Analysis of CT and MRI Image Fusion using Spatial Frequency Discrete Wavelet Transform (Haar) and Neutrosophic Set

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Abstract

Image fusion is an approach used to combine data from multimodality medical image data. The objective is to improve the image content by fusing images such as Computed Tomography (CT) and Magnetic Resonance Imaging (MRI) images, so as to provide more information to the doctor and clinical treatment planning system. This paper demonstrates the application of wavelet transform to multimodality medical image fusion. The proposed method is image fusion using spatial frequency discrete wavelet transform (Haar) and neutrosophic set system. The process is used in this is pixel-based image fusion. In this method, the images are decomposed into low level subbands and high level subbands by spatial frequency discrete wavelet transform (Haar). Then, neutrosophic set technique is applied for low level subband and average fusion method is applied for high level subbands. Finally, the two fused subbands are improved to form the final fused image by using inverse discrete wavelet transform (Haar). The fusion performance is evaluated with Peak Signal to Noise Ratio (PSNR), Root Mean Square Error (RMSE) and Correlation (CORR).

Keywords: Medical image fusion, spatial frequency, DWT, neutrosophic set, Peak Signal to Noise Ratio, Root Mean Square Error, Correlation.

1. Introduction

Image fusion is most extensively used in recent days in medical imaging. Image fusion is a technique used to fuse or unite two or more images of different kinds into a single image. Instance, doctors can combine the CT and MRI medical images of a patient to make a more accurate diagnosis. In the field of medical imaging, different multimodality images such as Computed Tomography (CT), Magnetic Resonance Image (MRI), Positron Emission Tomography (PET) and Single Photon Emission Computed Tomography (SPECT) are used to analyze different characteristics of human body part. Thus, it is necessary to develop the image fusion system to decrease doctor's workload and to improve the consistence of diagnosis. The techniques for image fusion have proposed in the literature [11]. CT images are taken from a cross-sectional image of the body by using X-rays. MRI images are used to detect the presence of fat, water and other fluids in the human body. The illustration of MRI images is response of brain functioning to an outer stimulus and also detects changes in the blood flow.

In view of recent study, many medical imaging fusion techniques were proposed by the researchers. The image fusion techniques are classified into region, pixel and decision levels [15]. The region and decision levels are not commonly used ones. Pixel based image fusion is most popular and it provides image fusion techniques into spatial fusion and transform fusion methods. The methods of spatial fusion include the average method, minimum method, maximum method, contrast pyramid, principal component analysis method, Laplacian pyramid and Gaussian pyramid method [12, 14]. These methods are applied directly on the image pixels. The transform based fusion methods include decomposition of image by stationary wavelet transform, discrete wavelet transform, lifting wavelet transform, Redundancy discrete wavelet transform and Dual tree complex wavelet transform[2, 10]. These methods have some draw backs such as additive noise in fused images. The details on the wavelet transform based medical image fusion are collected from [1, 3, 8, 9 & 17].

2. Discrete Wavelet Transform Based Image fusion

The wavelet transform is a mathematical tool that can detect local features in a signal process. It can be used to decompose two dimensional signals such as 2D gray scale image signals into different resolution levels for multiresolution analysis. Wavelet transform used in texture analysis, data compression, feature detection and image fusion.

2.1 Wavelet Transform

In wavelet transform, there are two main groups of transforms such as continuous and discrete which apply a two-dimensional channel filter bank iteratively to the low pass band. The wavelet representation consists of low-pass band at the lowest resolution and high-pass bands at the highest resolution and also evaluated at each step. This transform is invertible and non-redundant. In wavelet analysis, wavelet transform divides the image signal into wavelets representing each pixel of the original image as coefficients. Discrete wavelet Transform can be obtained by multiplying wavelet functions ψ(t) and scaling function ϕ(t), given by,

$$\psi(t) = \sum_{k=-\infty}^{\infty} \mathrm{q_k}\, \varphi(2\mathrm{t} - \mathrm{k})$$

and

$$\varphi(t) = \sum_{k=-\infty}^{\infty} \mathrm{p_k}\, \varphi(2\mathrm{t} - \mathrm{k})$$

.

The 2D image signals are broken down by a layer by layer decomposition process. The four bands namely low-low, low-high, high-low, high-high are obtained after first level of decomposition. The next level of decomposition is obtained by applying a decomposition procedure applied to the low-low band of the current decomposition stage. Thus N-level decomposition will finally result into 3N+1 different frequency bands, 3N high frequency bands and one Low-Low frequency band.

2.2 Haar Wavelet Transform

In wavelet transform, Haar transform is one of the simplest. Haar wavelet is a sequence of rescaled square-shaped functions which together form a wavelet family or basis [4]. The Haar sequence is recognized as the first known wavelet basis.

The Haar wavelet's mother wavelet function ψ(t) can be described as

$$\psi(t) = \begin{cases} 1 & 0 \le t \le \frac{1}{2}, \\ -1 & \frac{1}{2} \le t \le 1, \\ 0 & otherwise \end{cases}$$

Its scaling function φ(t) can be described as

$$\varphi(t) = \begin{cases} 1 & 0 \le t \le 1, \\ 0 & otherwise \end{cases}$$

3. Proposed Method

Block diagram of proposed spatial frequency discrete wavelet transform (Haar) neutrosophic method.

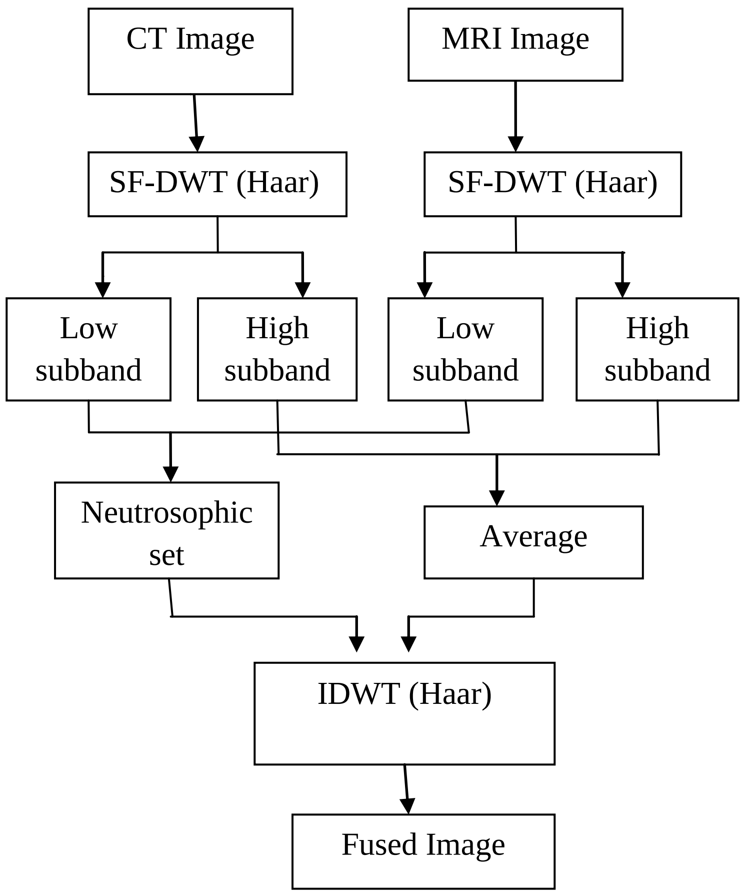


Fig.1

The steps involved in the proposed method are as follows:

1. Input- two images, (CT image (A) and MRI image (B)).
2. Decompose both input images using spatial frequency discrete wavelet transform (Haar).
3. Four images will be obtained approximate sub-image, Horizontal frequency subband, Vertical frequency Subband and Diagonal frequency subband.
4. Perform Neutrosophic set on the low-frequency subbands.
5. Apply average fusion rule for high-frequency subbands.
6. Apply inverse discrete wavelet transform (Haar) on the images to obtain a reconstructed fused image.

3.1 Image Fusion using Spatial Frequency Discrete Wavelet Transform

Image fusion using spatial frequency discrete wavelet transform (Haar) and neutrosophic set is proposed. In this Section Spatial frequency evaluates the amount of frequency contents present in the image. It determines sharpness and spectral quality of the image. The spatial frequency discrete wavelet transform (Haar) will be more absolute in images with high frequency contents [7].

Spatial Frequency (SF) defined as M×N image F with gray value F(i,j) at position (i,j) is $SF = \sqrt{RF^2 + CF^2}$ where

Row frequency,

$$RF = \sqrt{\frac{1}{M*N}\sum_{i=1}^{M}\sum_{j=2}^{N}(F(i,j) - F(i,j-1))^2}$$

and Column frequency,

$$CF = \sqrt{\frac{1}{M*N}\sum_{j=1}^{N}\sum_{i=2}^{M}(F(i,j) - F(i-1,j))^2}$$

where F represents fused image, M and N denote the dimensions of the fused image.

The proposed spatial frequency discrete wavelet transform (Haar) neutrosophic method consists of three steps: decomposition, fusion and reconstruction. The block diagram of the proposed spatial frequency discrete wavelet transform (Haar) neutrosophic method is shown in Fig.1.

3.1.1 Decomposition

In the proposed method, a two-level spatial frequency discrete wavelet transform (Haar) decomposition technique is employed to decompose the input images. Discrete wavelet transform (Haar) decomposes the image into a low-level subband and high-level subband. This is the first level of decomposition. The low-level subband is decomposed for the second time at second level to produce another set of low-level, high-level subbands. The four components selected for the fusion of the images are the approximate sub band, Horizontal detail subband, vertical subband and Diagonal subband. The decomposing procedure is defined as

$$[A_1, H_1, V_1, D_1] = dwt2\ (A, \text{'Haar'})$$

$$[A_2, H_2, V_2, D_2] = dwt2\ (B, \text{'Haar'})$$

Where A and B are source images, A_1, H_1, V_1, D_1 and A_2, H_2, V_2, D_2 are decomposed coefficients of A and B images respectively. The obtained high-frequency and low-frequency subbands of the two images are fused using a fusion algorithm.

3.1.2 Fusion

(i) Fusion of Low-frequency Sub-images:

Neutrosophic set is introduced by Florentin Smarandache in 1995. The neutrosophic logic deals with neutral values to determine the membership, non-membership and indeterministic values in a particular set. It is used to solve the problems of uncertainty.

Let X be a universe of discourse. A single valued neutrosophic set A over X is an object having the form A= $\{\langle x, \mu_A(x), \omega_A(x)$ and $\nu_A(x) \rangle : x \in X\}$ where $\mu_A(x)$: X⟶[0,1], $\omega_A(x)$: X⟶[0,1] and $\nu_A(x)$:X ⟶ [0,1] with $0 \leq \mu_A(x) + \omega_A(x) + \nu_A(x) \leq 3$ for all x∈ X. The intervals $\mu_A(x)$, $\omega_A(x)$ and $\nu_A(x)$ denote the truth membership degree, the indeterminacy membership degree and the falsity membership degree of x to A respectively.

Let U be a universe and W⊆U which is composed by the bright pixels. A neutrosophic image P_{NS} is characterized by three membership sets T, I and F. A pixel P in the image is described as P(t, i, f) and belongs to W in the following way: it is t% true, i% indeterminate, and f% false in the bright pixel set, where t varies in T, i varies in I and f varies in F. [5,13,16]

The pixel P(i,j) in the image domain is transformed into the neutrosophic domain and is given by, P_{NS}(i,j) ={T(i,j),I(i,j),F(i,j)}. T(i,j), I(i,j) and F(i,j) are the membership values defined as

$$\mathrm{T(i,j)} = \frac{\bar{g}(i,j) - \bar{g}_{min}}{\bar{g}_{max} - \bar{g}_{min}}$$

$$\bar{g}(\mathrm{i,j}) = \frac{1}{w \times w} \sum_{m=i-w/2}^{i+w/2} \sum_{n=j-w/2}^{j+w/2} g(m,n)$$

$$I(i,j) = \frac{\delta(i,j) - \delta_{min}}{\delta_{max} - \delta_{min}}$$

$$\delta(i,j) = abs\big(g(i,j) - \bar{g}(\mathrm{i,j})\big)$$

$$\mathrm{F(i,j) = 1 - T(i,j)}$$

Where g(i,j) is the intensity value of the pixel (i,j), $\bar{g}(\mathrm{i,j})$ is the local mean value of g(i,j), $\delta(i,j)$ is the absolute value of the difference between intensity g(i,j) and its local mean value $\bar{g}(\mathrm{i,j})$. We assume w=3, T, I and F denotes the approximate subbands of the images (A_1, A_2).

According to the information theory, a neutrosophic set entropy is calculated based on the following formula,

$$En_{NS} = En_T + En_I + En_F$$

$$En_T = - \sum_{i=\min\{T\}}^{\max\{T\}} P_T(i) \ln P_T(i)$$

$$En_I = - \sum_{i=\min\{T\}}^{\max\{T\}} P_I(i) \ln P_I(i)$$

$$En_F = -\sum_{i=\min\{T\}}^{\max\{T\}} P_F(i)\, ln\, P_F(i)$$

where En_T , En_I and En_F are the entropies of the sets T, I and F respectively and $P_T(i)$, $P_I(i)$ and $P_F(i)$ are the probabilities of the elements in T, I and F respectively.

Based on the entropy, corresponding values of the subbands are chosen to be present in the final image.

$$A_3 = \begin{cases} A_1, & if\ E_1 \geq E_2 \\ A_2, & otherwise \end{cases}$$

where E_1 and E_2 are the entropy of the approximate subbands of the images A and B respectively.

(ii) Fusion of High-frequency sub-images

The High-frequency subbands are fused using the averaging filter. CT and MRI image are fused along with its each detailed subbands. Hence, three fused sub-images are obtained by the process,

$$H_3 = \text{average } (H_1 + H_2)$$

$$V_3 = \text{average } (V_1 + V_2)$$

$$D_3 = \text{average } (D_1 + D_2)$$

3.1.3 Reconstruction

According to the fusion algorithms the four sub-images are fused and the inverse transformation is applied on the obtained four sub-images. Reconstruction is the inverse process of up-sampling of images. A rescaling filter is applied to the low frequency subband and wavelet filter is used for the high-frequency subbands. The reconstruction of the final image as follows:

$$F = \text{idwt2 } (A_3, H_3, V_3, D_3, \text{'Haar'})$$

where F represents the final image.

4. Performance Measures

To evaluate the performance of the fused image, subjective and objective measures are used. The subjective measure relates the evaluation of visual perception and the objective analysis of the fused image is done using various measures such as Peak Signal to Noise (PSNR), Root Mean Square Error (RMSE), and Correlation (CORR) [6]. Let us consider a source image S(i,j) and the fused image F(i,j) of size M∗N.

(i) Peak Signal to Noise Ratio (PSNR)

Peak Signal to Noise Ratio is used to access the improvement in the quality of the fused image. It is defined by,

$$\mathrm{PSNR} = 10\, log_{10}\left(\frac{MAX^2}{\frac{1}{M*N}\sum_{i=1}^{M}\sum_{j=1}^{N}[S(i,j)-F(i,j)]^2}\right)$$

Here M∗N, S(i,j) and F(i,j) denotes the size of the image, source image and fused image respectively. MAX is the maximum value of an image. A higher PSNR value determines a better quality of the fused image.

(ii) Root Mean Square Error (RMSE)

Root Mean Square Error between the source image and the fused image can be calculated as

$$RMSE = \sqrt{\frac{1}{M*N}\sum_{i=1}^{\mathrm{M}}\sum_{\mathrm{j}=1}^{\mathrm{N}}[S(i,j)-F(i,j)]^2}$$

RMSE value approaches zero whenever the reference and fused images are similar and it will increase when the similarity decreases.

(iii) Correlation (CORR)

The standard value is one when the ideal and fused images are similar and is less than one whenever dissimilarity increases.

$$\mathrm{CORR} = \frac{2C_{rf}}{C_r+C_f}$$

Here $C_r = \sum_{i=1}^{M}\sum_{j=1}^{N} S(i,j)^2$,$C_f = \sum_{i=1}^{M}\sum_{i=1}^{N} F(i,j)^2$ and $C_{rf} = \sum_{i=1}^{M}\sum_{j=1}^{N} S(i,j)F(i,j)$

5. Comparison Results

Comparison of SF-DWT (Haar) Neutrosophic and DWT (Haar) Neutrosophic Image Fusion Techniques interms of PSNR, RMSE and CORR are given in the following table.

Table 1

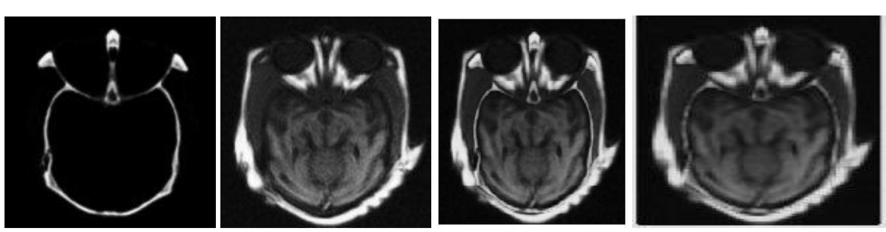
IMAGE	METHODS	PSNR	RMSE	CORR
Dataset 1	SFDWT(Haar)-Neutrosophic	46.7173	2.0259	0.9906
	DWT(Haar)-Neutrosophic	45.4826	2.4381	0.9140
Dataset 2	SFDWT(Haar)-Neutrosophic	44.6702	2.1196	0.9401
	DWT(Haar)-Neutrosophic	43.8110	2.1266	0.8189
Dataset 3	SFDWT(Haar)-Neutrosophic	46.4998	1.4558	0.9820
	DWT(Haar)-Neutrosophic	45.5284	2.8402	0.9361
Dataset 4	SFDWT(Haar)-Neutrosophic	44.3079	1.5331	0.9395
	DWT(Haar)-Neutrosophic	42.8203	3.3966	0.8661
Dataset 5	SFDWT(Haar)-Neutrosophic	44.3810	1.9066	0.9524
	DWT(Haar)-Neutrosophic	42.9735	2.5490	0.7190
Dataset 6	SFDWT(Haar)-Neutrosophic	46.2149	1.9915	0.9798
	DWT(Haar)-Neutrosophic	44.8189	2.1129	0.9444

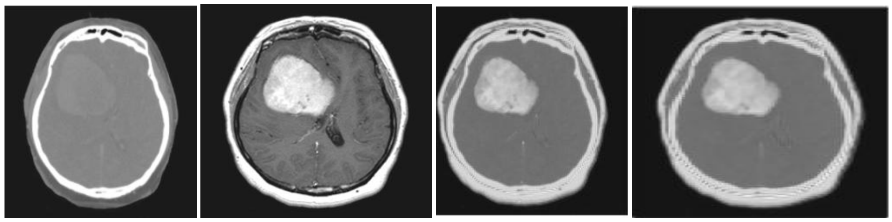
Dataset 7	SFDWT(Haar)-Neutrosophic	45.3570	1.8940	0.9616
	DWT(Haar)-Neutrosophic	44.6028	2.6298	0.9028
Dataset 8	SFDWT(Haar)-Neutrosophic	47.8409	1.3458	0.9857
	DWT(Haar)-Neutrosophic	46.3079	3.0190	0.9702
Dataset 9	SFDWT(Haar)-Neutrosophic	46.9878	1.3011	0.9817
	DWT(Haar)-Neutrosophic	46.6798	3.0357	0.9604
Dataset 10	SFDWT(Haar)-Neutrosophic	46.4100	1.4862	0.9802
	DWT(Haar)-Neutrosophic	46.0587	3.0674	0.9562

The efficiency of the proposed method can be seen from the following picture by comparing the obtained images with the previous images.

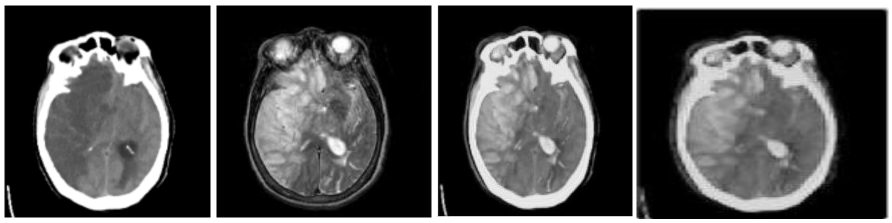
CT Images MRI Images DWT (Haar)-Neutrosophic SFDWT (Haar)-Neutrosophic

Dataset 1

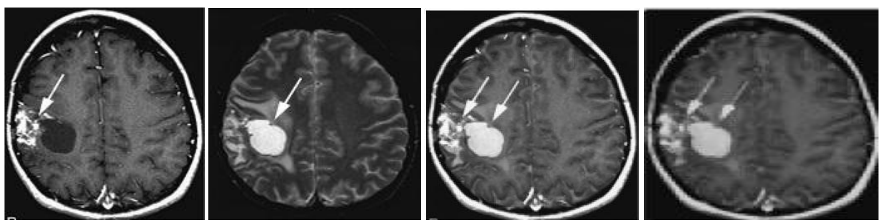




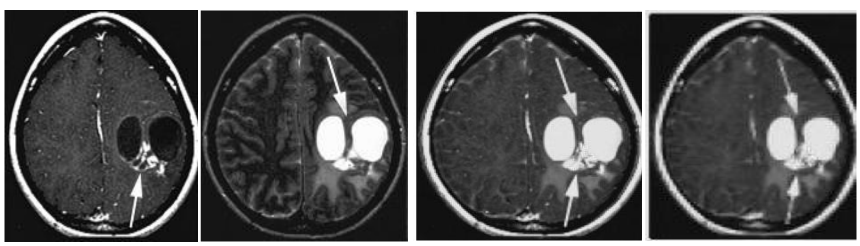
Dataset 2



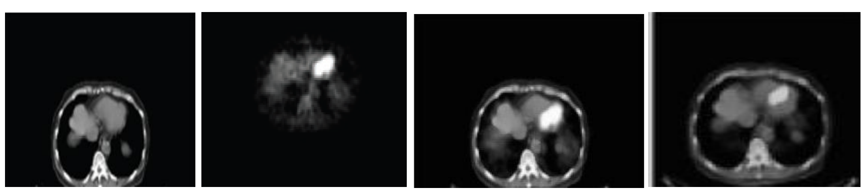
Dataset 3



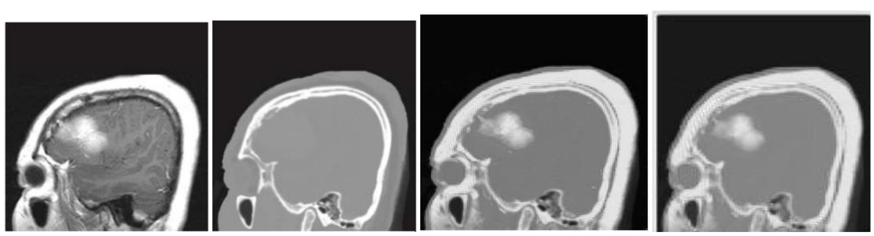
Dataset 4



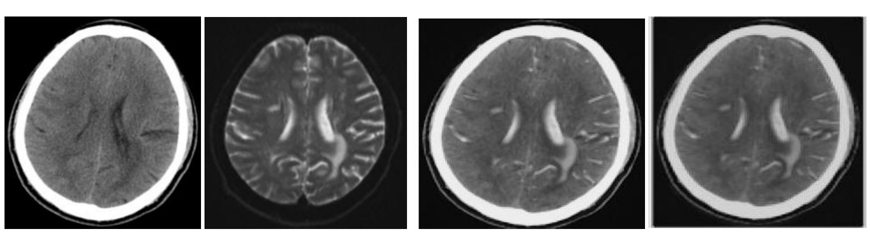
Dataset 5



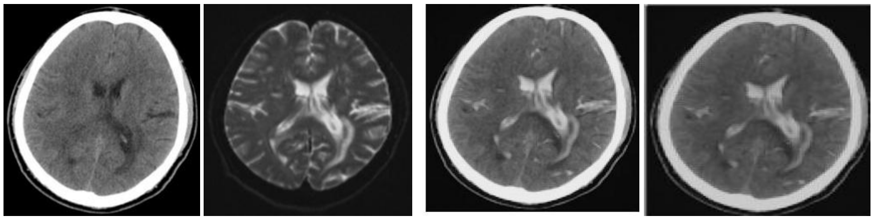
Dataset 6

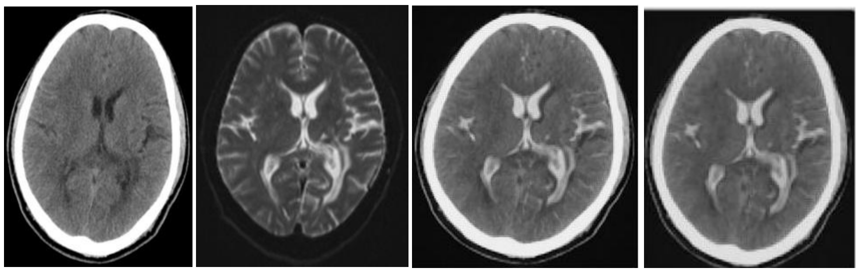


Dataset 7



Dataset 8

Dataset 9 

Dataset 10 

(i) Subjective Analysis:

The dataset 1 to 5 consists of CT - MRI brain images of different patients, the dataset 6 consists of CT- MRI abdomen image of different patients, the dataset 7 consists of CT-MRI Head image of different patients and dataset 8 to 10 consists of CT-MRI brain images of same patient with different modalities are used as input images for experimental purpose. Fused images are arranged as discrete wavelet transform (Haar) neutrosophic set and proposed spatial frequency discrete wavelet transform (Haar) neutrosophic set system. From the evaluation it is observed that the visibility of image is increased when compared to other methods. The proposed method gives better visualization because of the most important features is chosen based on the higher value of neutrosophic entropy to fuse the low subbands coefficients. The entropy gives the texture information of the image and it is important factor for the fusion of images. Hence the proposed method gives better result than the existing methods.

(ii) Objective Analysis:

Using subjective analysis, we cannot determine the completely fused image. Thus, objective analysis is results in fused images with measures mentioned in the previous section performance evaluation measures. For each measure, the result obtained from the proposed spatial frequency discrete wavelet transform (Haar) neutrosophic set is compared with discrete wavelet transform (Haar) neutrosophic set. The comparative analysis of different performance evaluation measures is tabulated in Table 1. From the result, one can observe that the proposed spatial frequency discrete wavelet transform (Haar) neutrosophic set produces a better result than the other existing fusion methods.

6. Conclusion

In this paper, a novel approach is proposed for fusion of images obtained from different modalities based on spatial frequency discrete wavelet transform (Haar) and neutrosophic set. Here, spatial frequency two-level discrete wavelet transform (Haar) decomposition is used to bring out the low-frequency and high-frequency subbands. For fusion process, neutrosophic set and average fusion rule is applied on low-level subbands and high-level subbands respectively. The fusion rule is applied on low-level sub-images to include the most important features with the highest degree of certainty. Then by using inverse discrete wavelet transform (Haar), fused images are reconstructed. Evaluation results of the fused image based on PSNR, RMSE and CORR measure shows that the proposed spatial frequency discrete wavelet transform (Haar) neutrosophic set provides better results than the existing methods.

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