A Novel MRI and CT Image Fusion Based on Discrete Wavelet Transform and Principal Component Averaging for Enhanced Clinical Diagnosis

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Abstract—Clinical professionals frequently employ combined analysis of medical pictures generated from numerous imaging modalities for rapid diagnosis, research and treatment of critical diseases. As a result, multimodal medical image fusion, which combines information from multiple medical pictures into a single fused image, has captivated academics' interest in recent years. A large percentage of healthcare resources, including imaging tools, like Magnetic Resonance Imaging (MRI) and Computed Tomography (CT) have been dedicated to the management of affected patients in this pandemic of Coronavirus disease 2019 (COVID-19). The diagnostic modalities in medical research are improving at a rapid pace with an objective to acquire maximum information with as little data as possible without any artifacts. That is where image fusion comes into the picture. It is a technique of merging source medical pictures to maximize the necessary information. CT is generally used for bony structures, whereas MRI is more appropriate for soft tissues. A fusion of MRI and CT images would lead to enhancement of the overall image quality while giving comprehensive information, at the same time artifacts are also eliminated. Image fusion methods are applied in medical science and various other sectors. Several image processing techniques are used in medical diagnostics, like Principal Component analysis (PCA), Intensity-Hue-Saturation, Discrete Wavelet Transform (DWT), and others. This study suggests an image fusion algorithm utilising the principal component averaging and the DWT along with the performance analysis of the fusion of the MRI and CT images of brain. The technique used in our study significantly enhances the image quality in terms of various fusion performance measures that helps the medical practitioners to diagnose any infection and aids in its treatment.

Keywords—medical images, multimodal, magnetic resonance imaging, computed tomography, image processing

1 Introduction

Image Fusion of medical images is generally considered as a technique that utilizes pixel-level and collects images to work on essential features. It consolidates at least two pictures from a single or numerous modalities to improve the details and minimize redundancy. The clinical use of medical imaging is increasing, and it can help with several diagnosis [1].

1.1 Modalities in medical imaging

The medical image fusion procedure combines components from different photos, which are merged to form a single fused image. Before using the fusion method, the images are improved in quality and redundant data is reduced. The clinical value of the generated image for diagnosing and assessing medical concerns is also improved by fusion multitude of sensors or imaging modalities can be used to obtain medical images. In this case, fusion helps extract characteristics and disclose information that would otherwise be invisible to the human eye in a single image modality [2]. Two options can be adopted to apply fusion on the CT and MRI images in real-time. The first is to employ a hybrid-scanner, which scans a person's MRI and CT images and combines them together to produce fusion results., and the second one is, which is more practical and cheaper than the above mentioned, is to use different software, which takes the images from different sources and then give the results of fused images.

MRI. A medical technique where magnetic field and radio frequency signals are connected to a computer and utilised to generate images of bodily sections is known as magnetic resonance imaging (MRI). One of its benefits is that MRI is safe for babies and women who are expecting a child because it does not utilize radiations but simply radio waves in the FM range. It also aids in the examination of non-bony or soft tissue structures such as the spine, brain, heart and eyes which is more accurate than the CT scans [3].

CT. In this medical technique images are formed with the help of computer and an array produced by X-Ray sensors. Bone and other hard structures are frequently examined with CT imaging. Depending on the clinical state, CT images are frequently used in many medical applications. The quick scan time and higher imaging resolution are two of the most significant CT scan benefits. However, CT scans have drawbacks, such as restricted tissue characterization.

2 Methodology

The study has been designed based on the initial studies and identified gaps. The research objectives are to develop an improved wavelet image fusion algorithm in transform domain and to estimate the performance of developed algorithm using performance parameters. In this article a novel algorithm using principal component averaging of DWT has been designed using which CT and MRI images of brain are superimposed to get one single image which will be more informative and clearer so that medical practitioner can get the better idea and more information of both skull and soft tissue part of the brain for diagnose of any infection or disease. The study is further carried out qualitatively and quantitatively using performance parameters such as MSE (Mean Square error), SNR (Signal to noise ratio), PSNR (Peak Signal to noise ratio), SSIM (structure similarity index measure), SD (Standard deviation), Corr (Correlation), SC (Structural Content), NCC (Normalized cross correlation), ESSIM (Edge Based structure similarity index measure), NAE (Normalized absolute error), and MD (Maximum Difference). The simulation tool for analysing the proposed work is MATLAB.

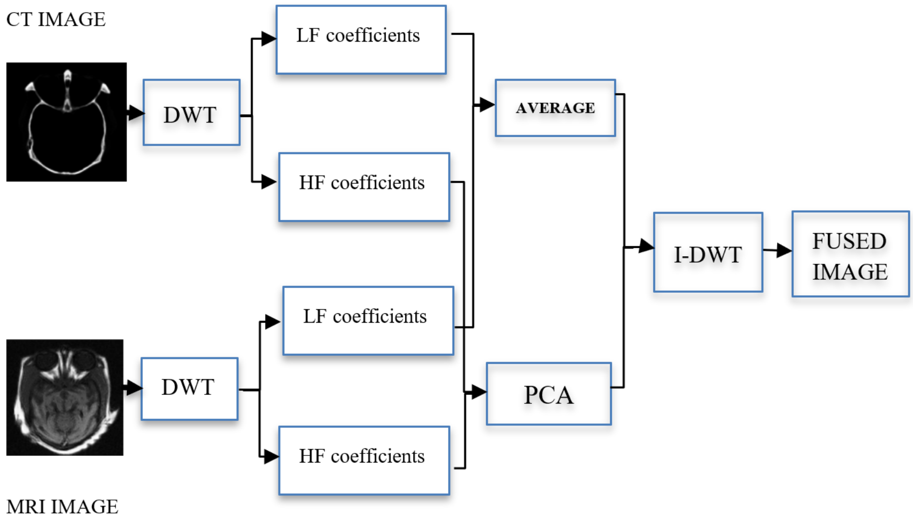

Fig. 1. Block diagram of proposed algorithm

2.1 Principal component averaging

In the spatial domain, PCA gives a straightforward weighted combination technique. In PCA pictures are combined by assessing principal components dependent on eigen esteems, allowing image information in the source images to be prioritized based on properties of co-variance. The main two components that addresses the pixels' variation provides the loads for the PCA approach fusion rule. PCA is a sort of weighted fusion which usually results in better fusing image characteristics and edge information when weights are appropriately evaluated. Local PCAv assesses loads for PCA fusion by parting the source pictures into several little blocks. The co-variance grid of important squares of source pictures is then utilized to construct the main components. The fusion rule's estimation is done by averaging the all principal components. The significant components of source images are examined for related blocks of main images after being divided into smaller blocks. Principal components m1 and m2 (explained in Section 5 below) are examined for each pair of the detailed coefficients. The weights for the fusion rule are calculated by taking the average of all these m1 and m2 values. The average of the m1s and m2s is used to compute the loads for fusion rule depicted in Figure 2 [4].

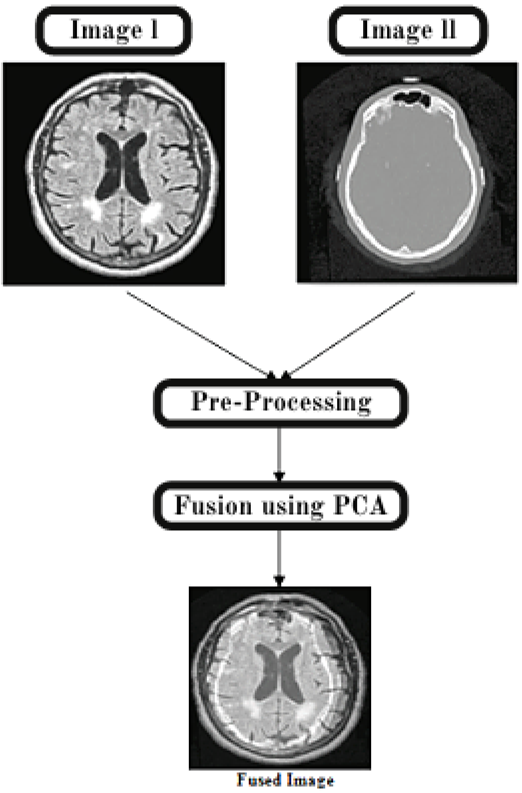

Fig. 2. PCAv fusion

2.2 Discrete wavelet transform

Image fusion techniques or rules are divided into pixel level fusion, feature level fusion, and decision level fusion based on the fusing of information at different levels. Pixel level fusion schemes combine raw source information into a composite image while preserving more source image details. In feature level fusion approaches, features like region and edges are employed to fuse source pictures. This method is resistant to noise and mis-registration. In application-dependent decision level fusion techniques, image descriptors are directly fused.

The most generic and commonly used approach for picture registration and fusion is wavelet transformation–based image fusion. The primary key behind wavelet-based fusion is that, in this process, the detailed and prominent information is extracted from one image and then fused into another image [5]. We can manipulate the frequencies in both space and time. With this advantage, wavelets can capture detailed information from high-frequency images. Clinical diagnosis, feature-based image fusion, medical segmentation, hyper resolution, lifting technique, 3D con-formal 3D-CRT diagnosis planning, and shade perception are just a few of the applications for wavelets in medical fusion [6]. The transforms of two pre-registered input pictures, T1 (a,

b) and T2 (a, b), which make up the fusion rule x0005φ, can be used to illustrate wavelet transform based image fusion more clearly. After that, the image is restored using the inverse wavelet transform $\omega - 1$ [9].

$$T(a,b) = \omega^{-1}\left(\varphi\left(\omega\left(T_1(a,b)\right), \omega\left(T_2(a,b)\right)\right)\right)$$

When the wavelet transform technique is employed, the selected parent wavelet function signals get decomposed, shifted (translated), and scaled (expansion and dilation) Figure 3. The term parent wavelet is utilized because various kid window capacities are created from primary wavelet functions [7] [8].

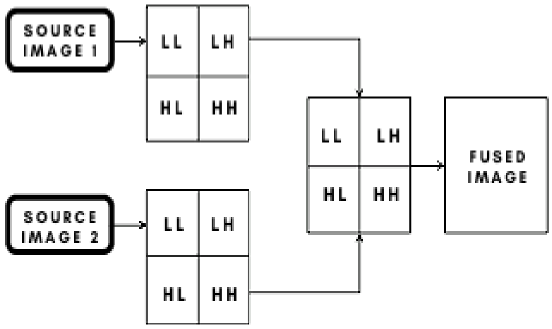

Fig. 3. DWT representation

The Discrete Wavelet Transform (DWT) is utilized in several applications such as image and bioinformatics, patter recognition, video compression, to name a few. Because of its significant advantages over discrete cosine transform, 2-D DWT is used to create picture fusion techniques. 2-D DWT with 9/7 filter achieves high PSNR and a clear fused image.

3 Literature review

Several research projects on clinical image fusion have been dispatched and completed throughout the previous two decades. Several scientific journals and conferences have been published on the subject. We look at a few of them in terms of their substantial contributions:

Yadav, S.P., Yadav, S. [9] investigated various methods of fusion that are transform and neural network based in their experimental setting. MATLAB software, which is well-known for neural networks and image processing, was employed in research. In a standard medical image fusion dataset, the researchers investigated at basic parameters including PSNR and SIM.

Alseelawi, N ey al. [10] suggested a fusion procedure based on NSCT, employing DTCWT and compared its results with simple DWT and other Wavelet Transform. Using this technique, they first decomposed each input source picture into its subbands, then split each sub-band into low-pass, high-pass bands based on the maximum absolute (max-abs) rule, image quality is worked on as far as differentiation, clarity and visual information in the merged findings as well as image energy in research.

Using a mean weighted fusion algorithm, Panguluri et al. [11] have fused low-frequency sub-bands. If implemented, the final image will be more visually appealing and pleasing to the eye than it now is. The optimal fusion rule was applied to merge sub-bands of high frequency in order to maximize edge information. IDWT is used as a tool to rebuild the final fused image. In this examination, they found that their suggested algorithm outperformed existing strategies emotionally and unbiasedly.

Using Otsu's technique, V. Rajangam, et al. [12] present an edge-based fusion approach for DWT coefficients. For example, the peak SNR ratio, the fusion factor, the average fusion factor, and the average quality index are all assessed for fusion performance. After conducting experiments on multimodal and same modality pictures, the researchers concluded that threshold-based fusion is better than other approaches.

Samadhan C .and Priti P. [13] have improved the fusion results of multi spectral images, An orthogonal Taguchi array is being used in the study to increase the exhibition of a half breed combination technique dependent on PCA and discrete wavelet transform (PCA-DWT). Visual analysis and acceptable quality standards are employed together to analyse the merged data. The results are better than those of prior hybrid-fusion algorithms utilised to combine SAR and multispectral imagery

Utilising PCA in combination with a neural network, Arthur C et al. [14] PCA was used to suggest a novel method for increasing picture fusion quality. By using an auto encoder neural network instead of weighted fusion approaches, this information may be fused at a higher level of visualisation.

For example, the diverse image extraction sources and the difficult in determining weights are among the problems Xinsai Wang, Mingming Li, and Xiaoer Feng [15] addressed in their novel spatial domain image fusion approach. According to testing results, despite preserving every detail of the source picture, this approach has considerably improved the overall grayscale of the fused image. It also has a strong quality of an image assessment index and excellent visual effects. It depends on the fundamental standard of network comparability, which involves diagonally transforming the infrared image matrix, mapping the noticeable light picture network onto the fundamental eigenvectors, processing the eigenvalue matrix using the weighted-fusion method then, diagonalising, inversely transforming and reconstructing the Fusion image matrix.

Tawfik et al. [16] used pixel and feature levels to provide a mixed strategy for medical picture fusion. The DWT is employed to segregate the source images into high and low frequency components for pixel-level fusion. The curvelet transform is then used to transform the high-frequency coefficient. Excessive noise, blurring effect, and misregistration are all well-known problems with pixel-level fusion that can be avoided by adopting their technique. Both important and complementary properties are kept in the photos from source images in the suggested fusion strategy.

Based on the non-subsampled shear let transform (NSST) and the moving frame-based decomposition framework (MFDF), Liu et al. [17] split raw pictures down into texture and approximation components. If you want to combine texture components, you may use the maximum selection fusion rule to ensure that the fused picture has a lot of gradient information. The approximate components are combined using NSST. Prior to NSST decomposition, their approach used an image decomposition framework to gather gradient information. Thus, the fused picture might have sharper edges and greater detail information.

Geng, P. et al. [18] proposed that not only CT and MR pictures can be combined, proton-density-loaded MR images, as well as T1 and T2 MR images. As evidenced by the testing results, our approach not only pulls additional useful visual information from the source photographs but also successfully inhibits the introduction of erroneous information into fused medical images. Prior medical image fusion methodologies pale in comparison as far as abstract execution and target appraisal measurements.

When considering how the human visual system works, Bhatnagar and colleagues [19] presented a unique paradigm for medical picture merging based on Framelet Transform (HVS). The suggested framework's main notion is to use the Framelet Transform to deconstruct all source images. The low and high frequency coefficients are composed using two separate HVS-inspired fusion approaches. When it comes to texturing data, the former relies on observable measurements. The composite coefficients and the inverse Framelet Transform are then used to build a composite image. The SUSAN feature extractor has been utilised as fusion measurements in low and high frequency bands, and they discovered that adopting the recommended approach maintained more information while increasing the nature of the fused image picture visible.

Ayush Dogra et al. [20] proposed an image-fusion technique based upon the IHS-wavelet transform and pre-fusing of the source picture in a predefined order of transform and spatial domain operations. As a matter of fact, it outperforms six other cutting-edge fusion methods as far as the quantitative appraisal.

4 Fusion performance measures

Image quality assessment is very much necessary as it talks about how much improvement is needed for a better visual of images for researchers. Image quality measures or parameters and their role in image quality assessment has been described in detail [21,22].

Peak Signal to noise ratio (PSNR). The peak SNR ratio is the proportion of an image's greatest potential power to the maximum power of corrupting noise, which defines the representation quality (PSNR). A picture's PSNR can be calculated by comparing it to a perfect, clean image with the most brightness and contrast.

$$PSNR_{x,y}(dB) = 10log_{10}\frac{25s^2}{\frac{1}{px}\sum\sum(x-y)^2} \tag{1}$$

Where px reflects the number of pixels in an image

Mean square error (MSE). Error projection using MSE is a widely used approach. Consequently, the mean of the square of this error reflects a mistake or the actual difference between the expected/ideal and obtained/calculated result.

$$MSE = \frac{1}{MN}\sum_{I=1}^{M}\sum_{J=1}^{N}\left(A_{ij} - B_{ij}\right)^2 \tag{2}$$

Structural Similarity Index Measure (SSIM). Comparing two photos based on their structural resemblance is made with the Structural Similarities Index (SSI). As a result, PSNR and MSE have been improved upon. One of the most effective and consistent measures is SSIM. In order to calculate the SSIM, you need to know two parameters. (I) The K vector, which is a constant in the SSIM index formula and (II) L being the dynamic range of images.

$$C_1 = (K_1 * L)^2 \qquad \& \qquad C_2 = (K_2 * L)^2$$

The SSIM value is calculated using the following formula:

$$SSIM = mean\frac{(2X\mu_1\mu_2+C_1)*(2X\sigma_{12}+C_2)}{(\mu_1^2+\mu_2^2+C_1)*(\mu_1^2+\mu_2^2+C_2)} \tag{3}$$

The SSIM index ranges from 0 to 1. 0 means that there is no association with the original image, whereas a score of 1 shows the exact same picture.

Standard Deviation. This measures the degree of variation in a collection of data, often known as the standard deviation (SD). As a result, low value of deviation shows values are grouped around the mean of the collection, whereas a larger value shows that values are distributed over a wider range.

$$SD = \left[\frac{1}{MN}\sum_{1}^{M}(f(N,M) - \mu)^2\right]^{\frac{1}{2}} \tag{4}$$

Signal to noise ratio (SNR). It measures the picture quality in imaging. An imaging system's sensitivity is often characterized in terms of the signal level that provides a threshold level of SNR.

$$SNR(dB) = 10log_{10}\frac{P_{signal}}{P_{noise}} \tag{5}$$

In this case, P_{signal} denotes the mean of the pixels. The Standard deviation of pixel values is called P_{noise}.

Edge Based structure similarity index measure (ESSIM). As the name suggests, edge-based structural similarity (ESSIM) is a quantitative metric that compares the edge information of two distorted images and original image blocks instead of structure comparison. In order to collect edge information, there are many techniques including basic edge detection approach and local gradients.

$$ESSIM(a,b) = \frac{1}{N}\sum_{I=1}^{N}\frac{2E(A,I)E(B,I)+C}{\left(E(A,I)\right)^2+\left(E(B,I)\right)^2+C} \tag{6}$$

In this case, the parameter C has two meanings. First, it prevents the denominator from being zero. Second, it can be considered as a scaling parameter, with varying magnitudes, resulting in a variable ESSIM score.

$$C = (BL)^2$$

The constant is B, and the powerful scope of edge-strength is L.

Correlation (CORR). The Correlation establishes the relationship between the referenced and generated images. The images are said to be identical if the values of reference and output images are one, and if they are less than one, the shots are more dissimilar.

Normalized Cross Correlation (NCC). Input and fused pictures are compared to see any similarity.

$$NCC = \frac{\sum_{i=1}^{m}\sum_{j=1}^{n}(A_{ij}*B_{ij})}{\sum_{i=1}^{m}\sum_{j=1}^{n}\left(A_{ij}^{2}\right)} \tag{7}$$

Normalized Absolute Error (NAE). It is a qualitative metric which normalizes the mistaken data compared to the standard or optimal worth. The difference between the real and desired results is calculated and then divided by the total of anticipated values. The following is the definition of this metric:

$$NAE = \frac{\sum_{i=1}^{m}\sum_{j=1}^{n}|(A_{ij}*B_{ij})|}{\sum_{i=1}^{m}\sum_{j=1}^{n}(A_{ij})} \tag{8}$$

Maximum Difference (MD). The maximum of the error signal (the difference between the processed and reference image) is provided by MD (Maximum Difference). MD stands for "medical doctor" and is defined as follows:

MD = Maximum e

Bij|j - Aij (6)

m,j = 1,2...... n=1,2...... n=1,2...... n=1,2...... n=1,2...... n=1,2...... n=1,2...... n=

The lower the value of the maximum difference, the lower the image quality.

5 Proposed algorithm

It is the primary goal of Clinical Image Fusion to merge the complementary details stored in the medical images, collected from various modalities, in order to conduct successful clinical research and diagnosis. The flowchart of the proposed approach is shown in Figure 4.

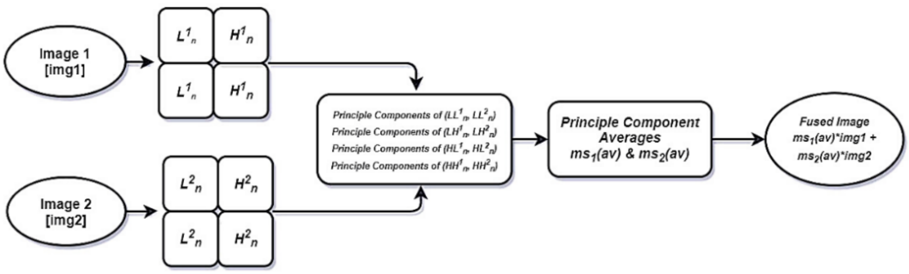

Fig. 4. Flow diagram of proposed algorithm

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Algorithm1: Multi-Modal Medical Images Fusion
 1. Initialization
 2. Take the first input image as img1 of size s1, and
    second image as img2 with size s2.
 3. Compare the size of img1 & img2, also s1 = s2.
 4. If s1 ≠ s2, then resize the images and make s1 = s2.
 5. Evaluate DWT of both source images and calculate
    mean values of all the pixels.
 6. Calculate the approximate and detailed coefficients
    for the primary component.
 7. Calculate principal component for the corresponding
    coefficient as ms1 and ms2.
 8. Calculate the average of the coefficient ms1 and
    ms2:
```

$$m_{s1(av)} = \frac{m_1(LL_n)^{1,2} + m_1(LH_n)^{1,2} + m_1(HL_n)^{1,2} + m_1(HH_n)^{1,2}}{N}$$

$$m_{s2(av)} = \frac{m_2(LL_a)^{1,2} + m_2(LH_a)^{1,2} + m_2(HL_a)^{1,2} + m_2(HH_a)^{1,2}}{A}$$

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    Where, a = 1 and A = 4; a = 2 and A = 7.
 9. Apply PCAv fusion using the average of principal
    components given in Figure 6.
 10.  Perform Evaluation of metrics to for proposed and
    existing algorithms.
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6 Result and discussion

The main findings of the study are to obtain the primary and secondary outcome parameters mentioned in Table 1 and Table 2 for a variety of medical picture sets. Various quality parameters are utilized to test the suggested algorithm. The image quality parameters with proposed algorithm are compared with pre-existing algorithms as follow:

6.1 Image set 1

Comparing results from [23] on DWT-based medical image fusion with the principal component averaging, four sets of medical pictures of CT and MRI [24] of brain Figure 5 that have been fused using PCAv are shown in Table 1. Based on experiments, the better fusion results using the proposed method are achieved for the maximum parameters, respectively. The visual image fusion results of the proposed method for the four sets of input images (MRI, CT) are shown in Figure 6(a), (b) and (c) which shows objective performance evaluation.

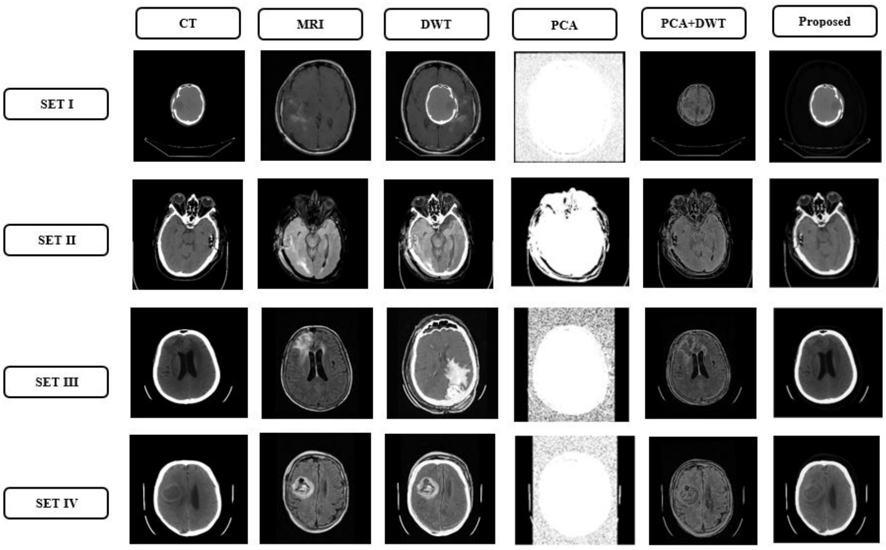


Fig. 5. Dataset-I

Table 1. Image set-1 parameter comparison table

.Set No	Metrics	PCA	DWT	PCA+DWT	Proposed
SET I	SNR	12.8	14.07	14.67	18.45
	PSNR	19.57	16.77	20.25	22.53
	RMSE	26.87	37.1	24.87	10.95
SET II	SNR	12.01	14.62	14.64	18.59
	PSNR	17.71	17.14	23.1	22.57
	RMSE	33.31	35.57	17.91	11.01
SET III	SNR	14.86	18.76	18.97	18.39
	PSNR	16.32	16.66	22.61	22.71
	RMSE	39.07	37.59	18.91	10.96
SET IV	SNR	13.59	16.82	17.01	18.63
	PSNR	14.76	13.73	19.5	22.32
	RMSE	46.76	52.65	27.1	10.89

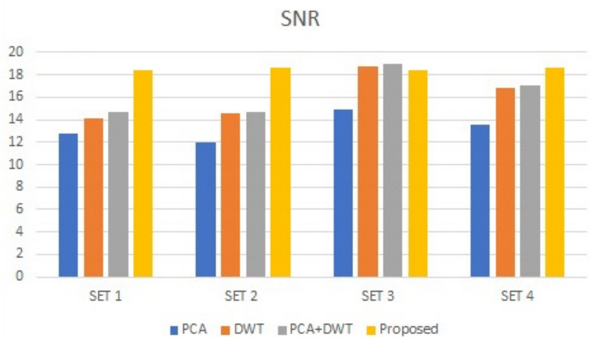


Fig. 6. (a)

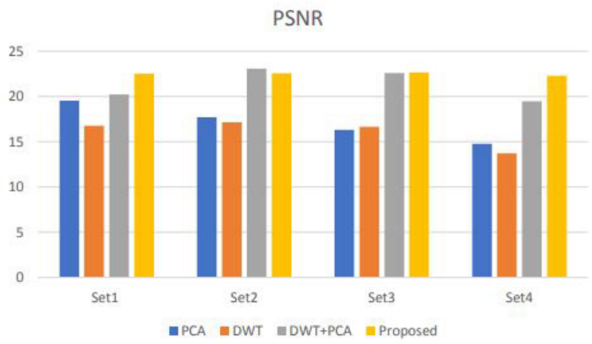


Fig. 6. (b)

Fig. 6. (c)

The PSNR, MSE AND SNR of the Proposed approach is higher than the DWT, DWT+PCA, and PCA methods, as shown in the above bar charts.

6.2 Image set 2

PCAv and DWT based medical fusion of images and the proposed method over ten different data sets of MRI and CT has been presented in Figure 7. A comparison table has been shown consisting of eight different performance objective metrics Table 2. Visual and objective comparisons have been shown to explain better performance results for the maximum metrics for all eight sets.

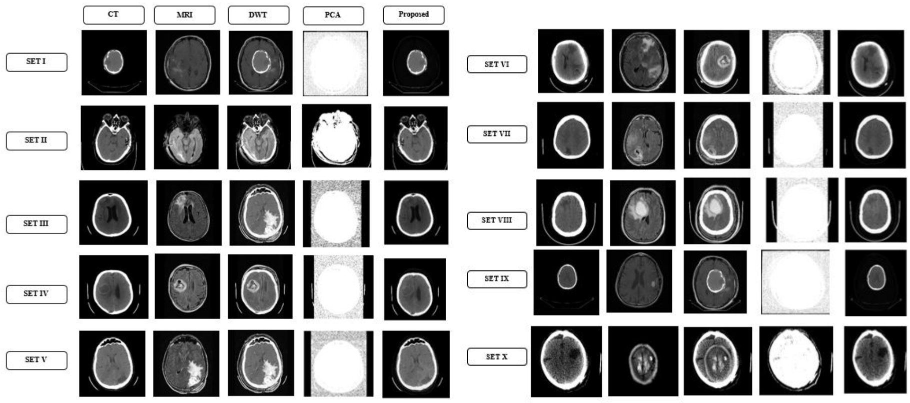


Fig. 7. Dataset-II

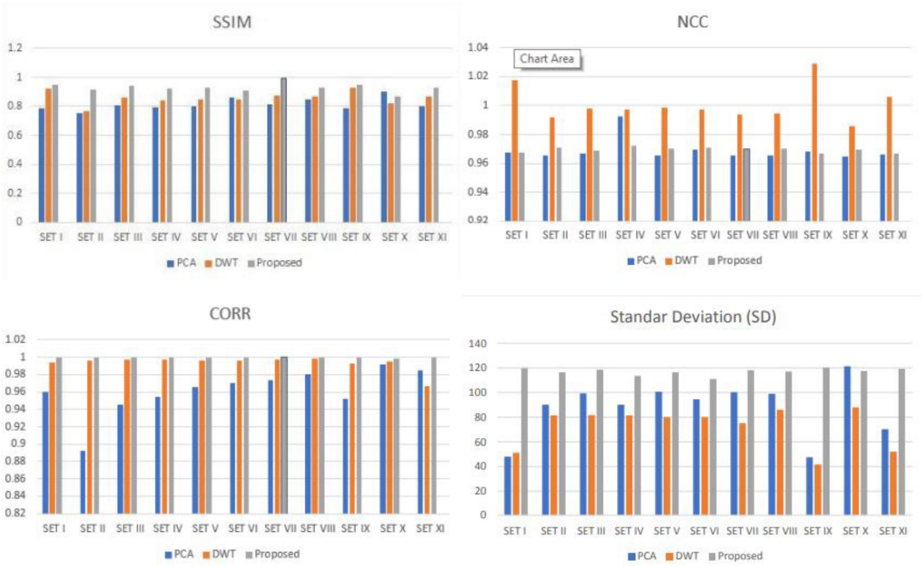
Table 2. Image dataset-2 parameter comparison table

.Set No	Parameters	PCA	DWT	Proposed
SET I	SSIM	0.7893	0.9239	0.948
	SD	48.02	51.112	119.896
	Corr	0.9596	0.9941	0.9995
	NCC	0.9678	1.0179	0.9672
	SC	1.0655	0.9139	1.0605
	MD	88	67	69
	NAE	0.0391	0.2886	0.1013
	ESSIM	0.9990	0.9941	0.9995
SET II	SSIM	0.7513	0.7668	0.9134
	SD	90.0835	81.3605	116.5413
	Corr	0.892	0.9961	0.9998
	NCC	0.9657	0.9922	0.9707
	SC	1.0699	0.9918	1.0536
	MD	78	77	74
	NAE	0.440	0.1953	0.0879
	ESSIM	0.990	0.995	0.9991
SET III	SSIM	0.8062	0.8638	0.9432
	SD	99.2862	81.7682	118.639
	Corr	0.958	0.9974	0.9999

	NCC	0.9665	0.9977	0.9688
	SC	1.0674	0.9844	1.0575
	MD	76	62	72
	NAE	0.0483	0.1630	0.0947
	ESSIM	0.9946	0.9995	0.9990
SET IV	SSIM	0.7912	0.8038	0.9252
	SD	90.0835	81.3605	113.5437
	Corr	0.9548	0.9974	0.9998
	NCC	0.9923	0.9974	0.9721
	SC	0.9654	0.9850	1.0505
	MD	71	72	70
	NAE	0.0448	0.1631	0.0865
	ESSIM	0.9947	0.9995	0.9996
SET V	SSIM	0.8027	0.8486	0.9255
	SD	100.6543	79.958	116.4756
	Corr	0.9654	0.9967	0.9999
	NCC	0.9659	0.9984	0.9704
	SC	1.0690	0.9744	1.0540
	MD	79	70	68
	NAE	0.0474	0.2249	0.0914
	ESSIM	0.9984	09994	0.9990
SET VI	SSIM	0.8587	0.8486	0.9103
	SD	94.532	79.958	111.0110
	Corr	0.9698	0.9967	0.9996
	NCC	0.9663	0.9973	0.9707
	SC	1.00681	0.9799	1.0537
	MD	74	70	76
	NAE	0.0467	0.2109	0.0878
	ESSIM	0.9943	0.9994	0.9990
SET VII	SSIM	0.8124	0.8757	0.99353
	SD	100.1986	75.2078	118.077
	Corr	0.9741	0.9976	0.9999
	NCC	0.9657	0.9937	0.9698
	SC	1.0694	0.9833	1.0555
	MD	84	66	80
	NAE	0.0472	0.2284	0.0917
	ESSIM	0.9945	0.9993	0.9990
SET VIII	SSIM	0.8457	0.8678	0.9288
	SD	98.9073	86.1892	117.0632
	Corr	0.9805	0.9984	0.9999
	NCC	0.9653	0.9944	0.9702
	SC	1.0706	0.9912	1.0550
	MD	73	70	74

	NAE	0.0459	0.1686	0.0865
	ESSIM	0.9942	0.9994	0.9991
SET IX	SSIM	0.7838	0.9293	0.9482
	SD	47.5477	41.5138	120.174
	Corr	0.9521	0.9933	0.9995
	NCC	0.9679	1.0228	0.9666
	SC	1.0651	0.8820	1.0619
	MD	80	65	70
	NAE	0.0396	0.3534	0.1034
	ESSIM	0.9949	0.9995	0.9989
SET X	SSIM	0.9031	0.819	0.8672
	SD	121.3198	87.9823	117.43
	Corr	0.9914	0.9953	0.9987
	NCC	0.9650	0.9858	0.9698
	SC	1.0700	1.0071	1.0562
	MD	77	76	75
	NAE	0.0591	0.1899	0.0831
	ESSIM	0.99938	0.9990	0.9992

Proposed technique clearly outperforms DWT and PCAv in terms of results. The evaluation parameters SSIM, SD, SC, ESSIM, MD, NCC, NAE and Corr are calculated using proposed DWT and PCAv algorithm and compared against pre-existing DWT and PCA algorithms. Table 2 clearly shows the better values of proposed algorithm and hence the better-quality images can be retrieved. Figure 8. (a) (b) (c) (d) (e) (f) (g) (h) shows objective evaluation parameters.



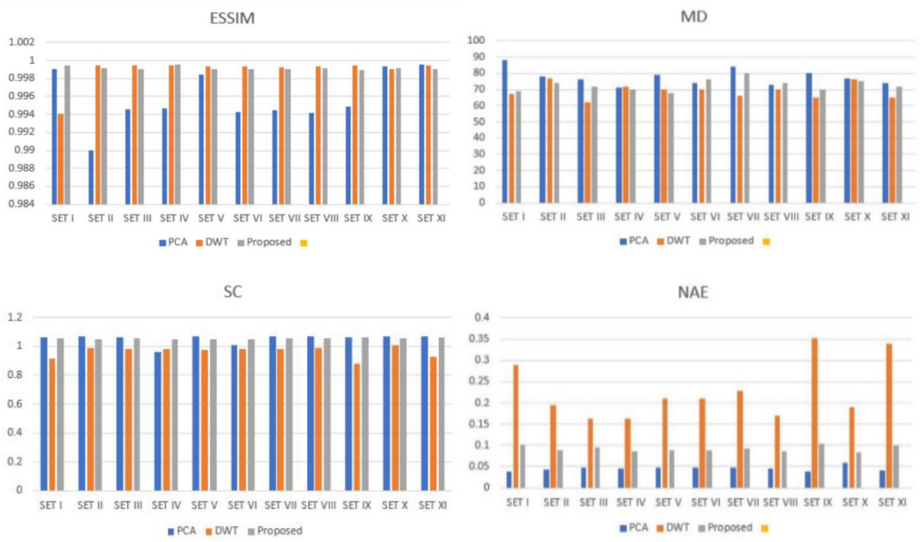


Fig. 8. (a) (b) (c) (d) (e) (f) (g) (h)

7 Conclusion

Using the Multimodal Medical Image Fusion Algorithm, medical practitioners may quickly diagnose and treat patients by combining complementary information from many photos into a single, higher quality image. A unique multi-modal medical image fusion algorithm based on DWT and PCAv is proposed in this research. The algorithm used in this study produces better-quality images. A comparison of the results calculated utilising the proposed technique with current fusion results computed using the DWT, PCA, and PCA+DWT methods. This model's performance is superior to that of other models that have been tested for which Kaggle Datasets were taken. Assessment of various parameters reveal that the fusion quality in terms of fusion parameters were considerably improved in the proposed technique. In future, noise present in the images can also be removed by using other wavelet techniques or a combination of hybrid techniques.

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