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Cuckoo Search Constrained Gamma Masking for MRI Image Detail Enhancement

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ABSTRACT

Nature-inspired algorithms are widely applied in the arena of image enhancement for various optimization purposes. To address the optimization complexities in various image enhancement approaches, nature-inspired optimization algorithms play a vital role. Cuckoo search is one of the prominent nature-inspired performance algorithms that we employed in this work for the enhancement of magnetic resonance imaging (MRI). We proposed a wavelet-based masking technique employing a cuckoo search algorithm whose masking value is corrected by gamma function for the contrast enhancement of MRI images. The cuckoo search algorithm can inevitably fine-tune the relation of nest building using genetic operatives like adaptive cusp and alteration. The proposed contrast enhancement scheme is examined quantitatively for different types of MRI images. Extensive simulation results compared with quantitative values have revealed that the traditional nest building of cuckoo search optimization is improved by adaptive gamma correction. Comparative analysis with the existing works establishes the usefulness of the proposed methodology over the other standard approaches.

1. INTRODUCTION

Image enhancement is often useful in innumerable image processing applications like contrast improvement, denoising, edge enhancement, edge restoration, etc. Image enhancement techniques fall under two wide-range of classes, i.e., spatial and frequency domain enhancement approaches [1]. Spatial domain operations directly manipulate or modify the pixel values in the image plane itself, while frequency-domain techniques transform the image to the frequency domain for modification/manipulation.

In medical image processing, contrast improvement procedures are cast-off as a preprocessing module that enables enhancing the purity of prognosis. Usually, enhancement techniques are example-based and intensity-based [2]. Intensity-based improvement is further categorized as histogram-based, transform domain-based, filter-based, and masking-based. The histogram equalization is a standard assessment approach. Different histogram methods are employed for better results; like instinctive precise histogram specification, sections reliant on active multi histogram equalization and threshold optimized histogram equalization, etc. Wavelet transformation methods have found a lot of applications in image processing like compression, segmentation, and enhancement, etc. Fourier domain is another common and traditional method in transform-based signal and image processing.

Filtering is the process of removing unwanted signals while selecting the specified values of signals. In image processing, filter-based methods are primarily intended for the reconstruction and enrichment of the signal [3]. Unsharp masking is an enhancement process, during which the scaled value of the image is employed for mask formulation. Traditional masking methods exploit static measure values which are determined in the arbitrary range [4]. Numerous optimization algorithms are a nature-inspired example: ant colony optimization (ACO), particle swarm optimization (PSO), genetic algorithm (GA), cuckoo search algorithm (CSA) [5, 6], etc. Nature-inspired optimization algorithms (NIOA) play a critical situation in the arena of image processing. They reduce the noise and blurring of images and also enhances their quality. They also help in image restoration, image segmentation, image edge detections, generation of images, the fusion of images, recognizing the patterns from the images, thresholding, and so on [7]. These sets of optimization algorithms are called nature-inspired as scholars have established the underneath motivation of these algorithms from several natural phenomena. Counting on the various sources of motivation from nature, these NIOA are largely classified into:(a) Evolutionary Algorithms (EA), (b) Biology-inspired, or Bio-inspired algorithms, (c) Physics and Chemistry based algorithms [8, 9]. Several NIOAs have been used for various image processing applications in recent years.

Bhandari et.al used the Social Spider optimization method for image enhancement [10]. They also used the salp swarm algorithm for image enhancement [11]. Chen et al employed an artificial bee colony-based NIOA for contrast enrichment [12] whereas Nandan et al. implemented a gray wolf optimization method to fuse masked-based medical images [13]. Dhal et al. [14, 15] used an animatedly revised and biased bat algorithm to enhance the image properties as well as did a review on nature-inspired optimization procedures used in image enrichment. Kandhway et al. [16] used a krill herd optimization algorithm to improve the contrast of histogram equalized images. Kanmani and Narsimhan [17] proposed an image contrast enrichment procedure for grayscale images utilizing particle swarm optimization. Rundo et al. [18] recently proposed a novel idea to enhance medical imaging using the modified genetic algorithm known as “MedGA”. Singh et al. [19] proposed neural network-based MRI enhancements using a bat optimization algorithm. This paper is constructed on the cuckoo search optimization procedure in which the scale value is adjusted for the masking and later the localized contrast enhancement is done with the help of gamma function and adaptive histogram equalization.

The remaining manuscript is systematized as: Section 2 reflects the literature of cuckoo search optimization algorithms that have been used in image processing in the current scenario. Section 3 epitomizes the proposed wavelet- based gamma-corrected masking method. Section 4 deliberates investigational outcomes and assessments with supplementary optimization algorithms. Section 5 concludes the work.

2. RELATED WORKS

There is relatively 1,000 type of birds in the world landscape, and these birds motivated different optimization techniques in the literature. For instance, all-female birds lay offspring that have one-of-a-kind of offspring beginning to each other. Additionally, exclusive nests are constructed by the numerous birds in inaccessible spaces to extend protection from predators. Birds those uses others nest to lay their eggs, referred as brood parasites. These sorts of birds don't shape their very individual nests instead lay their offspring within the nest of some other species, parting the host to require maintenance of its younger. The foremost well-known among the brood parasites is that the cuckoo. It has an excellent manner within the art of trickery. Its method comprises infiltration by doing away with one egg placed employing the host. It then cautiously fits its egg by mirroring the shape and shade of the host's offspring, a capability that involves high precision. The judgment of egg-laying is likewise a first-rate manner of picking the nest. Wherein the host bird just placed its progenies. The cuckoo’s offspring will access before the host offspring and therefore the first inborn motion of the host could also be to throw its spawns out of the nest by way of blind pushing, as a result, increasing the maintenance and nourishment furnished for the cuckoo's fledglings. However, just in the situation, the host acknowledges the cuckoo's offspring in its case, they moreover fling out the atypical egg or certainly get away their nest and figure a fresh one. The cuckoo duty consequently is greater precise in impersonating the host offspring, while the host must progress its aids in deciding the freeloading ovule. In that deceit the so-referred to as war for survival.

The usage of the Cuckoo search algorithm (CSA) within the optimization context was proposed with the help of Yang and Deb in 2009. To the current point, work on this procedure has notably expanded, and the CSA has thrived to be popular amongst the optimization practices. This procedure is predicated totally on the oblige brood parasitic actions originated in some cuckoo types, together with the Levy flight, which may be a sort of arbitrary wander that features a strength-regulation step length spreading with an important tail. The CSA is a competent metaheuristic swarm-based procedure that resourcefully maintains equilibrium among nearby manipulation and international- extensive investigation within the spatial domain [20].

Quite a lot of literature has been broadly published on the cuckoo search process. In 2009, CSA developed and evaluated the use of multimodal goal capabilities and then equated it with GA and PSO [21]. The CSA has been broadly used freshly in the field of image enhancement, segmentation, classification, and feature extraction. Regarding the usage of CSA, Bhandari and Maurya anticipated the brightness conserving histogram method to boost the dissimilarity of low contrast images using CSA [22]. Previously, he also proposed the image contrast enhancement technique for satellite imaging using CSA along with a discrete wavelet transform using singular value decomposition (DWT-SVD) [23]. Suresh et al. also proposed the adaptive CSA for the contrast enhancement of satellite images [24]. Prasath and Kumanan used CSA to get optimal histogram equalized images for underwater imaging [25]. Ashour et al. used CSA for the contrast enhancement of computed tomography (CT) images using the log transformation approach [26]. Further, Rai et al. used CSA along with singular value decomposition and adaptive gamma correction to increase the contrast of the CT images [27]. Kallel et al. have developed the masking technique using CSA and wavelet transform to increase the contrast of medicinal images [28]. Chen et al. used enhanced CSA for global optimization of the input images for growing the contrast [29]. Dhal et al. used a modified bi-histogram along with CSA to find out the cancerous tissues from the mammography images [30]. Chakraborty et al. used modified CSA for image segmentation of the hippocampus at the microscopic level [31], whereas Manju and Lenin Fred proposed the multi-balanced CSA using the K-means procedure for subdivision and compression of multipart images [32]. CSA has been also used for classification techniques in recent years. Sumathi et al. used Kapur's entropy-based CSA for optimization and reconstruction of morphological filters to extract tumors from MRI of the brain and breast [33]. Recently, this has been used along with a neural network classifier for breast cancer detection using ultrasonography [34]. Sathish and Elango also used a radiated source neural network with exponential CSA for the instinctive cataloging in MRI images [35]. Cuckoo search algorithm (CSA) has been also used along with other NIOAs known as the Hybrid Cuckoo search algorithm [36]. Recently in 2016, Choubey et al. proposed a novel idea of developing a Hybrid CS-BFO algorithm for getting the optimized multilevel image threshold value for edge magnitude information [37]. In 2020, he proposed a blend of the adaptive Cuckoo Search and Squirrel Search process for brain MRI image analysis [38]. Previously in 2015, Dhal et al. used a hybrid bat-cuckoo search procedure for the performance analysis of gray-level image enhancement [39].

CSA put a promising and interesting set of rules and can still be broadly utilized by researchers throughout distinctive grounds. Its benefits include supplementary optimization procedures, easiness, and a lesser amount of constraints as compared to other procedures. This aids easiness of hybridizing with further optimization algorithms. Nevertheless, CSA lacks mathematical evaluation. It doesn't have a theoretical study very comparable to other processes like PSO and GA.

3. PROPOSED METHODOLOGY

The projected technique is based on the gamma-corrected masking, during which the optimum scale selection of the gamma value is performed on the processed image via a cuckoo search optimization algorithm. The input image is decomposed as estimate quantities (coefficients) and high pass filter via a discrete wavelet transform (DWT). The estimated quantities are reconstructed using inverse DWT (IDWT). The reconstructed coefficients contain a wavelet low pass filter image which is taken into account for mask formulation. The reconstructed low pass signal scaled image is optimized by employing a cuckoo search algorithm. The optimized value dynamically improves the difference of the image. The optimized wavelet masked image is added to the first image and the contrast-enhanced image is attained within the spatial domain which has locally enhanced the contrast value. Due to the localized contrast-enhanced process, the intensity values are not uniform throughout the image, the darker pixel becomes darker and therefore the brighter one becomes brighter. Hence, the obtained image should be optimized globally such that the intensity of the image should be uniform.

This is done by using the adaptive gamma correction method followed by the adaptive histogram equalization (CLAHE) algorithm to clip out the over contrast values at localized pixels [40]. This method is often used on account of the pre-processing technique. The proposed technique is tested for an MRI image database collected from Medanta Global Hospital center situated at the Nalanda Medical College and Hospital, Patna, Bihar (India). The proposed methodology is shown in Figure 1.

3.1 Set of rules for proposed technique

Input: MR image
Output: Enhanced MR image
Step 1: Fetch input image.
Step 2: DWT decomposition in frequency sub-bands (LL, LH, HL, HH).
Step 3: Reconstruction of approximation coefficients of LL
Step 4: Hand-picked the optimal ascended rate of estimate factors employing cuckoo search
Step 5: Compute the outcome of the scaled value ratio and estimated the image.
Step 6: Deduct the product from the input image (masking).
Step 7: Add the mask with the first image
Step 8: Apply AGC to the contrast-enhanced image
Step 9: Apply CLAHE to urge the uniformly distributed intensity values of the image.

3.2 SUBBAND decomposition using DWT

3.2.1 Discrete wavelet transform (DWT)

DWT is a prominent and operative computational means within the area of image processing. The essential idea of DWT is to decompose the specified input into four portions via the use of translation and dilation, using a mother wavelet. For accurate wavelet decomposition, proper selection of mother wavelet is required. The 2-D DWT decomposition of any specified input image is often attained by implementing a 1-D wavelet decomposition along the rows and columns of the image.

This process breaks the specified input image into quatern decomposed sub-band images, which are referred to as LL, LH, HL, HH frequency groups as shown in Figure 2. The foremost significant advantage of the wavelet is its ability to achieve localized information for high-level signal or image processing problems. The low-frequency information is captured within the LL sub-band and therefore the edges are focused on further sub-bands. Hence, dividing the high-frequency subbands and applying the illumination enhancement and thresholding of the optimized value in LL sub-bands will only preserve the edge detail from the possible distortion. Thereafter, an inverse DWT has been applied to get the enhanced image [27].

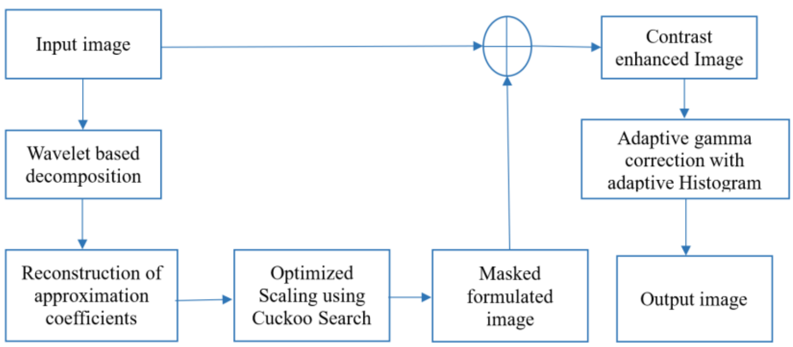


Figure 1. Block diagram of proposed enhancement technique

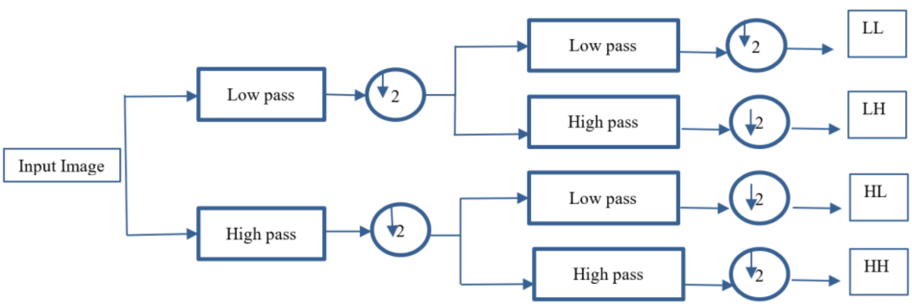


Figure 2. Block diagram of DWT filter banks of level 1

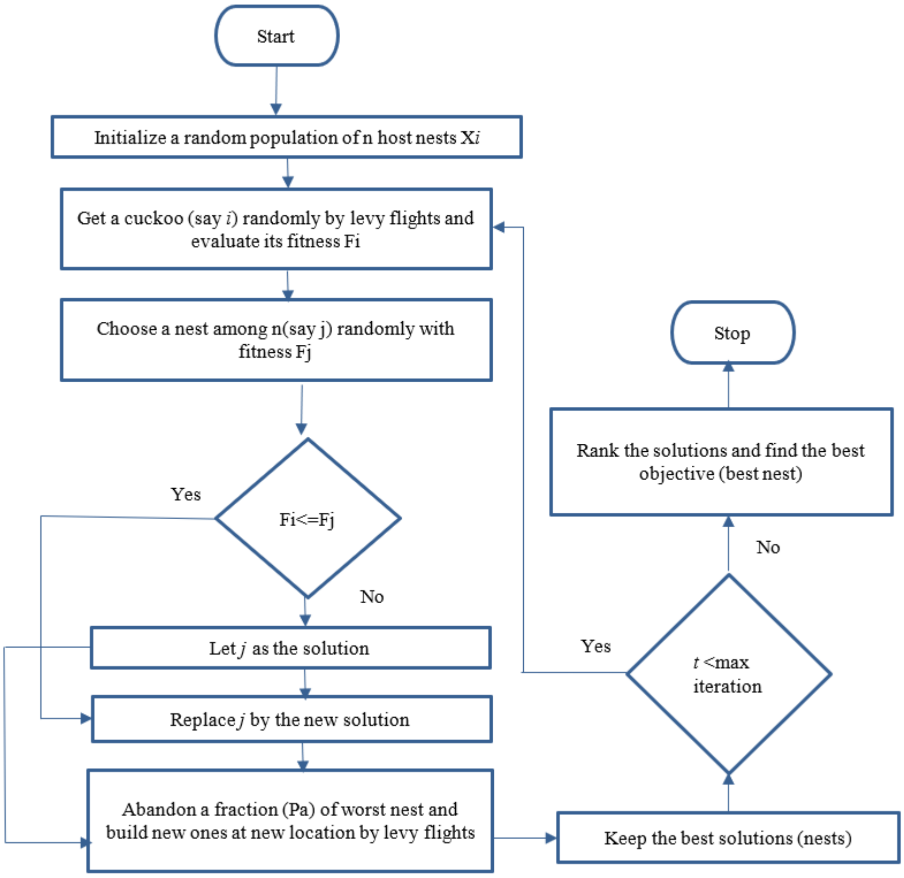


Figure 3. Flowchart of Cuckoo search algorithm

3.3 Cuckoo search algorithm (CS)

Cuckoo search is an optimization set of rules proposed by Deb and Yang in 2009 [21]. It had been inspired by the oblige offspring parasitism of some cuckoo types by placing their offspring within the nests of the opposite host birds. Some shelter birds usually neglect the interfering cuckoos and they used to throw their eggs or they used to build a new nest. For instance, if some bird discovers that the offspring aren't their personal then it'll moreover fling these foreign offspring away or shape a replacement nest at another place. The cuckoo search procedure is often implemented for several optimization problems.

The purpose behind the process is to practice the new and possibly optimum consequences to re-establish a not- so-better result within the nests. Within the coolest method, each nest has an egg. The process is often continuous to additional intricate cases during which somewhat nest has various offspring depicting a gaggle of explanations for the required persistence. The flowchart and algorithm of the cuckoo search are shown in Figure 3 and Figure 4 correspondingly [20, 41].

Cuckoo search stays on three model rules:

• A cuckoo puts one and the only offspring at a stretch and tips its egg cell thru a designated nest.

• The optimum nest with extra superiority of offspring will inheritance to subsequent creation to expand their population.

• The amount of valid host's nests is recognized, and therefore the home of offspring by a cuckoo search is conceived by the host bird with a possibility Pa ϵ (0, 1), Pb ϵ (0,1). Finding works on a couple of sets of poorest nests, and developed results are discarded from additional approximations.

Algorithm CSA

Start
{
Objective function f(x), x=(x1, x2, x3…..xd) T:
Create preliminary population of n host nests X*i* ; *i=1,2,…n*
While (t< max generation) or (Stopping criterion)
{
get a cuckoo arbitrarily by Levy flight
Estimate its fitness Fi
Select a nest among n (say k) arbitrarily
If (Fi > F*k*)
{
change k by the new result
} // End if
A portion of (Pa) of worst nest is left and new ones are figured
Save the best results
Rank the result and find the finest existing result
} // End while
After process results and visualization
}// End begin

Figure 4. Pseudocode of CS method

3.4 Adaptive gamma correction with weighting distribution (AGCWD)

To get the contrast-enhanced image, the Gamma correction method utilizes the shifting adaptive constraint γ, which is:

$$T(l) = lmax\ (l/lmax)\ \gamma \qquad (1)$$

where, *lmax* is the extreme intensity of the input. The strength l of every pixel within the input image is altered as T(l) later carrying out Eq. (1). Needless to say, the gamma curvatures exemplified with $\gamma > 1$ have exactly the contradictory outcome as those engendered with $\gamma < 1$. It can be noticed that gamma correction diminishes the uniqueness curve when $\gamma = 1$. However, once the contrast is reliably adapted by gamma correction, various images will display equivalent deviations in intensity as an outcome of the static restriction. This will be resolved by calculating the possible density of every intensity within the digital image given by the equation:

$$Pdf\,(l) = nl\,/(MN) \tag{2}$$

where, nl is that the numeral of pixels that take intensity *l* and *M, N* is that the whole amount of pixels within the image. The cumulative distribution function (CDF) is predicated on pdf (Probability density function). The normal histogram equalization straight uses CDF as a change curve articulated by:

$$T(l) = lmax\ (l/lmax)\gamma = lmax\ (l/lmax)1\text{-}CDF(l) \tag{3}$$

where, the gamma parameter supported CDF of the calculation is modified as:

$$\gamma = 1\text{-}CDF(l) \tag{4}$$

This is one of the efficient approaches to modify histograms and boost contrast within the digital image [42, 43]. The gamma parameter to switch the histogram is taken as 0.1 in the proposed method.

3.5 Contrast limited adaptive histogram equalization (CLAHE)

Contrasting the methods discussed in the aforementioned two segments, which operate on a whole image, this technique comprises of dealing with minor sections of the image (termed tiles) with histogram specifications for every tile exclusively. Bordering tiles are then united through bilinear interpolation to abolish theatrically tempted borders. The contrast, particularly in areas of homogenous intensity, is often limited to avoid amplifying noise [9]. Unlike the normal HE, CLAHE restrains the contrast by a clip point to cutoff the peak value of the histogram of each bin. The trimmed pixels are restructured to every gray level. The superior the clip point, the more the contrast is boosted. The clip point is calculated as:

$$\beta=M/N(1+(\alpha/100)\ {*}Smax) \tag{5}$$

where, M is that the quantity of pixels in the respective block, N is that the active range of this block, S_{max} is that the extreme gradient, and α is the clip factor. When α is 0, the clip point is going to be in such a way that the pixel during this chunk would be persistent. As α is fastened to 100, the contrast is boosted to an outsized mark. Thus, the clipping point is a vital feature to regulate contrast enhancement [4, 44, 45]. The clip limit is about 0.1 factor in the proposed methodology.

4. EXPERIMENTAL RESULTS AND ANALYSIS

4.1 Image data set

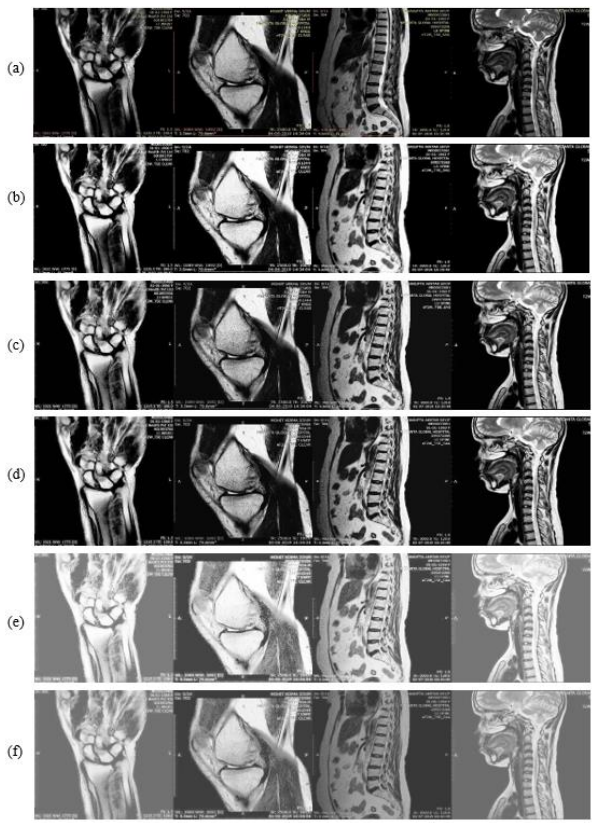
In this manuscript, the proposed scheme is evaluated with the image data set obtained from the Medanta Radiology Centre situated at the campus of Nalanda Medical College and Hospital, Patna, Bihar (India). The image data set consists of 100 MRI images of various body parts namely the brain, spine, shoulder, and knee, and have a resolution of 512 × 512 pixels. To check the competency of the proposed method, several experiments are conducted along with different other existing algorithms. For quantitative assessment, the average score of seven numerical metrics has been provided over hundred different MRI images.

4.2 Simulation setup

In the proposed method, the simulations have been done using MATLAB platform running on a system with Intel® Core i5 CPU @ 1.8 GHz processor with 8 GB of RAM. The image quantitative parameters like structural similarity index module (SSIM) [46], Gradient magnitude similarity deviation (GMSD) [47], Absolute Mean- Brightness Error (AMBE), Discrete entropy (DE) [48], Features Similarity Index Matrix (FSIM) [46], patch-based contrast quality index (PCQI) [49, 50], and Modified measure of enhancement by entropy (MEME) [47] values are computed to check the efficiency of the proposed method.

4.3 Performance evaluation and comparison

The performance of the proposed method is analyzed by qualitative and quantitative methods. The qualitative methods contain a comparison of output images attained from the proposed method and other methods reported in the literature. The proposed algorithm is evaluated on the 100 MRI images of various body parts. Figure 5(a) shows the input images of the brain, shoulder, spine, and knee. The corresponding enhanced images obtained are compared with the various existing algorithms namely, AGCWD [40], BBHE [51], DSIHE [52], DWT-SVD-AGC [32], DWT-SVD [3], HE [44], SHMS [53], WAHE [54], and Enhanced Cuckoo Search Algorithm (ECSA) [28] respectively.



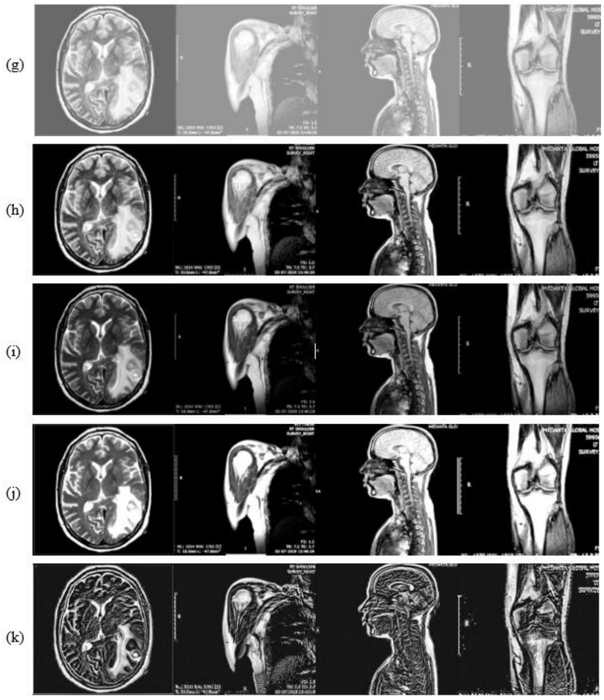


Figure 5. (a) Input images of various body parts. Enhanced output images using (b) AGCWD [40], (c) BBHE [51], (d) DSIHE [52], (e) DWT-SVD-AGC [32], (f) DWT-SVD [3], (g) HE [44], (h) SHMS [53], (i) WAHE [54], (j) ECSA [28] and (k)

In Figure 5 (a-k) and Figure 6 (a-k); the proposed method, Figure 5 (k) and Figure 6 (k) have clearly shown the distinct features of the input images as equated to other algorithms. The proposed method boosts contrast in such a manner that the detailed information can be fetched from the images clearly and features can be extracted for further processing. As compared to other algorithms, it has increased the contrast values in such a way that it has uniformly distributed the intensity values so that optimum contrast value can be reached.

Figure 7 and Figure 8 show the qualitative comparisons between the input images of various body parts and the corresponding enhanced output images attained from the proposed method. From the illustrations in Figure 7(b) and Figure 8(b), it is clear that the proposed method has enhanced contrast and sharpness which make the edges and curves quite visible in the MRI images. For example, considering Figure 7 (b) the input image of the brain shows the deep cut section but it is not visible whereas the corresponding processed output image shows the depth of the cut with increased sharpness.

The quantitative comparison is done using GMSD, SSIM, AMBE, MEME, DE, FSIM, and PCQI with various contrast enhancement techniques reported in the literature.

Table 1 and Figure 9(a-g) illustrate the tendency and variations of AMBE, SSIM, GMSD, DE, FSIM, PCQI, and MEME of different contrast enhancement techniques for the proposed one. The tendencies and variation of these qualitative indices for the proposed one is evaluated for the 100 MR image dataset. The comparison and variations of GMSD concerning the proposed scheme have been shown in the second column of Table 1 and Figure 9(a) respectively. From the table and Figure 9(a), it can be detected that the GMSD value for the proposed method is lowest between the other methods and slightly less than the BBHE method. Other methods have very much large values as compared to the proposed one. As mentioned earlier GMSD value specifies the quality of the image that has been enhanced by the integration of pixel-wise gradient magnitude similarity through the standard deviation. The more is deviation, the more inferior the image perceptual quality we get. Hence for better enhancement, we need the low value of GMSD.

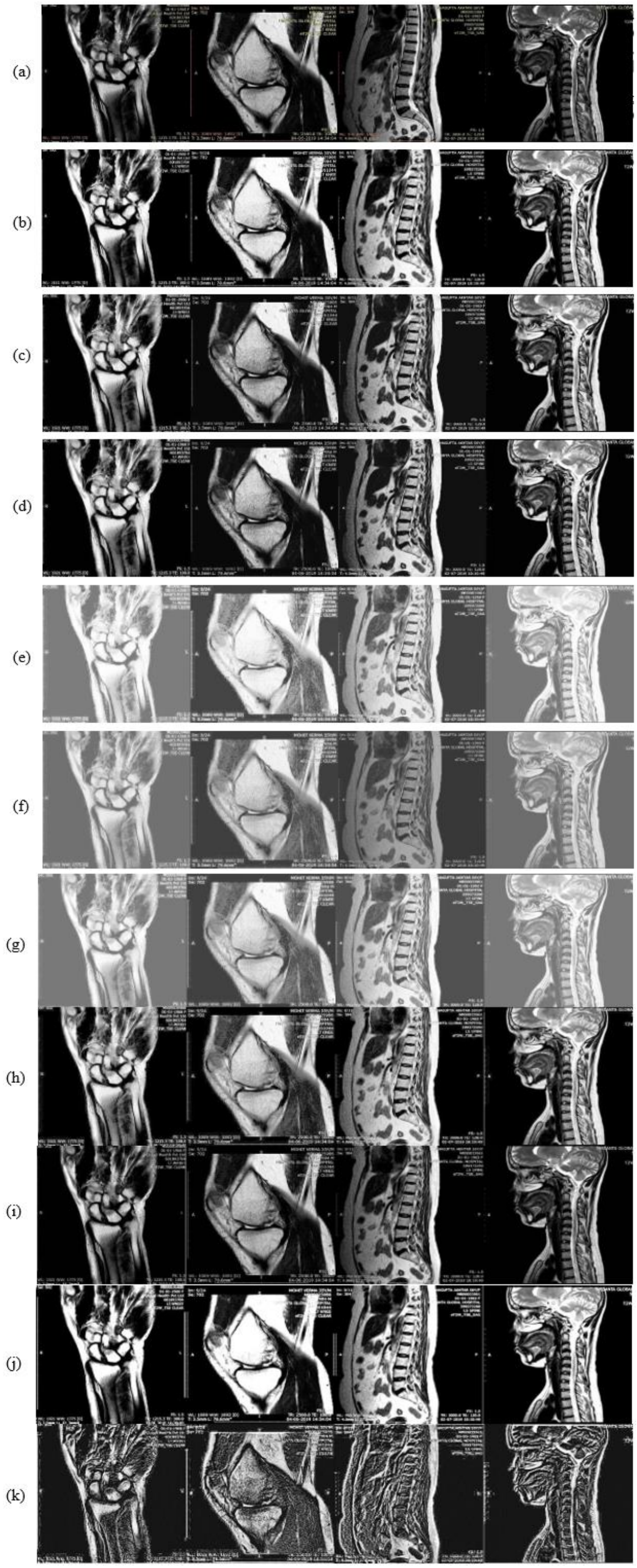
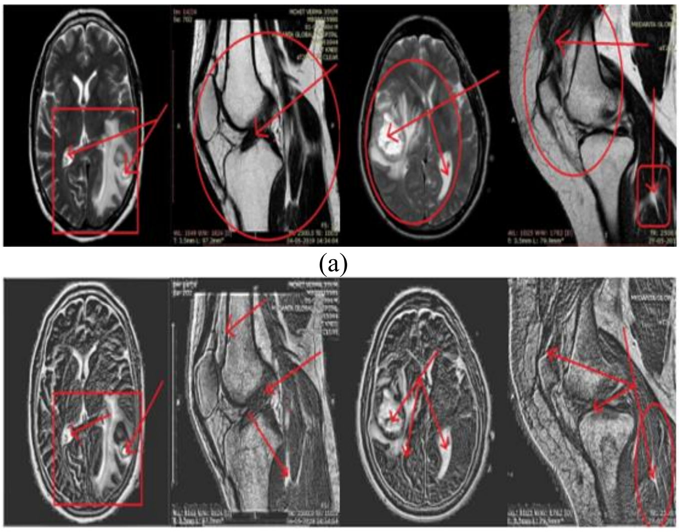


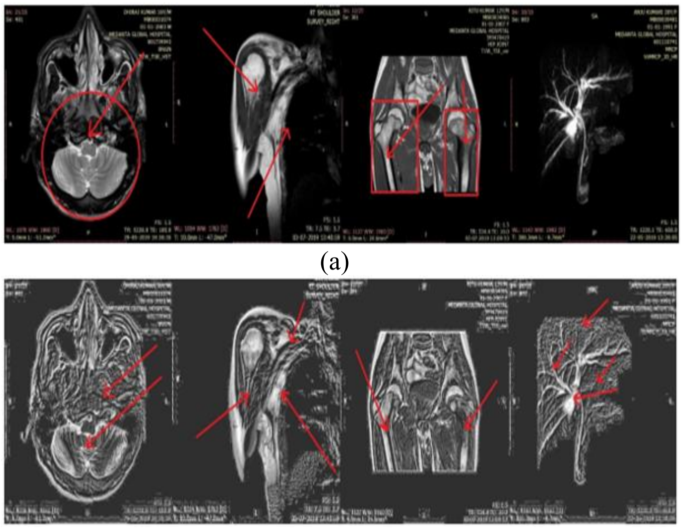
Figure 6. (a) Input images of various body parts. Enhanced output images using (b) AGCWD [40], (c) BBHE [51], (d) DSIHE [52], (e)DWT-SVD-AGC [32], (f) DWT-SVD [3], (g) HE [44], (h) SHMS [53], (i) WAHE [54], (j) ECSA [28] and (k) Proposed method



(a)

(b)

Figure 7. (a) Comparison of contrast enhancement concerning the input image of the knee cap and brain having a tumor, (b) Output generated by the proposed method



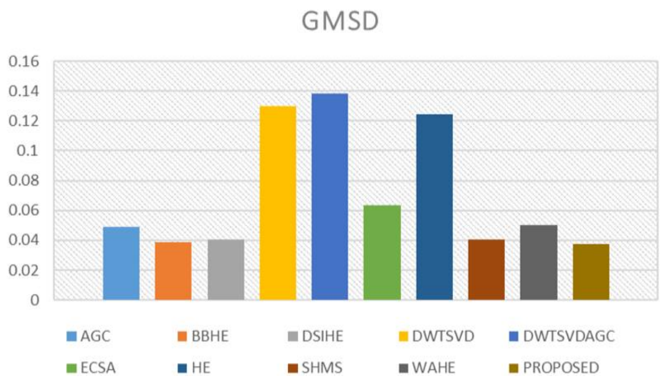
(a)

(b)

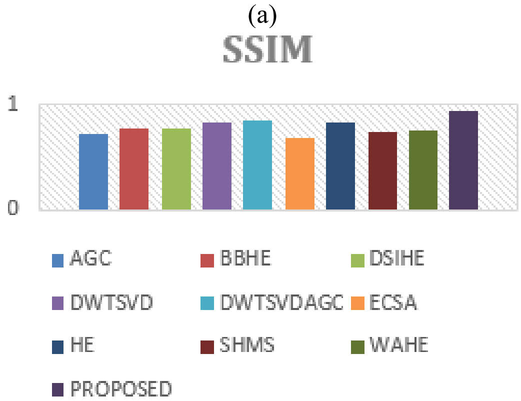
Figure 8. (a) Comparison of contrast enhancement concerning the input image of the various body parts, (b) Output generated by the proposed method

Table 1. Comparison of quantitative metrics for various algorithms evaluated on MRI image dataset over 100 images

Images	Methods	GMSD	SSIM	AMBE	MEME	DE	FSIM	PCQI
1	AGCWD [40]	0.049055	0.72521	9.121159	16.14581	3.42943	0.968645	0.957805
2	BBHE [51]	0.038482	0.783008	7.794701	13.07406	3.589383	0.983194	0.964659
3	DSIHE [52]	0.040538	0.782599	7.806443	16.16056	3.605931	0.982501	0.965652
4	DWT-SVD [3]	0.130101	0.825131	25.0637	18.56317	3.284034	0.876128	0.997015
5	DWT-SVD-AGC [32]	0.138375	0.841767	25.72234	22.11485	3.367302	0.873603	0.985906
6	ECSA [28]	0.063299	0.680763	9.74636	17.26918	3.348376	0.950194	0.942161
7	HE [44]	0.124507	0.83567	28.99013	20.32463	3.422041	0.89856	0.971505
8	SHMS [53]	0.040516	0.736982	8.710111	16.42714	3.628348	0.982083	0.952008
9	WAHE [54]	0.05031	0.762476	13.7933	9.659269	3.484226	0.962141	0.984254
10	Proposed Method	**0.03781**	**0.933395**	**6.64568**	**28.28679**	**3.677221**	**0.988143**	**1.032783**



(a)



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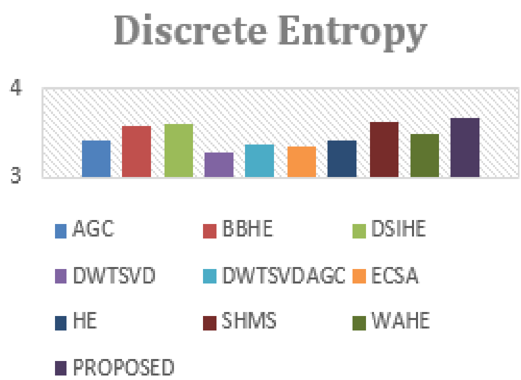

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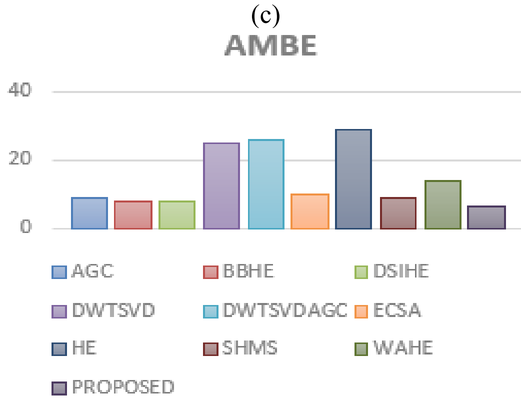

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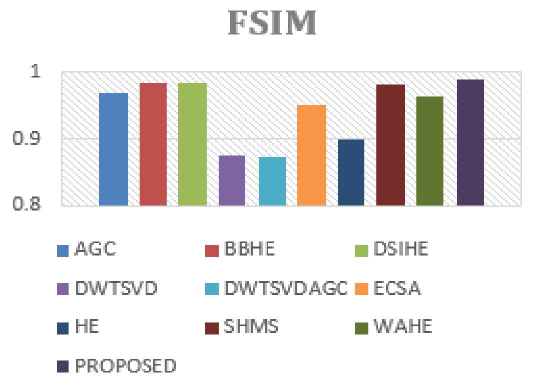

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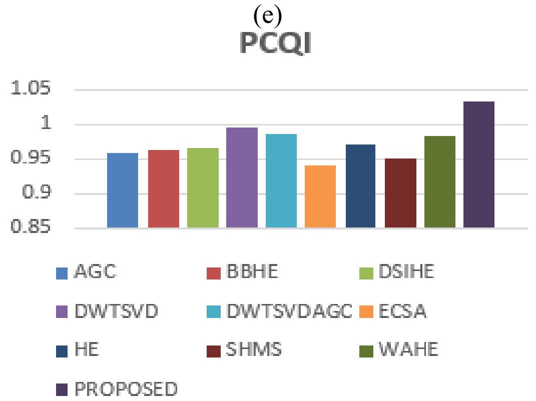

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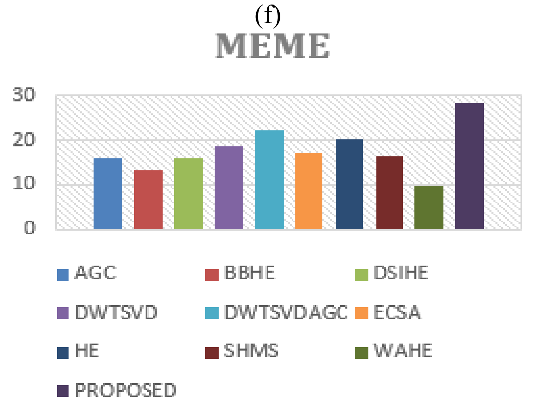

(g)

Figure 9. Quantitative comparisons of different method with proposed method (a) GMSD [47], (b) SSIM [46], (c) Discrete Entropy [48], (d) AMBE [48], (e) FSIM [46], (f) PCQI [49] and (g) MEME [48]

The third column of Table 1 and Figure 9(b) depicts the variations and the nature of the SSIM quantitative index. As reported in the literature and aforementioned that SSIM varies between zero to one. SSIM having equal to one shows the precise structural likeness of two images. For better-enhanced output, the SSIM values should be near to unity and from the second column of Table 1 and Figure 9(b), the proposed method shows the highest value among the other compared existing methods and has nearer to unity value.

The fourth column of Table 1 and Figure 9 (d) represents the values and comparison plots of AMBE. AMBE indicates the absolute error of the mean brightness of the input and output image. For better enhancement of the image the values of the AMBE should be less and from Table 1 and Figure 9 (d), we can observe the proposed technique has the lowest AMBE value among the other mentioned methods. In the fifth column of Table 1 and Figure 9 (g) the comparison of MEME values has been represented. From the figure and numerical values tabulated in the fourth column of a table, it can be inferred that the proposed method has the highest MEME value. All other methods whose values lie in between (9 to 23) whereas our method has the highest value of 28.28679. The MEME value indicates a measure of enhancement by approximating the mean contrast within the image by separating the image into non-overlapping subgroups and evaluating the amount supported for least and extreme intensity values in each subgroup. For better enhancement, the values should be high as possible.

Entropy measure defines the richness of information contained in the given image. A processed image with high and comparably nearer entropy value to the reference image holds the most information content. DE (discrete entropy) values are tabulated in the sixth column of Table 1 and represented in Figure 9 (c). The Discrete entropy computes the information content from the image, the higher the rate of entropy, the more information content is fetched from the image. From the table and the figure mentioned, it can be observed that the proposed method fetches slightly more data content from the input image as related to other mentioned methods. On analyzing, the proposed method holds higher and closer entropy value to the reference image while compared with the other approaches.

FSIM is used for comparing the features and processing the resemblances between two images. The variation and trend are tabulated and represented in Figure 9 (e) and the seventh column of Table 1 respectively. From the literature, it has been found that the FSIM is standardized between 0 and 1. The table and figure representing the FSIM of different methods, it is inferred that the proposed method has the highest score among the other existing methods. BBHE and DSIHE methods show similar trends of FSIM and have near about values to the proposed one, but other parameter does not satisfy so much as ours.

The last column of Table 1 and Figure 9 (f) shows the trends and variation of PCQI values. PCQI values are used to find out the relation between input and processed output image such that how much contrast has been altered by preprocessing methods can be found out. From the literature, it has been found that higher values of PCQI show better contrast value in an output image. Hence from Table 1 and Fig. 9 (a-g), it can be observed that the proposed algorithm has lower AMBE and GMSD, higher SSIM, DE, FSIM, PCQI, and MEME compared to other contrast enhancement techniques. In Table 1, bold faces represent the best score among all methods for 100 medical images and second best values are represented through underline mark. Hence, it can be concluded from this comparative analysis that the proposed method is the better contrast enhancement approach as compared to the existing methods in the literature.

Table 1 demonstrates the objective score of different methods for an average of 100 images. Table 1 clearly states that the proposed method outperforms all other existing methods for all objective metrics. On summarizing visual and objective assessment, the proposed method shows its superior performance in enhancing details, exposing scene content, removing contrast noise and improving natural gray tone. Hence the proposed method becomes a better choice for medical application in revealing the contrast distorted content.

5. CONCLUSIONS

In this paper, a novel method is proposed for the contrast enhancement of medical MRI images. The contrast optimization value is first calculated using the cuckoo search algorithm through which dynamic scale selection is completed for the reconstruction of approximation coefficients of frequency sub-bands of the wavelet transform. The dynamic scale selection is then corrected by gamma correction and followed by a limited histogram equalization approach. For performance assessment, the projected method is initially compared with the acquired database image from Nalanda medical college and hospital, Patna (Bihar) with SSIM, PSNR, GMSD, and AMBE values compared with different existing approaches. It's found that our proposed approach has better performance in terms of better contrast enhancement than other existing states of the art enhancement methods. In medical image analysis, the better contrast of image has quite an importance as it brings more clarity and visibility to the hidden and invisible clinical details present in the MRI images. Experimental findings demonstrate that the proposed method produces comparable or better visual quality enhanced medical images than nine state-of-the-art enhancement methods.

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