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Multimodal Medical Image Fusion Based on Fuzzy Enhancement and Fuzzy Transform

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Abstract

Multimodal medical image fusion is a process of extracting information from different medical images to obtain a single image called fused image. Fused image analysis is extensively used by clinical professionals for quick diagnosis and treatment of critical diseases. This paper is developed using fuzzy logic enhancement and fuzzy transform (FT) for integrated multimodal medical image fusion. FT based fusion helps in preservation as well as effective transfer of detailed information present in input images into a fused image. The proposed work is effective and generates better fused images compared to existing techniques such as discrete wavelet transform (DWT) and non-subsampled contourlet transform (NSCT). The fused image is also compared with quality metrics such as Entropy (E), Mutual Information (MI) and Edge based quality metric ($Q^{AB/F}$).

Key words – Image Fusion, Fuzzy Transform, DWT, Entropy.

1 INTRODUCTION

The process of combining two or multiple images of same modality or different modalities [1] to produce a single fused image which is more informative than any of the individual input image is known as Image Fusion. The main aim of image fusion is to preserve all salient, interrelated and relevant information present in input images without introducing any variation, noise and artifact in the fused image. Image fusion not only provides better information but also minimize the storage cost by minimizing the memory requirement for storage of multiple input images to that needed for storing only a single fused image. Due to unique and improved representation of information, image fusion is used in many medical applications [2] such as oncology, neurology, cardiology, and radiation therapy.

The main necessity of image fusion [3] is that it must preserve all useful and valid information from the source images without introducing any artefact . To measure the quality of images that is for objective evaluation of image fusion [4] different performance measures like entropy, correlation coefficient, peak signal to noise ratio, root mean square error, standard deviation, structure similarity index, high pass correlation, edge detection, average gradient etc., has been used. Entropy gives a measure of information quantity, correlation coefficient is used to find the similarities between registered and the fused image, average gradient reflects the clarity of the fused image, root mean square error is cumulative error between the fused and the original image whereas peak signal to noise ratio is a measure of image error and so on.

So far, many image fusion algorithms have been developed in literature. These algorithms can be categorized into pixel-level [5], feature-level [6] and decision-level [7] image fusion algorithms. Pixel-level image fusion algorithms fuse directly the raw input images based on their pixel intensities or on arbitrarily small regions of pixels. Feature-level fusion algorithms fuse input images using their salient features [8] such as edges and line segments. The algorithm says that correspondence among features present in input images is usually known and are very much image dependent. A decision-level algorithm fuses image descriptions directly, either in the form of probabilistic variables or in the form of relational graphs to produce a high quality fused image. These methods however completely rely and very much application dependent. Compared to feature-level and decision-level image fusion algorithms, pixel-level algorithms [9] are capable of retaining most of the image information and are not only easy to implement but also computationally more efficient and are therefore preferred for multimodal medical image fusion.

A straightforward multimodal image fusion method is to overcome the source images by manipulating their transparency attributes, or assigning them by different color channels. This overlying scheme is a fundamental approach in color fusion, a type of image fusion that used color to expand the amount of information conveyed in a single image.

2 PRELIMINARIES

2.1 DWT for image fusion

Dwt Discrete wavelet transform [10] provides a framework in different modality images to be analysed is passed through filter with different cut off frequency at different scales so that images get converted to frequency domain from spatial domain. The resultant output gives the detail coefficient (from the high pass filter) and approximation coefficient (from the low pass filter). It finds application mainly in medical imaging and speech signals. The wavelet transform decomposes the input images into spatial frequency bands of various levels such as low- high, high- low, high- high and low- low groups. Now a general fusion rule is applied to select the coefficients whose values are higher such that most dominant feature is preserved in the multi resolution representation. A new image is formed by performing an Inverse wavelet Transform.

This gives introduction to image fusion methods based on wavelet transform. Fusion of CT scanned images and MRI images using multi-resolution wavelet transform with necessary pre-processing of it is proposed. It also compares the performance of the various types of wavelet basis families used and the different fusion rules used to fuse the approximation and detail wavelet coefficients. Advantages of DWT (Discrete wavelet transform) is Better Signal to Noise ratio than pixel based approach. Disadvantages of DWT **(**Discrete wavelet transform**)** are Less Spatial Resolution, Less Colour Distortion and Low anatomical Information

2.2 NSCT based image fusion

The non-subsampled contourlet transform [11] is built upon non sub-sampled pyramids and non sub-sampled directional filter banks and provides a shift-invariant directional multi-resolution image representation. The source medical images are first transformed by NSCT followed by combining low- and high-frequency components. Two different fusion rules based on phase congruency and directive contrast are proposed and used to fuse low- and high-frequency coefficients. Finally, the fused image is constructed by the inverse NSCT with all composite coefficients. Advantages of NSCT (non-subsampled contourlet transform) are, It extracts the geometric information of images, which can be used to distinguish noises from weak edges, High Anatomical Information. Low contract Image output is one of the drawbacks of NSCT.

2.3 Fuzzy transform (FT)

Fuzzy Transform is a powerful transformation technique that is capable of preserving features especially for fuzzy models introduced by Perfilieva [12]. It has been effectively applied to a wide range of applications such as image fusion, image compression, noise removal [13], data analysis, and solution of differential and integral equations. FTR establishes a correspondence between a set of functions in a closed interval into a finite (say N) dimensional vector space. It has an improvement of producing a simple and unique re-enactment of an original function which if used in place of original function makes complex computations easier. FTR is as helpful as traditional transforms such as wavelet transform and Fourier transform, but FTR has a potential advantage over these transforms as it can use several basis functions of different shapes whereas wavelet transform utilizes a single mother wavelet to define all basis functions and Fourier transform uses only a single kind of basis function i.e. e^{jwx}. The contrast quality of image is not good is drawback of Fourier Transform.

The following are the advantages of Fourier Transform:

1. Since FTR deals with vectors and matrices, it has low computational complexity and is faster to implement than other traditional transforms.
2. FTR is invariant with respect to interpolating and least square approximation of input data.
3. It possesses noise removing abilities as well as smoothing abilities and is also successful in

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preserving true image edges, hence is successful in image processing applications.

4. Inverse FTR approximates the original function in such a way that universal convergence holds true.

5. It preserves the summation of the approximated function that translated to the invariance of the fuzziness of a fuzzy number.

6. It is shift invariant.

7. FTR has the capability of preserving monotonicity and Lipschitz continuity of a function that helps in improving the quality of reconstructed image.

2.4 Fuzzy Enhancement

Whatever the results we got by applying FT for multimodal medical image fusion [14], the contrast quality of image is not that much good. So, for improving the contrast quality we used fuzzy logic. Image enhancement means to enrich the perception of images for human viewers. It can reduce impulsive noise; sharpen the edges with the help of different image enhancement techniques. Fuzzy techniques can manage the uncertainty and imperfection of an image which can be represented as a fuzzy set. Fuzzy logic can be used to process human knowledge in the form of fuzzy if-then rules. The accumulation of all these approaches comes up to the theory of fuzzy image processing, which is divided into 3 phases: Image fuzzification, membership values modification, and image defuzzification. On the basis of following fuzzy rules, an image enhancement algorithm has been developed and implemented:

- if pixel intensity is dark then output is darker.
- if pixel intensity is gray then output is gray.
- if pixel intensity is bright then output is brighter.

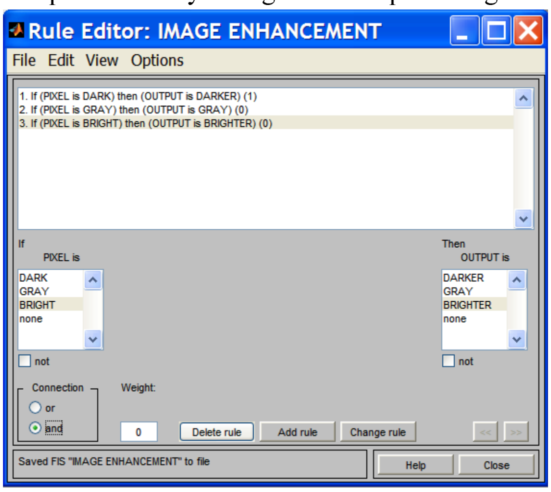

Fig.1 Fuzzy rules for proposed image enhancement

3 PROPOSED METHOD

Multimodal medical image fusion combines both the functional information as well as anatomical information for better applications of medical imaging that result in efficient clinical investigation and disease diagnosis. The proposed method performs FTR based fusion of multimodal medical images [15] . In order to obtain a better quality of fused image, the proper fusion rules should be carefully selected. Averaging based fusion rule and select maxima based fusion rule are most commonly used for fusion of images. Averaging based image fusion produces a fused image by performing pixel-wise averaging on input images which tends to reduce the contrast and blurs the resultant fused image. Select maxima based fusion rule selects the salient features from the input images but this method is sensitive to noise and it also discards the information from the less bright image if used directly over pixel intensity.

The fused image obtained using proposed method contains richer feature and detailed information than other fused images. FTR based fusion helps in preservation as well as effective transfer of detailed information present in input images into a fused image.

ALGORITHM

Assuming perfectly registered input images *A* and *B*, the proposed fusion.

There in all six steps in our proposed work

1. Select proper Input Images (two different modality images)
2. Apply FTR to sub blocks of these image (we considered 32*32,64*64 and 128*128 block sizes).

$$F_{NM} = \begin{bmatrix} F_{11} & F_{12} & \cdots & F_{1Y} \\ F_{21} & F_{22} & \cdots & F_{2Y} \\ . & . & & . \\ . & . & & . \\ . & . & & . \\ . & . & & . \\ F_{Y1} & F_{Y2} & \cdots & F_{YX} \end{bmatrix}$$

3. Fuse using maximum based entropy rules.

BLOCK DIAGRAM

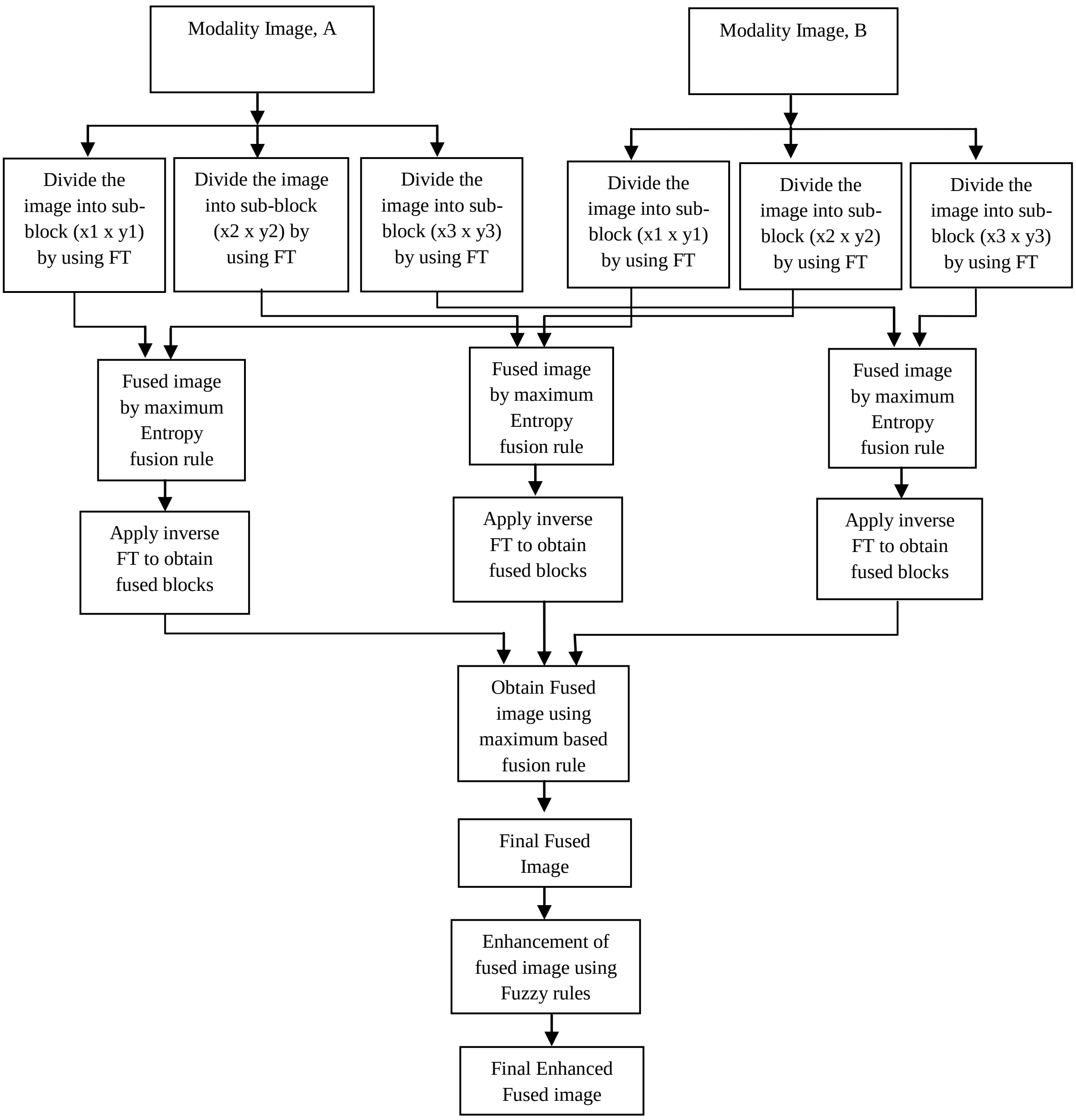

Fig.2 Block diagram of proposed method for multimodal medical image fusion

Table 1: Fuzzy rules developed by FIS for two input entropies.

INPUT 1	INPUT 2	OUTPUT
High	Low	Input 1
Low	High	Input 2

4. Apply Inverse FTR and resize the image.

$$F_{ij} = \frac{\sum_{v-1}^{x}\sum_{u-1}^{y} f(p_u, q_v) S_i(p_u) T_J(q_v)}{\sum_{v-1}^{x}\sum_{u-1}^{y} S_i(p_u) T_J(q_v)},$$

for i = 1,2,.......,Y and j=1,2,.....,X.

5. Fuse using maximum based fusion rules

Table 2: Fuzzy rules developed by FIS for 3 input entropies.

Input 1	Input 2	Input 3	Output
High	Low	Low	Input 1
Low	High	Low	Input 2
Low	Low	High	Input 3

We will get Fused Image; calculate quality assessment parameter for output image

4. EXPERIMENTAL RESULTS

Experiments on two different modality images are performed .The first example shown in Figure 3 deals with CT Modality and MRI Modality which provides information regarding bones, hard and soft tissues. The two images are fused using the proposed method and are compared with existing methods like discrete wavelet Transform and Non sampled counterlet Transform. Fused image is also compared objective parameters like Entropy, Mutual Information and Edge based quality metric and found the better performance of proposed method. The fused image obtained by proposed method is seen in fig 3 (f) where the contrast quality of image is improved. The fused image average information content (entropy) is observed as 6.0781, Mutual Information (0.1831) and Edge based quality metric (0.1208) which can be observed in table 3.

The second example shown in Figure 4 deals with CT Modality and MRI Modality which provides information regarding bones, hard and soft tissues. The two images are fused using the proposed method and are compared with existing methods like Discrete wavelet Transform and Non sampled counterlet Transform. Fused image is also compared objective parameters like Entropy, Mutual Information and Edge based quality metric and found the better performance of proposed method. The fused image obtained by proposed method is seen in fig 4 (f) where the contrast quality of image is improved. The fused image average information content (entropy) is observed as 5.9550, Mutual Information (0.0968) and Edge based quality metric (0.1790) which can be observed in table 3.

The third example shown in Figure 5 deals with MRI Modality and PET Modality which provides anatomy of brain tissues and functional information of brains.The two images are fused using the proposed method and are compared with existing methods like Discrete wavelet Transform and Non sampled counterlet Transform. Fused image is also compared objective parameters like Entropy, Mutual Information and Edge based quality metric and found the better performance of proposed method. The fused image obtained by proposed method is seen in fig 5 (f) where the contrast quality of image is improved. The fused image average information content (entropy) is observed as 10.3443 , Mutual Information (0.5009) and Edge based quality metric (0.1142) which can be observed in table 4.

The fourth example shown in Figure 6 deals with MR Modality and MRA Modality which provides soft tissues information and to evaluate blood vessels and functional information of brain..The two images are fused using the proposed method and are compared with existing methods like Discrete wavelet Transform and Non sampled counterlet Transform. Fused image is also compared objective parameters like Entropy, Mutual Information and Edge based quality metric and found the better performance of proposed method. The fused image obtained by proposed method is seen in fig 6 (f) where the contrast quality of image is improved. The fused image average information content (entropy) is observed as 10.3443 , Mutual Information (0.5009) and Edge based quality metric (0.1142) which can be observed in table 4.

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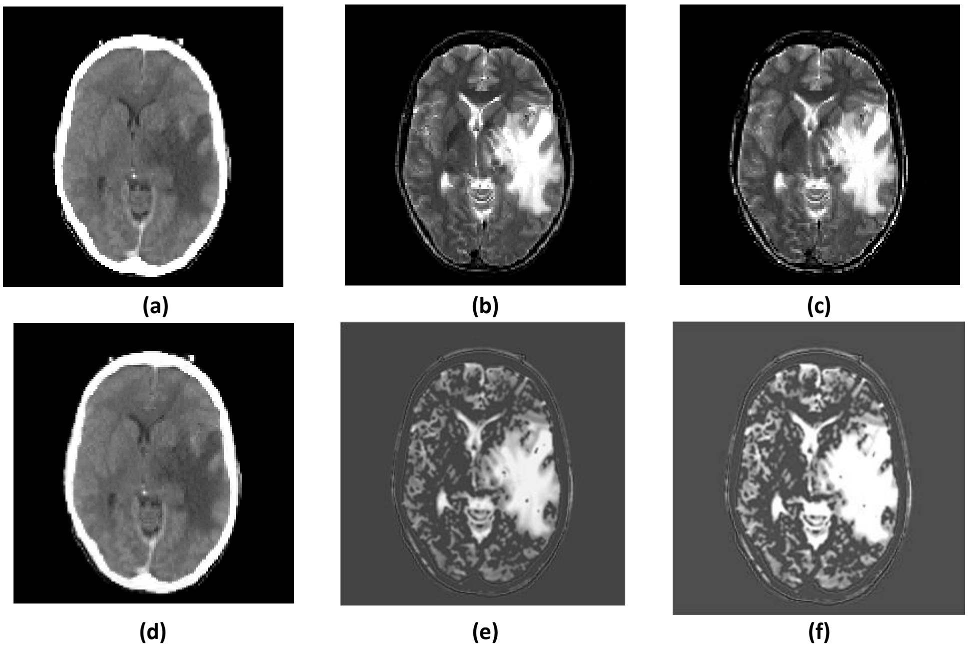

Fig. 3 Fusion results for CT and MRI images. (a) CT image (b) MRI image (c) Fused image by DWT (d) Fused image by NSCT (e) Fused image by Fuzzy Transform (f) Enhanced Output

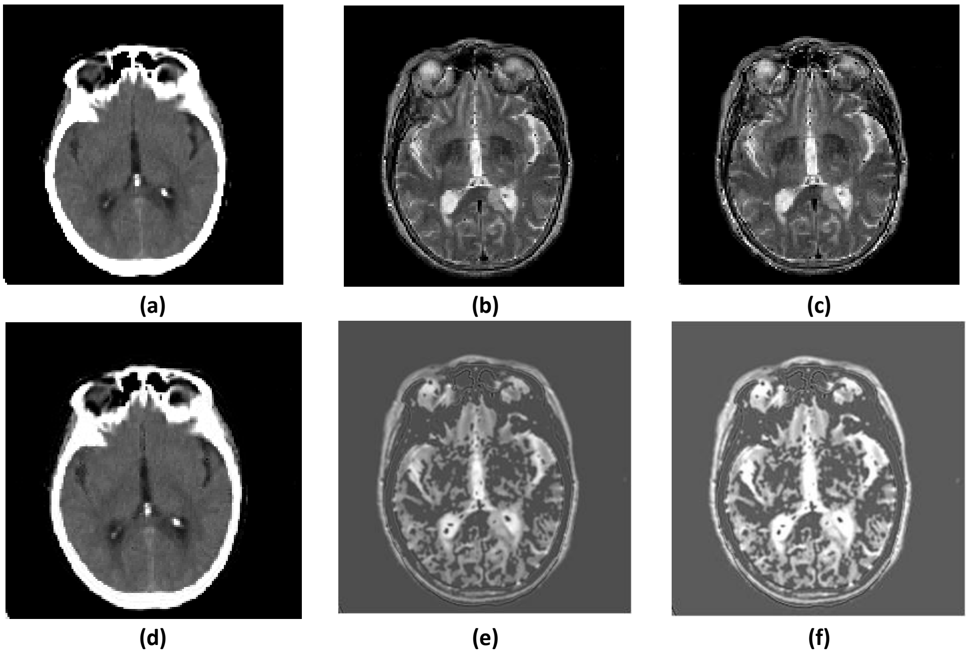

Fig. 4 Fusion results for CT and MRI images. (a) CT image (b) MRI image (c) Fused image by DWT (d) Fused image by NSCT (e) Fused image by Fuzzy Transform (f) Enhanced output

Table 3 Objective evaluation of different fuzzy image fusion methods for Fig. 3 & Fig 4

	Figure 3			Figure 4		
Fusion Methods	Entropy (bits/symbol)	Feature Mutual Information	Edge Information Preservation	Entropy (bits/symbol)	Feature Mutual Information	Edge Information Preservation
DWT	4.5954	0.0028	0.4683	4.9142	0.0037	0.4410
NSCT	4.0189	0.0020	0.4290	4.0407	0.0034	0.4170

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Fuzzy Transform	6.0781	0.2481	0.1554	5.9550	0.1838	0.1860
Proposed Method	6.0781	0.1831	0.1208	5.9550	0.0968	0.1790

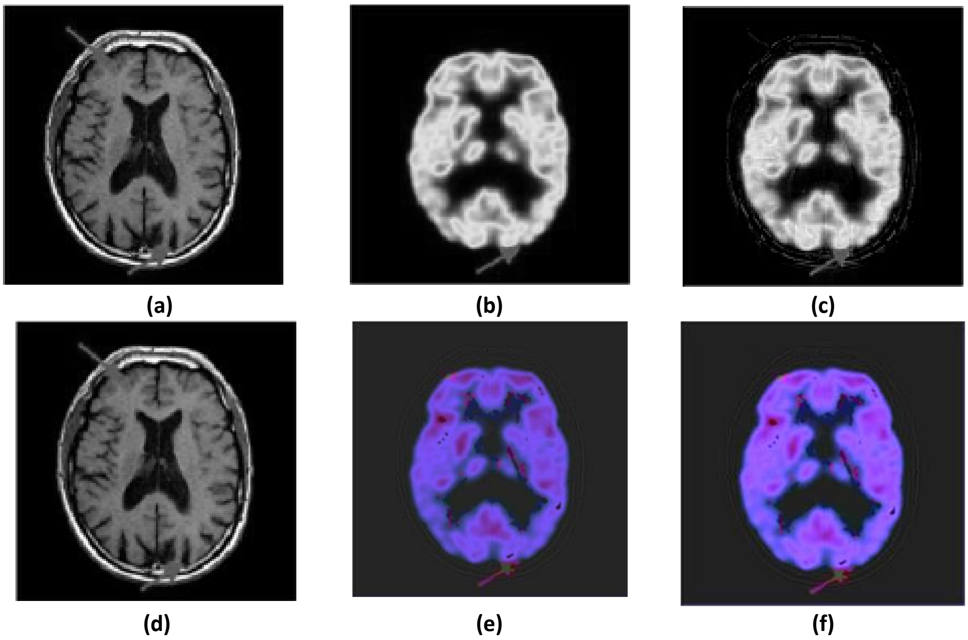

Fig. 5 Fusion results for MRI and PET images. (a) MRI image (b) PET image (c) Fused image by DWT (d) Fused image by NSCT (e) Fused image by Fuzzy Transform (f) Enhanced Output

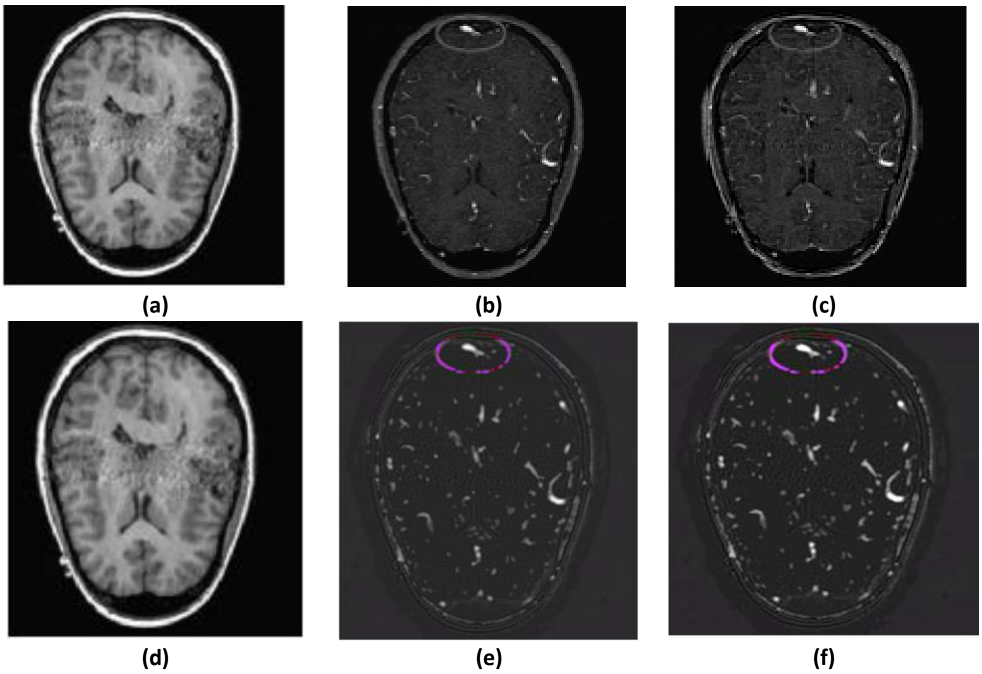

Fig. 6 Fusion results for Mr and Mra images. (a) Mr image (b) Mra image (c) Fused image by DWT (d) Fused image by NSCT (e) Fused image by Fuzzy Transform (f) Enhanced Output

Table 4 Objective evaluation of different fuzzy image fusion methods for Fig. 5 & Fig .6

	Figure 3			Figure 4		
Fusion Methods	Entropy (bits/symbol)	Feature Mutual Information	Edge Information	Entropy (bits/symbol)	Feature Mutual Information	Edge Information

			Preservation			Preservation
DWT	5.3099	0.0033	0.3081	4.9681	0.0047	0.2698
NSCT	5.5010	0.0044	0.5826	5.6626	0.0044	0.6305
Fuzzy Transform	10.3443	0.6115	0.0789	9.9978	0.0682	0.0980
Proposed Method	10.3443	0.5009	0.1142	9.9978	0.1109	0.0945

6 CONCLUSIONS

Multimodal medical image fusion combines anatomical data with purposeful data. This paper proposes a completely unique multimodal medical image fusion technique supported FTR. For fusion, entropy and choose maxima based mostly fusion rules area unit employed in FTR domain that manufacture extremely informative amalgamate image with higher distinction. The projected algorithmic program was performed on different form of medical cinema. Results obtained from projected algorithmic program area unit visually still as quantitatively compared with those obtained mistreatment alternative normal and up to date strategies.

The amalgamate image obtained mistreatment projected technique contains richer feature and careful data than alternative amalgamate pictures. The final results are not having that much good contrast so we extended our proposed work for image enhancement using Fuzzy Logic.Matlab execution results show that out proposed method is better compare to all the existing methods.

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