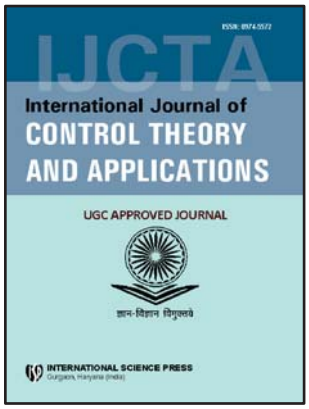

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Adaptive Fuzzy Based Particle Swarm Optimized Histogram Equalization for Contrast Enhancement of Mammograms

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Abstract: A novel technique, fuzzy based particle swarm optimized histogram equalization has been proposed for enhancement of mammographic images. The novelty of the proposed work is the automatic enhancement of the mammograms by fully adaptive calculation of the parameters based on the characteristics of the image. This technique consists of three stages. In the first stage, the grey level intensities of the mammographic images are transformed to an adaptive fuzzy domain with values ranging from 0 to 1. In the second stage, weighted threshold histogram equalization is applied to the fuzzy set where the optimal values of the parameters required for computing constrained PDF is obtained using particle swarm optimization. In the final stage, the fuzzy domain is converted back to spatial domain. Performance of the proposed algorithm is evaluated using well known image quality assessment techniques like SSIM, NCC, UIQI and DE. Experimental results show that proposed method being adaptive to different mammographic images provides controlled contrast enhancement while maintaining the richness of details and preserving the brightness level.

Keywords: *HE, PSO, WTHE, fuzzy logic, PSNR, SSIM, NCC, UIQI, DE.*

1. INTRODUCTION

Breast Cancer is the most common cancer among women worldwide constituting more than 25% of all cancer incidences occurring in the world [1]. There is also steady increase in the breast cancer incidence among the young generation in the world. Statistics have shown that cancer mortality is highest in India among all other nations in the world [2].

Several screening modalities are available for early detection of breast cancer of which mammography is considered to be the most effective method [3]. It is a low cost low dose x-ray procedure which provides internal view of the breast parenchyma.

Mammogramsthough highly reliable are not perfect. Mammograms may be of poor quality due to low contrast, presence of unwanted artefacts', labels, unknown noise, weak boundaries and presence of unrelated parts like pectoral muscles. The poor quality of mammograms can result in malignancies remaining undetected as there is only a small difference in X-ray attenuation of malignant and normal tissue. Also subtle abnormalities can remain unnoticed due to low contrast [4].

Reasons for low contrast in mammograms may be due to low radiation dose, different modes of storage, transmission and acquisition and may also be due to display devices[5]. Also partial volume effects and noise can lead to low contrast. Usage of some denoising filters to reduce noise can also lower contrast [6].

The aim of pre-processing in mammograms is to enhance the visual quality of the images and to obtain a clear distinction of image components which will help in correct interpretation. It includes image enhancement and noise removal[7].

Spatial and frequency domain techniques are the two common methods used for contrast enhancement. For medical images, spatial domain methods are considered to be most effective because of their direct application on the images. They can also be applied locally on a region of the image or globally on the entire image. Spatial domain methods include HE [8], log and power law functions [9][10], normalization [11], contrast stretching [12] and sigmoid functions [13]. HE and its variations are highly popular due to their simplicity, ease of use and speed. They are comparatively effective on all types of images.

2. HISTOGRAM EQUALIZATION AND ITS VARIATIONS

The early application of HE were on CT images and this proves that it can be used on medical images for contrast enhancement. HE stretches and flattens the dynamic range of input image's histogram resulting in overall contrast enhancement [14]. In mammograms, the ROI and the background have close contrast values. The major disadvantage of HE is that it increases the contrast of the ROI along with that of the background resulting in visual deterioration and thus creating an intensity saturation effect [15].

In order to overcome the limitations of HE, several variations of HE has been proposed and applied like BBHE, DSIHE, MMBEBHE, RMSE, WTHE etc.

BBHE [16] proposed by Kim divides the input image histogram into two non-overlapped sub histograms based on the mean brightness and then each part is equalized independently. But, BBHE is found to be unsuccessful if the histogram has a quasi-symmetrical distribution about its mean.DSIHE [17] proposed by Wan etal uses the median of the input image's histogram instead of the mean to divide the histogram. DSIHF was not found good at preserving the mean brightness and also produced images with unnatural looks.MMBEBHE [18] proposed by Chen and Ramli employs a threshold level to divide the histogram. Here the threshold level is chosen by enumeration. It works well for images with uniform grey level distribution else it causes unwanted side effects.RMSHE [19] proposed by Chen and Ramli uses BBHE iteratively where the histogram of the image is partitioned recursively and equalized independently.

RSIHE [20]proposed by Sim et al is similar to RMSHE but uses grey level with CDF equal to 0.5 as the separation point.The demerit of these two recursive algorithms are that the recursion level if not chosen carefully can lead to computational complexityand can produce images with checker board effect andwith washed out appearance.Weighted thresholded histogram equalization (WTHE)[21] proposed by Q. Wang et al provides a good trade-offbetween adaptivity and ease of control. Here, HE is applied after the PDF is modified using weighting and thresholding. The major disadvantage of WTHE is that there can be an uncontrollable change in luminance if there are outlier pixels in the input image.

Due to major drawbacks in HE and its variations mentioned above, soft computing techniques like particle swarm optimization, fuzzy logic etc. have gained popularity for image enhancement. They can be used along with HE and its variations to overcome the flaws.

Fuzzy set provides a formalism to deal with situations having imprecise and vague information by incorporating human knowledge [22].Two major applications in image processing where fuzzy techniques have gained popularity among researchers are intensity transformation and spatial filtering which helps in image enhancement[23]. Particle swarm optimization techniques [24]have also been used in contrast enhancement of images. The merit of PSO lies in the fact that they are simple to execute and take less time to converge to an optimal solution [25].

In this paper, an adaptive fuzzy logic based WTHE is proposed for contrast enhancement of mammograms. PSO has been applied to obtain optimal values for lower and upper constraints for probability density function in WTHE. The proposed algorithm is found to be superior as compared to other conventional HE techniques in improving the contrast of the mammograms while preserving the brightness and richness of details.

The rest of the paper is organized as follows. The proposed algorithm is presented in section 3. Evaluation measures are described in section 4. Section 5 gives the experimental results and performance analysis. Section 6 concludes the paper.

3. PROPOSED WORK

The proposed algorithm combines fuzzy logic, WTHEand PSO.The novelty of the proposed method is that it is adaptive in nature because all the parameters required in the algorithm arecomputed based on the characteristics of the image. To the best of the knowledge, a fully adaptive fuzzy enhancement of mammograms has not been attempted by researchers before. The algorithm is as follows.

Step 1: Read the input image.

Step 2: Transform the grey level intensities of the input image to fuzzy domain with values ranging from [0, 1] using membership function.

Step 3: Modify the fuzzifieddata using contrast intensification operator.

Step 4: Apply WTHE on the modified fuzzy data where the optimal values for *v* and *r* in WTHE is obtained using PSO.

Step 5: Convert the data in fuzzy domain to spatial domain by applying inverse transformation.

3.1. Fuzzy image enhancement

The fuzzy image enhancement consists of three steps-image fuzzification, modification of membership values for image enhancement and image defuzzification[26].

3.1.1. Fuzzification

An image G with grey level values ranging from [0, L-1] is transformed from its spatial domain to the fuzzy domain whose values range from [0,1] based on a membership function.This function is based on a suitable characteristic of the image such as edge, texture, brightness etc. It can be defined globally for the entire image or locally for a part of the image[27]. The membership function for the conversion of mammographic images from its spatial domain to fuzzydomain is defined as follows[28].

$$\begin{aligned} \mu_{ij} &= T(g_{ij}) \\ &= \left[1+\frac{g_{\max}-g_{ij}}{F_d}\right]^{-F_e} \end{aligned} \tag{1}$$

Here, g_{max} = maximum intensity value in image G. F_e = Exponential fuzzifier and F_d = denominational fuzzifier. Here, $\mu_{ij} = 1$ indicates maximum brightness and $\mu_{ij} = 0$ indicates totaldarkness.

Most researchers take the value of F_e as 2. In this proposed work, the value of F_e is calculated adaptively for each image using the sigmoid function [29]

$$F_e = \frac{1}{1+\exp(-m)} \tag{2}$$

m can be the mean, median, maximumintensity, first and second order moment, SD etc. Various experiments conducted on mammographic images proved that the median value of the input image provides the best results for F_e. Here m represents the median.

$$F_d = \frac{g_{max} - g_{min}}{0.5^{-1/F_e} - 1} \quad (3)$$

Here g_{min} is the minimum intensity value in the image. As F_e and F_d are calculated based on the median of the image, F_e and F_d are adaptive in nature.

3.1.2. Modification of membership values

This step is the most powerful step in fuzzy image enhancement. Appropriate techniques can be incorporated with fuzzy techniques to modify the fuzzy plane to obtain the desired results[26].Contrast intensification operator [30] is applied to reduce the fuzziness of μ_{ij} by monotonically increasing the values for μ_{ij} which is greater than 0.5 and monotonically reducing the values of μ_{ij} which are less than 0.5. It generates another fuzzy set μ'_{ij} which is expressed as

$$\mu'_{ij} = \begin{cases} 2[\mu_{ij}]^2 & 0 \le \mu_{ij} < 0.5 \\ 1 - 2*[1-\mu_{ij}]^2 & 0.5 < \mu_{ij} \le 1 \end{cases} \quad (4)$$

Since image enhancement is the main criteria, dark pixels are to be made darker and bright pixels brighter. This is achieved by applying WTHE to the modified fuzzy set.

3.1.3. Defuzzification

The image is transformed from the fuzzy plane to the spatial domain by applying inverse transformation.

$$X = T^{-1}(\mu'_{ij}) = g_{max} - F_d * \left((m'_{ij})^{\frac{-1}{F_e}} \right) + F_d \quad (5)$$

3.2. Proposed Algorithm

PROCEDURE AFPSHE

Input : An image G of size M X N with intensity values ranging from [0, L-1], *v*, *r*

Output : An enhanced image G_e

BEGIN

Step 1: Fuzzify the image G using equation (1) to obtain μ_{ij} ..

Step 2: Modify the fuzzified data μ_{ij} by applying the contrast intensification operator given in equation (4) to obtain μ'_{ij}. Let F (*i*, *j*) = μ'_{ij}.

Step 3: Calculate the PDF of F (*i*, *j*). Here P $(r_i) = n_i / n$ where n_i is the no. of pixels having grey level r_i in F(*i*, *j*). P(r_i) is the PDF of r_i. $0 \le r_i \le 1$. $r_i \in$ F(*i*, *j*). *n* is the total no of pixels in F(*i*, *j*).

Step 4: Compute the upper constraint $P_u = v * \max(PDF)$ where $0.1 \le v \le 1.0$. Here, max(PDF) = maximum of all P(r_i)

Step 5: Set lower constraint P_l as 0

Step 6: Compute the constrained PDF $P_c(r_i)$

$$P_c(r_i) = \begin{cases} P_u & \text{if } P(r_i) > P_u \\ \left(\frac{P(r_i) - P_l}{P_u - P_l} \right) * P_u & \text{if } P_l < P(r_i) < P_u \\ 0 & \text{if } P(r_i) \le P_l \end{cases}$$

Step 7: Compute the constrained cumulative density function $C_c(r_k)$

Step 8: Apply HE procedure as follows

$$F'(x, y) = T(F(x, y))$$
$$= F_{min} + (F_{max} - F_{min}) * C_c(F(i, j))\}$$

where F_{min} = minimum gray level intensity in $F(x, y)$ usually 0.

F_{max} = maximum gray level intensity value in $F(x, y)$ which can have a value atmost 1

$F(i, j)$ = intensity value at $(i, j)^{th}$ position.

Step 9: Convert the data from fuzzy domain to spatial domain by applying inverse transformation given in equation (5)

Step 10: END

Here, the optimal values for the parameters v and rare found using PSO so that the proposed algorithm enhances the image in such a manner that both brightness and information are preserved.

3.3. Particle Swarm optimization (PSO)

Particle Swarm Optimization [24] is a stochastic population based optimization method which is inspired by bird flocking, fish schooling and swarm theory. PSO algorithm initializes a set of random solutions called particles. Each particle is also associated with initial velocity and a fitness value. Particles fly around the search plane searching for optimal solution by dynamically adjusting their velocities and position based on the optimisation fitness function. In every iteration each particle maintains two best values. One is the best solution it has achieved so far(pbest) and the other is the best value obtained by the group(gbest)[31].The velocity of each particle can be modified using the equation(6).

$$V_i^{j+1} = \omega V_i^j + C_1 r \text{ and } () (\text{pbest}_i - x_i^j) + C_2 R \text{ and } () (g\text{best} - x_i^j) \quad (6)$$

Particle position can be updated as

$$S_i^{j+1} = S_i^j + V_i^{j+1} \quad (7)$$

Here V_i^j and V_i^{j+1} are the velocities of particle i at iteration j and iteration $j + 1$ respectively. (usually in the range [0.1,0.9]).

C_1 and C_2 are positive constants in the range 0 – 4 (usually taken as 2)

Rand ( ) and rand ( ) are two random functions in the range [0,1]. x_i^j and x_i^{j+1} are the positions of particle i in the j^{th} and $j + 1^{th}$ iteration. The inertia weight ω is in the range [0.1, 0.9] and is computed as

$$\omega = 0.5 + ((\text{rand}( ))/2.0) \quad (8)$$

The optimal values of v and r in WTHE are essential in order to enhance the contrast of the image while preserving brightness. They are found using PSO.

Here v and r are taken as particles. Their values should be between [0.1, 0.9]. No. of iterations (k) is usually between 50 and 100.

No. of random values assigned to a particle is between 10 and 40.

PROCEDURE find_*vr*

Input : Image $F(x, y)$

Output : Optimal values for v and r

BEGIN

Step 1 : Initialize the position of *v* and *r*

$$ipv = \text{Rnd } (0,1)$$
$$ipr = \text{Rnd } (0,1)$$

Step 2 : Find the D.E of the original image

Obtain the enhanced image using procedure AFPSHE with $v = ipv$ and $r = ipr$. Find the D.E of the enhanced image. Find the difference (*d*) between both the D.E values.

Step 3: Generate n random values for *v* and *r*

$$pv[1] \quad pr[1]$$
$$pv[2] \quad pr[2]$$
$$\ldots\ldots\ldots\ldots$$
$$pv[n] \quad pr[n]$$

Step 4: Let pbest[*i*] represent the best position of i^{th} particle so far. Let *vv*[*i*] and *vr*[*i*] represent the velocities of v and r respectively. They can be initialized as follows.

for all $i \in [1, n]$

$$pbest[i] = d$$
$$vv[i] = 0$$
$$vr[i] = 0$$

end for

Step 5: for all iterations $j = 1$ to k

Step 5.1: for all particles 1 to *n*

5.1.1: find D.E of the enhanced image using procedure AFPSHE with *pv*[*i*] and *pr*[*i*]

5.1.2: find the difference (*d*) of the enhanced image and original image.

If ($d < pbest[i]$)

$$pbest[i] = d$$

5.1.3: go to step 5.1

Step 5.2: $gbest = \min_{1 \le i \le n} pbest[i]$

bv and *br* contain the values of *pv* and *pr* whose *pbest* is minimum

$$bv = pv[i]$$
$$br = pr[i]$$

where $i \in [1, n]$

Step 5.3: Update the particles velocity and position

for $i =$ to *n*

$vv[i] = \omega * vv[i] + C_1 * \text{Rnd}\,() * (pbest[i] - pv[i]) + C_2 * \text{Rnd}() * (gbest - pv[i])$

$pv[i] = pv[i] + vv[i]$

$vr[i] = \omega * vr[i] + C_1 * \text{Rnd}\,() * (pbest[i] - pr[i]) + C_2 * \text{Rnd}() * (gbest - pr[i])$

$pr[i] = pr[i] + vr[i]$

go to step 5.3

Step 5.4: go to step 5

Step 6: Output gbest with optimal values for *v* and *r i.e. bv* and *br*

Step 7: Stop.

It is important to choose the fitness function for PSO carefully so that it finds optimal values for *v* and *r* in such a way that proposed algorithm enhances the image without any loss of information due to excess brightness, noise amplification and any unbalanced contrast. There are several objective quality measures available such as PSNR, SSIM, DE, NCC etc. which can be the used to compute the degree of contrast enhancement. One of these can be chosen as the fitness function. Here Discrete Entropy (DE)[32] has been chosen as the fitness function. This is because it has been found that closer the values of DE of the enhanced image to that of the original image, the former preserves the richness of the details better. In other words, the minimum difference in DE between the original and enhanced image helps in detail preservation without over enhancement.

In the proposed work, the swarm size in PSO was varied from10 to 40 and the iteration from 10 to 70 in order to find the optimal values for *v* and *r*. It was found that the algorithm produced optimal results when the swarm size was 20 and the iterations 40. The iterations can also be terminated using a minimum error condition, but in this algorithm it did not yield good results.

4. EVALUATION MEASURES

The most accurate evaluation of image quality is through the eyes of the human observer who makes use of the image. This is known as subjective evaluation. Though it is the most accurate method, it is time consuming, expensive and also depends on the mood, lighting and visual ability of the observer [33].

They are several objective IQA methods making use of mathematical models which measures the image quality, the accuracy of which is almost at par with subjective evaluation. Evaluation measures used here to assess the image quality of enhanced mammograms include Peak signal to Noise Ratio (PSNR), structural similarity index metric (SSIM), Universal image quality index (UIQI), normalized correlation coefficient (NCC) and Discrete Entropy (DE). In all the metrics defined here, I_{ij} refers to the intensity value of the original image and E_{ij} refers to the intensity value of the enhanced image at i and j respectively. M and N refers to the width and height of the image.

4.1. Peak signal to noise ratio(PSNR)

PSNR [27] is a deviation of the current image from the original image with respect to the peak value of the grey level and is given below

$$\text{PSNR} = 10 \log \frac{\text{MAX}^2}{\text{MSE}} \tag{9}$$

Here MAX is the possible maximum value in the image usually 255.

MSE is the mean squared error difference between the original and enhanced image and is given by equation (10).

$$\text{MSE} = \frac{1}{\text{MN}} \sum_{i=1}^{\text{M}} \sum_{j=1}^{\text{N}} (\text{E}_{ij} - \text{I}_{ij})^2 \tag{10}$$

Higher the value of PSNR better is the quality of the enhanced image.

4.2. Structural similarity Index metric(SSIM)

SSIM [34] is a HVS metric for measuring the similarity between the images based on luminance, contrast and structure of images

$$\text{SSIM(I, E)} = \frac{(2\mu_I\mu_E + C_1)(2\sigma_{IE} + C_2)}{(\mu_I^2 + \mu_E^2 + C_1)(\sigma_I^2 + \sigma_E^2 + C_2)} \tag{11}$$

Here μ_I = average of I,

μ_E = average of E,

σ_I^2 = variance of I,

σ^2_E = variance of E,

σ_{IE} = covariance of I and E,

C_1 = K_1L^2 is a constant used to avoid instability when $\mu_I^2 + \mu_E^2$ is close to zero.

K_1 = 0.01.

C_2 = K_2L^2 is the constant used to avoid instability when $\sigma_I^2 + \sigma_E^2$ is close to zero.

K_2 = 0.03,

L = 255.

The value of SSIM is between (– 1, 1). When SSIM is closer to 1, better is the quality of enhanced image.

4.3. Universal image quality index (UIQI)

UIQI [35] models image distortion as a combination of three factors -loss of correlation, luminance distortion and contrast distortion.

$$\text{UIQI} = \frac{(4*\sigma_{IE})(\mu_I*\mu_E)}{(\mu_I^2+\mu_E^2)(\sigma_I^2+\sigma_E^2)} \tag{12}$$

The valuesofUIQI range from –1 to 1. UIQI value of 1 indicates full similarity and UIQI value of –1 indicates total dissimilarity.

4.4. Normalized correlation coefficient (NCC)

NCC[36] is also used to indicate similarity between images

$$\text{NCC} = \frac{\sum_{i=1}^{M}\sum_{j=1}^{N} I_{ij} * E_{ij}}{\sqrt{\sum_{i=1}^{M}\sum_{j=1}^{N} I_{ij}^2} * \sqrt{\sum_{i=1}^{M}\sum_{j=1}^{N} E_{ij}^2}} \tag{13}$$

The NCC values ranges between 0 and 1. NCC values closer to 1 indicate high similarity and 0 indicates no similarity.

4.5. Discrete Entropy (DE)

DE[32] measures the richness of details in an image after enhancement.

$$E(I) = \sum_{K=0}^{255} P(I_K)\log_2(P(I_K)) \tag{14}$$

$P(I_K)$ is the pdf of the k^{th} gray level. Higher value of DE indicates an image with higher detail preservation.

5. RESULTS AND DISCUSSIONS

The performance of the proposed method is tested on 322 mammograms belonging to normal,benign and malignant category with fatty,fatty glandular and dense breast tissues. The mammograms have been obtained from mini-MIAS database [37].

In order to evaluate the performance of the proposed method, each mammographic image has been enhanced using contemporary HE techniques like HE, BBHE, WTHE and also using the proposed algorithm and their performance have been compared. The performance has been analysed subjectively with respect to human visual perception and objectively by computing the metrics mentioned above.

5.1. Subjective Evaluation of the results obtained

Fig 1 shows a sample mammogram mdb025 and the enhancement results obtained using HE, BBHE, WTHE and the proposed method. The results obtained using HE in Fig 1(*b*) clearly shows that the contrast of the background as well as foreground has significantly increased giving rise to a blurring effect. This has reduced the clarity of the image and has also amplified the noise level. The BBHE enhancement results in Fig 1(*c*) shows that the contrast of the foreground has increased significantly whereas the contrast of the background remains the name. It provides significant improvement over HE results. But this enhancement produces an unnatural look and has a washed out appearance. It has also failed to preserve the details of the image.

WTHE as compared to HE, BBHE show better results with regard to visual perception but does not preserve the naturalness of the image due to over enhancement in original brightness as can be been in Fig 1(*d*). They also fail to achieve a smooth distribution among high and low grey levels.

The proposed method provides a better visualization as compared to other HE techniques as seen in Fig1 (*e*). A controlled enhancement has been obtained which gives rise to a more natural looking image with a greater degree of detail preservation. There is also a greater improvement in image quality as compared to other HE techniques.

5.2. Objective evaluation of the results obtained

The quality of the enhanced images obtained by various methods described above are analysed using PSNR,SSIM, UIQI, NCC and DE and their comparative analysis is tabulated in table 1-5. Each table shows the values obtained with respect to a particular metric for 5 mammograms belonging to different categories. The last row of each table shows the average value of the metric obtained for 322 images. From table1, it is clear that PSNR value is highest for the proposed method which indicates that the image quality obtained using the proposed work is superior compared to other.

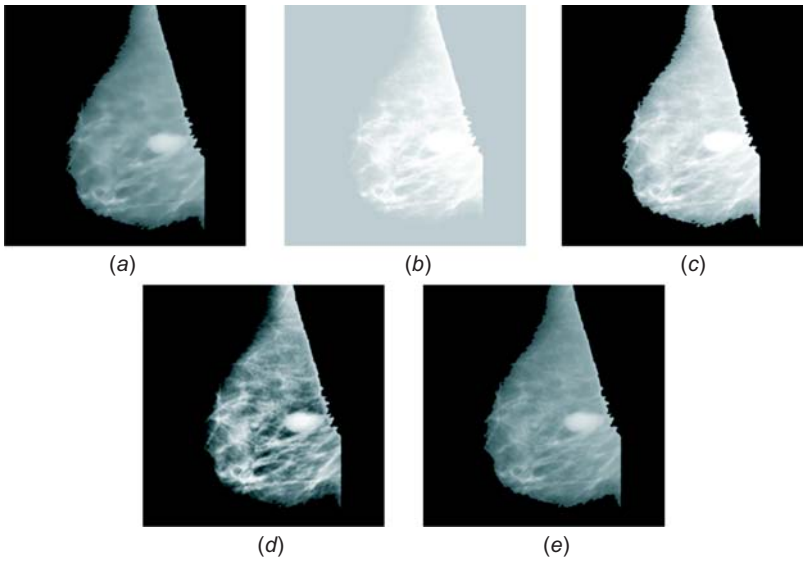

Figure 1: Sample image mdb025 and enhanced images. (*a*) Original image (*b*) HE- *ed* image (*c*) BBHE- *ed* image (*d*) WTHE- *ed* image (*e*) Proposed method.

Table 2 indicates that SSIM values are closer to 1 for the proposed algorithm which means that there is a high level of similarity with respect to luminance and contrast between the enhanced and the original image resulting in a natural looking image with greater preservation of details.

From table 3 and 4, it is clear that NCC value and UIQI value is closer to 1 compared to other techniques for the proposed method which means a high level of similarity between the original and the enhanced image. Table 5 gives the DE values of the original image and the enhanced image obtained using various techniques. It shows that DE values is highest for WTHE which indicates richness of details with respect to brightness in the output image. But the difference between the D.E values of the original image and the proposed method is found to be the least. According to authors Wang and Ye[33], this means that the retention of details is of highest order in the output image of the proposed method.

Table 1
PSNR Values

	HE	*BBHE*	*WTHE*	*Proposed Method*
Mdb002	4.6553387	14.7205544	23.47935	30.37068
Mdb005	6.907995	13.7861272	21.58282	32.83815
Mdb058	5.364734	12.88536011	26.27159	31.35696
Mdb229	6.100698	13.49087176	22.2725	30.4197
Mdb313	8.59132	13.669500	22.09372	27.71567
Average value for 322 images	4.6002	14.32586	23.55101	30.12367

Table 2
SSIM values

	HE	*BBHE*	*WTHE*	*Proposed Method*
Mdb002	0.181738	0.2742	0.487551	0.758947
Mdb005	0.29005	0.35334	0.47541	0.693134
Mdb058	0.254375	0.28050	0.573998	0.792237
Mdb229	0.329924	0.4309	0.502763	0.785287
Mdb313	0.394984	0.329924	0.497904	0.761245
Average value for 322 images	0.261449	0.31306942	0.502020	0.766243

Table 3
NCC values

	HE	*BBHE*	*WTHE*	*Proposed Method*
Mdb002	0.642692	0.66814253	0.79591	0.81321
Mdb005	0.567799	0.656225	0.66781	0.92467
Mdb058	0.609245	0.645418	0.775501	0.800216
Mdb229	0.633582	0.645678	0.81261	0.79522
Mdb313	0.575415	0.707857	0.95532	0.82326
Average value for 322 images	0.606676	0.6763198	0.652817	0.81249

Table 4
UIQI values

	HE	*BBHE*	*WTHE*	*Proposed Method*
Mdb002	0.193764	0.265743	0.2554	0.72867
Mdb005	0.248454	0.30317	0.322604	0.728741
Mdb058	0.190342	0.2637	0.282693	0.752581
Mdb229	0.223533	0.319226	0.282422	0.79873
Mdb313	0.287506	0.349528	0.36248	0.743715
Average value for 322 images	0.196735	0.2927	0.2938	0.73214

Table 5
Entropy values

	Original Image	*HE*	*BBHE*	*WTHE*	*Proposed Method*
Mdb002	3.290927	2.578181	3.590208	4.437	3.2908
Mdb005	3.884217	3.371318	3.97521	4.95922	3.8831
Mdb058	3.271279	2.677673	3.4054	3.85946	3.2774
Mdb229	3.658644	3.088338	3.89148	3.87581	3.6543
Mdb313	4.29054	3.962426	4.52763	3.915169	4.29912
Average value for 322 images	3.67126	2.263691	3.82641	3.95126	3.6743

6. CONCLUSION

HE and BBHE enhanced the contrast of the image more than it was desired. This proved a major disadvantage in case of mammograms with dense breast tissues. Such mammograms tend to have brighter areas and the over enhancement of brightness by HE techniques gave rise to a washed our appearance with blurring effect. This made the detection of malignancies such as subtle masses and micro calcifications difficult as they are small in size and of low contrast. The proposed algorithm overcame these problems by obtaining controlled contrast enhancement while preserving the richness of details.

The merit of the proposed method is that it is simple and easy to implement because it is non recursive in nature. Also the proposed method is adaptive in nature as the exponential fuzzifier is calculated using the sigmoid function which makes use of the median value of the input image. The denominational fuzzifier is calculated from the exponential fuzzifier.

The demerit of the proposed method is that the swarm size and the number of iterations in PSO has to the chosen carefully as the execution time of the proposed method is highly influenced by these two parameters.

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