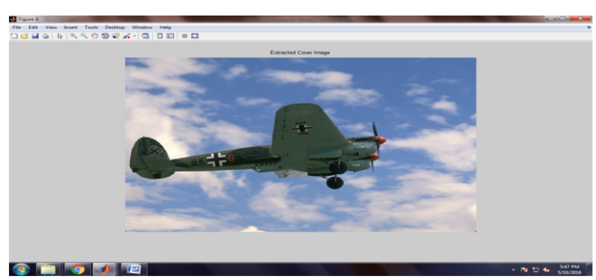

Fig15 Extracted Original Image

Fig 15 shows that the extracted original image. This image extracted from the contrast enhanced image.

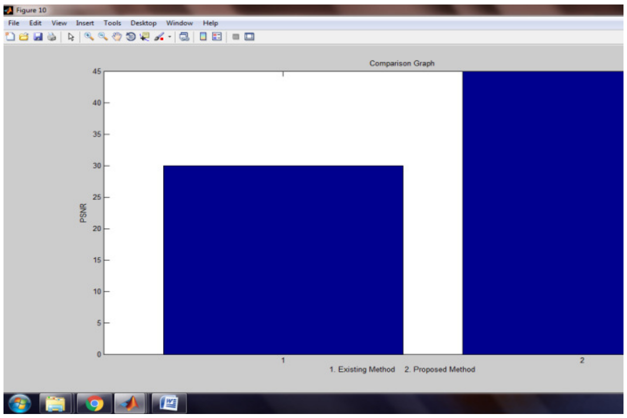

Fig16 PSNR graph

Fig 16 shows that the PSNR graph. Peak signal-to-noise ratio, often abbreviated PSNR, is an engineering term for the ratio between the maximum possible power of a signal and the power of corrupting noise that affects the fidelity of its representation. Because many signals have a very wide dynamic range, PSNR is usually expressed in terms of the logarithmic decibel scale. This graph shows that the proposed Gaussian mixture model having higher peak to signal ratio than existing.

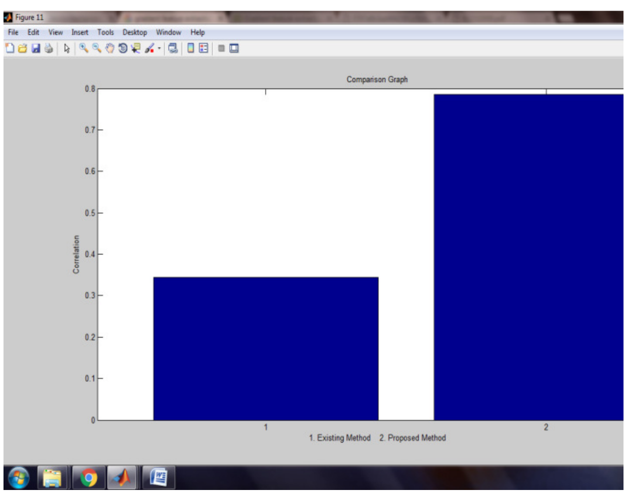

Fig 17 Correlation

Fig 17 shows that correlation graph. Digital image correlation (DIC) techniques have been increasing in popularity, especially in micro- and nano-scale mechanical testing applications due to its relative ease of implementation and use. Advances in computer technology and digital cameras have been the enabling technologies for this method and while white-light optics has been the predominant approach, DIC can be and has been extended to almost any imaging technology. From this graph the correlation between original image and extracted original image is high compared to existing.

V. CONCLUSION

In this project, a new reversible data hiding algorithm has been proposed with the property of contrast enhancement. In this, a new contrast enhancement method named Gaussian Mixture Model based Contrast Enhancement (GMMCE) has been introduced. First, it is claimed that the shape preservation of narrow histograms during contrast enhancement can avoid unnatural artifacts, such as saturation and wash-out. Based on this claim, the proposed method models the histogram of low contrast image by the combination of a limited number of Gaussians where each Gaussian presents a dominant intensity level of the image. This modeling attempts to reflect the shape of a narrow histogram in the parameters of individual Gaussians, to convey it to a broadened version. The global contrast enhancement of the image was achieved by the enhancement of sub-histograms separated by the mean value of the Gaussians of the GMM. Basically, the two peaks (i.e. the highest two bins) in the histogram are selected for data embedding so that histogram equalization can be simultaneously performed by repeating the process.

REFERENCES

[1] J. Tian, “Reversible data embedding using a difference expansion,” IEEE Trans. Circuits Syst. Video Technol., vol. 13, no. 8, pp. 890–896, Aug. 2003.

[2] Z. Ni, Y. Q. Shi, N. Ansari, andW. Su, “Reversible data hiding,” IEEE Trans. Circuits Syst. Video Technol., vol. 16, no. 3, pp. 354–362, Mar. 2006.

[3] D.M. Thodi and J. J. Rodriguez, “Expansion embedding techniques for reversible watermarking,” IEEE Trans. Image Process., vol. 16, no. 3, pp. 721–730, Mar. 2007.

[4] D. Coltuc and J.-M. Chassery, “Very fast watermarking by reversible contrast mapping,” IEEE Signal Process. Lett., vol. 14, no. 4, pp. 255–258, Apr. 2007.

[5] V. Sachnev, H. J. Kim, J. Nam, S. Suresh, and Y. Q. Shi, “Reversible watermarking algorithm using sorting and prediction,” IEEE Trans. Circuits Syst. Video Technol., vol. 19, no. 7, pp. 989–999, Jul. 2009.

[6] X. Li, B. Yang, and T. Zeng, “Efficient reversible watermarking based on adaptive prediction-error expansion and pixel selection,” IEEE Trans. Image Process., vol. 20, no. 12, pp. 3524–3533, Jan. 2011.

[7] Z. Zhao,H.Luo,Z.-M. Lu, and J.-S. Pan, “Reversible data hiding based on multilevel histogram modification and sequential recovery,” Int. J. Electron. Commun. (AEÜ), vol. 65, pp. 814–826, 2011.

[8] H. T.Wu and J. Huang, “Reversible image watermarking on prediction error by efficient histogram modification,” Signal Process., vol. 92, no. 12, pp. 3000–3009, Dec. 2012.

[9] Y. Yang, X. Sun, H. Yang, C.-T. Li, and R. Xiao, “A contrast-sensitive reversible visible image watermarking technique,” IEEE Trans. Circuits Syst. Video Technol., vol. 19, no. 5, pp. 656–667, May 2009.

[10] J. A. Stark, “Adaptive image contrast enhancement using generalizations of histogram equalization,” IEEE Trans. Image Process., vol. 9, no. 5, pp. 889–896, May 2000.

[11] P. G. Howard, F. Kossentini, B. Martins, S. Forchhammer, and W. J. Rucklidge, “The emerging JBIG2 standard,” IEEE Trans. Circuits Syst. Video Technol., vol. 8, no. 7, pp. 838–848, Jul. 1998.

[12] The USC-SIPI Image Database [Online]. Available: http://sipi.usc.edu/ database/

[13] Kodak Lossless True Color Image Suite [Online]. Available: http:// www.r0k.us/graphics/kodak/

[14] M.-Z.Gao, Z.-G.Wu, and L.Wang, “Comprehensive evaluation for HE based contrast enhancement techniques,” Adv. Intell. Syst. Applicat., vol. 2, pp. 331–338, 2013.