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Dynamic Histogram Equalization for contrast enhancement for digital images

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ABSTRACT

Magnetic Resonance Imaging (MRI) is an efficient tool, produced by applying radio waves and magnetic fields which is being useful in the diagnosis of various diseases like cancer, epilepsy and stroke etc. The quality of the resulting image is needed to be enhanced because it is challenging for the specialists to investigate. Modified Histogram Equalization on Fuzzy based Improved Particle Swarm Optimization (FIPSO) is proposed for Dynamic Histogram Equalization which resolves this problem through image contrast enhancement. The details of an images are captured by smoothing and it uses Gaussian function to distribute pixel intensity to nearest pixel. It uses normal distribution and here blur is removed by applying Non subsampled Contourlet Transform. Then local maxima are calculated to extract dark and bright pixel values. The smoothed images are fuzzified with TSK (*Takagi-Sugeno-Kang*) model and it provides importance to all the local maxima intervals. An Improved particle swarm optimization (IPSO) algorithm is obtained by combining Galactic Swarm Optimization (GSO) with PSO which equalizes histogram of an image. FIPSO algorithm is used to the minimum contrast images of MRI brain images. Non-subsampled Contourlet transform (NSCT) based modified histogram equalization enhances image contrast. Here IPSO generates optimum values and these value are used to calculate cumulative distribution function in histogram equalization. The quality measures demonstrate that the current equalization technique attains highest performance against existing techniques in terms of brightness and contrast.

1. Introduction

Image processing (IP) is an incredible and demanding area which is being a part of different fields like, remote sensing, robot vision, security systems etc., [1,2]. Magnetic Resonance Imaging (MRI) is a medical imaging method which creates great determination images of anatomical parts of human body like chest, brain and so on [3]. IP comprises of Image Enhancement (IE) utilizing Histogram Equalization (HE) [4]. Histogram Equalization is a mainstream method for improving picture contrast. Global HE (GHE) is a standout amongst the most ordinarily used techniques in Contrast Enhancement (CE) since it has maximum efficiency and straight forwardness [5].

Image contrast enhancement is an important objective in digital image processing. This enhancement strategy is more useful applications in PDA, mobile phones and surveillance systems. Histogram equalization is one of the efficient techniques and it is a computationally fast technique.

As a rule, HE based CE is accomplished over the redistribution of intensity values [6]. The minimum contrast are seen in shade and cloudy background, in which capture images are within a short range of Light Emitting Diodes (LEDs) [7]. To manage the low quality or low contrast X-ray images, image enhancement techniques are used. IE helps in enhancing the quality and appearance of an image [8]. To enhance characteristics of normal images, certain modifications like CE, filtering, smoothening has been made [9]. The principle target of an IE is to draw out the hidden image details or to expand the contrast from another dynamic range (DR) [10]. Low quality CE makes HE procedure unsatisfactory for the majority of customer hardware applications, for example, cameras and television [11].

To solve this problem, the DHE (Dynamic HE) approach has been suggested. Compared to earlier HE process, DHE technique enhances the quality of an image [12,13]. Objective of IE is to adjust qualities of an image to describe changes in radio density [14]. In general, enhancement systems for dark images can be extensively isolated into direct and indirect enhancement classifications [15].

Many works had been affected with an illumination issue. A few systems attempted to discover an enhancement representation through illumination subspace learning [16]. These assessment stated that the spontaneous HE-based methods remained

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not good for noise. In order to tackle this issue, image quality measure (IQM) is used [17]. This processing has the advantages over dynamic range and spatial distribution of scene illumination [18]. In spite of the fact that GHE can effectively use high intensity display, it inclines to conclude CE [19]. HE is accomplished by regularizing cumulative distribution function, here the subsequent image should have uniform distribution [20].

Limitations of existing methods are shown below:

Image quality measure [17] had high complexity to yield an accuracy. Also in [20], Bi-Level Weighted Histogram Equalization (BWHE) mentioned that it had greater degree of Structural Similarity Index Measure (SSIM) [20] value to show the performance enhancement but it is quite low while comparing with the recent algorithms. As a conclusion our proposed work uses IPSO algorithm for equalizing the histogram values and produce high contrast enhancement. Additionally, in [21] the contrast enhancement is deliberated with that PSNR values. But it is quite low than our work. Our main motivation is to preserve the best details of HE, and introduce novel techniques which overcome the drawbacks of existing system.

Initially some points regarding Particle Swarm optimization (PSO) [22] is given below:

PSO algorithm was invented by Kennedy and Eberhart in the year of 1995. This is the algorithm with the behavior based on social organisms in groups, such as bird and fish schooling. PSO is one of the algorithm which can combined with any kind of optimization algorithms. Compared to other algorithms like Adaptive Genetic algorithm (AGA), Genetic Algorithm (GA) and Particle Swarm Optimization (PSO) [23], our proposed algorithm is intended to reduce the complexity of local optima by position updating with Galactic Swarm optimization. This leads to maximum PSNR, SSIM and MSSIM. It has minimum computational complexity and hence the processing time also minimized. Nevertheless, the stochastic properties of the algorithm guarantees the solution space exploitation.

The objective of this work is to introduce a novel Fuzzy based Improved Particle Swarm Optimization (FIPSO) algorithm for enhancing the contrast of the image. In which initially the image smoothening and blur is removed by applying NSCT. Local maximum finds the darkest and brightest points in the histogram. In order to provide distance between two successive local maxima, fuzzified TSK model is used. Also novel Improved particle swarm optimization algorithm equalizes the histogram by adjusting the weights. The contrast of the image is obtained from the ratio of brightest and darkest intensity pixels. Intensities are distributed using histogram and in which optimum weight values are obtained using improved particle swarm optimization.

The IPSO tries to improve the global optimum. During the operation of IPSO, the social components are increased against cognitive component and IPSO modifies the acceleration coefficients to achieve this. The optimum value is high at initial stage and it will be reduced to low. IPSO technique is used to find optimum values with low reference range. Novelty in Improved PSO, is to combine PSO with Galactic Swarm Optimization (GSO) for preventing PSO from local minima. So the best positions from GSO found so far is recorded and the neighborhood best is randomly selected from the list instead of the current best solution. This explosion phenomenon maintains the balance among the exploration best. This prevents the PSO from local minima. It reduces complexity of local optima and improves the convergence speed and the exploitation ability of the algorithm.

The remaining part of the work described as follows: Section 2 provides the related works regarding histogram equalization. Background of the work is given in Section 3. The proposed dynamic histogram based contrast enhancement is explained in Section 4. The performance evaluation of the proposed work with result analysis is discussed in Section 5. Finally, the paper conclusion and future work is given in Section 6.

2. Related work

Some of the current research works related to dynamic histogram equalization for contrast enhancement: applications to brain MRI images was listed underneath:

Zhang et al. 2017 [24] were introduced an algorithm which increased the medical image ordering schedules and decreased the semantic gap in large degree. It was deliberated a multi-scale nonnegative thin coding based on medical image classification algorithm to minimize the semantic gap. Initially, this method was applied on a decay images with several scale layers, since, multi-scale data works efficiently. Furthermore, non-negative coding system with fisher discriminative strategy, which entirely neglected the connected data. This was reduced the gap between high level and low level features. Here SVM classifiers were used for the classification. This work has the time complexity since [24] algorithm was portioned into 10 parts and each part take 10 runs.

Isa et al. 2017 [21] were considered a novel image contrast algorithm named as Average Intensity Replacement-Adaptive Histogram Equalization (AIR-AHE). Moreover, an information related to edge relating to the potential White matter hyper intensity regions can efficiently improve the results in terms of accuracy. Affording to qualitative outcomes, it deliberated that the contrast of image was improved. Here the PSNR value is nearer to 57 and in case of proposed algorithm the value is 76, so the proposed work achieves higher performance.

Cao et al. 2017 [25] were gave universal histogram-based image contrast enhancement (CE) algorithms. Both gray-level and spatial selective down sampling of images are embraced to minimize computational cost, though the quality of enhancement was quite conserved and deprived of apparent degradation. Mapping function standardization was innovated to modify the pixels with down sampling. Computational efficiency of this method was improved with this methodology and perceptual quality of image enhancement was still preserved. Finally contrast measure obtained in [25] is 37.9 and for the proposed method, the value is 39.

Abdoli et al. 2015 [26] was introduced a method namely Gaussian mixture model-based contrast enhancement (GMMCE) and it avoids unnatural artifacts termed as wash-out and saturation. This was also concentrated on shape preservation. Through the combination of a limited number of Gaussians, it models the histogram of low-contrast image. The global contrast improvement of the system was attained through the sub-histograms enhancement which was detached through the mean of Gaussians. So this method was improved the contrast and it yielded low complexity while processing it with the real time applications. In this case, the computational time for the [26] is 0.241 ms and for the proposed work it is 20 s.

Cheng et al. 2013 [27] was proposed a CE method for Bezier curve video and image. Here processing time was reduced and quality of the image was enhanced. This was achieved through Bezier curve and it operated separately on both dark and bright regions. With the accurate and fast histogram modifications and which was good for both video and image. Prominently, the current methodology applied on the adapted arithmetic functions towards efficiently decrease processing time. Similarity index for the [27] is 0.99 and the for our proposed work it is one.

Muniyappan S et al. 2019 [23] was proposed an adaptive genetic algorithm for enhancing the contrast of an image. Here, initially chromosomes were generated for each gray levels and then fitness function was evaluated. This fitness was depended on the overall intensity. This work provided better accuracy and comparing to this method, proposed work achieves better performance in case of SSIM, MSSIM, PSNR, MSE and computational time.

Problem definition:

The major problem related to histogram equalization using PSO algorithm is, individuals should search on the entire space without grouping local optima's. It is necessary for the convergence to move towards global optima's at later stages. Attain optimum convergence intensely inclined over the inertia weight. Once the method converges, the static standards of the limitations may found the excessive variation of element. Also drawback of literatures from [21,23–27] are given in Section 2.

3. Background

3.1. Fuzzy Dynamic Histogram Equalization

The low contrast image is partitioned into sub histogram depend on its median. Histogram based method is used for segmentation and it is required to pass through all the pixels. In this method histogram is computed for an image and clusters are created for the image based on peak histogram. This procedure is repeated until no more clusters are appeared in an image. Histogram based equalization is efficient than other methods also it requires only one pass to each pixel. In Dynamic Histogram Equalization (DHE), first smoothing is applied to each histogram. Then the local maximum points are captured by comparing with nearest pixels. After finding local maxima's, length of histogram is obtained to balance the enhancement distance using TSK model.

3.1.1. Smoothing

The high frequency components of the image generates some jagged points due to noise which are removed with the help of smoothing. Smoothing captures specific details of the image by modifying intensity of pixels. Gaussian function is used for smoothing which increase or decrease the pixel's intensity. In Gaussian function, transformation is applied to each pixel to remove blur and it uses normal distribution. The Gaussian function is described as,

$$G(h, v) = \frac{1}{2\Pi\sigma^2} e^{\frac{-h^2+v^2}{2\sigma^2}} \quad (1)$$

where h is the distance between origins of horizontal axes, v is the distance between origins of vertical axes and σ denotes standard deviation. So the smoothed image becomes flexible for CE. The redundant, minimum and maximum noisy peaks are removed using this function. Next to smoothening maximum points in the ROC is found out to separate darkest and brightest point in the region.

3.1.2. Finding local maxima

Local maxima indicates the highest point of the histogram than its neighbors. From this darkest and brightest point can be easily separated. Local maximum and minimum points are traced from the histogram of smoothed image. The local maxima and minima are derived using highest and lowest intensity values of image. 0 denotes the lowest intensity value and 255 denote the highest intensity value. The image needs to be partitioned based on the highest and lowest intensity values. The histograms are collected to segment the image. Histogram based method is used for partitioning. Here the median is calculated based on image histogram. Median is calculated by,

$$I_{median} = L_m + \left[\frac{\frac{N}{2} F_{m-1}}{f_m} \right] C \quad (2)$$

where, L_m is the lowest value of median, N is the number of observations, F_{m-1} is a Cumulative frequency, f_m is the frequency of each image and C is a median value. Image is segmented based on this median value. The distance between two successive local maxima's are called interval. Partitioning is needed to place the related pixel values collectively to make it easier for analyzing.

3.1.3. TSK model

Here, the fuzzy model is identified through its monotonic function. This TSK model gives importance to each interval. Depend on the frequency one interval can be changed to another interval. Fuzzy parameters are separable at important pixel in an image. Let 'u' is a fuzzy system's input with interval X

IF $c \le u^1 < v^2 \le b$ and $F(u^1) \le F(u^2)$

THEN F: X →Y increased monotonically.

$$\textit{membership function} = \begin{cases} F\left(u^1\right) \textit{is small} \rightarrow \textit{function positive} \\ F\left(u^1\right) \textit{is big} \rightarrow \textit{function negative} \end{cases} \quad (3)$$

There is M amount of rules in fuzzy system. The procedures are signified as $R^1, R^2 \dots R^m$.

R^1IF u is F_1

THEN v is $a_1^1 u + a_0^1$,

R^2: IF u is F_2

THEN v is $a_1^2 u + a_0^2 \dots$

R^M: IF u is F_m

THEN v is A

$$A = a_1^M u + a_0^M \quad (4)$$

where, a_1^l and a_0^l is constant parameters. In X, F_1 and C is entire sets through 0≤l ≤M.

The TSK output is modeled as

$$v = F(u) = \frac{\sum_{i=1}^{M} (a_1^l u + a_0^l) \mu^1(x)}{\sum_{i=1}^{M} \mu^1(x)} \quad (5)$$

where $\mu^1(x)$ is the membership function and its range is [0, 1]. While differentiating equation (5) the fuzzy system parameters are said to be monotonic. Next process is to decompose the image into sub bands on which the modified histogram is done to enhance the contrast of an image.

First the source data is partitioned into image with sub regions depend on the technique of fuzzy dynamic histogram equalization. The output of image and its histogram after partitioning is shown in Fig. 1.

Then, each sub histogram is applied to histogram equalization. The highest and lowest intensities are obtained and the enhancement distance between the images intensities are analyzed.

4. Proposed methodology for dynamic histogram equalization using FIPSO

Medical image processing is a technique for creating visual representation of interior part of the organs or tissues for clinical analysis. Radiography, MRI, Nuclear medicine, ultra sound, Elastography, Tactile imaging, Thermography and Tomography are the various brain imaging system for analyzing abnormalities. Magnetic Resonance Image is mostly used for brain image investigation. If we increase the quality of the images, it is efficient for the specialists to investigate. In this paper MRI images are taken into account for image contrast enhancement. Dynamic Histogram on FIPSO is proposed to increase the contrast of the images used in the medical field. First, smoothing is applied to the input images to capture the specific details. In this Gaussian process, smaller kernels perform better for higher input SNRs and wider kernels perform better for low input SNRs. This leads to increase in filter width, with decreasing SNR improvement. The smoothing with Gaussian operator removes 'blur' images and noise.

Next, the input image is allocated into sub regions depend on its median. Based upon the median, an image is separated into blocks of non-overlapping rows. Here more number of input images are segmented. Here equal amount of pixels are included when using median instead of mean.

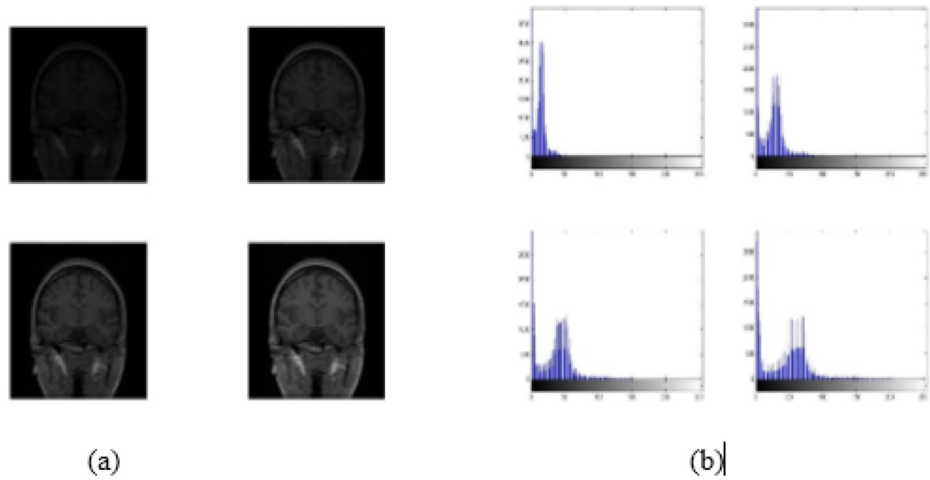


Fig. 1. (a) Partitioned sub image and (b) Sub histogram of partitioned image.

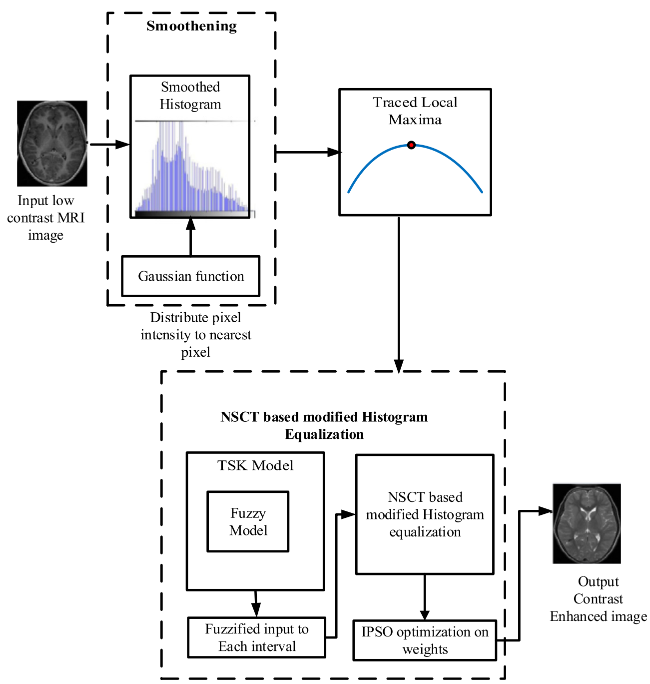


Fig. 2. Architecture of the FIPSO proposed work.

TSK model is expressed to level the distance between local maxima's. Here brightest and darkest point can be easily separated with the maximum point identification around the region of curve. NSCT with Improved Particle Swarm Optimization is a method of finding optimum values of weights. Finally histogram is equalized for output image to avoid improper modification of original image.

The input MRI brain images are basically grayscale images and have low contrast and noise sensitivity. The quality of the input image is not sufficient for analyzing the disease. Hence the images are applied for processing with Fuzzy Dynamic Histogram Equalization. The architecture of the FIPSO framework is illustrated in Fig. 2.

Initially an input image is taken and which is given for the smoothening process. Based on the median of image pixels, the original brain image was segmented into four sub image histograms. In the next step, Dynamic equalization technique was applied with TSK model to enhance the image contrast. Here good quality image is recognized with IPSO with 50 runs.

4.1. NSCT based gray level modified histogram equalization

A novel Multi-scale decomposition based smoothing techniques effectively smoothen the image into perfect images. Consider the image with pixel range $(x_1, x_2, \ldots .x_n)$. In order to decompose the image Non-Subsampled Contourlet Transform (NSCT) is used. NSCT is the combination of Non-subsampled pyramid filter bank and the Non-subsampled Directional Filter Bank.

4.1.1. Non-subsampled pyramid filter bank (NSPFB)

Non-subsampled 2-D filter banks are used for achieving multi-scale property. Reconstruction is attained by the following equation (6).

$$M_1(z)\, N_1(z) + M_2(z)\, N_2(z) = 1 \tag{6}$$

where $M_1(z)$ is the filter with low frequency, $N_1(z)$ is the low pass reconstruction filter, $M_2(z)$ is the high pass decomposition filter and $N_2(z)$ is the reconstruction filter with high frequency.

Filters are upsampled for the next level and the function of NSPFB are given by the below equation (7)

$$M_n^{eq}(z) = \begin{cases} M_2\left(z^{2^{n-1}}\right) \prod_{j=0}^{n=2} M_1(z), & 1 \le n \le 2^k \\ \prod_{j=0}^{n=2} M_1\left(z^{2^j}\right) & n = 2^k \end{cases} \tag{7}$$

4.1.2. Non-subsampled directional filter bank (NSDFB)

In this technique it eliminates the need of sampling technique. Then the perfect decomposition is attained by the following equation.

$$Q = \begin{bmatrix} 1 & 1 \\ 1 & -1 \end{bmatrix} \tag{8}$$

Finally the decomposition is achieved by combining both NSPFB and NSDFB. The resultant filtering configuration approaches an ideal detachment of the frequency plane. Then this decomposed image will be given to the filtering section.

These NSCT coefficients are applied to the horizontal and vertical coefficients to attain the decomposed region.

$$C_\psi^H(X, Y) = \frac{1}{mn} \sum_{x=0}^{m-1} \sum_{y=0}^{n-1} g(X, Y) \,.\, \psi(X) \,.\varphi(Y) \tag{9}$$

$$C_{\psi}^{V}(X,Y)=\frac{1}{mn}\sum_{x=0}^{m-1}\sum_{y=0}^{n-1}g(X,Y).\psi(Y).\varphi(X) \tag{10}$$

In Eq. (10), ψ means the number of non-subsampled contourlet transform and φ means the scaling function. With these functions, gradient of the image will be generated using the following equation (11).

$$\varpi(X,Y)=\left|C_{\psi}^{H}(X,Y)+C_{\psi}^{V}(X,Y)\right| \tag{11}$$

Each block is divided into sub blocks based on the fuzzy rules which are generated ($R^1, R^2 \ldots R^m$). These fuzzy rules are calculated consequentially using the optimal conditions.

IF the value of ($\varpi(X,Y) \leq R^1$)

THEN pixel (X, Y) goes to first region

ELSE IF the rate of ($R^1 < \varpi(X,Y) \leq R^2$)

THEN pixel (X, Y) belongs to region two

ELSE IF the value of ($R^2 < \varpi(X,Y) \leq R^n$) THEN (X, Y) belongs to region three

ELSE pixel (X, Y) belongs to region four.

Then the histogram is calculated with the optimization strategy. For the histogram calculation we use number of edge pixels in an image and weight is calculated using following formula (12).

$$W(I)=\sum_{X=0}^{n-1}\sum_{y=0}^{n-1} Count\ (I)\,/Maximum\ Count \tag{12}$$

Eq. (12) will be optimized using IPSO. A weight in the histogram equalization is optimized with the Improved Particle Swarm Optimization (IPSO).

4.1.3. Finding optimum values with IPSO

Improved particle swarm optimization technique is used to find optimum values with low reference range. At the initial stage of PSO, individuals should search on the entire space without grouping local optima's. Here we hybrid PSO with Galactic Swarm Optimization (GSO). So the best positions from GSO found so far are recorded and the best neighborhood is randomly selected from the list instead of the current best neighborhood. This prevents the PSO from local minima. It reduces local optima complexity and improves the convergence speed of the algorithm. It is necessary for the convergence to move towards global optima's at later stages. The concept of IPSO is to converge toward the global optimum at the final phases of the search by increasing overall search at the beginning. The optimum value is high at initial stage and it is reduced to low. In particle swarm, swarm migrates toward other particles to find the solution of improved particle. In solution space, the coordinates of the particles are traced to find the best solution and the solution is not depending on related particle. The parameters called pbest and gbest which are obtained by considering the nearest location of the particles. By using the random weight of each particle, it moves around the pbest and gbest position in IPSO. Velocity of the particles, recent position, distance of the recent and past best position, distance of the enhanced and global best position are the parameters to modify the pixel position. The velocity of each element is improved using following condition,

$$\begin{aligned}U_i^{K+1}&=wU_i^K+a_1\times rand()\times(Pbest_i-S_i^k)\\&+a_2\times rand()\times(gbest_i-S_i^K)\end{aligned} \tag{13}$$

where, U_i^k is the velocity at Kth iteration with agent i, and it ranges from 0.1 to 0.9, a_1 and a_2 are factors of learning which ranges from 0 to 4, rand () is a random number distributed uniformly from 0 to 1, S_i^k is a position of current location at Kth iteration, pbest is the present best of the group, gbest is a global best of agent I, w is the inertia weight which ranges from 0.1 to 0.9.

The position of the particle is updated using modified with Galactic Swarm Optimization (GSO) velocity,

$$\begin{aligned}&V_j(i)\leftarrow I_{w2}V(i)+C_1R_3\left(P_b(i)-z^{(i)}\right)+\\&C_2R_4\left(G_b-z^{(i)}\right)\end{aligned} \tag{14}$$

where, I_w is the inertial weight and C_1, C_2 are the acceleration coefficients in the range of 0 to 2, R_i varies from -1 to 1.

$$z^{(i)}\leftarrow\omega_{ij2}z^{(i)}+\omega'_{ij2}V(i)+\alpha_2r_2.G_b \tag{15}$$

$$\omega_{ij}=\frac{\exp\left(F(j)/m\right)}{\left(1+\exp(-F(j)/m)\right)^{C_i}} \tag{16}$$

$$\omega'_{ij}=1-\omega_{ij} \tag{17}$$

where, ω_{ij} and ω'_{ij} are the dynamic weights, α is the acceleration coefficient and r is the random number within the range of 0 to 1. $F(j)$ Represents the fitness of jth particle, m denotes the mean fitness value of first iteration and c_i is the current iteration.

The following procedure is used to obtain optimum values.

Step 1: The elements of the image are initialized with random location and velocity of the particles.

Step 2: Then the difference between velocities are being evaluated to loop the process again.

Step 3: Set the values with required entropy to find the pbest and gbest values. Alter the position with GSO and velocity of the particle using Eqs. (13) and (14). The gbest values are selected from Eq. (13) to find optimum solutions.

The histogram H is calculated using following equations (18).

$$H(l)=h(l,i)*W(I) \tag{18}$$

Modified histogram increases the contrast of the image globally when the processed data of the image is represented with close contrast values. The contrast of the image is obtained from the ratio between brightest and darkest intensity of pixels. Intensities are distributed using histogram and optimum weight values required for processing is obtained using improved particle swarm optimization. Discrete gray levels are collected as an image with dynamic ranges [0, L−1] and where L is the gray level of an image. The CDF for the input image is defined as in Eq. (19),

$$C_k=S(t_k)=\sum_{i=0}^{k}P(t_i)=\sum_{i=0}^{k}\frac{v_i}{v} \tag{19}$$

where v is the quantity of pixels in the image, $S(t_k)$ is the CDF of the pixels, v_i is the quantity of pixel having gray level t_i, $P(t_i)$ is the PDF of the pixels and K=0, 1, 2 … L−1 with $0 \leq S_k \leq 1$. The contrast of the resulting image is enhanced with the proposed method.

Thus the contrast of the MRI medical image is increased with the novel FIPSO technique and finally NSCT based gray level modified histogram equalization is used. In which optimum weight selection in the histogram equalization efficiently enhances the performance of the proposed work.

5. Experimental results and discussion

MRI brain image is taken from the dataset for original input image. Based on the median of image pixels, the original brain image is segmented into four sub image histograms. Dynamic histogram equalization technique is applied with TSK model to enhance the image contrast. The good quality image is recognized with IPSO with 50 runs and sub histograms are equalized. The performance of the input image in various stages was compared with previous techniques. Mean squared deviation, contrast, Michelson contrast and weber contrast, SSIM, EME and AMBE are the quality measures which are used to evaluate the performance of the proposed work. Here Section 5 gives the detailed explanation about the result evaluation.

Parameters setting:

Here the velocity of ith agent at Kth iteration has ranges from 0.1 to 0.9, a_1 and a_2 are factors of learning which ranges from 0 to 4, rand () is a random number distributed uniformly from 0 to 1, S_i^k is a position of current location at Kth iteration, w is the inertia weight which ranges from 0.1 to 0.9 and these values are selected based on [28].

5.1. Quality measures

The following quality measures are evaluated to show the performance of our work. Also here we have used MIRIAD dataset [29] and this database is available at the link http://miriad.drc.ion.ucl.ac.uk/. These dataset have 708 images and the size of each image is 256×256 also dimension is three. Also training and testing process in this evaluation has taken 80% and 20% respectively.

5.1.1. Mean squared deviation (MSD)

Mean squared deviation is evaluated from original input image and enhanced image. MSD is used to calculate available noise in an input image. The enhanced image E_i is defined from the original U ×V image I. This calculation is done over two images. MSD of the image is defined as,

$$MSD = \frac{1}{nUV}\sum_{i=1}^{u}\sum_{j=1}^{v}(I(i,j) - E_i(i,j))^2 \tag{20}$$

where, $I(i,j)$ is the mean of the original image and $E_i(i,j)$ is the mean of the enhanced image. The histogram of enhanced image shows better performance in terms of MSD quality measures.

5.1.2. Contrast

In contrast C the ratio C:1 is traced from the highest and lowest luminance of the image. The compared performance C:1 is obtained from,

$$CT_r = \frac{l_{\max imum}}{l_{\min imum}} \tag{21}$$

where, $l_{\max imum}$ is the high luminance and $l_{\min imum}$ is the low luminance. The performance of contrast is normally white. The influence of ambient illumination is ignored to black for enlarging the contrast in typical observation settings.

5.1.3. Measure of enhancement entropy

Maximum value of entropy refer to the maximum contrast of the image and average is calculated to find the proposed work efficiency.

$$E = 20\log\left(\frac{\max imum \operatorname{int} ensity}{\min imum \operatorname{int} ensity}\right) \tag{22}$$

5.1.4. Michelson contrast

Michelson contrast is used for finding the relation between the levels of luminance. This kind of contrast is used and it proceeds with essential portion of the image histogram. The contrast from the enhanced image is acquired using,

$$MC = \frac{M_{\max} - M_{\min}}{M_{\max} + M_{\min}} \tag{23}$$

$M_{\max}$ and $M_{\min}$ indicates the highest and lowest intensity values of the image. The constant value has to be maintained for the total image range and it should be 1.

5.1.5. Weber contrast

It is the relation of luminance of brighter and darker area. Weber contrast WC is expressed as,

$$WC = \frac{C_{\max} - C_{\min}}{C_{\max}} \tag{24}$$

where, $C_{\max}$, $C_{\min}$ is the maximum and minimum luminance of an image. It is also known as fraction of weber.

5.1.6. Structural similarity measure (SSIM)

Mean Structural Similarity Measure (SSIM) should be nearer to one.

$$SSIM = \frac{1}{n}\sum\frac{(2xy + k_1)\left(2\sigma_{xy} + k_2\right)}{(x + y)\left(\sigma_x^2 + \sigma_y^2\right)} \tag{25}$$

where n is the number of images, x is the input image, y is the output image $k_{1,}$ and k_2 are the constants.

5.1.7. Measure of enhancement by entropy (EME)

A maximum value of EME shows a high contrast. It is the relation between minimum (mn_i) and maximum (mx_i) values of intensity in every block.

$$E_i = 20 \times \log\left(\frac{mx_i}{mn_i}\right)$$

$$EME = \frac{1}{n}\sum_{i=1}^{N} E_i \tag{26}$$

5.1.8. AMBE

It should be small to show the enhanced brightness of an image.

$$AMBE = \mu_{org} - \mu_{contrast\ enhanced} \tag{27}$$

Where μ is the mean value.

5.2. Performance measures

Table 1 gives the results about the proposed work and all the image evaluations shows that our proposed work produce better performance (all the parameters are high) than other techniques. Also here we evaluated the firefly-CE, ACO-CE and GA-CE methods among those techniques IPSO-CE has better performance. Also these all the algorithms are implemented for the comparison purpose with the proposed algorithm.

From Table 1, we observe that MSD of IPSO-CE is 162 and this is greater than other techniques. In case of contrast measurement, the value is 39 and this should be high to show an efficiency of the work and here compared with the traditional PSO, our work has 15% more better results. For a while Michelson Contrast also have higher values than existing which is 7% improved. For weber contrast, the current performance is 3% greater than other techniques.

Bench mark functions [30] of each algorithm and the efficiency is given in the below section (see Table 2).

All the bench mark functions are evaluated for the above mentioned algorithms and the efficiency of those algorithms are measured and compared with the proposed algorithm. Among these we can deliberate the proposed efficiency is higher.

In Fig. 3, (a1) to (a4) depicts the enhanced MRI brain images corresponding to the techniques GA, Firefly, PSO and IPSO respectively. Similarly (b1) to (b4) and (c1) to (c4) shows the enhanced MRI brain images obtained from the same algorithms. Also (d1) to (d4), and (e1) to (e4), (f1) to (f4) and (g1) to (g4) illustrate the enhanced normal digital images. The enhanced image have

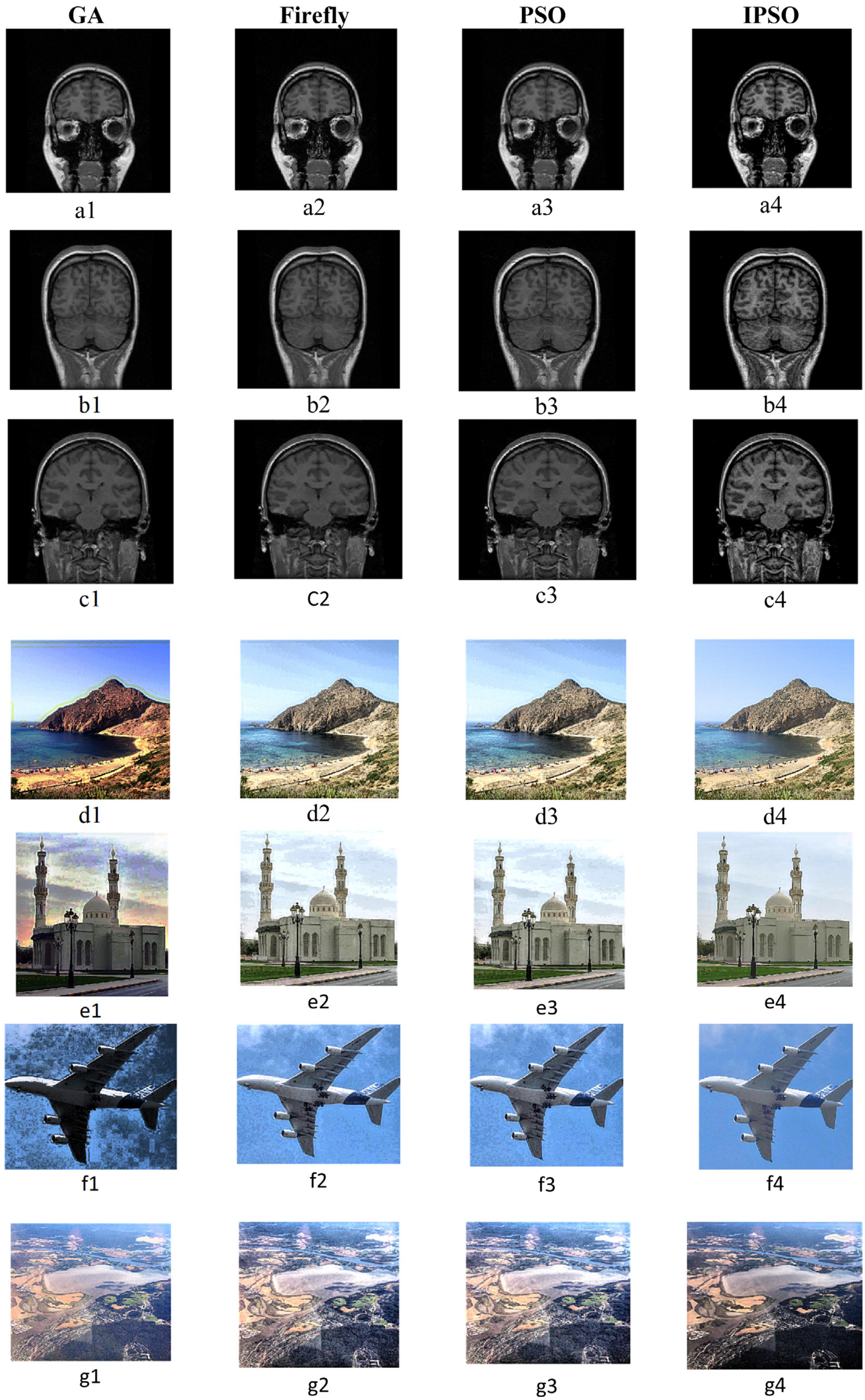


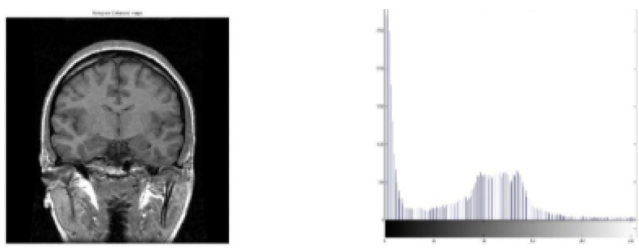
Fig. 3. Enhanced Output Image of each algorithm.

Table 1
Performance measures.

Methods	MSD	Contrast	Michelson contrast	Weber contrast	SSIM	EME	AMBE
PSO-CE	81.251	24.4265	0.3452	0.6532	0.39	3.87	4.03
Firefly-CE	84.524	23.846	0.4213	0.7524	0.456	5.05	5.13
ACO-CE	48.21	31.254	1	0.5231	0.64	2.99	8.1
GA-CE	27.541	34.456	0.7254	0.6245	0.99	2.12	5.99
IPSO-CE (proposed)	162	39	1	1	0.98	6.98	2

Table 2
Benchmark functions of each algorithm.

Benchmark functions	GA	Firefly	PSO	IPSO
Rosenbrock	55723 ± 8901 (90%)	6040 ± 535 (100%)	32756 ± 5325 (98%)	5012 ± 584 (100%)
Rastringen	110523 ± 5199 (77%)	12075 ± 3750 (100%)	79491 ± 3715 (90%)	11952 ± 2754 (100%)
De Jong	25412 ± 1237 (100%)	5657 ± 730 (100%)	17040 ± 1123 (100%)	5427 ± 690 (100%)
Michalewicz	89325 ± 7914 (95%)	2889 ± 719 (100%)	6922 ± 537 (98%)	2553 ± 695 (100%)



(a) (b)

Fig. 4. (a) FIPSO image and (b) Histogram of FIPSO image.

good quality while comparing it with the original input image as shown in Fig. 3. Because of high quality it is easy to evaluate the necessary details (see Fig. 4).

Using mean squared deviation, the performance of the proposed method (Improved particle Swarm Optimization based Contrast Enhancement (IPSO-CE) is compared with Particle Swarm Optimization based Contrast Enhancement (PSO-CE), firefly based Contrast Enhancement (firefly-CE), Ant Colony Optimization based Contrast Enhancement (ACO-CE) and Genetic Algorithm based Contrast Enhancement (GA-CE). The value 1 is achieved using proposed technique while using other; the performance is less than 0.8. The bar chart shown in Fig. 5 represents the performance of the MSD and contrast.

Compared with other techniques like PSO-CE, Firefly-CE, ACO-CE and GA-CE and these all the techniques are implemented in Matlab. According to [31], these above mentioned comparison algorithms are swarm intelligence techniques. So these algorithms are taken for the comparison since proposed algorithm is based on the swarm intelligence technique. In previous works only the values up to 34.456 is achieved for the contrast but contrast 39 for our IPSO-CE. Fig. 6 shows the performance comparison in terms of Michelson contrast and weber contrast.

In Fig. 6, Michelson Contrast and Weber contrast values for the proposed is one also this should be high for efficient performance. For PSO-CE, Michelson contrast have 0.3 and Weber contrast have 0.62. In firefly-CE, Michelson contrast and Weber contrast attained 0.4213 and 0.7524 respectively. In case of ACO-CE and GA-CE, Michelson contrast are 0.892 and 0.71 respectively. For the weber contrast, the values are 0.532 and 0.605 respectively.

AMBE and EME for the proposed scheme has 2 and 6.93 respectively. In PSO-CE, AMBE had 4.1 and EME achieved 4.02. In Firefly-CE, EME and AMBE provide 5.05 and 6.13 respectively. For ACO-CE, values of AMBE and EME are 8.02, 3.05 respectively. For GA-CE, both AMBE and EME yielded 6.04 and 2.01 respectively (see Fig. 7).

Using MSSIM performance 0.989 is attained in proposed method. In PSO-CE, the value of SSIM is 0.4. In firefly-CE, it achieved 0.51. For ACO-CE and GA-CE, the value of SSIM are 0.602 and 0.805 respectively. The highest value indicates the execution of proposed method is efficient with all quality measures with respect to its contrast (see Fig. 8).

5.3. Comparison analysis for the digital images

For this case, the dataset is taken from [32]. Here ordinary digital images are taken for analyzing the contrast enhancement.

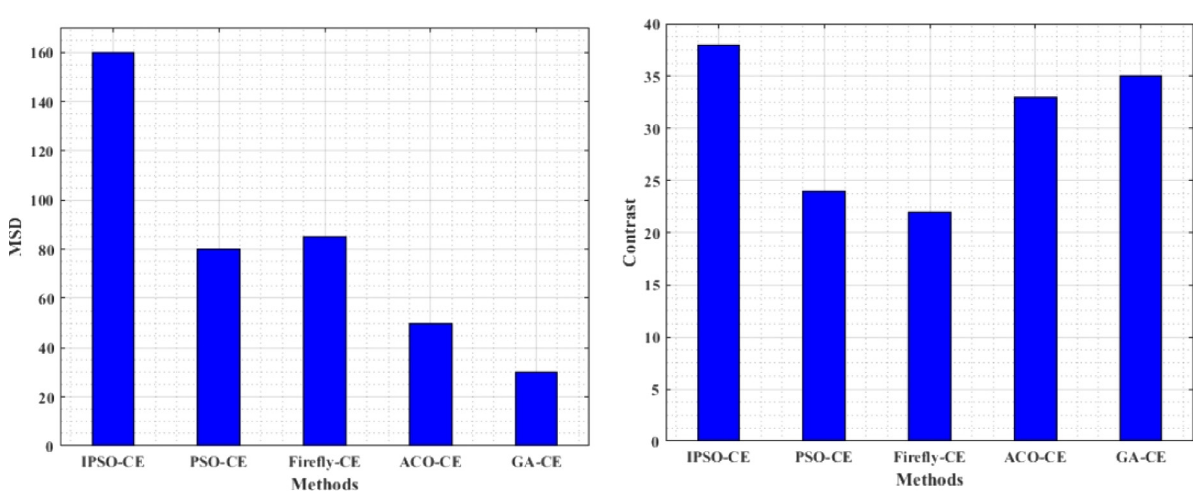
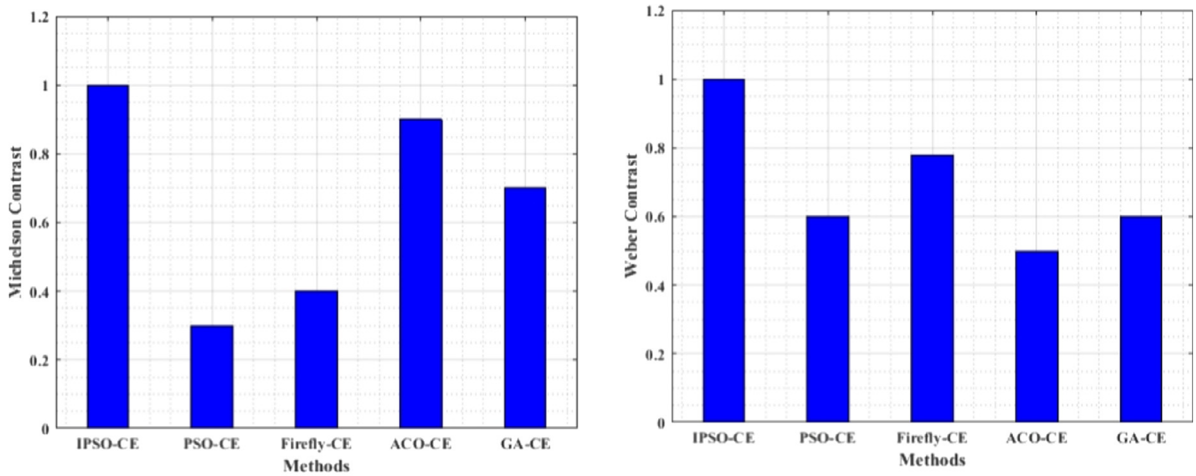
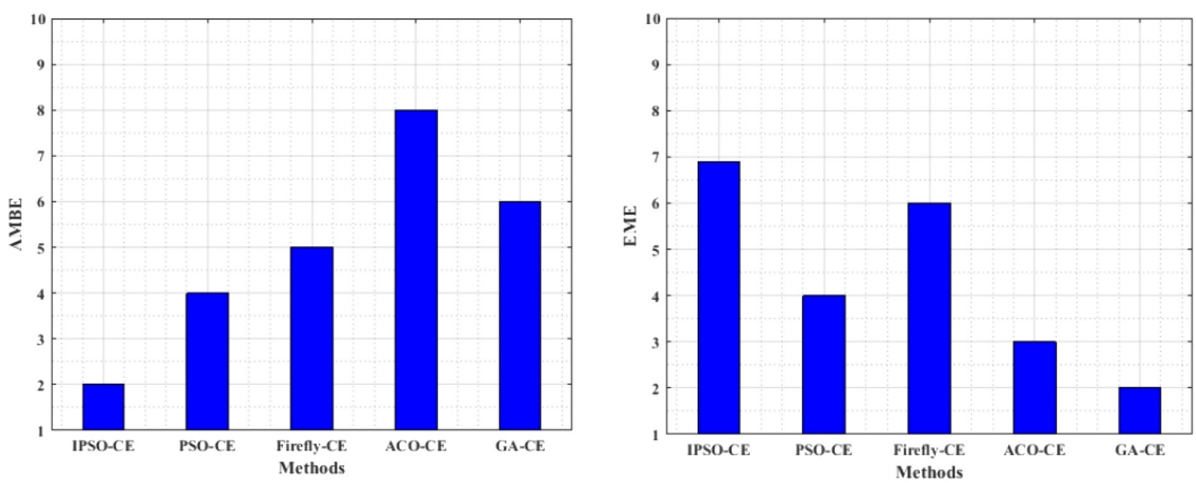


Fig. 5. Comparison using MSD and contrast.



(a) (b)

Fig. 6. (a) Michelson contrast and (b) Weber Contrast.



(a) (b)

Fig. 7. Comparison using (a) AMBE and (b) EME.

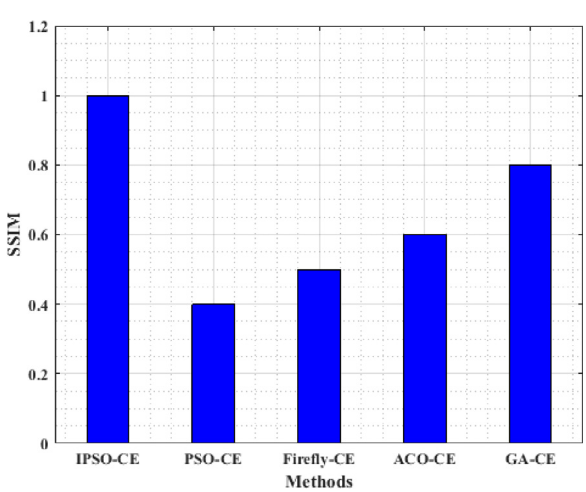


Fig. 8. SSIM comparison analysis.

The performances are taken in terms of Peak Signal to Noise Ratio, SSIM, MSSIM and MSE. This database contains 30 original color images and 180 enhanced images. Size of each image is 512×512 and two dimensional.

The Fig. 9 represents the original and enhanced version of the digital images using TSK fuzzy model. Original image is represented in figure a1 to a10 and enhanced image is given in figure b1 to b10. Here histogram equalization also measured for all the images which is given in c1 to c10.

Statistical performance:

Fig. 10, gives the statistical performance of Fig. 9. Here we have taken the performance values of c1 to c10. From Fig. 10, we can show that the peak values as observed region and remaining area as un-observed region.

Figs. 11 to 14 represented the performance comparison in terms of PSNR, SSIM, MSE and MSSIM. Here the evaluations are taken for Fig. 9. In case of SSIM and MSSIM, the achieved value is one termed to better performance. MSE should be low for well-defined contrast enhancement and PSNR should be high for better performance.

Tables 3 and 4 gives the tabular form of Figs. 11 to 14. Various algorithms AGA, GA, PSO are compared with FIPSO.

Tables 3–5 represents the comparison of proposed algorithm with different algorithms. All the figures from 11 to 15 represented the performances in terms of PSNR, SSIM, MSE, MSSIM

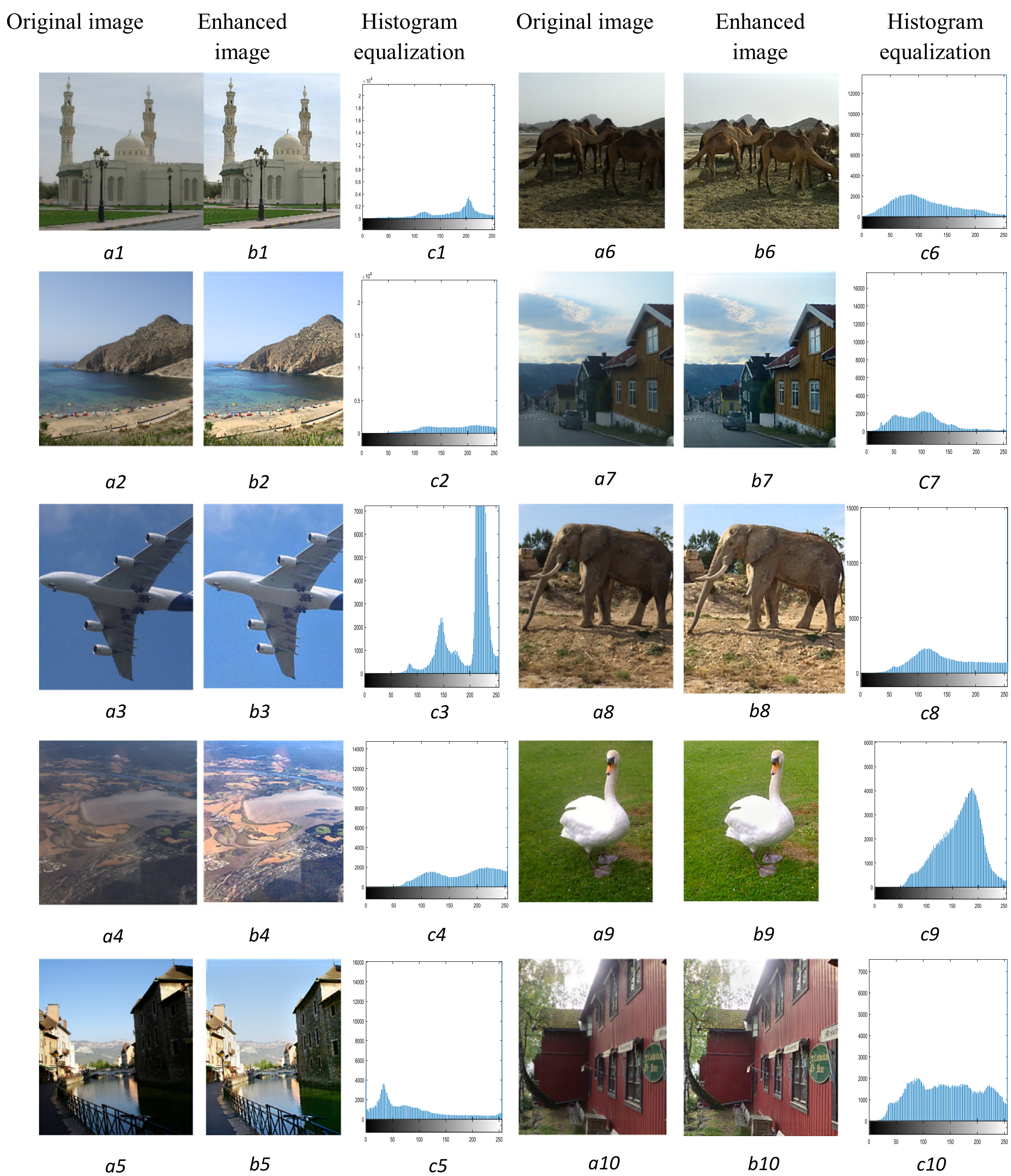


Fig. 9. Result from digital images.

and computational time. For PSNR, SSIM, MSSIM and MSE, the evaluations are taken for ten digital images. Except MSE and computational time, all the parameters should be high to show the proposed work efficiency. Here we compare proposed work with the [23] reference since compared to all the methods our proposed work achieves better performance.

6. Conclusion and future work

6.1. Conclusion

In this paper, Fuzzified histogram equalization with improved swarm optimization is developed to enhance the contrast of MRI brain images and normal digital images. Here, MRI and ordinary digital image is used as an input. Gaussian function with normal distribution is applied to smooth the image. Highest and lowest intensity values are obtained with local maxima detection. The distance between local maxima is obtained with TSK model. IPSO is proposed to find the optimum weight value and this optimum value is used in modified histogram equalization. The contrast of the image was enhanced by adjusting the intensities in modified histogram equalization. The obtained PSNR, SSIM, MSSIM and MSE are compared with existing methods. The resultant quality measures shows that the proposed method is efficient against

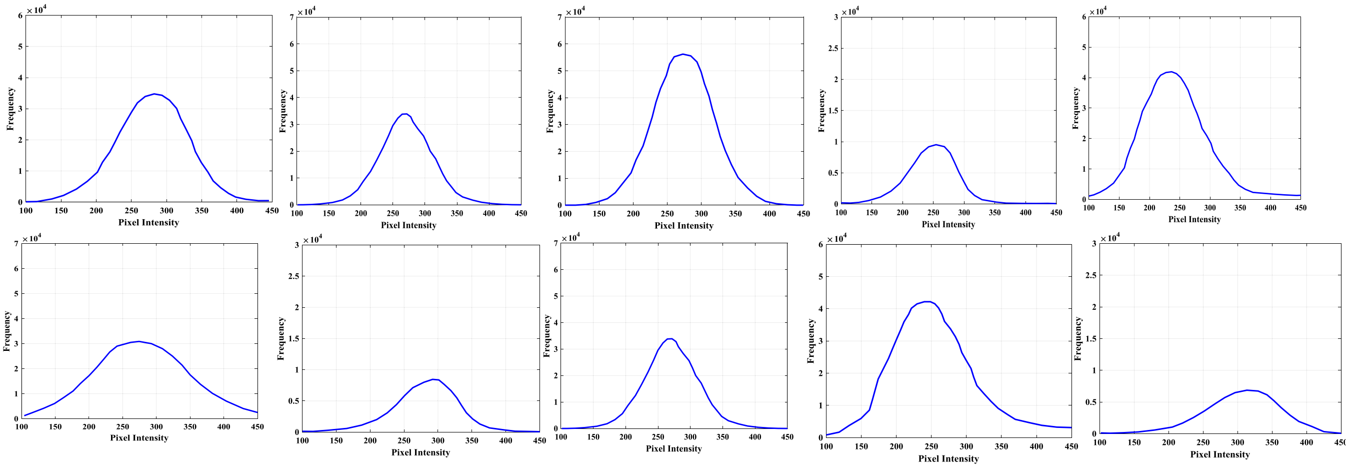


Fig. 10. Statistical significance performance.

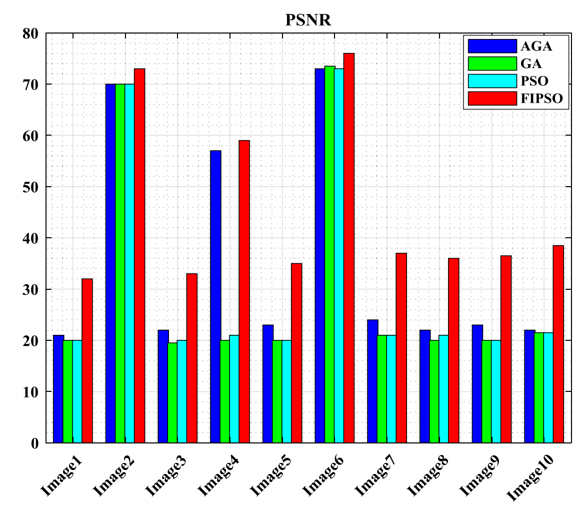


Fig. 11. PSNR analysis for different images.

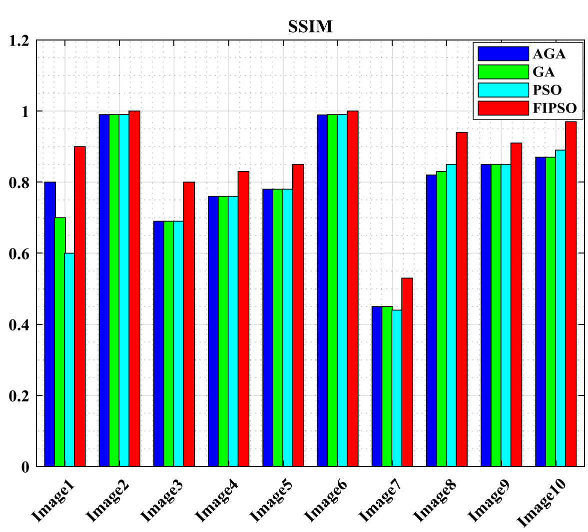


Fig. 12. SSIM analysis for different images.

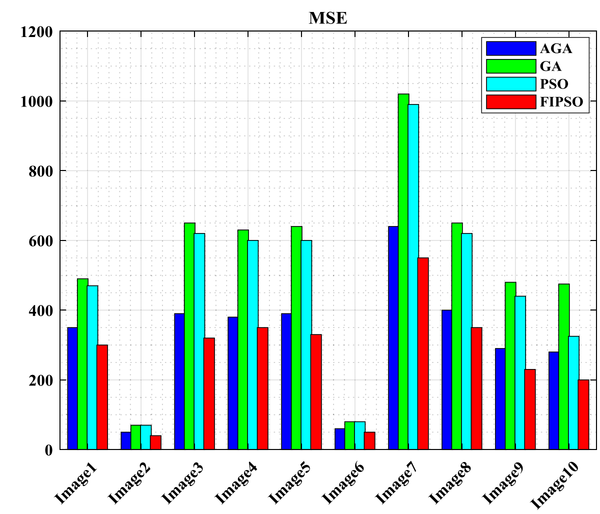


Fig. 13. MSE analysis for different images.

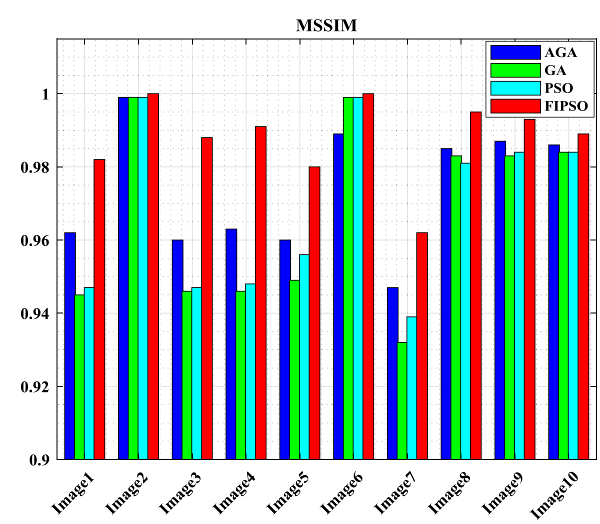


Fig. 14. MSSIM analysis for different images.

Table 3
Comparison of different PSNR, SSIM and MSE algorithms.

PSNR					SSIM				MSE			
Image	AGA	GA	PSO	FIPSO	AGA	GA	PSO	FIPSO	AGA	GA	PSO	FIPSO
Image1	21	20	20	32	0.8	0.7	0.6	0.9	350	490	470	300
Image2	70	70	70	73	0.99	0.99	0.99	1	50	70	70	40
Image3	22	19.5	20	33	0.69	0.69	0.69	0.8	390	650	620	320
Image4	57	20	21	59	0.76	0.76	0.76	0.83	380	630	600	350
Image5	23	20	20	35	0.78	0.78	0.78	0.85	390	640	600	330
Image6	73	73.5	73	76	0.989	0.99	0.99	1	60	80	80	50
Image7	24	21	21	37	0.45	0.45	0.44	0.53	640	1020	990	550
Image8	22	20	21	36	0.82	0.83	0.85	0.94	400	650	620	350
Image9	23	20	20	36.5	0.85	0.85	0.85	0.91	290	480	440	230
Image10	22	21.5	21.5	38.5	0.87	0.87	0.89	0.97	280	475	325	200

Table 4
MSSIM comparison.

MSSIM				
Image	AGA	GA	PSO	FIPSO
Image1	0.962	0.945	0.947	0.982
Image2	0.999	0.999	0.999	1
Image3	0.96	0.946	0.947	0.988
Image4	0.963	0.946	0.948	0.991
Image5	0.96	0.949	0.956	0.98
Image6	0.989	0.999	0.999	1
Image7	0.947	0.932	0.939	0.962
Image8	0.985	0.983	0.981	0.995
Image9	0.987	0.983	0.984	0.993
Image10	0.986	0.984	0.984	0.989

Table 5
Time complexity comparison.

Time complexity	
Technique	Time (s)
AGA	23.236
GA	23.021
PSO	22.187
FIPSO	20.126

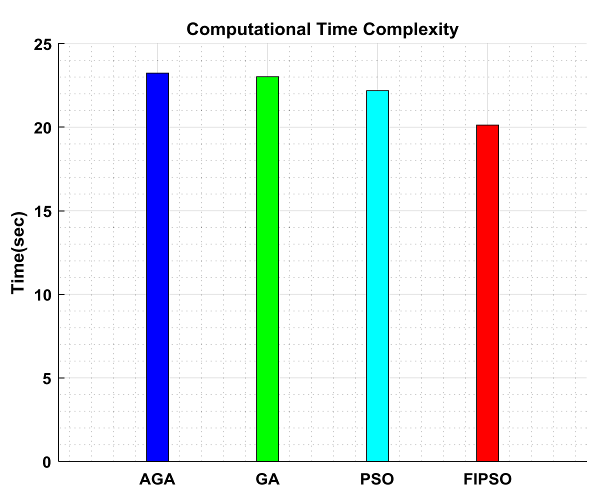


Fig. 15. Computational time analysis for different images.

PSO-CE, ACO-CE, GA-CE and firefly-CE equalizations in terms of pixel contrast.

Future directions:

There is enough scope for future work. Future work concerns analysis of more techniques based on histogram equalization. Proposed work is based on Histogram equalization and fuzzy logic. In future we can modify this techniques with more advanced techniques. The image can be divided into layers depending on the RGB colors and then histogram is generated for that layers. This processing will apply for each layers separately. This will be an extension to the current work and it will be able to reduce computational time further, while using evolutionary algorithm for finding optimum values.

Declaration of competing interest

No author associated with this paper has disclosed any potential or pertinent conflicts which may be perceived to have impending conflict with this work. For full disclosure statements refer to https://doi.org/10.1016/j.asoc.2020.106114.

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