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Performance Analysis of Multi-Modal Medical Image Fusion Using Fuzzy Rules

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Abstract: In medical image processing, image fusion technique is used to enhance the lesions or inertial component for better medical diagnosis and treatment. In this research, the fuzzy logic based medical brain MRI fusion technique is proposed. The edge pixels always have broad information than the other pixels. The mamdani fuzzy rules are constructed to fuse this edge oriented pixel information. The fused image has more complete information which is useful for human or machine perception. The fused image with such rich information will improve the performance of image analysis algorithms for medical applications. The final fused image of the method possesses a better performance with respect to values of PSNR, mean square error and entropy.

Key words: Fusion, fuzzy, multi-modal, medical imaging, PSNR

INTRODUCTION

Medical image processing has developed as one of the critical factors in regular clinical applications such as disease diagnosis and treatment planning. Owing to the technical limitations, the quality of medical images is usually unsatisfactory, degrading the accuracy of human interpretation and further medical image analysis, thereby, requiring the quality of these images to be enhanced. One approach to enhance the image quality is by image denoising. Several denoising approaches, like adaptive filters, wavelet-based methods (Rabbani *et al*., 2009; Becerikli and Karan, 2005), etc. were proposed. Another efficient technique is by image fusion which improves the image quality by combining the corresponding information from multimodal images into a single fused image. This resulting image called as fused image, provides an accurate sketch of the human body, thereby improving the accuracy in diagnosis. Researchers know that Magnetic Resonance Imaging (MRI) provides detailed information of only soft tissues in the body and Computed Tomography (CT) scanning helps in visualizing the dense structures like bones. Combining both MRI and CT images, researchers get an image which describes both the soft tissues and bones. The image fusion techniques mostly depend on multi-resolution analysis which includes discrete wavelet transforms, stationary wavelet transforms, etc.

However, all these imaging modalities provide information only within a limited field. Therefore, it requires the imaging data to be collected from the same patient using different modalities to undergo joint analysis. Joint analysis made image fusion technique to enter the medical field and in the improvement of data-oriented medical fusion techniques (Li *et al*., 2012; Jain and Aggarwal, 2012; Sapkal and Kulkarni, 2012). Image fusion aims at providing a single fused image which provides more accurate and reliable information than individual source images and more distinguishable features. Such a fused image helps radiologists in visual diagnosis and further treatment. Image fusion is most probably used for its compact and enhanced representation of information. In the case of T1-Weighted (T1W) and T2-Weighted (T2W) Magnetic Resonance Imaging (MRI) scans, they were fused to segment white matter lesions and cerebral iron deposits to help neurosurgical resection of epileptogenic lesions.

MRI images and Positron Emission Tomography (PET) images were fused in detecting intracranial tumors. MRI images and Single Photon Emission Computed Tomography (SPECT) were fused for abnormality localization in patients with tinnitus. MRI images were fused with Computed Tomography (CT) images for neuro navigation in skull base tumor surgery. Multiple fetal cardiac ultrasound scans were fused to reduce imaging artifacts. Even though image fusion is not performed in

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most systems, it is usually performed subconsciously by radiologists for better identification of abnormalities. In fundamental multi-modal image fusion methodologies, the source image is just overlaid by assigning them to different color channels. In color image fusion, this overlay approach is used to expand the amount of information over a single image but it does not affect the image contrast or distinguish the image features.

In this study, a fusion rule which aims at combining the pixel values of the source images using Discrete Wavelet Transform (DWT) while preserving the contrast has been proposed. Then, certain fusion rules are applied for merging of coefficients at various scales. Lastly, researchers apply an Inverse DWT (IDWT) over the fuzzy rule applied image to generate the final fused image.

Literature review: Shen *et al.* (2013) proposed a Medical Image Fusion algorithm employing cross-scale fusion rule for multi-scale decomposition based fusion of volumetric medical images. This method was designed for joint analysis of medical data from various imaging modalities and also for efficient color image fusion. An optimal set of coefficients from the multi-scale representations of the source image is effectively determined using neighborhood information. Experiment results show that the fusion method produces better results compared to other existing techniques.

A Dictionary-Learning Method with Group Sparsity and Graph Regularization (DL-GSGR) was presented by Li *et al.* (2012). First, the geometrical structure of atoms was modeled as graph regularization. Then, combining group sparsity and graph regularization, the DL-GSGR is presented which is solved by alternating the group sparse coding and dictionary updating. In this way, the group coherence of learned dictionary can be enforced small enough such that any signal can be group sparse coded effectively. Finally, group sparse representation with DL-GSGR is applied to 3D medical image denoising and image fusion. Specifically, in 3D medical image denoising, a 3D processing mechanism (using the similarity among nearby slices) and temporal regularization (to perverse the correlations across nearby slices) are exploited. The experimental results on 3D image denoising and image fusion demonstrate the superiority of the proposed denoising and fusion approaches.

Jain and Aggarwal (2012) fused text data with medical images. In their research, the Area of Interest (AOI) for a particular image is found out and the text data of the patient is appended/fused in the Non-Area of Interest (NAOI) of the image. They proposed a fusion rule based on matrix scanning to find the AOI and then finds the noisy pixels of the image to embed data in that noisy portions to save the border size. Their system used MATLAB for implementation and to store text data in pixels.

An image fusion algorithm based on wavelet transform was proposed by Sapkal and Kulkarni (2012). It includes multi resolution analysis ability in wavelet transform. The method applies pixel-based algorithm for approximations involving fusion based on taking the maximum valued pixels from approximations of source images. Based on the maximum pixel values, a binary decision map is formulated. Then, inverse wavelet transform is applied to reconstruct the resultant fused image and display the result. The wavelet sharpened images have a very good spectral quality.

The wavelet denoising methodology is used for the removal of various noises from PET medical images (Lin *et al*., 2001). This method fails to meet the quality objective of the medical image processing due to its low PSNR and high MSE. Rabbani *et al*. (2009) used bivariate Laplacian Mixture Model for denoising the medical images. This achieved high PSNR which makes this system as efficient one but it was based on wavelet multi mode method which degrades its performance. The fuzzy logic was used to find the edge pixels in the image by constructing and applying fuzzy rules (Becerikli and Karan, 2005). The fuzzy rules were based on pixel variations in the images. The fuzzy logic was formed to classify the images in various image foreground and background environment (Mathur and Ahlawat, 2008).

MATERIALS AND METHODS

Image fusion overview: The block diagram given in Fig. 1 explains the process flow of the proposed fuzzy based system. The input images, namely MRI and PET images from two different sources are employed with Discrete Wavelet Transform (DWT) at the initial stage. The fusion of these images occurs at the second stage based on the fuzzy rules formulated in the algorithm. Then, inverse DWT is applied at the consecutive level which produces a single combined output image called as fused image.

Proposed fusion algorithm

Fuzzy logic matrix: Fuzzy is a set or combination of rules and decisions. The proposed fuzzy system is designed with 4 inputs and a single output, such that the 4 inputs indicate the 4 pixels present in the window mask. In this, the number of fuzzy sets used for the input black and

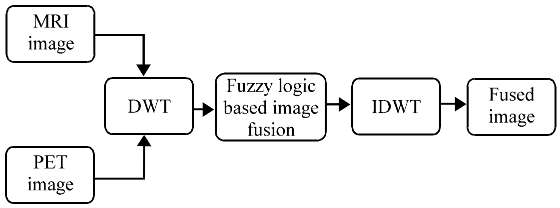

Fig. 1: Overall process flow of proposed multi modal image fusion methodology

Table 1: Fuzzy rules for input and output variables

Input/Output	Name	Range	MF type
Fuzzy input 1 = Pixel P1	Black	[0 0 255]	Triangular
	White	[0 255 255]	Triangular
Fuzzy input 2 = Pixel P2	Black	[0 0 255]	Triangular
	White	[0 255 255]	Triangular
Fuzzy input 3 = Pixel P3	Black	[0 0 255]	Triangular
	White	[0 255 255]	Triangular
Fuzzy input 4 = Pixel P4	Black	[0 0 255]	Triangular
	White	[0 255 255]	Triangular
Fuzzy output 1 = Pixel P4_out	Black	[0 3 5]	Triangular
	White	[249 252 255]	Triangular
	Edge	[130 133 135]	Triangular

Table 2: Fuzzy logic matrix for each sub-block

Fuzzy inputs				Fuzzy output
P1	P2	P3	P4	P4_out
B	B	B	B	B
B	B	B	W	E
B	B	W	B	E
B	B	W	W	E
B	W	B	B	E
B	W	B	W	E
B	W	W	B	E
B	W	W	W	E
W	B	B	B	E
W	B	B	W	E
W	B	W	B	E
W	B	W	W	E
W	W	B	B	E
W	W	B	W	E
W	W	W	B	E
W	W	W	W	W

white is 2 and for the output, 3 fuzzy sets are used. The fuzzy rules are formulated as shown in Table 1 for the input and output variables.

The accuracy level of edge detection in the image will be improved by using fuzzy logic. The 16 fuzzy rules are constructed for every 2×2 pixel sub-block. The output value indicates to which fuzzy set (Black fuzzy set, White fuzzy set or Edge fuzzy set) the output pixel 'P4' belongs to. The fuzzy matrix is shown in Table 2. The notation 'B' represents black pixel and 'W' represents white pixel and 'E' represents edge pixel. For the construction of 2×2 sub block, the edge pixel is noted if any pixel variation occurs in this sub-block.

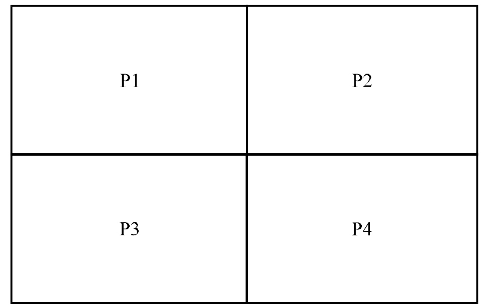

Fig. 2: The 2×2 scanning mask used in edge pixels detection

Implementation of the algorithm: The proposed algorithm is developed on the basis of a set of four pixels, part of a 2×2 mask window to a set of fuzzy rules that determine all the edges of the image. The fuzzy rules also assist in testing the relative values of pixels whether it is doubted as an edge pixel or not, therefore relative pixel values help to extract all the edges of an image. The edge pixel is present in an image if the difference in intensity between adjacent pixels is of large value. The described procedure can be achieved by formulating 16 rules. Next, the results are compared with the existing techniques using a Graphical User Interface (GUI).

Figure 2 shows a window mask used in scanning the image. Let P1, P2, P3 and P4 be the pixels in a 2×2 sub-block. The pixel P4 is checked if it is either black or white or edge based on P1, P2, P3 and P4 combinations. The pixel P4 is considered as edge pixel if the abrupt change in pixel P4 with respect to any P1, P2 and P3. Therefore, $2^4 = 16$ rules will be constructed.

The window mask is laid over an area of the input image. The mask alters the value of pixel P4 and then shifts one pixel to the right and continues to the right up to the end of a row. Then, it goes to the beginning of the next row and does the same process till the entire image is scanned. The mask is applied over the full image and the output is generated by the fuzzy system based upon the formulated rules and the pixels P1, P2, P3 and P4 (Fig. 3 and 4).

Step 1: Form or construct sub-blocks and each sub-block contain four pixels such as P1, P2, P3 and P4 which are fuzzified into different fuzzy sets, containing conventional membership functions.

Step 2: Fuzzy membership functions are determined for three categories of pixels such as black, white and edge pixels.

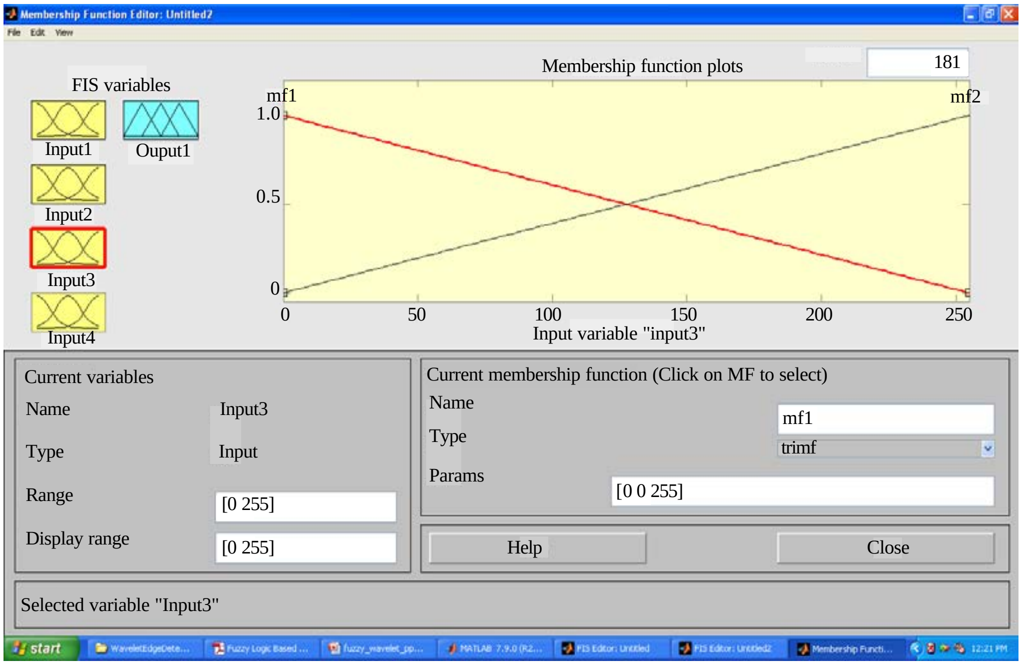

Fig. 3: Membership function for input variables

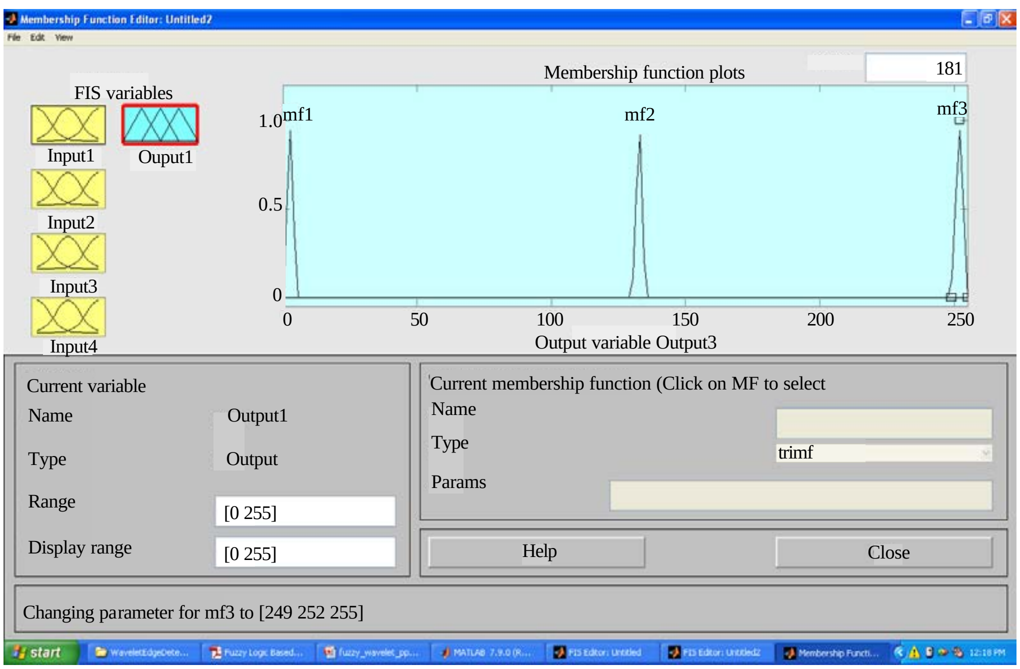

Fig. 4: Membership function for output variables

Step 3: Fuzzy rules are constructed in accordance with fuzzy membership function.

Step 4: 2 input membership function such as 'mf1' for black and 'mf2' for white is constructed.

Step 5: 3 output membership function such as 'mf1' for black, 'mf2' for edge and 'mf3' for white are constructed.

Step 6: The triangular membership functions are used for the inputs and single output.

The overall working of the algorithm is explained as a pseudo code as:

Pseudo code for proposed multi modal image fusion:
Input: MRI and PET Brain Images
Output: Fused image
1. Upon receiving MRI and PET brain images
2. Apply DWT on MRI brain image and obtain its coefficients
3. Apply DWT on PET brain image and obtain its coefficients
4. Remove the lower resolution sub bands from both images
5. Construct membership functions for input variables
6. Construct membership functions for output variables
7. Check the membership function as triangular
8. If triangular membership is found then
9. Construct the fuzzy rules based on membership function
10. End
11. If fuzzy rules are constructed then
12. Apply fuzzy rules to DWT transformed images
13. End
14. Perform inverse DWT on the fuzzy applied image
15. If IDWT is successful then
16. Do performance analysis
17. End

RESULTS AND DISCUSSION

Fusion of PET/MRI: The dataset used for the experimentation includes color PET scan images and normal brain MRI images. Both scan images have a resolution of 256×256 with 8 bit precision in the luminance channel. The metabolisms exposed by the PET scan are fused with the anatomical structures shown in the MRI scan in the final image which provides an enhanced spatial relationship. All the fused results are assessed by three clinicians who all have over 5 years working experience in the relevant field. They point that a clear and accurate adjacent relationship of soft tissue and bone structure is very important for intra operative orientation. Among those fused images, they think that the proposed fusion method provides clearer adjacent relationship and it is superior to the other existing methods for surgical navigation. The original image and the fused image are compared by the two quality metrics such as PSNR (Peak Signal to Noise Ratio), MMSE (Minimum Mean Square Error), entropy and elapsed time.

The proposed fusion method is quantitatively evaluated and compared in terms of subjective testing, i.e., visual quality where recommended parameters are used. For the quantitative testing of the fused images, researchers make use of the Peak Signal to Noise Ratio (PSNR) is a prime evaluation factor. From the results, it is observed that the proposed fusion methodology performs very well. To prove the visual quality, the fused image of proposed method is compared with that of images obtained by other state of arts methods employing various set of MRI and PET images. It has been proven that the fused image obtained by the proposed method

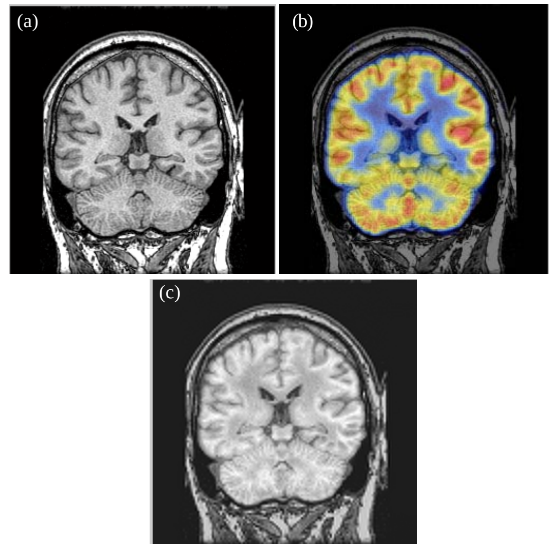

Fig. 5: Simulation results: a) MRI brain image; b) PET brain image; c) fused brain image

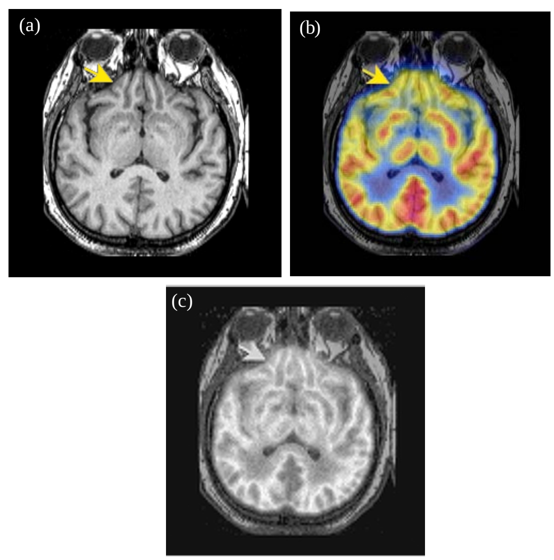

Fig. 6: Simulation results: a) MRI brain image; b) PET brain Image; c) fused brain image

has a better visual quality than others and is shown in Fig. 5 and 6. Entropy is an important evaluation parameter to estimate the quality adherence of the fused image. It is a statistical measure of randomness that can be used to characterize the texture of the fused brain image. The values of PSNR and MMSE are represented mathematically as:

$$\mathrm{PSNR} = 20\log_{10}\frac{\mathrm{MAX_f}}{\sqrt{\mathrm{MSE}}} \quad (1)$$

Table 3: Performance comparison of proposed fusion method in terms of quality metrics

Methodology	PSNR	MSE	Entropy
Proposed methodology	56.23	27.41	2.0958
Group-Sparse algorithm (Li *et al*., 2012)	29.54	32.56	1.7864
Bivariate Laplacian Mixture Model (Rabbani *et al*., 2009)	22.16	37.19	1.9652

Table 4: Performance comparison of proposed method in terms of fusion latency

Methodology	Elapsed latency (msec)
Proposed methodology	0.17
Group-Sparse algorithm (Li *et al*., 2012)	0.38
Bivariate Laplacian Mixture Model (Rabbani *et al*., 2009)	0.45

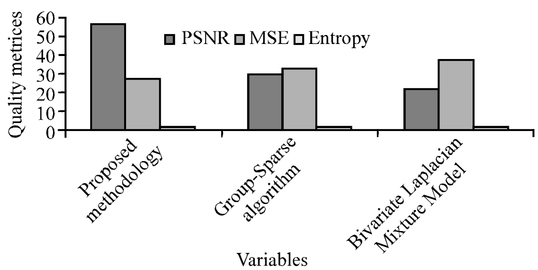

Fig. 7: Graphical representation of the performance comparisons in terms of PSNR, MSE and entropy

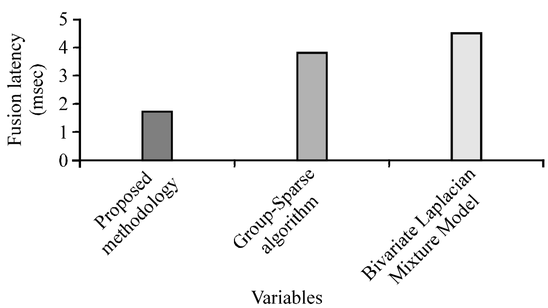

Fig. 8: Graphical plot of performance comparison in terms of fusion latency

$$MSE = \frac{1}{mn}\sum_{0}^{m-1}\sum_{0}^{n-1}\left\|f(i,j)-g(i,j)\right\|^2 \quad (2)$$

Where:
m = Width of the fused image
n = Height of the fused image

$$Entropy = -\sum p\times\log(p) \quad (3)$$

where, p represents histogram counts of each pixel value in an fused brain image. Table 3 illustrates the variation of PSNR, MSE and entropy and Table 4 shows the time taken for fusion. Figure 7 and 8 graphically represent the variation of PSNR, MSE and entropy and elapsed time variation in fusion, respectively.

CONCLUSION

In this study, a fuzzy logic based multimodal medical image fusion method is employed. Future research in this field is planned for extension to other types of image modalities and to objectively evaluate image fusion methods in real time. The simulation results have shown higher accuracy in detecting the non area of interest over other algorithms. The proposed fuzzy logic based algorithm was implemented and executed for various sets of images and proved successful in obtaining the noisy pixels present in an image. The simulation outputs of certain images have been shown to make the readers understand the accuracy of the algorithm. Thus, the proposed fusion algorithm finds its application in diverse areas of digital image processing in medical field. The fused image has better performance in terms of PSNR, mean square error, latency and entropy.

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