IMAGE BLURRINESS REDUCTION BY ADAPTIVE PRIOR USING PARTICLE SWARM OPTIMIZATION WITH GENETIC ALGORITHM

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Abstract- **Color and contrast of the taken pictures are usually degraded below foggy climate conditions and this destruction is often related to proliferate blurriness in pictures along with degraded images. To be able to reduce the amount of road accidents in the conditions of turbid weather through vision augmentation, a competent fog removal technique plays an essential role to lessen the fog and blurriness. In paper, the propose strategy is based upon obtaining enhanced (optimized) texture region and less texture region simply by the concept of particle swarm optimization (PSO) hybridization and further it uses genetic algorithm that make use of wiener filtration system for minimizing fog which usually cause blurriness. In test evaluation the contrast gain, colourfulness index, and colour entropy parameters are improved in proposed strategy**.
*Keywords- **optimization, blurriness, fog, pso, ga***

I. INTRODUCTION

Digital image processing is a broad subject who includes the complex mathematical functions and procedures but it is very simple idea for images. The main aim of DIP is to understand the information, interpret the images [1]. This process is implemented in many areas of science and engineering. Underwater images are affected by illumination, external noise and temperature fluctuations. Various domain techniques in digital image processing.

- Spatial domain: In this technique, we directly deal with the signal or image matrix to produce an output image. The pixel values changes with respect to scene. A direct manipulation of pixels is performed in an image. It is used for smoothing filters, sharpening filters, un-sharp masking and laplacian.
- Frequency domain: Unlike spatial, this technique analyses signal with respect to frequency. The image is transformed to its frequency distribution. The output of this processing is a transformation rather than an image. An inverse transformation is performed to produce an image which, in result, is viewed in spatial domain.
- Time domain: It is continuous, infinite domain. In this the measurement is a function of time. One axis that plots the signal is time while the other is amplitude that gives time-amplitude representation of signal as an output.
- Temporal domain: It is ratio or relative interval between the events which contains information about the distance between events relative to the distance between other events rather than the frequency and sequence.

An image is an array which is basically a collection of pixels in rows and columns. The intensity range of a grey scale image is ranges from 0 to 255. A Grey scale image is normally called as black and white image but the name represents that such an image will also include many shades of grey [2]. The possible range of the pixel values depend on the color depth of the image, here 8 bit = 256 tones or grey scales. A normal grey scale image has 8 bit color depth = 256 grey scales. A “true color” image has 24 bit color depth = 8 x 8 x 8 bits = 256 x 256 x 256 colors = ~16 million colors. Image processing is an approach which is used to convert and image into digital form by performing some operations on it. This process is used to enhance the quality of the image and extract the useful information from it. Basically it is a process like image dispensation in which input is like image and video frame and the output may be image or the characteristics related with that image [3]. Usually Image Processing system includes treating images as two dimensional signals while applying already set signal processing methods to them. It is one of the rapid growing technologies with its application in aspects of business. Image Processing forms core research area within engineering and computer science disciplines too. Following are the steps which are basically included in image processing.

- Firstly import the image by using digital scanner of by digital photography.
- Analysing and manipulating the image which includes data compression and image enhancement and spotting patterns that are not to human eyes like satellite photographs [4].
- The output of the image is in last stage in which result can be altered image o report that it is based on image analysis.

1.1 Types of Blur

Different types of blur are represented as follows [4] [5]:

1. Average Blur: The blur can be scattered in the horizontal and vertical direction. Average filter is used to remove this type of blurriness and it is very useful when noise is present and affects the whole image.

Figure 1: Average Blur

2. Motion Blur: This type of blur is occurred when relative motion is occurred between the camera and scene during the capturing time.

Figure 2: Motion Blur

3. Defocus Blur: This blur is caused by an optical imaging system. This blur is employed to blur a background and pop out the main object using large aperture lenses.

Figure 3: Defocus Blur

4. Gaussian Blur: In this blur the image is dense on the centre and fluff at the edge side. Gaussian function is used to simulate the Gaussian blur. Gaussian filter is used to remove this filter and it follows the bell-shaped curve.

Figure 4: Gaussian Blur

2.2 De-blurring Techniques

Image restoration is an important part in the high level image processing. Image restoration approaches are used to obtain the original image from the degraded image or blur image. In the applications like remote sensing, microscopy, medical imaging, optics, photography, super-resolution applications, and motion tracking applications PSF is unknown or partially known among others. Blind image super resolution methods have also presented in this work which provides the effective image with higher spatial resolution. Image deblurring is an inverse approach which is used to recover the image which has suffered from the blurriness or linear degradation. There are two approaches for image deblurring that are non-blind and blind. In non-blind image deblurring, blurring operator is known and in blind deblurring method operator is unknown [9] [10]. Basically image deblurring process is to recover the original scene image from a degraded image using knowledge about its nature. In the non-blind image de-blurring approach some noise is not removed and it does not gives effective results. Blurriness in image is appears when the relative motion is present between the camera and scene and it reduces the quality of the images. The recovering of original image from the blurred image is called as image restoration. Blind deconvolution approach gives better result as compared to bling restoration approach. Hence in recent years various blind deconvolution techniques have been the degraded image. There are two methods of image deblurring as shown below:

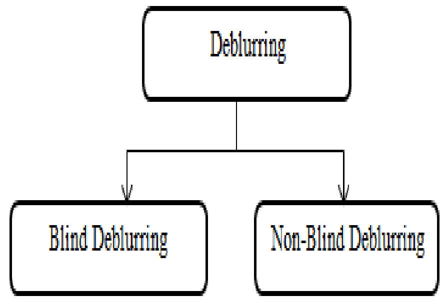

Figure 5: Types of Deblurring

1.1.1 Blind Deblurring

Image deconvolution is an approach which is used to restore the image from the degraded image. Blurriness in image is degradation of interest. A blurred image is denoted as the convolution of a true image u(x) with a point spread function (PSF). Basically it is the set of all pixels within the image. The convolution can be interpreted as an operator K, which is acting upon the true image. A PSF can take on the variety of functional forms. For example, convolution with a Gaussian PSF has the effect of smoothing or averaging out for an image. When the image is convoluted by square PSF it results in motion blurred image. When we have a true image and PSF, producing a blurred image is straightforward [6] [7]. However we typically wish to de reverse. We have a blurred form of an image and we want to recover its original value. The previous statement is the general inverse problem which is called as deconvolution. By solving the problem of deconvolution problem we are able to recover the true image and the PSF which initially caused the deblurring in image [9]. When the information about the blurring PSF is known, the process of image restoration is referred to as "non-blind" deconvolution. If the functional knowledge of the PSF is known then it makes the deconvolution problem straight forward to solve by using variation methods. Within this approach, an optimal image u(x) is found that minimizes energy functional of the form

$$E(u)=\int_{\Omega}\left|(ku)(x)-u_0(x)\right|^2dx+\alpha(Ru)(x) \quad \ldots\ldots\ldots (2.1)$$

However, functional knowledge of k(x; y) or u(x) may not always be known prior to the restoration process, hence \blind" to the solution techniques of the previous. A variational approach can also be used to solve the blind deconvolution problem. The solution to the variational model is the resultant image and PSF which minimizes the following energy functional.

$$E(u)=\int_{\Omega}\left|(ku)(x)-u_0(x)\right|^2dx+\alpha_1(Ru)(x)+\alpha_2(Rk)(x,y) \quad \ldots\ldots (2.2)$$

Figure 6: Blind Deblurring

1.1.2 Non-Blind Deblurring

Image blur (e.g., camera shake) is one of the main sources of image corruption in digital photography and hard to undo. Image deblurring has thus been an active area of research, starting with the pioneering work of Lucy and Richardson. Recent work has predominantly focused on blind deblurring, particularly on estimating the blur from images (stationary and non-stationary). However, relatively little attention has been paid to non-blind deblurring, that is, restoring the image given known or estimated image blur [11]. Yet, this is an important problem since most blind deblurring approaches separate the problem into blur estimation and non-blind deblurring (theoretically justified by Levin et al.). To this date, most approaches rely on the classical Lucy-Richardson algorithm as non-blind deblurring component, or use manually-defined image priors formulated as Markov random fields (MRFs) with sparse, i.e. non-Gaussian, potential functions. Learning-based approaches have been restricted to generatively trained models, but have found limited adoption due to computational challenges in inference. This is in contrast to image denoising, where discriminative approaches have been used extensively, and are often characterized by state-of-the-art restoration performance combined with low computational effort.

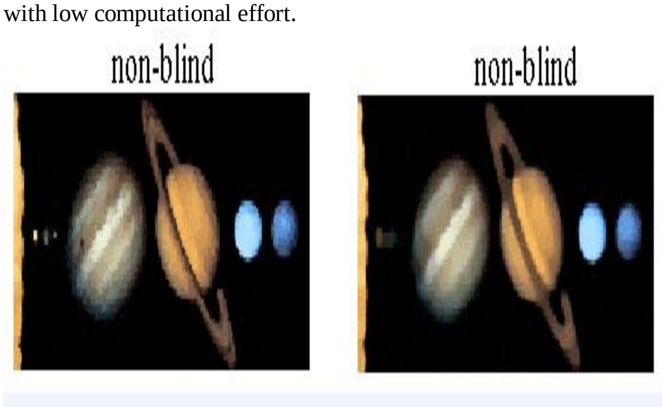

Figure 7: Non Blind Deblurring

Image deblurring is an issue related to the image recover in which sharp image is recovered from the blurred image. This issue appears due to shaking in camera position and exposures with moving objects. In some cases, to solve the blind-deconvolution problem only one blurry image is given to recover the image and characterization of the blur image. The blind-deconvolution problem is solved by using estimating the blur of sharp image and blur image. In particular, the latter step is called non-blind deconvolution. The selection non-blind deconvolution method is based on the error free blur estimate. Due to small errors in the estimation of blur appears in restored image and these are not possible to remove by the future iterations. In blur estimation process only few methods considered the uncertainty. These methods depend on the robust norms which are used in the data item and use iterative approach to detect the outliers. Small error problem in the blur estimation process is considered as highly ill problem in both blind and non-blind deconvolution. This issue is resolved by restricting the class of possible solution by using the concept of regularization. The most effective method of regularization firstly captures and then exploits the reconstructed image. The most famous image prior method is Total Variation (TV) which is used for good results in deblurring and denoising. The total variation is based on the natural image which is constant and these assumptions come from the recent work on image statistics. However TV is a global prior and it is not consider when the sub-regions in the image have different statistics. e.g., the texture of a tree is different from that of a house. To avoid the drawback of the TV, some approaches relax the global prior assumption and use the texture statistics should change smoothly across an image. To represent a natural image some wavelet bases methods are chosen on the deblurring process. These methods are based strongly depend on the wavelet and used for successfully restore the image. Other methods use dictionaries to represent the local statistics [12] [13]. Dictionary based approach is most popular for denoising and deblurring. These methods avoid choosing a pre defined basis set, but instead learn a dictionary (usually over complete) from a dataset of images. Then, each image patch is denoised or deblurred by expressing it as a linear combination of patches from the dictionary. Methods differ in the choices for learning the dictionary and determining the linear combination coefficients. These methods determine correspondences between pixels with a similar local appearance in large areas, and not just in a neighborhood of a pixel. While these methods can greatly improve the quality of the restored images, when they are applied to noisy and blurry patches they produce artifacts or are less effective due to ambiguities in the correspondences.

II. RELATED WORK

Tofighi, et al. [1] proposed an approach of blind image deblurring using row-column sparse representation. A model is prepared for the outer product of kernel and image coefficient and ranks one matrix and solves the problem of rank minimization. In this work, two optimization problems are solved by row and column sparsity. Singular value decomposition is used to recover the image and kernel. The proposed BD-RCS achieves effective results and it estimates the blur kernel support and solves deblurred image problem. Cao, Shan, et al. [2] formulated the problem of blurred image by reducing the effect of ringing using Bayesian estimation. This method is used for image restoration and it uses Richardson Lucy algorithm to restore the image. This algorithm reduced the noise and ringing artifacts and also preserves the useful information. In this work, a prior probability model is built of the original image and then applies degradation function. Bayesian model is applied and then reduced the ringing in the image. Mosleh, Ali, et al. [3] proposed a simple and effective method of image deblurring by using Linear Approximation method which handles the saturation in deblurring method. This work is motivated from the measurable ringing artifacts through the multi-resolution pyramid. Quantification function is used to reduce the cost function and also reduce the ringing in deblurring process. For optimization Primal-dual algorithm is proposed to provide the effective biased patterns of the image. The results show the image quality is enhanced by the proposed method. Chandramouli, Paramanand, et al. [4] presented a method of blurriness removal in the image captured by the plenoptic camera. Blind convolution method is used for identification of blur point and latent sharp image identification. In the absence of motion, the plenoptic camera images are affected by aliasing and defocus. The plenoptic cameras introduced the periodic patterns which are used to obtain numerical schemes to synthesize images. These methods are implemented on the effective GPU to enables the iterative models. The proposed method improves the image quality in non-uniform motion blur. Qin, Zhengcai, et al. [5] worked on the text image deblurring by using Intensity Extermums Prior. This work is based on the white and black pixels of the blurred image are less in quantity as compared to the clear image. To prove this thing mathematically Intensity Extermums Prior method is used in this work. It is basically an optimization approach which utilizes the half quadratic splitting approach. The performance evaluation of the proposed approach is also done on the complex text image which contains cluttered background regions and it performs effectively on it. Pu, Haitao, et al. [6] explained an approach of double convolution neural network which is used to solve the blurriness problem in the 2D blur image. Convolution neural network is used to deblur the barcode image. This technique is combined with deep learning to fill the gap between the traditional approaches. The proposed method achieves the effectiveness of the superior performance of the image. Xu, Xiangyu, et al. [7] proposed Deep Convolution Neural network approach to extract the sharp edges from the blurred image. This work is done by the motivation of existing filtering methods that are used to deblurr the images. This model work on two approaches the first one is to remove the extra edges and enhance the sharp edges. In this work, no any deblurring algorithm is required to sharpen the edges and their selection. The result shows that it reduces the computation load and improves the image quality. Chang, et al. [8] formulated the problem of motion image blurring by using the hybrid approaches. In this work, Patch-based edge restoration and bilateral filtering method are used to deblur the motion image. In edge-based approach, edges are sharpened and the used for these edges to estimates the blur kernel. The present work is based on the deblurring algorithm which separates the blurred edges and smooth edges. The bilateral filtering method is used here to remove the narrow edges and the noise which generates the ringing effects. This approach provides the effective results in deblurring. Tang, Yibin, et al. [9] proposed blind image deblurring method with sparse representation and external patch priors. In the existing methods internal prior is only considered in the deblurring process but in the proposed method external priors are used to reconstruct the latent image. In this work author proposed External patch Log Likelihood method with Gaussian mixture model which is used to describe the external patches. The proposed EPLL method is used with the existing sparse-based deblurring method where it designed each patch of the latent image very carefully. This iterative procedure effectively optimizes the latent image and blur kernel and provides effective deblurring result in the image. O'Connor, et al. [10] proposed convex optimization approach called as total variation deblurring which is mostly used for non-differentiable optimization. In this work, Fast Fourier Transformation method is used to solve the linear equations. In this approach, two models are used that are Space Varying operators and the Nagy-O'Leary model and efficient filter flow model. Douglas -Rachford algorithm is implemented with low complexity per iteration which is dominated by a small number of FFTs. Jeon, et al. [11] worked on multi-image deblurring by using complementary sets of fluttering patterns. This work is done on the video frames which enable us to preserve all spectrum bands of the latent image. An algorithm is proposed in this work which generates the complementary sets of binary sequences and implements the code in the video system. Performance analysis of the proposed work is done on the basis of theoretical bounds and spectral gains and results better with the security of the video also. Marnissi, Yosra, et al. [12] proposed the Bayesian approach for image restoration with Poisson Gaussian noise. This algorithm is used to measure the reliable parameters from the observations. The proposed algorithm provides the good approximation model to compute the posterior mean estimates. The result of the proposed approach shows its effectiveness in image restoration and improves the image quality. Azzari, et al. [13] proposed a method to overcome the issue of image Poisson noise by using variance-stabilizing

transformations. In this proposed work image is deconvolved by using a linear regularized inverse filter and then it is transformed by using VST and then denoise the image by using the filter for Gaussian noise. The proposed approach gives effectiveness in image deblurring by using BM3D denoise filter.

III. THE PROPOSED METHOD

3.1 Proposed Methodology

Step1: In this step input is given in the form of image which is blurred in nature.

Step2: This step deals to select the appropriate prior. Prior is basically prior information of the image. Here prior is a subset of image that is used for processing.

Step3: In this step value of prior is initialized. In this prior value is converted into mathematical form and merged for processing. By using any algorithm we select the best features from the set.

Step4: In this step Flower Pollination method is implemented for the best solution.

FPA is a global optimization algorithm which is used for the optimization of the solutions. Global pollination is considered under cross pollination and Biotic Pollination. In global pollination process pollen travel a long distance because insects can fly over long distance. This algorithm works in the four steps that are following:-

1. Population Initialization
2. Exploration Process
3. Exploitation Process
4. Solutions Update

Search by Flower Pollination method.

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Step I: Min or max Objective F(u), where $u=(u_1,u_2,\ldots\ldots u_d)$.

Step II: Initialize m pollen gametes or flower population having random solutions.

Step III: The best solution $\boldsymbol{S_*}$ is found in the initial population.

Step IV: A switch probability is defined as $\boldsymbol{p_S} \in [\boldsymbol{0}, \boldsymbol{1}]$.

Step V: In case T< MaxGen, for i=1:m

A step vector l (obeys Levy distribution) is drawn as $\boldsymbol{p_S} > \boldsymbol{rand}$, the global pollination

$$\boldsymbol{u_x^{1+1}} = \boldsymbol{\gamma l(S_* - u_x^t) + u}$$

Where,

$\boldsymbol{\gamma}$ is the scaling factor for step size control,

$\boldsymbol{u_x^t}$ is the solution vector at t iteration,

$\boldsymbol{x, y}$ $\boldsymbol{and}$ $\boldsymbol{n}$ are the pollens

B : Otherwise, drawing $\boldsymbol{\epsilon}$ with uniform distribution [0,1]

So, local pollination $\boldsymbol{u_x^{1+t}} = \boldsymbol{\epsilon(u_y^t - u_n^t)}$

Step VI: New solution is evaluated as the solution obtained are better and updating the population.

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Step 6: If value is optimized then apply weirner Filter. Otherwise again initialize the value.

$$X(n) = d(n) + v(n)$$

Here d(n) and v(n) are stationary random process

X(n) mean square estimate of d(n) and v(n).

Weirner Filter: This filter is used to remove the blurriness from the image which occurred due to linear motion in image. It is basically used to reduce the noise in image. It reduces the mean square error as much as possible.

Step 7: Analyze the value of Color Information Entropy (CIE), colorfulness Index (CI) and Contrast gain (CG)

3.2 Proposed methodology: Flowchart

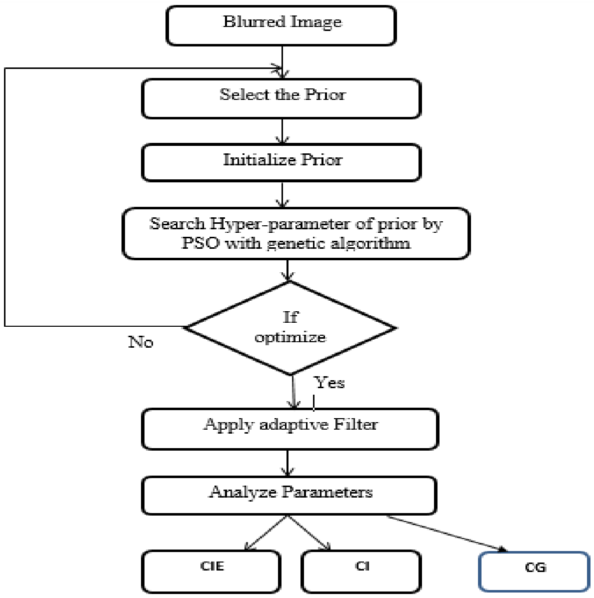

Figure 8: Proposed Flowchart

IV. RESULT ANALYSIS

4.1 Result Analysis

Figure 9: Proposed Approach Images before and after

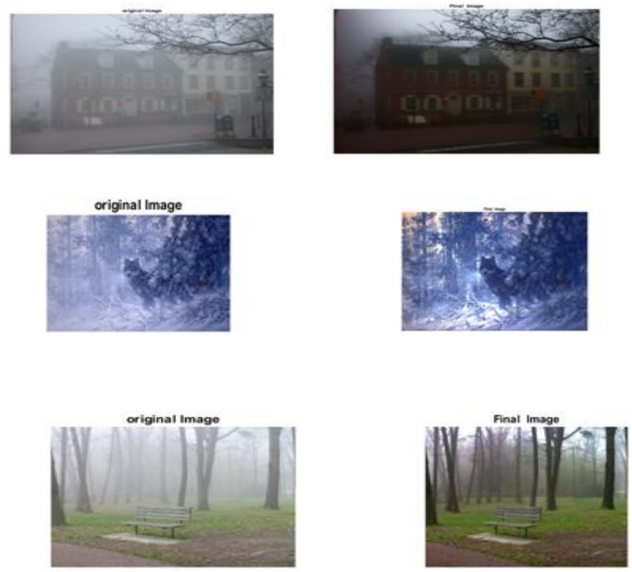

Figure 10: Existing Approach Images before and after

Table 1 Images with their existing and proposed approaches

Images	CIE (existing)	CI (existing)	CG (existing)	CIE (Proposed)	CI (Proposed)	CG (Proposed)
foggy_forest	7.6035	23.736	0.4798	8.2955	25.365	0.6632
Foggy-school	7.3747	22.9683	0.2305	8.2029	24.8978	0.952
foggy-bench	8.0367	23.1076	0.6878	8.7363	25.3355	0.7886
foggy House	7.4633	22.454	0.6734	8.234	26.34	0.8993
tree_foggy	8.123	22.678	0.3456	8.9874	25.789	0.7863
Wolf	8.234	23.456	0.5645	8.456	24.673	0.6783
foggy_oaks	7.234	23.678	0.4673	8.789	25.345	0.5678

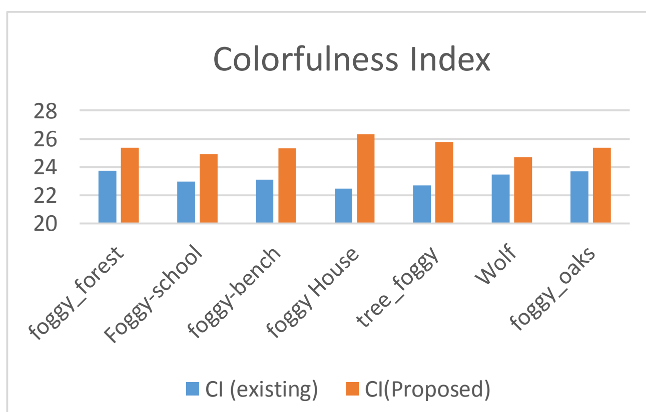

Figure 11 CI-based colourfulness index

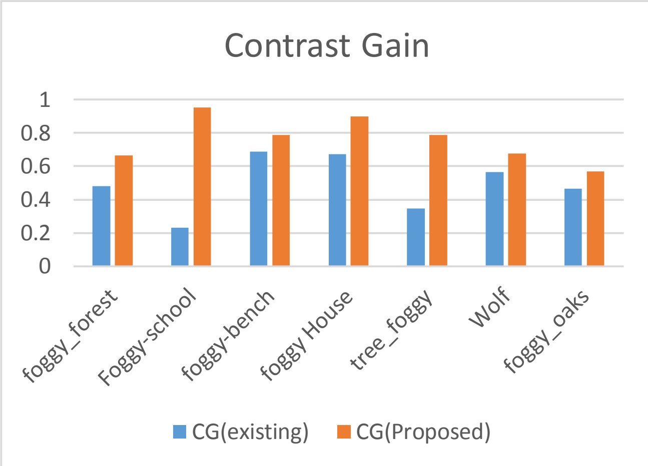

Figure 12: CG-based contrast Gain

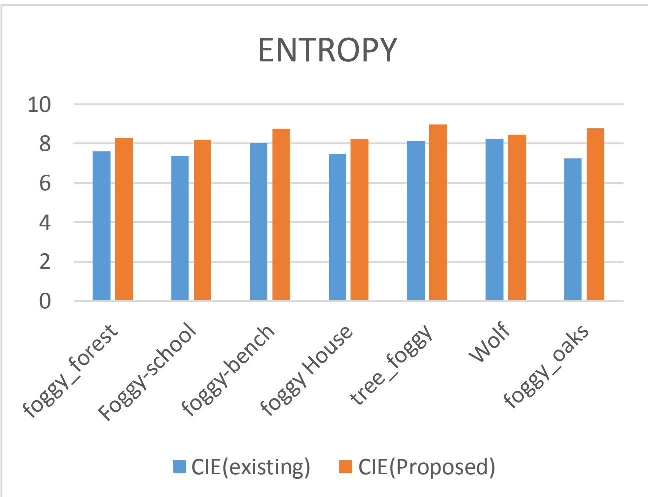

Figure 13: CIE-based contrast Gain

IV CONCLUSION

Solitary image fog removal is among the significant and basic task to build up a strong and versatile computer vision program for object tracking, recognition of traffic sign, and FVES system. In this study article, an efficient and novel single image fog removal algorithm is proposed for both colour and gray images. In the proposed approach the optimized part of colourfulness finds and gets removed by threshold provided by PSO-GA approach. In the experiment all the significant parameters were improved because of PSO-GA approach as it effectively converges with given threshold.

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