An Iterative Quantitative Measure Based Image Enhancement Diagnostic Algorithm for Healthcare Improvement

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Abstract
Image processing is one of the important dimensions of healthcare which helps in timely diagnosis and treatment of many human healthcare hazards. A quantitative measure based image enhancement diagnostic algorithm to improve healthcare is proposed. The algorithm regulates PDF of input medical image and then the histogram and contrast of given medical image is improved continuously. Quantitative measuring techniques are used to find an optimal output image. The resultant images show improvement in contrast and enlighten the darker regions of the image for better perception to diagnose a particular healthcare hazard.

Keywords: - Image enhancement, Image quality measure, Healthcare, Artifacts, Mean Square Error, Peak Signal to Noise Ratio.

INTRODUCTION

There are various dimensions in healthcare viz. Image processing, Computer vision, Pattern recognition, Machine learning, deep learning etc. Image processing is one of the important dimensions of healthcare which not only helps in detection of healthcare hazards but also helps in planning and monitoring treatment of the patients. Image processing is a subfield of signal processing, for which input signal is an image and outputs are again an image and/or various parameters defining various characteristics of the image and applied operations [1]. Various imaging techniques are used for diagnosis of particular diseases. These techniques find their applications in X-rays [2], CT-scan, MRI [3], Ultrasound etc. for detecting various diseases [4]. Each of these imaging techniques suffers due to artifacts present in it [5]. Medical Images produced by these imaging techniques are often affected by noise due to interference that effect data acquisition system. Medical images are also affected by low contrast and less visibility of details. Ultra Sonography (US) images encounter various types of artifacts which can lead to inaccurate diagnosis. Recognition, identification and removal of these artifacts is an important aid in diagnosis and optimal patient care [6] [7]. Artifacts in ultrasonic images can be classified into three categories: Artifacts related to instrument problems, Technique dependent artifacts and Artifacts due to the way tissues affect sound [8]. Ultra Sonography (US) images also suffer from low contrast which can lead to over diagnosis. In all such cases, some improvements in the visual quality and appearance may help in interpretation of these images by a radiologist or medical specialist. Computer-aided detection or diagnosis (CAD) systems have been developed to help radiologists to increase the accuracy of diagnosis [9]. New techniques like a Column-Row-Parallel imaging frontend architecture for integrated and low power 3D medical ultrasound imaging has been developed to support volumetric imaging functionality [10]. Integrated processing of contrast pulse sequencing ultrasound imaging has also been developed for enhanced active contrast of hollow gas filled silica nano-shells and micro-shells [11].

Image enhancement techniques are aimed to improve the quality of an input image. The resultant image demonstrates certain features in a better manner compared to the original input image. Most enhancement techniques are applied to improve image quality for a particular observer or application. Goal of image enhancement is to transform a given image so that it is easier for human observer or computer algorithm to see details in images that may not be computable or observable in the original form. There are various image enhancement techniques like Log Transformation, Histogram Equalization, Contrast Stretching, Adaptive Histogram Equalization etc. which can be used for contrast enhancement of medical images. Unfortunately these techniques may not simultaneously enhance the contrast and at the same time produce good results as far as quality measuring techniques like Peak Signal to Noise Ratio (PSNR), Mean Square Error (MSE) are concerned.

In this context a novel hybrid quality measurement based image enhancement technique is proposed. The algorithm is applied on medical images to improve contrast and value of image quality measurement. At the same time an illusion of a video is created in order to perceive an image sharply for better diagnosis of some health hazard. The probability distribution function of input image is calculated to enhance and regulate the probability distribution function of output image. Log transformation and gamma correction is used to correct the luminance of the input image. Image filtering technique is used to overcome the inherent noise from an input image [12]. To overcome the degrading of edge details due to de-noising, image sharpening techniques are used to enhance the edge details. The values of image quality measuring technique like Enhancement Measurement Error (EME) is compared with previous values in order to get the optimal image as far as image quality measuring technique is concerned [13].

LITERARTURE REVIEW

Various algorithms have been developed to improve the contrast of a medical image. Zhou et al developed a Contrast enhancement technique for medical images using a new version of the World Cup Optimization algorithm to improve the Gamma correction method to enhance and highlight the image information and the details based on a new design of the World Cup Optimization (WCO) algorithm [24]. A new efficient method to detect malignancy in melanoma via images was developed where, at first, the extra scales are eliminated by using edge detection and smoothing and in the process cancer images are also segmented. Finally, the extra information is eliminated by morphological operations and used to focus on the area which melanoma boundary potentially exists. To do this, World Cup Optimization algorithm is utilized to optimize an MLP neural Network [14]. Another method of contrast enhancement of RGB color images, without mapping the colors to different color spaces has been proposed. In this method Histogram Equalization is applied to the intensities of the color vectors and the images obtained are similar to the images produced in HSV (Hue, Saturation, Value) and L*a*b* color spaces [15].

Also a variational model is being developed for contrast enhancement of color images based on local gamma correction. It uses energy functional to determine a local gamma function and gamma values are set to local information of the input image. A spatial regularization of the gamma function is incorporated into the functional so that the contrast in an image can be modified by using the information of each pixel and its neighboring pixels [16]. A highly adaptive swarm intelligence optimized dark image enhancement approach is being developed for remotely sensed satellite images. It uses weighted summation framework to impart "on-demand entropy restoration and contrast enhancement". It utilizes both gamma correction and histogram equalization without losing original image features of dark satellite images. To improve images gamma correction is also employed separately for dark as well as light pixel values, so that over-saturation and other related unnatural artifacts can be removed [17].

A contrast enhancement technique combining classical contrast enhancement with an evolutionary approach to increase the information content and enhance the details of an image using an adaptive gamma correction technique aided by particle swarm optimization has been proposed. Swarm intelligence based particle swarm optimization is used to estimate an optimal gamma value. In the proposed method, edge and information content (entropy) are the parameters used to formulate the fitness function [18]. Again an adaptive genetic algorithm is being developed for medical image contrast enhancement. Initially, the chromosomes having gene value of the image gray levels have been generated. After that the fitness function is calculated for each generated chromosome based on the image edge and their overall intensity values. The selected best chromosomes which have the high fitness value will be given to crossover and mutation operation [19].

THE PROPOSED ALGORITHM

Consider a gray scale medical image with levels [0, L-1] and n pixels. The probability distribution function of the image is given by

$$p(i) = \frac{n_i}{N} \qquad i = 0, \dots, L-1 \qquad [1]$$

Where i is the ith gray level and n_i is total number of pixels in the image with gray i level.
The probability distribution function was regulated using the following equation.

$$p(i) = \left(\frac{p(i)}{p_{max}}\right)^{r} . p_{max} \qquad 0 < p(i) < p_{max} \quad [2]$$

The Cumulative Distribution Function can be computed by the following equation

$$cT(k) = \sum_{i=0}^{k} pT(i) \qquad 0 \le k \le 255 \qquad [3]$$

Log Transformation was applied to enhance brightness of input ultrasound image using the following equation

$$R(i,j) = c * \log\big(1 + g(i,j)\big) \qquad [4]$$

Where c is a constant and $r \geq 0$.

In order to remove the inherent noise in an image, mean filtering is used. Mean filtering is simple and easy to implement method to make an image smooth and is used to reduce noise in an image. Input noisy image is convolved using (2M+1x 2N+1) kernel in which each coefficient value is reciprocal of number of coefficients in the kernel. Gamma correction is applied to map the pixel numerical value to its actual luminance using the following equation.

$$O(i,j) = aR(i,j)^{\gamma} \qquad [5]$$

Where **a** is a constant.

Image sharpening is applied to enhance the edge details of an input using the following equation.

$$s(i,j) = O(i,j) + \lambda f(i,j) \qquad [6]$$

Where $O(i,j)$ is original pixel value, $f(i,j)$ is the high pass filter and λ is tuning parameter.

Input-output transfer function can be represented as

$$ft\,(k) = \left(\frac{255.\,cT(k)}{cT(255)}\right) \qquad [7]$$

Where $ft(k)$ denotes the value of the kth grey level after enhancement. After that we calculate Enhancement Measurement Error (EME) which divides the input image into n1n2 non-overlapping sub blocks. The EME value is computed as follows

$$EME = \frac{1}{n_1 n_2} \sum_{i=1}^{n1} \sum\nolimits_{j=1}^{n1} 20\ln \frac{\max(x_{i,j})}{\min(x_{i,j})} \qquad [8]$$

Where $max\ (x(i,j))$ is the maximum grey level in a block and $min\ (x(i,j))$ is the minimum grey level in a block. Greater the value of EME, more is the quality of input image [Scanlan, 1991] [Gonzalez & Woods, 2008] [Umbaugh, S. E., 1997]. Finally an enhanced optimal image is obtained.

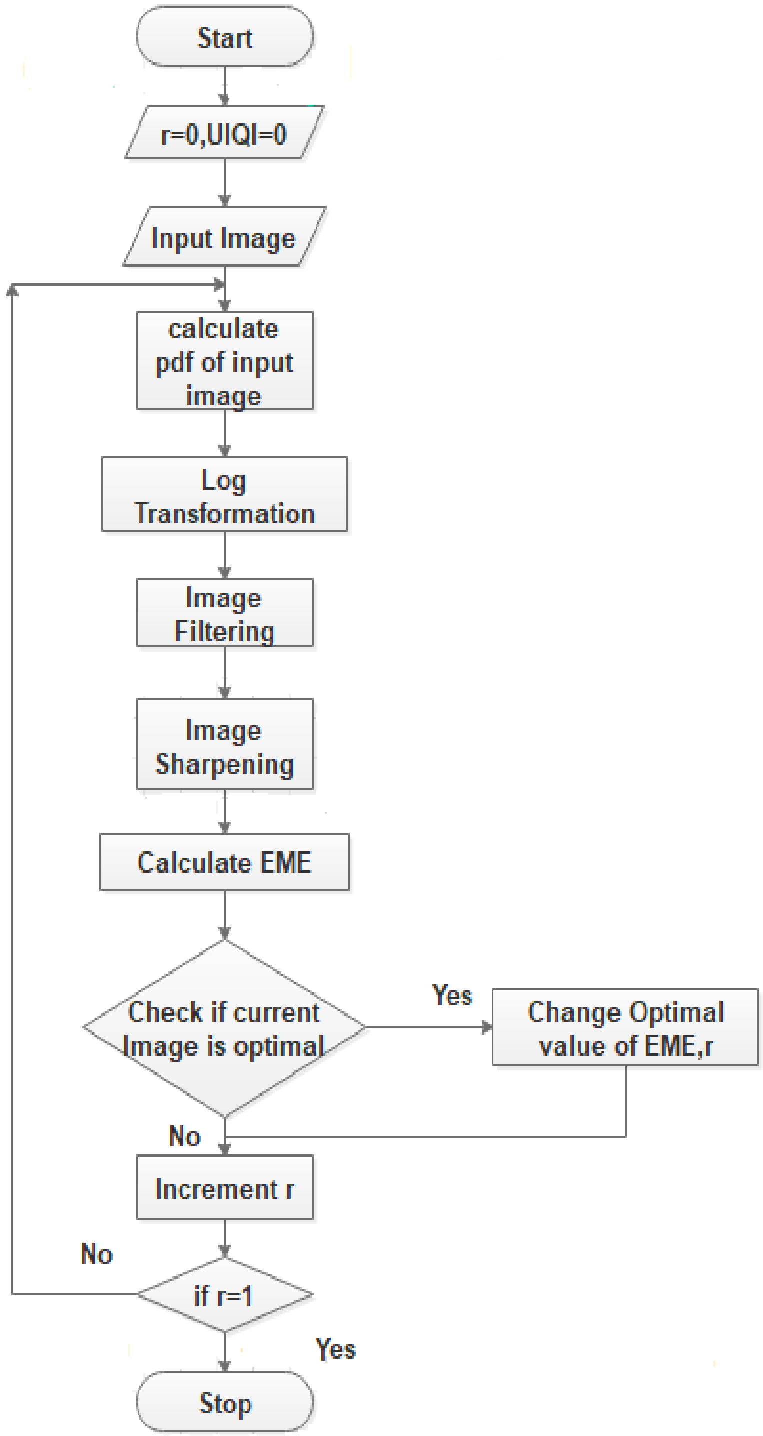

Figure 1: Algorithm flowchart

EXPERIMENTAL RESULTS AND DISCUSSION

This section discusses simulation results carried out in Matlab R2009 on source images. After applying the proposed technique and other techniques on different types of medical images, we obtained the quantitative and qualitative results for all values of r from 0.01 to 1.0 which are shown in figures 2 to 5.

Figure 2. Resultant r values (0.01-1.0)

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	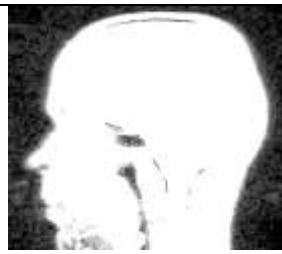	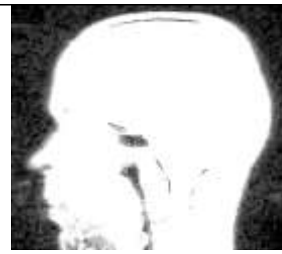	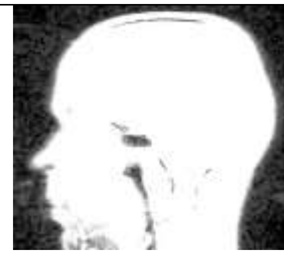
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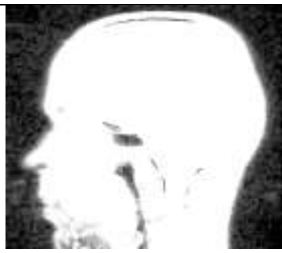	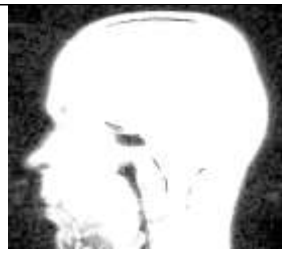	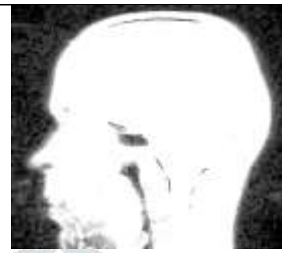	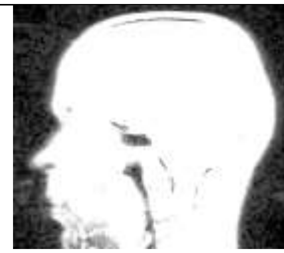
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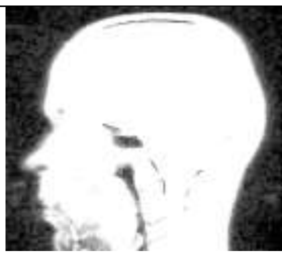		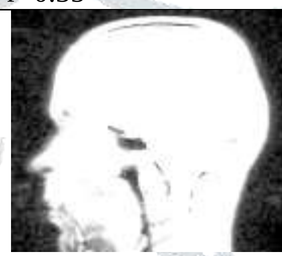	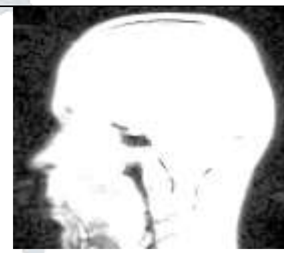
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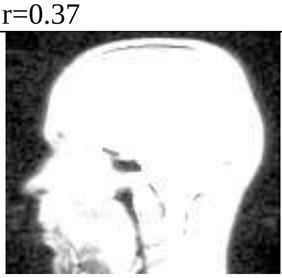	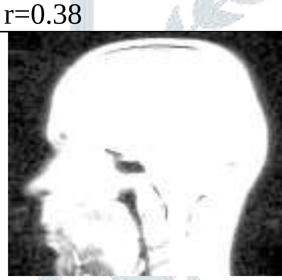	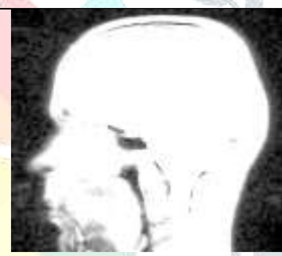	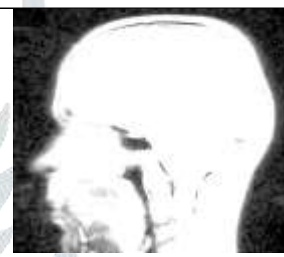
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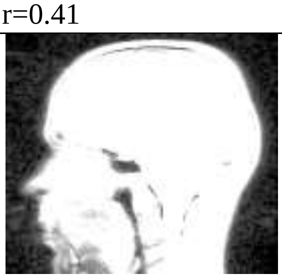	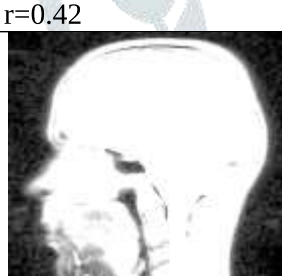	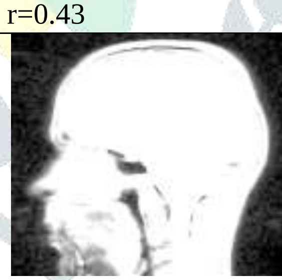	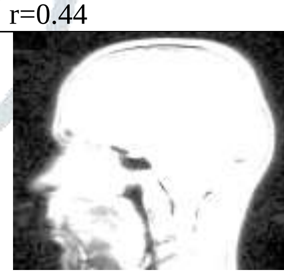
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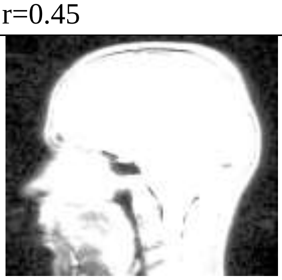	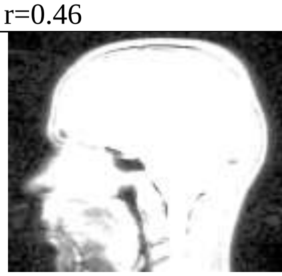	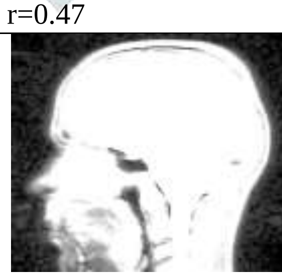	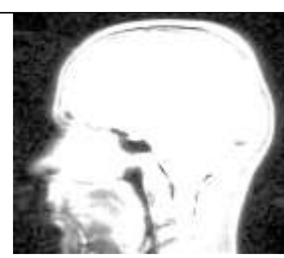
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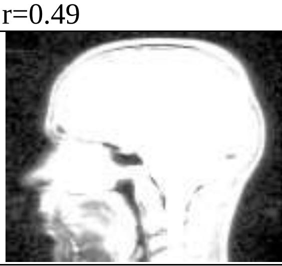	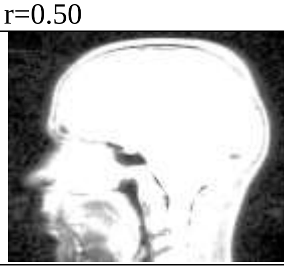	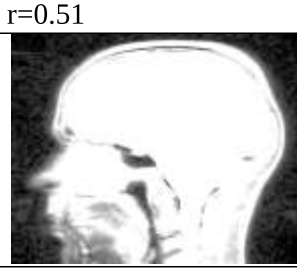	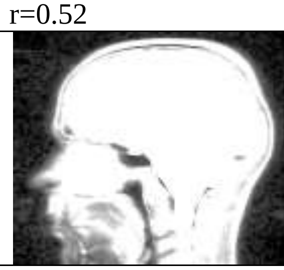

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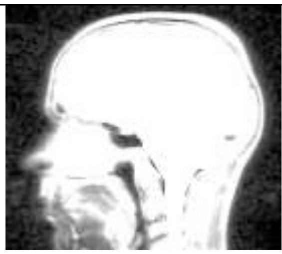	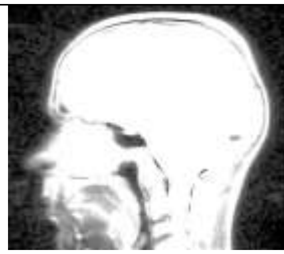	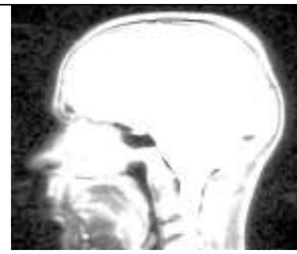	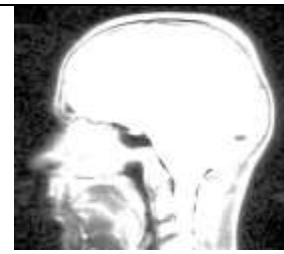
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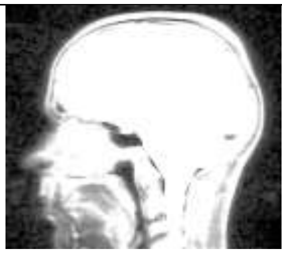	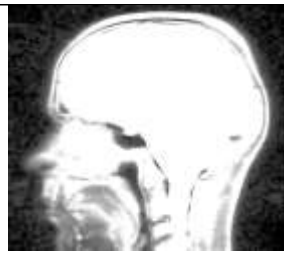	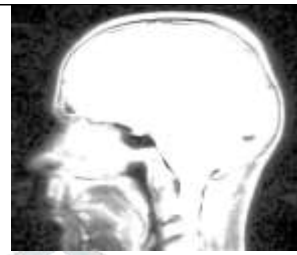	
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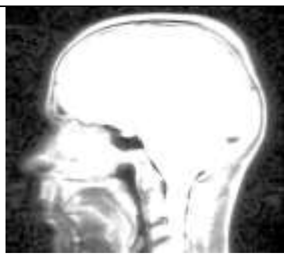	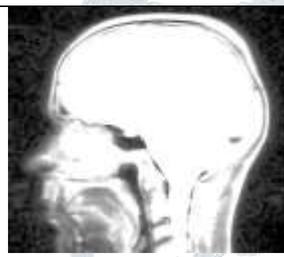	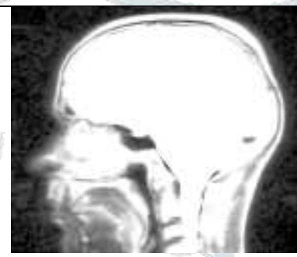	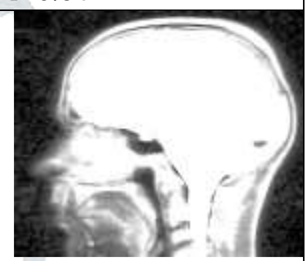
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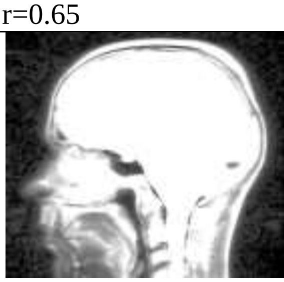	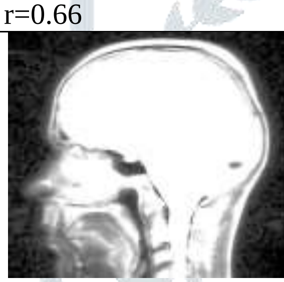	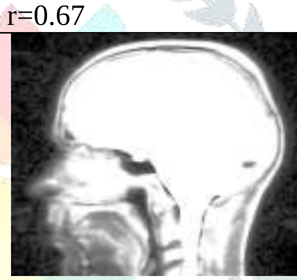	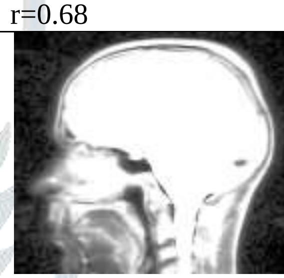
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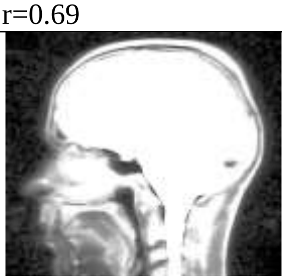	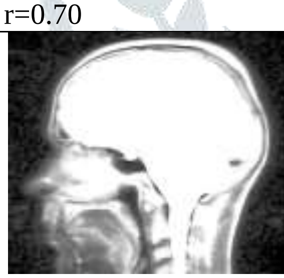		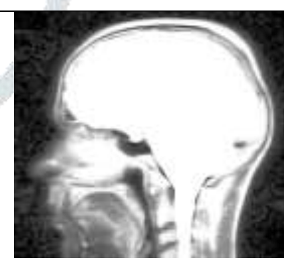
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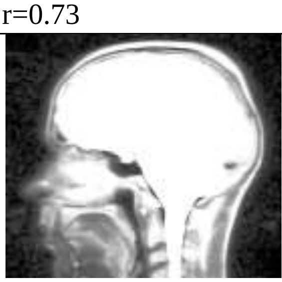	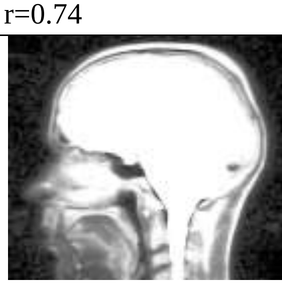	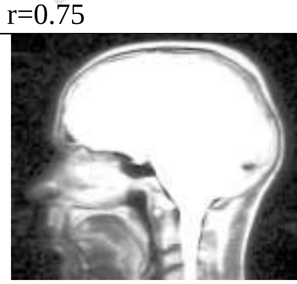	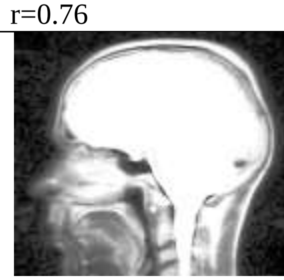
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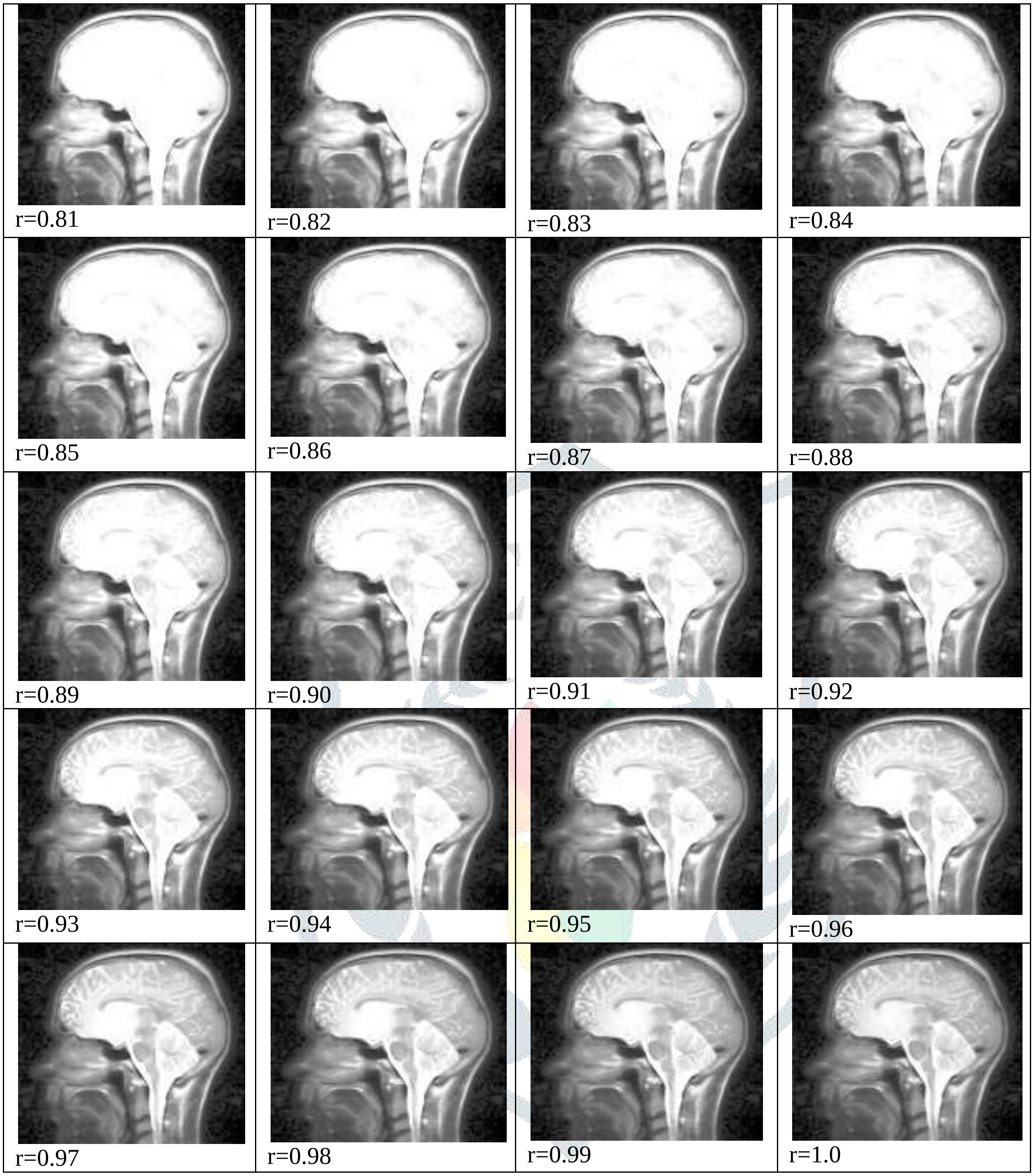
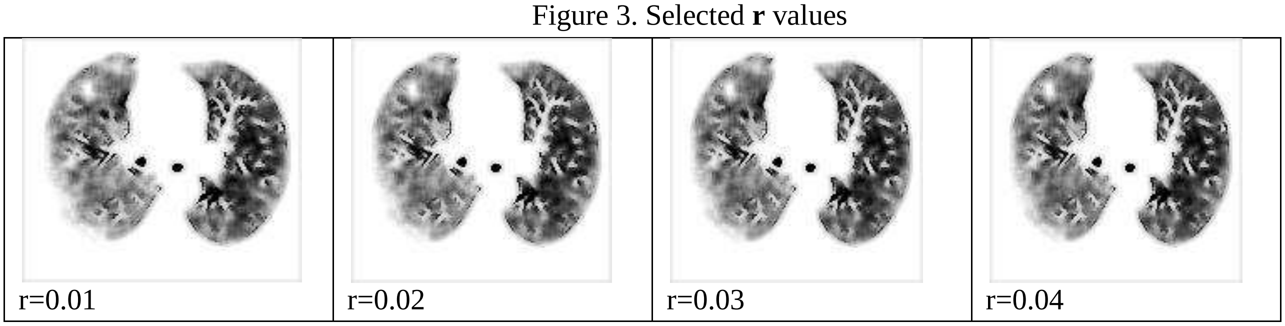


Figure 3. Selected **r** values



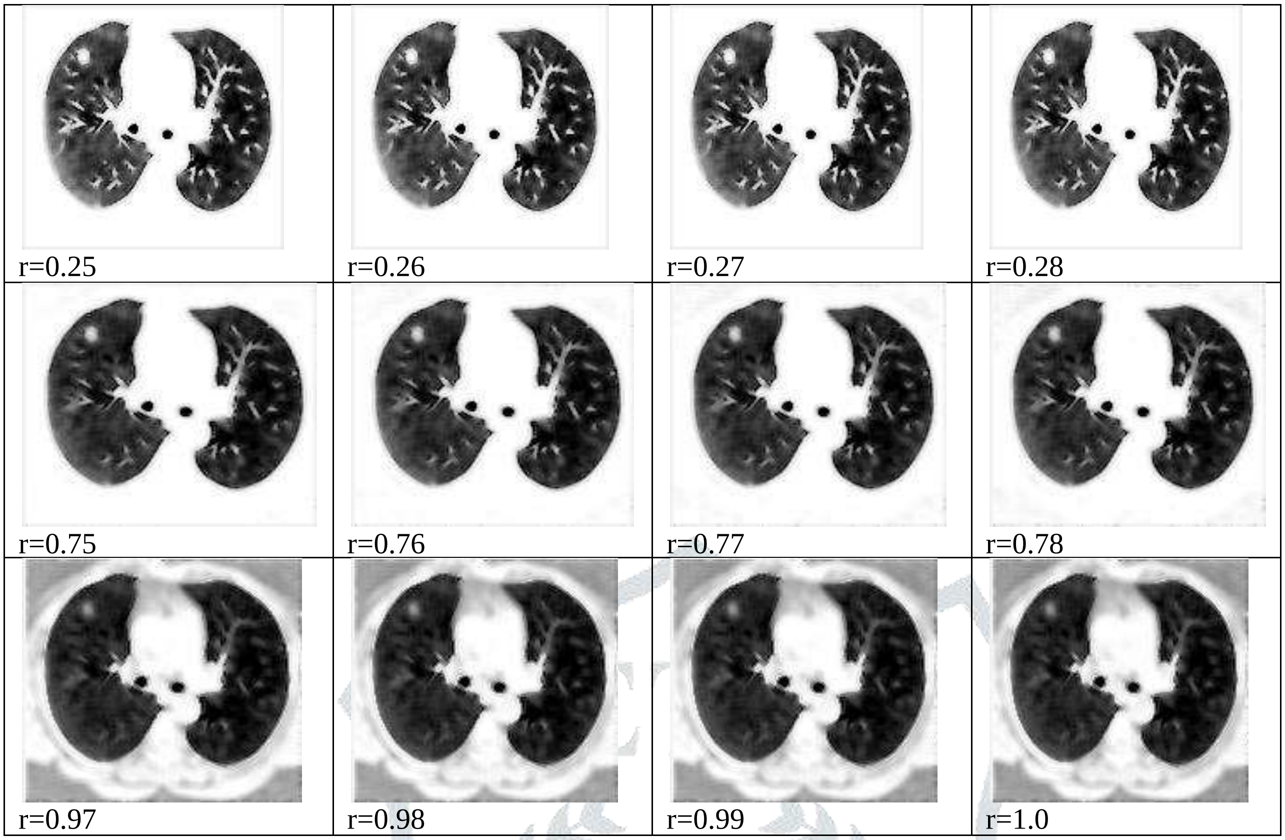


Figure 4. Selected **r** values

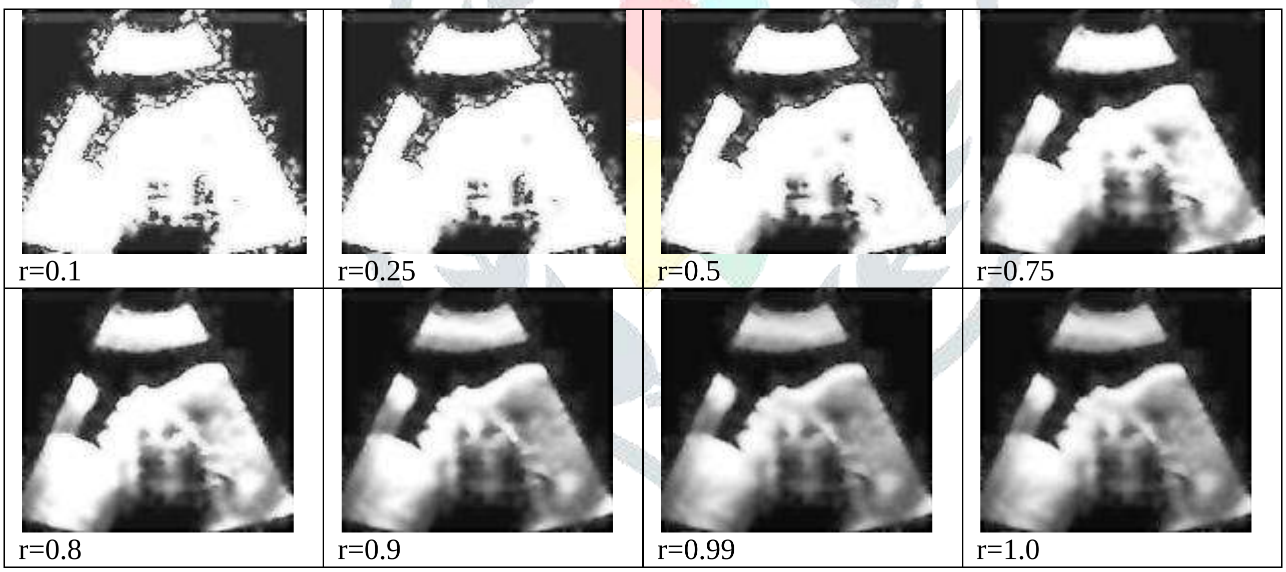
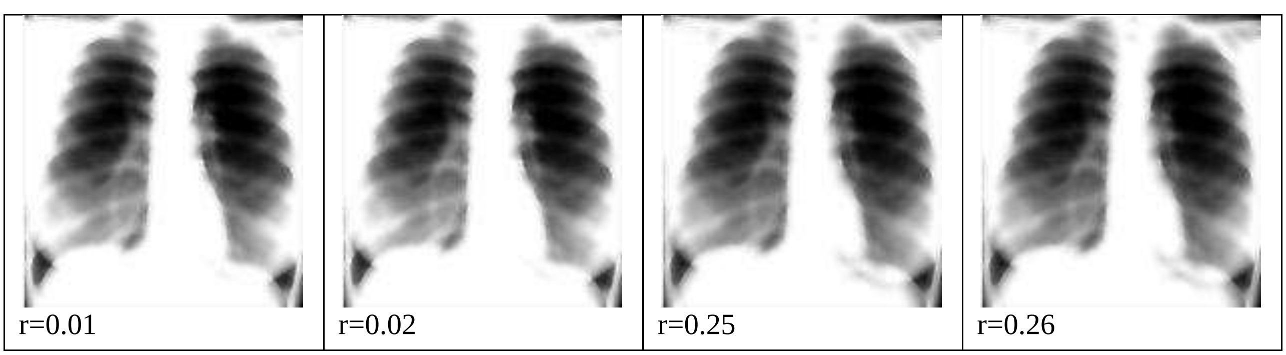
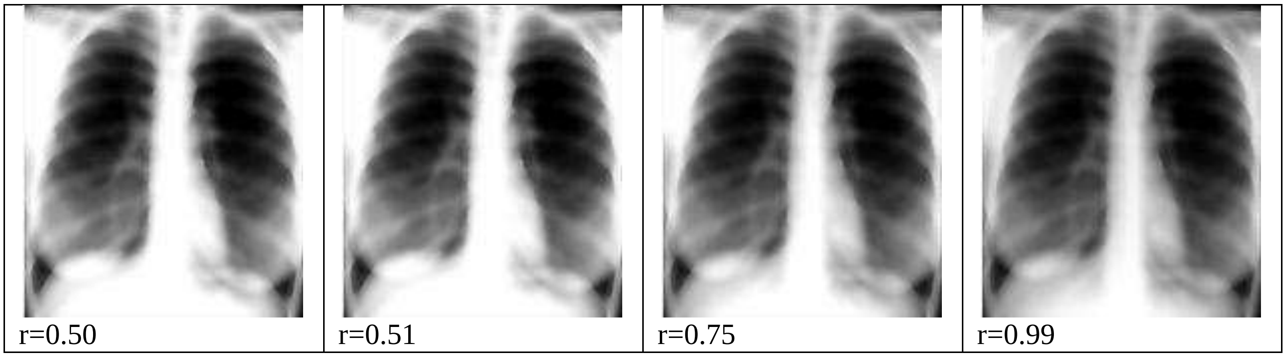


Figure 5. Selected **r** values



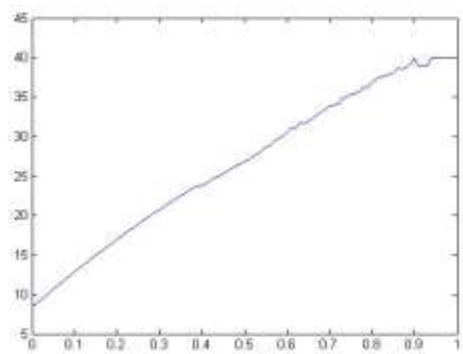


Simulation of regulation of r.

The value of r is set to 0.01 initially then it is incremented by 0.01 till it reaches 1.0. In each iteration, image contrast and luminance are increased using the proposed method and the EME value is calculated. Figure 6 shows EME and r curve obtained. It can be clearly seen that best enhanced image is obtained at r=.90 on CT image. This value can be different for different images.

Figure 6. EME and r curve

EME



r

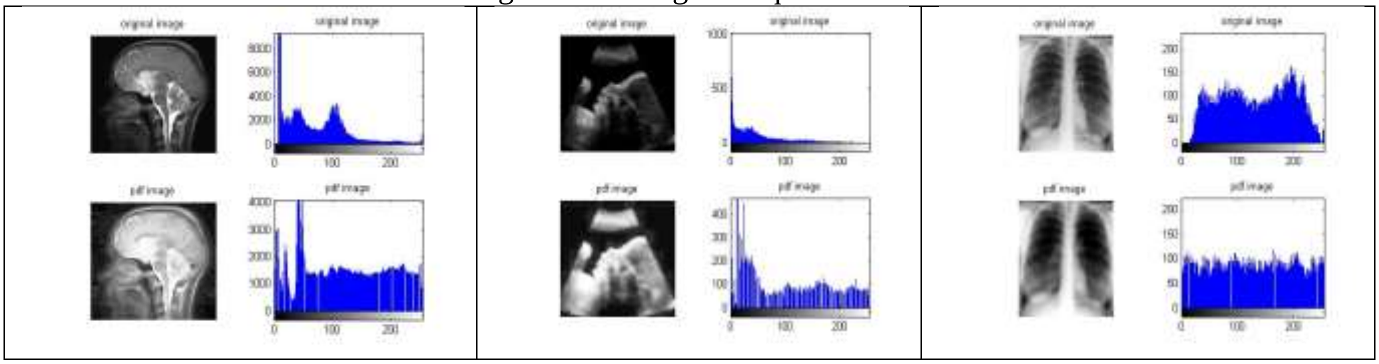
Method Performance

After applying the proposed technique the results obtained, as illustrated in Figures 2 to 5, reveal that there is significant enhancement in input images. As image enhancement is difficult to quantify [21], both subjective as well as objective methods have been used for evaluation of proposed method. Visual inspection shows that the method is helpful to diagnose and highlight the dark spots in subject images as illustrated. It also produces illusion of a video and helps in perceiving the subject image in much better way. As far as quantitative measuring techniques are concerned, the proposed method produces optimum resultant image as far as quantitative measure EME is concerned. It results in an image that shows optimal EME value. The proposed method also enhances the dynamic range of resultant image and equalizes the histogram of the resultant image as shown in Figure 7. The EME results shown in table 1 explicitly reveal that the proposed method out performs other methods. However the proposed method is a bit slow than other enhancement methods because it is an iterative algorithm. However the availability of fast computing device nullifies this shortcoming [20].

Table 1. Performance Comparison using EME

	Original Image	**Histogram Equalization**	**Adaptive Histogram Equalization**	**Log Transformation**	**Proposed Method**
EME	9.40	7.619	10.96	8.54	15.02

Figure 7. Histogram Equalization



CONCLUSION

Image processing is playing a vital role in healthcare by means of detecting and treating health related hazards. In this direction, a quantitative measure based iterative image enhancement algorithm has been proposed to enhance medical images to aid in diagnosis of health related hazards. The probability distribution function of the input image and the parameter **r** are calculated. The value of EME is calculated to compare with its previous value. The value of **r** is stored for the optimal value of EME as far as image quality measuring technique is concerned. As per the quantitative measures our method performs well as compared to other existing methods. The proposed technique also helps in diagnosis by producing various images that can be visually inspected by radiologists. The method also enhances the luminance of input image so that dark spots are highlighted. It also enhances the dynamic range of input image in order to differentiate various objects in target image and equalizes the histogram of resultant image to help radiologist to better perceive the image contents and diagnose abnormalities with good performance.

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