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A novel brightness preserving joint histogram equalization technique for contrast enhancement of brain MR images

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ABSTRACT

Low contrast is a challenging factor in brain magnetic resonance (MR) images due to its structural complexity. Histogram equalization (HE) approach is often used in enhancing the contrast in brain MR images. However, the spatial information is not taken into account in this approach. Further, the problem of preserving structural details while retaining the brightness is also an important concern. To solve these, we suggest a novel stationary wavelet transform based brightness preserving joint histogram equalization (SWT-BPJHE) scheme for brain MR image contrast enhancement. Our contributions are – i) use of SWT to extract the low sub-band wavelength coefficients from the low contrast input image for enhancement, ii) to isolate the high frequency wavelength coefficients from enhancement, retaining the structural details, iii) to preserve brightness. The suggested scheme is experimented with synthetic brain MR images from BrainWeb and clinical images from Howard Whole Atlas databases. The performance is evaluated in terms of several validation indices followed by statistical analysis. The outcomes reveal the superiority of the suggested scheme in comparison to state-of-the-art methods.

1. Introduction

Magnetic resonance (MR) imaging is a commonly used modality in clinical image analysis and disease diagnosis. Usually, they provide detailed tissue structures in the human anatomy. Low contrast in MR images occurs due to poor imaging environment. It eliminates the structural details from the edge and indiscriminate tissue regions in the case of brain MR images. Hence, low contrast is a major concern while identifying the details in the tissue regions. In the last decade, several techniques are reported in the literature [1–4]. These techniques are mainly categorized into two groups: spatial domain and transform domain.

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In the spatial domain, histogram equalization (HE) is a widely used technique for enhancing the contrast in brain MR images. The method employs the mapping of grey levels from the low contrast input image to the enhanced image using a cumulative distribution function (CDF). This mapping stretches the intensity levels with a larger pixel population to occupy a broader range while the smaller pixel population is compressed [5]. It has gained popularity due to its computational simplicity. However, the images may get over enhanced due to the presence of high peaks in the histogram. This results in eliminating the structural details in the brain MR images. This also enhances the noise in the MR image, resulting in uneven brighten appearances in the enhanced image. Therefore, preserving the structural details, retaining the brightness of the MR image, isolating noise from the enhancement process are some of the major challenges in the brain MR image enhancement problem.

Many researchers have implemented histogram based techniques for enhancing brain MR images [6–9]. The adaptive histogram equalization (AHE) approach with a suitable clip limit results in better enhancement. However, it introduces blocky artifacts and noisy appearances in the enhanced images [6]. The sub-image HE approach is found to be suitable for preserving brightness while enhancing the brain MR image. However, over enhancement and structural detail elimination are the inherent problems [7]. In [8], the authors suggested a weighted grey scale histogram feature for automatic brain hemorrhage segmentation and classification. They used the median filter to enhance the quality of the CT image. Then some thresholding techniques and functions were used to enhance the image using the histogram. The authors in [9] presented a study on the different histogram equalization techniques for brain MR image enhancement. They compared five different modifications of the HE technique using four different objective quality metrics. However, the authors were silent about the best method for enhancement.

Ismail and Sim [10] suggested the dynamic histogram equalization (DHE) scheme for preserving the brightness in low contrast MR images. This is achieved by normalizing and smoothing the histogram of the input image, followed by sub-image HE processing. The method preserves mean brightness in the brain MR images. However, the structural details are eliminated due to the smoothing estimation in the equalization process. Wei et al. [11] suggested an entropy maximization histogram modification (EMHM) technique for contrast enhancement. The pixel population of the input image is computed using an entropy maximization rule. Then the grey levels are redistributed using a log-based function. This helps in enhancing the structural details within the tissue regions. However, the logarithmic approach of redistributing the pixel values to approximately extreme values results in reduced brightness.

Chen et al. [12] suggested a hierarchical correlation histogram analysis. The method is employed for enhancing the lesions in brain MR images due to Parkinson's disease. However, bright patches are observed within the tissue regions due to over enhancement. Besides, it also eliminates the structural details. Isa et al. [13] suggested an average intensity replacement adaptive histogram equalization (AIRAHE) technique for identifying the abnormalities in the cerebral white matter region. The proposed algorithm employs a sliding kernel operation for obtaining an average intensity value of the neighboring pixels. The technique results in partial contrast stretching and enhancement in the brain MR images. However, the structural details are eliminated in the edge regions due to the spatial average filtering.

Agarwal and Mahajan [14] suggested a technique based on sub-image histogram formulation and gamma correction for enhancing contrast in brain MR images. The authors integrated range limited and weighted HE techniques. The cascade structure of adaptive gamma correction and homomorphic filtering is used for preserving edge details while enhancing contrast. However, a small amount of noise in the MR image may reduce the visibility of the tissue structures in the enhanced image. In [15], the authors suggested a contrast limited fuzzy AHE (CLFAHE) techniques for enhancing the contrast in brain MR images. A contrast intensification operator is used for representing the intensity levels in terms of membership values. Then, the contrast limited AHE (CLAHE) is employed for contrast enhancement and brightness preservation.

From the above discussions, it is observed that the enhancement techniques in the spatial domain suffer from over enhancement and elimination of important tissue regions from the brain MR images. In the transform domain, the low contrast image is first transformed into a suitable frequency domain. The frequency components are then decomposed into sub-bands using the high pass and low pass filters. The desired spectral band is enhanced locally or globally using multiscale HE. Then, the enhanced spectrums along with the other spectrums are recombined to form the enhanced image. However, they are computationally intensive. Further, halo artifacts are introduced in the enhanced image along the edge regions. On the other hand, the use of wavelet transform (WT) does not introduce halo artifacts [16]. Yang et al. [17] suggested a nonlinear HE technique on WT coefficients for enhancing contrast in the brain MR images. The lower sub-band of the transformed wavelet coefficients are enhanced using the non-linear HE. Finally, inverse WT is used for reconstructing the enhanced image.

Lidong et al. [18] suggested a CLAHE technique in the WT domain (WT-CLAHE) for image enhancement. The method decomposes the image into two sub-bands: low and high frequency wavelet coefficients. Then, the image with lower frequency sub-band is enhanced using the CLAHE technique. The method is effectively enhancing the image without amplifying the background noise. However, the image details on the edge region may get eliminated due to the rotational and shift variance properties of the WT. Murugachandravel and Anand [19] suggested a two-stage AHE approach in the WT domain for enhancement. The low contrast brain MR image is split into sixteen sub-images using wavelet transform. Then, each sub-image is enhanced using the AHE technique. Javadi et al. [20] suggested a piecewise linear HE technique for enhancing the contrast in the frequency domain. Their technique enhances the contrast by stretching the whole spectral intensity. However, the resulting images are over enhancement within the tissue regions with the elimination of the edge details. In [21], the author suggested a model by combining the DHE with particle swarm optimization (DHE-PSO) algorithm for determining the optimal fuzzy parameters. This is to preserve the brightness in the actual brain MR image while enhancing its tissue regions. The method works simultaneously on particular nodes in the histogram to make it faster in comparison to the conventional approach. However, the structural details within the tissue regions are eliminated.

Nigam et al. [22] suggested a morphological filtering based method for enhancing contrast in brain MR images. The method used disk shaped structuring element for enhancing tumor region in the brain MR images. Sahnoun et al. [23] suggested a wavelet based singular value decomposition [DWT-SVD] algorithm for brain tissue exploration, where general HE is used for contrast enhancement. Ullah et al. [24] focused on brain image classification using deep neural network. They used CLAHE technique for contrast enhancement in the pre-processing stage. Veluchamy et al. [25] suggested an enhanced fuzzy level set approach for segmenting different tissue regions in brain MR images. The bi-histogram equalization [BPHE] process for contrast enhancement is employed in its pre-processing stage. Wadhwa and Bhardwaj [26] suggested G-L fractional differential mask for enhancing the edges and texture. The input image is divided into edges, texture and smooth areas by using a gradient based threshold value. The method enhances only the edges and the textures, while leaving out the smooth areas in the image. In [27,28], the authors suggested a method for detecting gadolinium deposit in gliomas associated with tumor contrast enhancement. Eichinger et al. [29] presented an investigation on the methods used in detecting multiple sclerosis lesions from unenhanced brain MR images. Bot et al. [30] presented a study on the methods used for enhancing miliary on T1-weighted brain MR images.

It is conclusive from the above discussions that the conventional HE based methods suffer from over enhancement problem, while the WT based contrast enhancement approaches suffer from loss of structural details in the edge regions. The reason may be the rotational variance property of the WT. Hence, we are motivated to suggest a new method for contrast enhancement of brain MR images. In this paper, we suggest the SWT-BPJHE technique for enhancing the contrast in brain MR images. The SWT is an undecimated and rotationally invariant transform. Therefore, the structural details are preserved irrespective of rotation or shifting of the image. Firstly, we use SWT to decompose the input image into four sub-bands. The lowest sub-band of wavelet coefficients only are extracted for the enhancement using the BPJHE technique, while the other higher sub-bands are kept isolated. This helps in preserving the structural details (present in the high sub-band coefficients) in the brain MR images while isolating the noise from the enhancement process [31]. Then the lower sub-band wavelet coefficients are again decomposed into two sub-images based on the image mean value. Each sub-image is enhanced using the proposed technique. Finally, all the sub-bands are recombined using inverse SWT (ISWT). The method is incorporating the spatial information using the joint histogram in the equalization process [32], i.e. the correlation information is incorporated into the enhancement process. This eliminates the over enhancement problem of the conventional approach. It also preserves the actual brightness of the MR image effectively. The proposed method does not require the decimation and interpolation in the enhancement process. Therefore, it reduces the computational complexity in comparison to the WT based methods.

The suggested technique is experimented on healthy synthetic brain MR images [33] and clinical brain MR images [34]. The performance of the suggested technique is compared with some standard and recently published techniques. The suggested technique is examined using a set of standard validation indices. The experimental results are shown in Table 1–4 and Figs. 4–8. The proposed technique is found to be effective and may be useful in pre-processing stages in any of the image processing applications. The remaining of the manuscript is organized as follows: Section 2 presents the related work. The proposed SWT-BPJHE technique is explained in Section 3. The results are shown in Section 4. In Section 5, a brief discussion on the experimental results is presented. Lastly, Section 6 presents the conclusion and future scope.

2. Related studies

In recent years, several research articles are reported on brain MR image contrast enhancement. It is observed that HE based approaches are commonly used. In this section, some of the classic and recent state-of-the-art methods are briefly discussed. It particularly explains the methods used for a comparison with the proposed technique.

A. HE method

This is a commonly used method in image contrast enhancement due to its simplicity in implementation. The method stretches the dynamic range of the image along with the possible intensity values. Let $X = \{x(i, j)\}$ represent the low contrast brain MR image of dimension $M \times N$ consisting of L intensity levels denoted as $\{X_0, X_1, \ldots, X_{L-1}\}$. Here L is the number of possible intensity levels (usually 256), $x(i, j)$ denotes the image intensity level at the spatial location (i, j). For the given image X, the probability density function $p(X_k)$ is defined as:

$$p(X_k) = \frac{1}{MN} n^k \quad (1)$$

for $k = 0,1,\ldots, L-1$, where, MN is the total number of pixels in X, n^k is the pixel population count of an intensity level X_k. Then, the CDF is computed as:

$$CDF(X_k) = \sum_{j=0}^{k} p(X_j) \quad (2)$$

for $k = 0, 1,\ldots, L-1$. The enhanced pixel intensities are computed with the use of these CDF values as:

$$S_k = T(X_k) = \lceil (L-1)\{CDF(X_k) - (CDF(X_k))_{\min}\} \rceil \quad (3)$$

where $\lceil . \rceil$ indicates the ceiling operator and CDF_{min} is the minimum of the CDF values.

The method is a straightforward mechanism of mapping the grey levels from input to the output. However, over

Table 1 – Comparison of different methods using synthetic brain MR images.

Methods	MSE	H	AMBE	DE_N	EBCM	QRCM	PCQI
HE [9]	114.16	5.2189	0.3520	0.4539	0.5219	0.1909	0.9941
EMHM [11]	101.95	4.8203	0.4210	0.4755	0.5103	−0.0314	0.9378
AIRAHE [13]	106.73	5.7055	0.6289	**0.4958**	0.5346	0.2917	1.1648
CLFAHE [15]	97.52	5.0833	0.4592	0.4516	0.5434	0.0774	1.0243
WT-CLAHE [18]	74.75	4.9193	0.5401	0.4112	0.5424	0.2501	1.1734
DHE-PSO [21]	90.76	5.4721	0.6089	0.4223	0.5347	0.2756	1.0041
DWT-SVD [23]	80.25	4.7452	0.5251	0.4101	0.5152	0.2647	1.1212
BPHE [25]	85.37	5.1313	0.5874	0.4227	0.5234	0.2824	1.0849
SWT-BPJHE	**63.68**	**5.8708**	**0.6836**	0.4934	**0.5621**	**0.3320**	**1.5545**

Table 2 – Comparison of different methods using clinical brain MR images without lesion.

Methods	MSE	H	AMBE	DE_N	EBCM	QRCM	PCQI
HE [9]	98.29	5.7908	0.3121	0.5196	0.5321	0.1768	1.1998
EMHM [11]	66.90	6.9955	0.4505	0.5151	0.4921	0.1703	1.8461
AIRAHE [13]	52.53	5.7278	0.5252	**0.5266**	0.5034	0.2092	2.3418
CLFAHE [15]	55.09	6.1750	0.4657	0.4355	0.5129	0.0993	1.3757
WT-CLAHE [18]	77.03	6.2888	0.4130	0.4452	0.4825	0.2451	2.0306
DHE-PSO [21]	48.61	6.4280	0.5241	0.4821	0.5346	0.1521	1.5478
DWT-SVD [23]	75.46	5.9802	0.4954	0.4562	0.5014	0.2016	1.8475
BPHE [25]	60.27	6.0124	0.5127	0.4749	0.5127	0.2124	1.9587
SWT-BPJHE	**41.96**	**7.2783**	**0.5966**	0.5208	**0.5411**	**0.2489**	**2.4191**

Table 3 – Comparison of different methods using clinical brain MR images with lesion.

Methods	MSE	H	AMBE	DE_N	EBCM	QRCM	PCQI
HE [9]	106.20	6.6315	0.4168	0.4640	0.5321	0.1740	1.7308
EMHM [11]	85.00	5.5020	0.4489	0.4609	0.4419	−0.0237	2.2077
AIRAHE [13]	78.36	5.7462	0.5191	0.4591	0.5472	0.2512	2.5371
CLFAHE [15]	87.24	6.3339	0.4730	0.4720	0.4651	−0.0414	2.1899
WT-CLAHE [18]	68.55	6.8564	0.4522	0.4398	0.5126	0.1802	2.3539
DHE-PSO [21]	65.29	6.1475	0.4825	0.4189	0.5152	0.1824	2.3425
DWT-SVD [23]	70.24	6.5921	0.4342	0.4215	0.5017	0.1951	2.0154
BPHE [25]	67.33	6.4512	0.4457	0.4134	0.4956	0.2018	2.0202
SWT-BPJHE	**51.66**	**7.2080**	**0.5240**	**0.4955**	**0.5524**	**0.2930**	**2.7954**

Table 4 – Statistical analysis using Friedman Test.

Methods	MSE	H	AMBE	DE_N	EBCM	QRCM	PCQI
HE	0.0061	0.0017	0.0342	0.0199	0.0115	0.0001	0.0001
EMHM	0.0065	0.0015	0.0412	0.0274	0.0202	0.0001	0.0001
AIRAHE	0.0057	0.0010	0.0365	0.0374	0.0248	0.0001	0.0001
CLFAHE	0.0083	0.0024	0.0433	0.0298	0.0237	0.0001	0.0001
WT-CLAHE	0.0087	0.0023	0.0341	0.0225	0.0198	0.0001	0.0001
DHE-PSO	0.0112	0.0037	0.0426	0.0387	0.0254	0.0001	0.0001
DWT-SVD	0.0075	0.0028	0.0347	0.0324	0.0284	0.0001	0.0001
BBHE	0.0080	0.0049	0.0401	0.0279	0.03142	0.0001	0.0001

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enhancement may occur due to peaks in the histogram. Various modifications to the conventional HE technique are reported in the literature for solving this problem. The methods are AHE, CLAHE, DHE etc. However, spatial information of a pixel, which carries almost similar features in the neighborhood, is not considered in the computation process, [9].

B. EMHM method

This technique consists of an entropy maximization histogram modification technique in combination with pixel population merging and grey level distribution. The entropy maximization is achieved by minimizing the reduction of entropy in the pixel population merging stage. This is achieved in two steps. 1) Identifying a grey scale (X_k) with a minimum pixel count in the histogram. 2) Merging the pixel count of (X_k) with a nearby intensity value with similar pixel count, while making its pixel count zero in the resulting histogram. These two steps are repeated T_m times, where T_m is the mergence time. This maximizes the entropy of the output by minimizing the decrease in entropy. The reducing entropy of the grey level (X_k) with probability distribution $p(X_k)$ in the input histogram is expressed as:

$$\frac{\partial E_d}{\partial k} = p(X_k)\{(1+q)\log(1+q) - q\log(q)\}. \tag{4}$$

This indicates a monotonically increasing function with q iterations. For smaller values of q, more similar grey scales are merged.

The over enhancement problem is addressed using a log-based function in the grey level distribution stage. This transform function is expressed as follows:

$$T(l) = \sum_{j=0}^{L-1}\log\left(\frac{h_{op}(j)}{\bar{h}} \times 10^{-m} + 1\right) \quad \forall\, l = \{1, \ldots, L\}, \tag{5}$$

In this expression, $h_{op}(j)$ and $\bar{h}$ are the pixel population and mean value of the j^{th} grey level in the output histogram respectively. m is a controlling parameter for the logarithmic distribution function. The maximum intensity value is L. The pixel population merging in EMHM reduces the redundancy in the actual image. This also controls the number of non-zero grey scale pixel population in the contrast enhanced image. However, the structural details are lost and the noise in the MR image also gets enhanced [11].

C. AIRAHE method

This is an intensity adjustment approach based on the contrast mapping technique for contrast enhancement. The method employs multiple enhancement techniques in stages for improving the contrast in the brain MR images. The first stage of the scheme is partial contrast stretching. This improves the visibility of the tissue regions in the brain MR image. In the second stage, the image is processed through a contrast enhancement procedure using the CLAHE technique. This stage enhances the contrast of each local region while avoiding the enhancement of noise in the brain MR images. In the third stage, the MR image is convoluted with a weighted averaging window. Here, each pixel intensity value is replaced with the average intensity of the pixels in its neighbourhood. The algorithm is tested on enhancing the contrast in brain MR images while segmenting the white matter hyper-intensity regions. However, structural details from the tissue regions are eliminated with checker artifacts in the enhanced brain MR image [13].

D. CLFAHE method

This is an extension of the bi-histogram based technique for preserving the original brightness in an MR image while enhancing the contrast. Here, each intensity value is assigned with a membership value for representing the image in a fuzzy plane. The fuzzy membership values are used to form the sub-images. This is achieved by assigning larger weight to the grey levels approximating the mean intensity value of the image. The membership values are computed as:

$$P_{mn} = \begin{cases} 2 \times \mu_{mn}^2 \text{ if } \mu_{\mathrm{mn}} \leqslant 0.5 \\ 1 - 2(1-\mu_{mn})^2 \text{ if } 0.5 \leqslant \mu_{\mathrm{mn}} \leqslant 1 \end{cases} \tag{6}$$

where $\mu_{mn} = \exp - \left(\frac{(L - \frac{x_{mn}}{\sigma})^2}{2}\right)$ is the membership function, x_{mn} indicates any pixel value at location (m, n). L is the maximum intensity value with variance σ. The contrast enhanced MR image (g_{mn}) is reformed as:

$$g_{mn} = L - S(\sqrt{-2\log\mu_{mn}}) \tag{7}$$

Finally, the intensity mapping transform is employed for reforming contrast enhanced brain MR image. The method is found to be effective in enhancing the brain MR images. However, the problem of preserving the structural details remains unsolved [15].

E. WT-CLAHE method

This method combines the WT with CLAHE for contrast enhancement in the MR images. It consists of three stages. Firstly, decomposing the image into two sub-bands using WT. A two-channel filter bank is used to form low frequency and high frequency sub-bands of the input MR image. The multi-resolution decomposition is achieved by employing down samplers in combination with the filters repetitively. Usually, the detailed information is contained in the high frequency regions. In this scheme, this sub-band is separated from the enhancement process. Secondly, the low frequency coefficients are processed for contrast enhancement using the CLAHE technique, while keeping the high frequency components unchanged. This also limits the noise components in the high frequency region from the enhancement process, i.e. it limits the noise enhancement. Finally, recombining the enhanced wavelet coefficients to form the contrast enhanced image using inverse WT. However, this approach needs the size of the input image to be the power of two. Further, there may be loss of features from the same object with trivial movement due to translation variant property of discrete WT [18].

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F. DHE-PSO method

This is an optimizing approach to the conventional dynamic HE technique. Here, an improved PSO algorithm is employed for optimizing the local minima values in the dynamic histogram. In the first step, the MR image is processed through a smoothing filter. This reduces the noise in the image. In the second step, the image is segmented into four non-overlapping regions based on its median values. The segmented images contain an equal amount of pixels using the median value. In the third step, the brightest and darkest pixels are separated by identifying maximum points along the curve regions. The weights ($W(I)$) at local maximum are computed using pixel counts(n^k) from the histogram of the input image, as:

$$W(I) = \sum_{x=1}^{M}\sum_{y=1}^{N} \frac{n^k}{\max(n^k)} \quad (8)$$

The optimum weights are computed using the improved PSO algorithm. Here, the image elements (location and velocity) are randomly initialized and processed to get the process gain. The modified histogram is constructed using the input histogram and the optimal weight as:

$$H(l) = h(l, i) * W(I) \quad (9)$$

Finally, the contrast enhanced brain MR image is reconstructed from the dynamically equalized histogram without any proper modification [21].

3. Proposed methodology

As discussed above, the histogram-based techniques are popularly used for contrast enhancement due to their computational simplicity and implementation. However, they do not include spatial information and fail to preserve the brightness and tissue structure. Further, over enhancement and noisy appearance are the inherent problems with such techniques. Here, we propose a new SWT-BPJHE technique for enhancement. The flowchart of the proposed technique is given in Fig. 1.

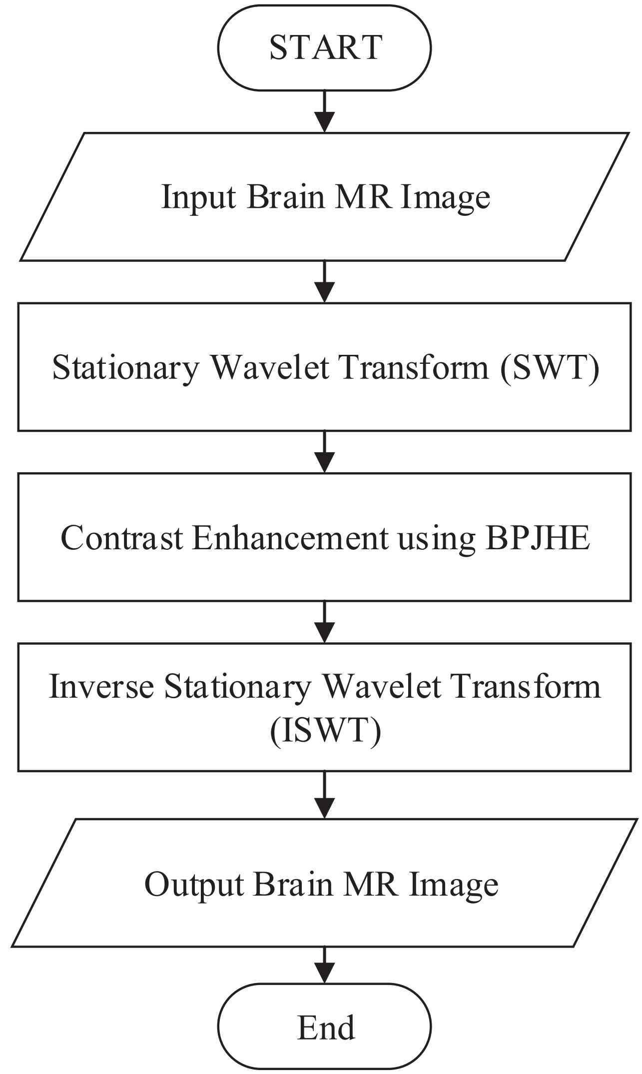

Fig. 1 – Flowchart of the suggested technique.

The transform domain method of contrast enhancement is followed in this paper. The low contrast input image is first decomposed into four sub-bands using SWT as shown in Fig. 2. The sub-bands are computed as:

$$[A(m,n), H(m,n), V(m,n), D(m,n)] = swt(X(m,n)) \quad (10)$$

where (m, n) represents pixel coordinates in the image. X is the low contrast input image. A represents the low sub-band wavelet coefficients. H, V, D represents the high sub-band wavelength coefficients [31]. It is to be noted that only the A coefficients are considered for enhancement using the proposed method. The high sub-band wavelength coefficients (H, V, D) are isolated from the enhancement process for retaining the structural details of the brain MR image.

A. Problem formulation

A schematic representation of the proposed technique is shown in Fig. 3. The joint histogram equalization (JHE) technique proposed in [32] is successfully implemented for the enhancement of standard images. Its application to brain MR image enhancement is new. Further, the feature of preserving brightness is added, while enhancing the contrast. The suggested technique incorporates the spatial information in the equalization process. An average image is formed by computing the mean value of a pixel in its neighbourhood. The pixel intensity and its spatial information are taken together for computing the pixel pair population in the joint histogram [32]. As stated above, $A = \{a(m,n) | 1 \leqslant m \leqslant M, 1 \leqslant n \leqslant N\}$ is the low sub-band coefficient of the input image (X) of dimension $M \times N$ in the wavelet domain. The image A consists of the grey levels in the range {0 to $L-1$}.

Firstly, the image mean value (A_m) of A is computed. Based on this value, the image A is divided into two sub-images (A_L and A_U) where,

$$A_L \in \{a(m,n) | a(m,n) \leqslant A_m, \ \forall a(m,n) \in A\} \quad (11)$$

and

$$A_U \in \{a(m,n) | a(m,n) > A_m, \ \forall a(m,n) \in A\} \quad (12)$$

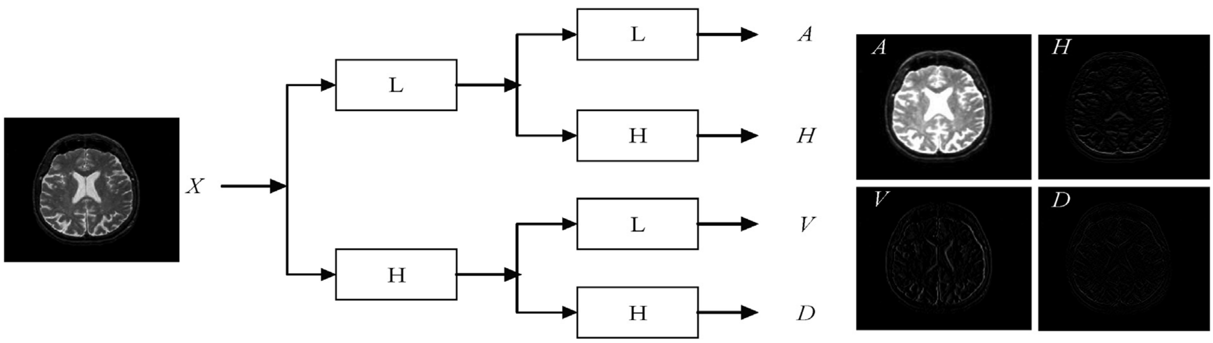

Fig. 2 – SWT representation of the image.

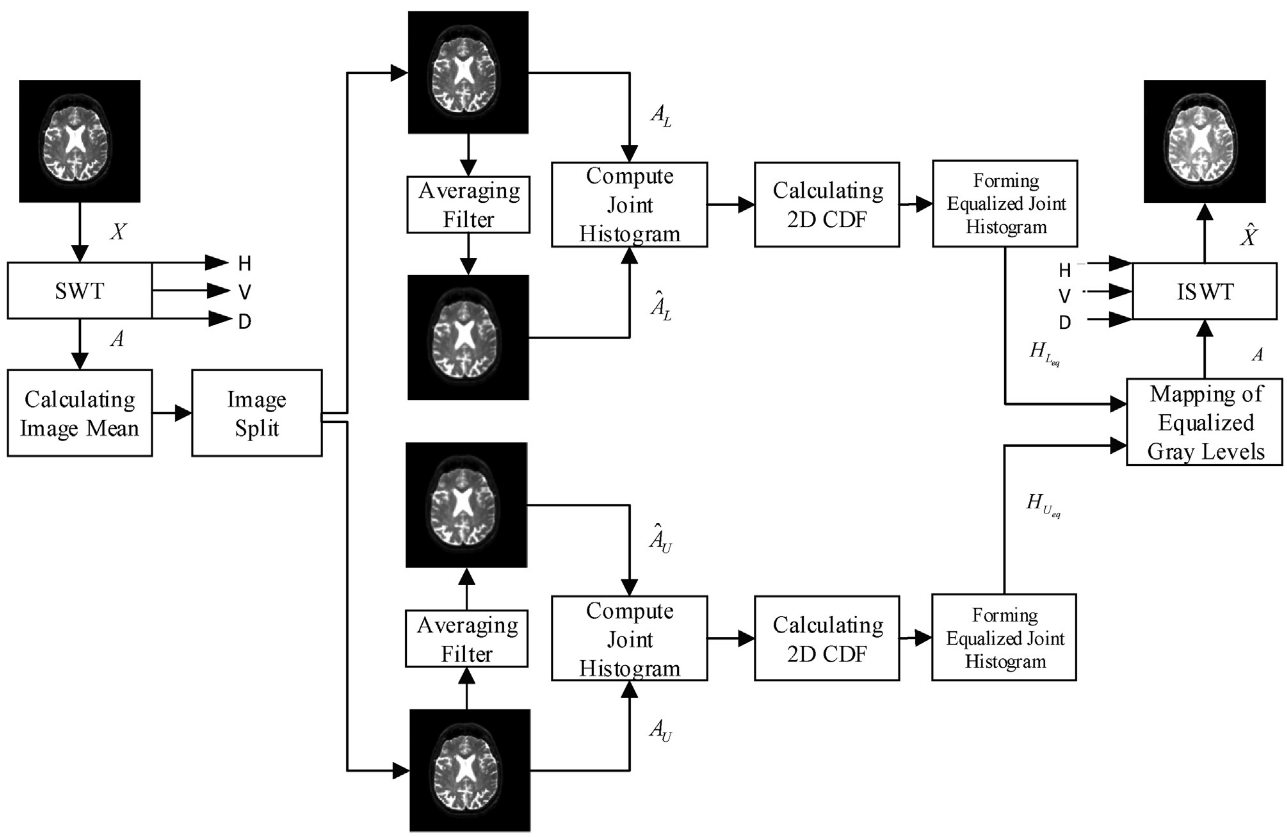

Fig. 3 – Schematic representation of the suggested technique.

i.e. the sub-images consist of $A_L = \{0, ..., A_m\}$ and $A_U = \{A_m + 1, ..., L - 1\}$ intensity values. The relationship between the image A and the decomposed images is represented as:

$$A = A_L \cup A_U \tag{13}$$

Now, these sub-images are processed for contrast enhancement using the proposed technique. Let $f_L(m,n)$ be the intensity value of a pixel at coordinate (m,n) in the image A_L, where $m \in \{1, ..., M\}, n \in \{1, ..., N\}$. Let $\hat{A}_L$ represent the spatial information image formed from A_L with intensity values $g_L(m,n)$. These intensity values are computed by using a $w \times w$ averaging kernel. The size of both the images A_L and $\hat{A}_L$ is $M \times N$ with intensity values in the range $[0, ..., A_m]$. The intensity value $g_L(m,n)$ in the spatial information image is computed as:

$$g_L(m,n) = \left\lfloor \frac{1}{w \times w} \sum_{i=-k}^{k} \sum_{j=-k}^{k} f_L(m+i, n+j) \right\rfloor \tag{14}$$

where $k = \lfloor w/2 \rfloor$, $\lfloor . \rfloor$ denotes the floor operator. Note that $w \leqslant \min(M,N)$. 'w' is normally an odd number. In this paper, this value is taken as three. For constructing the joint histogram, the intensity values $f_L(m,n) = x$ and $g_L(m,n) = y$ are taken from the image (A_L) and spatial information image $(\hat{A}_L)$, respectively. Similarly, the spatial information image

($\hat{A}_U$) is formed from the other sub-image (A_U) using the similar Eq. (14). The joint histograms for the sub-images are expressed as follows:

$$H_L = \{h_L(x,y)|0 \leqslant x \leqslant A_m, 0 \leqslant y \leqslant A_m\} \tag{15}$$

and

$$H_U = \{h_U(x,y)|A_m + 1 \leqslant x \leqslant L-1, A_m + 1 \leqslant y \leqslant L-1\} \tag{16}$$

Here, $h_L(x,y)$ is the pixel pair population for the intensity pair $f_L(m,n)$ and $g_L(m,n)$ at the same spatial coordinate (m,n) of the images A_L and $\hat{A}_L$, respectively. Similarly $h_U(x,y)$ is the pixel pair population for the intensity pair $f_U(m,n)$ and $g_U(m,n)$ at the same spatial coordinate (m,n) of the images A_U and $\hat{A}_U$, respectively. Note that $g_U(m,n)$ is computed exactly as in (14) $g_U(m,n) = \left\lfloor \frac{1}{w \times w} \sum_{i=-k}^{k} \sum_{j=-k}^{k} f_U(m+i, n+j) \right\rfloor$. Each entry in the joint histograms indicates the pixel pair population at the same location in the two images.

The two-dimensional (2D) CDF for the sub-images is computed using the pixel pair population, as:

$$CDF_L(x,y) = \sum_{p=1}^{x} \sum_{q=1}^{y} h_L(p,q) \tag{17}$$

and

$$CDF_U(x,y) = \sum_{p=1}^{x} \sum_{q=1}^{y} h_U(p,q) \tag{18}$$

Here, the computation of 2D CDF values is independent of the size $(M \times N)$ of the image. Further, these values are used in computing the contrast enhanced pixel intensities. The equalized values of pixel intensity pairs (x,y) in the output sub-images are computed as:

$$h_{L_{eq}}(x,y) = round\left(\frac{A_m}{MN-1}\left(CDF_L(x,y) - (CDF_L(x,y))_{\min}\right)\right) \tag{19}$$

and

$$h_{U_{eq}}(x,y) = round\left(\frac{L-1}{MN-1}\left(CDF_U(x,y) - (CDF_U(x,y))_{\min}\right)\right) \tag{20}$$

where $(CDF_L(x,y))_{\min}$ and $(CDF_U(x,y))_{\min}$ are the minimum non-zero CDF values of both the sub-images respectively. Further, the equalized joint histograms of the sub-images are formulated as:

$$H_{L_{eq}} = \{h_{L_{eq}}(x,y)|0 \leqslant x \leqslant A_m, 0 \leqslant y \leqslant A_m\} \tag{21}$$

and

$$H_{U_{eq}} = \{h_{U_{eq}}(x,y)|A_m + 1 \leqslant x \leqslant L-1, A_m + 1 \leqslant y \leqslant L-1\} \tag{22}$$

The equalization process extends the dynamic range of the entries of the joint histogram. Now the original intensity values $f_L(m,n) = x$ are replaced by $h_{L_{eq}}(x,y)$ at all the occurrences of x with y only in A_L. Similarly, the original intensity values $f_U(m,n) = x$ are replaced by $h_{U_{eq}}(x,y)$ at all the occurrences of x with y only in A_U. The output image A is now formed by combining the equalized intensity values of both the sub-images to form a single image:

$$A = \{A_L \cup A_U\} \tag{23}$$

The proposed SWT-BPJHE technique equalizes each sub-image identically based on their joint histograms. Here, one of the sub-image (A_L) is enhanced by equalizing the grey-scale in the range$[0, \ldots, A_m]$, while the other sub-image (A_U) is enhanced in the range $[A_m + 1, \ldots, L-1]$. In total, the low contrast image (A) is enhanced over the whole dynamic range $[0, \ldots, L-1]$. Therefore, the mean brightness is preserved around the mean value of the input brain MR image. This is evident from the bounding of the resulting equalized sub-images around the mean value of the input image. Now the high sub-band wavelet coefficients along with the enhanced low sub-band wavelet coefficient are combined using ISWT as follows:

$$\hat{X}(m,n) = iswt(A(m,n), H(m,n), D(m,n), V(m,n)) \tag{24}$$

here $A(m,n)$ is now the enhanced wavelet coefficient of the low frequency sub-band and $\hat{X}(m,n)$ is the contrast enhanced image.

B. The pseudocode.

Input: Low contrast brain MR image.
Initialize: maximum grey scale value ($L = 256$), size of the averaging kernel ($w = 3$).
Step_1. Representing the low contrast MR image in the transform domain using SWT.
Decompose the image into four sub-bands using SWT using (10)
Step_2. Enhancing contrast using BPJHE.
i. Process the lowest frequency wavelet sub-band image (A) for contrast enhancement.
ii. Calculate the image mean value (A_m) and split the image into two sub-images A_L and A_U as in (11,12).
iii. Compute the spatial information image ($\hat{A}_L$) and ($\hat{A}_U$) using the averaging filter as in (14).
iv. Compute the joint histograms for both the sub-images using (15,16).
v. Compute the 2D CDF of both the sub-images using the pixel pair population using (17,18).
vi. Calculate the equalized pixel intensities of each sub-image for each pixel coordinate (x, y) using (19,20).
vii. Formulate the equalized joint histograms of the sub-images using (21,22)
viii. Map the equalized intensity values of the sub-images to form a single low contrast enhanced image (A) using (23). This is resulting in a wider dynamic range of intensity values in the output image.
Step_3. Reconstruct the image by ISWT using (24).
Combine the high frequency wavelet coefficients along with the enhanced low frequency wavelet coefficient using ISWT (24).
Output: Contrast enhanced brain MR image.

4. Results

The suggested technique is experimented with healthy synthetic brain MR images from the BrainWeb database [33] and clinical brain MR images from the Harvard Whole Brain Atlas database [34]. The evaluation process is conducted with a set of 100 selected T1-w synthetic brain MR images. Further, T1-w clinical brain MR images with and without lesion region are also experimented, because these images provide the least contrast among other modalities. The experimented MR images have the following specifications: Slice thickness: 1 mm, Scan type: SFLASH, Repetition time: 18 ms, Flip angle: 30, Echo time 10 ms, Image type: Magnitude. The proposed scheme is simulated with a core-i7 processor system with 8 GB RAM. The performance of the suggested technique is compared with HE [9], EMHM [11], AIRAHE [13], CLFAHE [15], WT-CLAHE [18], DHE-PSO [21], DWT-SVD [23] and BPHE [25] methods using different validation indices, such as: mean square error (MSE) [35], entropy (H) [36], normalised discrete entropy (DE_N) [37], absolute mean brightness error (AMBE) [36], edge based contrast measure (EBCM) [38], quality-aware relative contrast measure (QRCM) [39] and the patch-based contrast quality index (PCQI) [40]. The details of these indices are mentioned in the corresponding references. The experimental outcomes of different contrast enhancement techniques are presented in Figs. 4–6 and Tables 1–3. To strengthen the claim, a statistical analysis is also conducted. Further, a 2D histogram based analysis is presented in Fig. 7 and the overall best winning results for better visualization are presented in Fig. 8.

Fig. 4 shows the subjective assessment of different contrast enhancement techniques using synthetic T1-w brain MR images. Fig. 4(a) is the input low contrast synthetic brain MR image abstracted from the BrainWeb database. Fig. 4(b–j) represent the enhanced images obtained from different methods. Fig. 5(a) shows the input clinical brain MR image without lesion from Harvard Whole Brain Atlas database. The contrast enhanced images using different algorithms are shown in Fig. 5(b-j). Fig. 6(a) shows the input clinical image with lesion (a) and the contrast enhanced brain MR images (b–j) using different algorithms.

Fig. 7 shows the 2D histograms of the input and the output images. The figures in column (a) show the input low contrast synthetic and clinical brain MR images. The figures in column (b) represent the corresponding 2D histograms of the input images. The figures in column (c) represent the contrast enhanced images using the proposed SWT-BPJHE technique. The last column (d) represent the corresponding equalized 2D histograms of the output images. It is observed that the proposed technique successfully stretches the 2D histograms in all the cases thereby extending the dynamic range of the input images.

The visual assessment of the discussed techniques is supported by a set of quantitative evaluation indices shown in Tables 1–3. Table 1 presents the quantitative assessment of different contrast enhancement techniques using synthetic brain MR images. It shows the values of MSE, H, DE_N, AMBE, EBCM, QRCM, and PCQI. The results with the proposed method shown in Table 1 are computed with a set of 100 selected T1-w synthetic brain MR images. The best-in-class value of each index is marked in bold. They indicate a higher degree of similarity between the enhanced image and the reference brain MR image. Similarly, the quantitative assessment of different contrast enhancement techniques using clinical brain MR images is presented in Table 2 and 3. It shows a similar trend as observed with the synthetic brain MR images.

For the statistical analysis [41], Friedman test is conducted on synthetic and clinical brain MR images. This is a common way for computing the hypothesis between two validation indices over various datasets. The test is conducted on all the results obtained for each validation indices, which examines the hypothesis of the proposed method at 5% significance level. Table 4 presents the average p-values of different validation indices at a significance level of 0.05 between the suggested SWT-BPJHE technique and other state-of-the-art schemes. The p-values indicate that our results are significantly different from the compared methods.

The overall best winning results are presented in graph for better visualization in Fig. 8.

5. Discussion

The suggested method is experimented with synthetic brain MR images and clinical brain MR images with and without lesion region. The comparing methods are a mix of classic

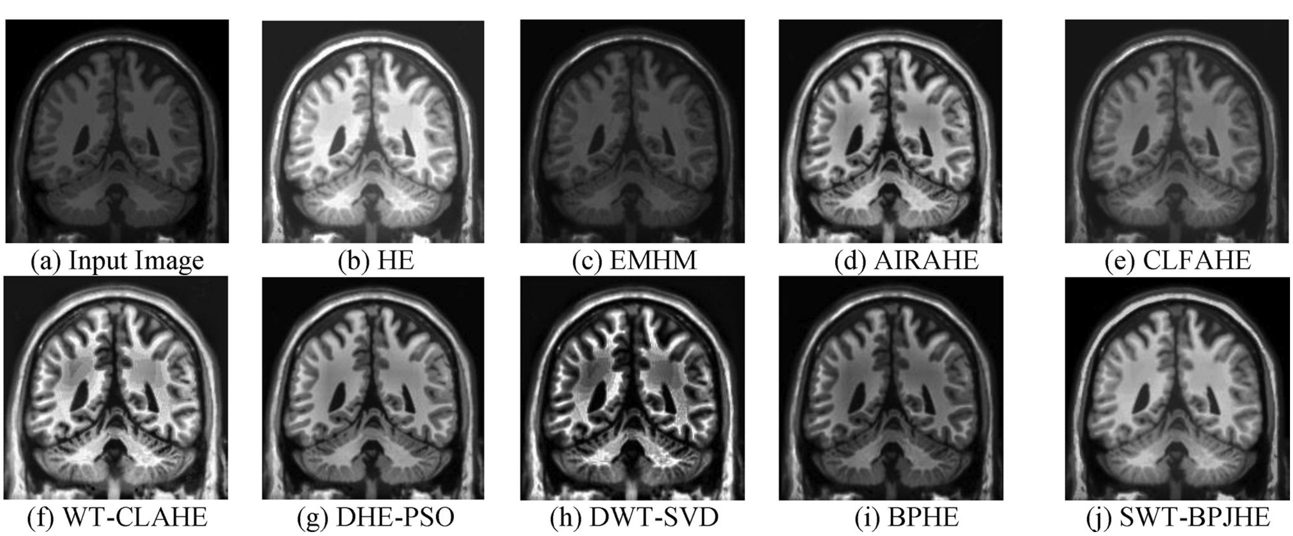

Fig. 4 – Subjective analysis of different contrast enhancement techniques using synthetic T1-w brain MR images.

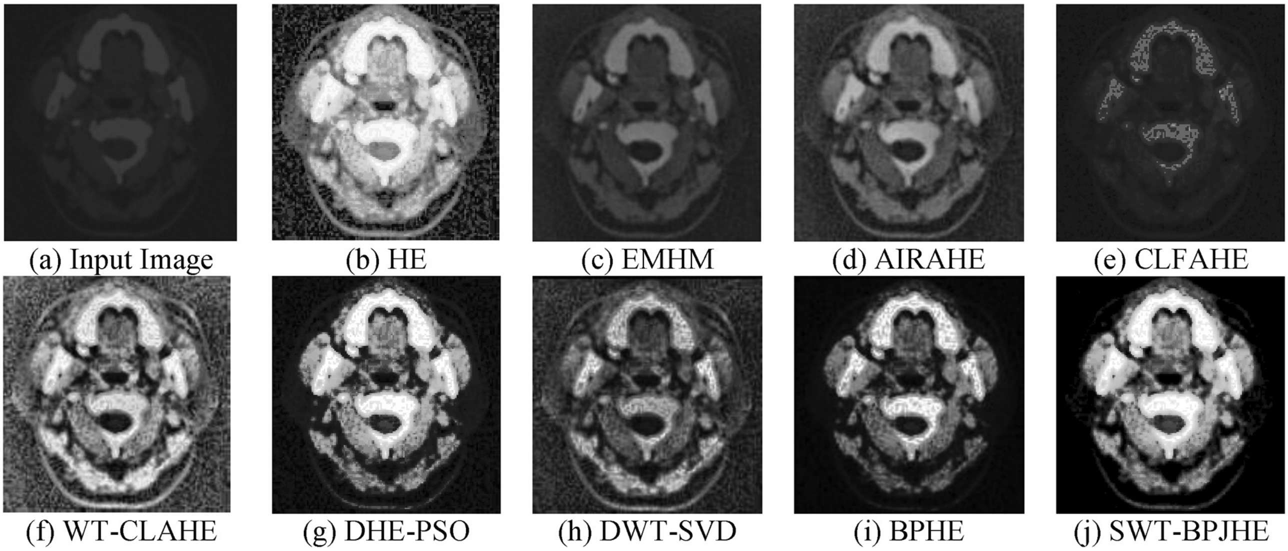

Fig. 5 – Subjective analysis of different contrast enhancement techniques using clinical brain MR images without lesion.

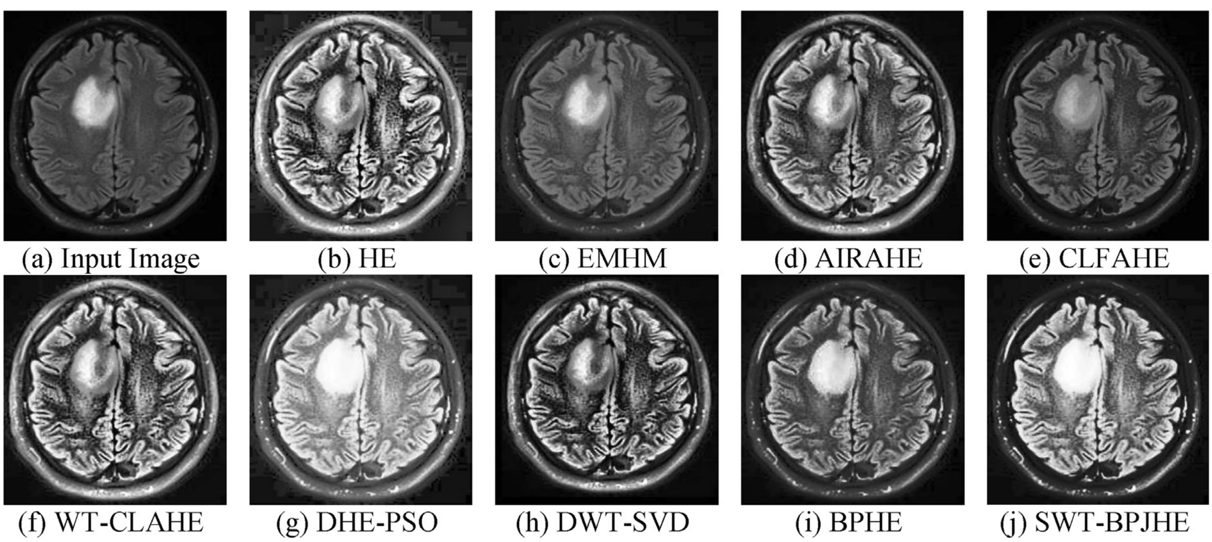

Fig. 6 – Subjective analysis of different contrast enhancement techniques using clinical brain MR images with lesion.

and recent state-of-the-art enhancement methods. Even though quantifying the improved perception is a tedious task, the assessment of contrast enhancement techniques is carried out using different standard evaluation indices. The results in tables are collected from different published papers. In this section, we compared our own results with the results of other authors.

The subjective assessment of different contrast enhancement techniques using synthetic T1-w brain MR images is presented in Fig. 4. Here, Fig. 4(a) is a low contrast synthetic brain MR image. Fig. 4(b–j) shows the enhanced images from different methods. A careful analysis of the results in Fig. 4 reveals that the conventional HE technique successfully stretches the grey scales as seen in Fig. 4(b). However, it reduces the contrast within the tissue regions considerably. Because of the mapping of grey levels to a brighter scale, most of the structural details get eliminated. Fig. 4(c) shows the outcome of the EMHM technique. Here, the whole image is mapped to darker intensity values leading to an inaccurate visual interpretation of the tissue regions. Fig. 4(d) shows the contrast enhanced output using AIRAHE technique. Although the image contrast is enhanced, the edge regions in the image are blurred due to the average spatial filtering used in the model. This leads to structural detail elimination, especially in the grey matter and white matter regions of the brain MR image. Fig. 4(e) shows the outcome using CLFAHE technique. It is found to be effective in preserving the structural details. However, noise enhancement is a remarkable problem with this approach. In Fig. 4(f, j), the contrast enhanced image using WT-CLAHE and DWT-SVD techniques are shown. It shows improved contrast within the tissue regions. However, the noise in the background of the MR image is also enhanced. Further, this approach eliminates the structural details in the tissue regions in the MR image.

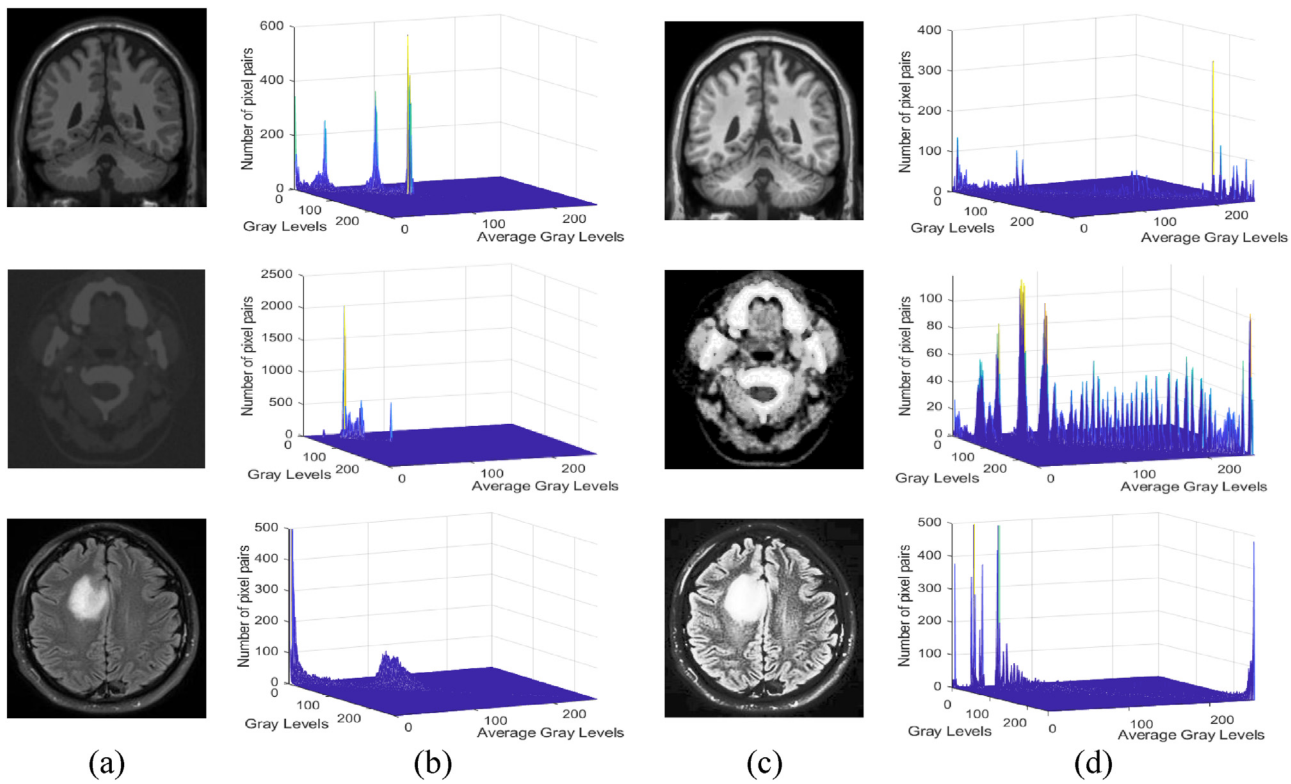

Fig. 7 – 2D histograms of enhanced output using proposed method, (a) Input low contrast brain MR images, (b) 2D histograms of input images, (c) Enhanced images, (d) Equalized 2D histograms.

In Fig. 4(g, i), the output using DHE-PSO and BPHE algorithms are presented. It is found to be effective in preserving the actual brightness in the brain MR image. However, the elimination of structural details in the tissue regions is observed. Fig. 4(j) shows the contrast enhanced brain MR image using the proposed SWT-BPJHE technique. It gives distinctive tissue regions without over enhancement problem, i.e. the brightness is preserved as in the actual MR image. Further, the structural details in the tissue regions are retained. This may be due to the use of SWT which isolates the structural details from the enhancement process. Further, the spatial information in the JHE approach also supports restoring the structural details in the lower sub-band region. A similar trend is observed with the other clinical images as shown in Figs. 5 and 6.

By observing Fig. 5, the outcome with HE technique enhanced the image in its whole spectral range. However, the details in the tissue regions are eliminated due to over enhancement. The outcomes from the EMHM and CLFAHE methods are seen to have darkening effects over the whole image. In Fig. 5(d), the output using AIRAHE technique enhances the grey scale values. However, it reduces the contrast within the tissue regions considerably. Among the different schemes, only the WT-CLAHE, DHE-PSO, DWT-SVD and the proposed SWT-BPJHE techniques preserve the structural details in the tissue regions in a better way. However, the output images with WT-CLAHE and DHE-PSO contain significant noise in the background of the MR image. On the other hand, the proposed technique successfully restricts the background noise. It also preserves the brightness of the input image.

From Fig. 6, it can be observed that the outcomes with AIRAHE and WT-CLAHE techniques are similar. The grey matter region is clear up to certain extent. However, the white matter region looks to be deformed due to the mapping functions. Further, the lesion area in this region is ineffectively enhanced. The output images of EMHM and CLFAHE schemes have darken effects over the whole image. They degrade the visual quality of the tissue regions in the brain MR image. The HE, EMHM, and DHE-PSO, BPHE techniques successfully enhance the tissue regions. However, they also enhance the background noise significantly. Fig. 6(h) shows the resulting enhanced image using the proposed SWT-BPJHE technique. It preserves the structural details and the brightness of the actual brain MR image while enhancing the tissue regions. The background noise is successfully isolated from the enhancement process. Further, the lesion region is clearly identifiable in the contrast enhanced image.

From Table 1, it is observed that the proposed scheme outperforms the other methods. For instance, the values of MSE, H, AMBE, EBCM, QRCM, and PCQI are found to be the best for the proposed method. A low value of MSE is desired. The proposed method yields this value because of isolation of noise from the enhancement process. Thus, the observed value and the desired value are close resulting in a low MSE. A high value of H is preferred which is obtained with the proposed method. The preservation of structural details and removal of noise increases the overall information thus increasing the entropy value. The AMBE value is also obtained the best with the proposed method. The inbuilt brightness-preserving concept of joint histogram processing on sub-

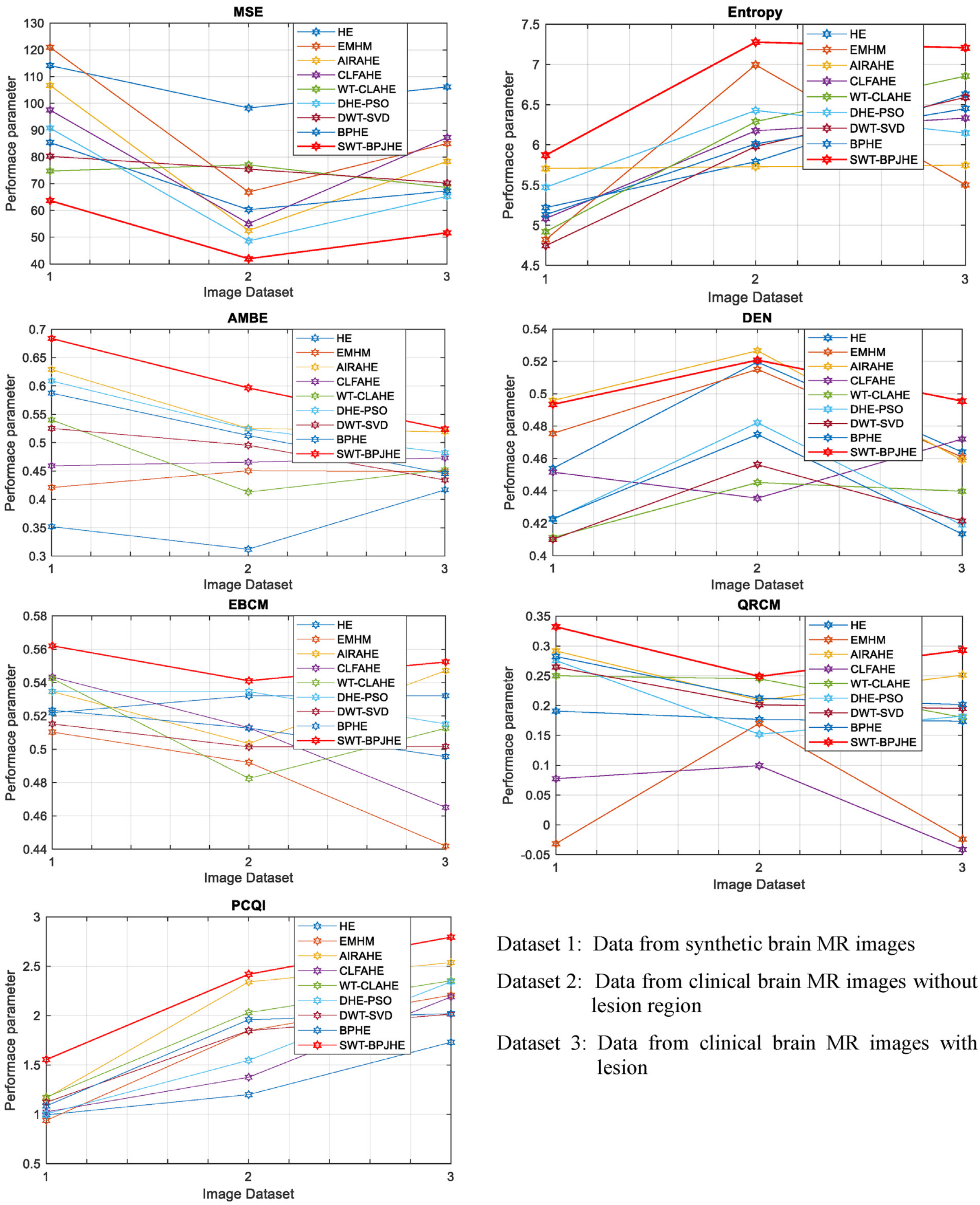

Fig. 8 – Graphical representation of overall best winning results.

images helps in achieving the desired value for AMBE. The EBCM value obtained is the best for the proposed method because of isolation of high sub-band coefficients from the enhancement process. The edge information is retained resulting in a better value of EBCM. The QRCM and PCQI values are also the best in class for the proposed method. The reason may be the use of the SWT in isolating the high frequency components and noise from the enhancement process. The features of the input are retained resulting in a better quality output image. However, the DE_N value is 0.4934 with the proposed technique, whereas in the case of AIRAHE technique it is 0.4958 (best). Nonetheless, it is the second contestant. A similar trend is observed with the quantitative assessment of different contrast enhancement techniques using clinical brain MR images. This is presented in Tables 2 and 3. For instance, the validation indices (MSE, H, DE_N, AMBE, EBCM, QRCM and PCQI) shows the best value in Table 2, whereas, DE_N shows the best value with AIR-AHE technique. Further, the outcomes of the clinical brain MR images with lesion shows the best values for all validation indices as shown in Table 3. The overall best winning results are presented in graph for better visualization in Fig. 8. From the graphs, it is observed that the proposed method outperforms other methods in terms of almost all the validation indices.

6. Conclusion

In this paper, an efficient SWT-BPJHE scheme is introduced for enhancing the low contrast in brain MR images. The scheme suggests a robust solution for preserving the structural details in the MR image. The use of SWT helps in isolating the structural details along with the noise from the enhancement process by isolating the high sub-band coefficients. This results in preserving the structural details in the enhanced brain MR image. The low sub-band coefficients only, of the brain MR image, are enhanced. The joint histogram equalization incorporates the spatial information of each pixel in enhancing the image. The proposed BPJHE technique follows the sub-image joint histogram equalization process to preserve the brightness of the input image. In the process, the structural details in the low sub-band coefficients also get retained. However, the computational complexity could not be reduced. Some more datasets can also be used for experiment. The proposed method is experimented with synthetic and clinical brain MR images and found to be effective in enhancing the contrast. This is evident from the qualitative and quantitative analysis of the results obtained with the suggested technique in comparison to state-of-the-art techniques. This may set a new direction in brain MR image contrast enhancement problem.

CRediT authorship contribution statement

Pranaba K Mishro: . **Sanjay Agrawal:** Methodology, Validation, Supervision. **Rutuparna Panda:** Methodology. **Ajith Abraham:** Supervision.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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