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Image Fusion Based on DWT Type-2 Fuzzy Logic System

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Abstract—In the medical field, medical imaging requires capturing different aspects of a human body. To take images of tissue, cartilages, bones, and nerves one requires different modalities, which produces different images from different modality of the same body part. Image fusion is the technique to integrate the essential information present in the set of source images to one fused image. Image fusion technique is widely used in medical field to improve the clinical accuracy to take better decisions. In medical imaging, different modality images convey different information of human body like Compute Tomography (CT) scan image provides the information on hard structures. Magnetic Resonance Imaging (MRI) scan image provides the information of soft tissue. Fusion of these medical images is useful for doctors to diagnose and plan treatment for patients. In this paper, an image fusion methodology for fusing medical images using novel Discrete Wavelet Transform Type-2 fuzzy logic system (FLS) is presented. Experiments are conducted for already existing methods, also for Sugeno type Fuzzy Logic System and Mamdani type Fuzzy Logic System with varying number of the membership function. The results are analyzed using various performance metrics. From the results observed that the proposed method provides an improvement over existing methods.

Index Terms—DWT, Medical image, multimodal sensor fusion, Type-2 fuzzy logic.

1 Introduction

The rapid development of medical imaging and information processing technologies provides many types of medical images for clinical diagnosis, monitoring, and analysis. The medical images are widely used in disease diagnosis, surgery, and radiotherapy [1], [2]. The medical images obtained from different modalities captures different information about the human body and have their own uses. For example, computed tomography (CT) images provide information of dense structures like bones and hard tissues, while magnetic resonance imaging (MRI) images can depict details of soft tissue [3]. Similarly, T1-MRI images provide details about normal and pathological tissues [4]. Positron emission tomography (PET) images can provide information on brain regions such as motor or speech region by using specific activation tasks. And single-photon emission computed tomography (SPECT) images can depict metabolic changes. Therefore these individual images often cannot provide enough information to doctors in the actual clinical situation. It is necessary to combine the images from different modalities to obtain a clear picture of diseased tissue or organs for efficient diagnosis. This can be achieved with image fusion techniques, which automatically combines images from different modalities into the single image [5]. The resultant fused image gives the accurate and clear description of a target and also reduces the randomness and redundancies present in the input source images obtained from different modalities.

In image fusion, many fusion techniques were proposed and developed. These fusion techniques are categorized into pixel-level, feature-level and decision-level [5]. Pixel-level image fusion is carried out directly on the acquired source image, retaining most of its detail information without any artifacts. Nowadays most research and application uses pixel-level image fusion and those algorithms are categorized into two classes, spatial domain based and transform domain based [6]. Spatial domain techniques are performed directly on source images using the local spatial feature and spatial domain based methods include the minimum method, average method, maximum method, and principal component analysis (PCA) method. However pixel-level spatial domain methods usually lead to several undesirable side effects including spatial, spectral distortion and reduced contrast in the fused image.

In the current scenario, the transform domain related image fusion algorithms have become a popular fusion method. The Stationary wavelet transform (SWT), Discrete wavelet transform (DWT) are used successfully in image fusion [7], [8]. But these methods have one or the other drawbacks but all of them have one or the other drawback but all of them have some common drawback such as insertion of an additive noise-infused image.

Soft computing technology, especially fuzzy logic theory is successfully used in image processing. Because of their ability to handle uncertainty, fuzzy logic based image fusion method results from better performance than basic image fusion methods. Fuzzy logic is used as either a feature transform operator or a decision operator for image fusion [9]. In recent years research is going on in the higher order of fuzzy logic in the particular type-2 fuzzy logic system and is used for image fusion process. Compared to type-1 fuzzy logic, the membership functions of type-2 fuzzy logic are also fuzzy and this extended degree of fuzziness handles the higher degree of uncertainty.

In this paper, a novel fusion framework based on DWT and type-2 fuzzy logic is proposed for multimodal medical images. In proposed image fusion method, source images are decomposed into low-level sub-band and high-level sub-bands using DWT. Next, low-level sub-image is fused using type-2 fuzzy fusion rule and high-level sub-images are fused using maximum fusion rule. Finally at the end inverse DWT is applied on the fused sub-image components to obtain the fused image.

The rest of the paper is arranged as follow: In the section-2 brief introduction of related work is given. In section-3 proposed image fusion method is elaborated. Section-4 discusses the performance evaluation measures, in Section-5 experimental results and performance analysis is depicted, Conclusion is summarized at the end.

2 Related Work

2.1 Discrete Wavelet Transform (DWT)

Wavelet transform process is a multi-resolution analysis that gives the image variation at various wavelet scales. A wavelet is an attenuated and oscillating function with integration as zero. In image processing always we get the discrete signal that is mostly obtained by the pixel intensity values. So to process discrete pixel intensity value of an image, DWT is preferred a wavelet transform wavelet transform in which the wavelets or the input function is discretely sampled. Compared to other wavelet transformation, the advantage of DWT over Fourier transform or any other transform is that of temporal resolution. Other transforms only capture the location details, but DWT captures the information of frequency and location.

The estimation of the wavelet transform of an image comprises recursive filtering and sub-sampling. The decomposition of the image gives three detail high-level sub-images. These detail high-level images are denoted as LH (presence of horizontal data in high frequency), HL (presence of vertical data in high frequency) and HH (presence of diagonal data in high frequency). The wavelet transform also yields single approximation image represented as LL that is low-level sub-image, which is sensitive to human eyes. In DWT implementation scaling function is related to smooth filters or low pass filters and wavelet function linked with high pass filter.

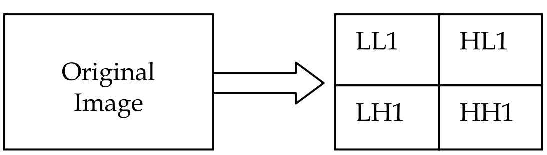

Fig. 1.Dwt based image decomposition.

2.2 Type-2 Fuzzy Logic System

The fuzzy set concept created by Zadeh [10],[11], which effectively solves the fuzziness problem which is difficult to handle by using classic mathematics. Type-1 fuzzy is not flexible, so it is difficult to minimize uncertainty effects by using any kind of membership function algorithm. To address this problem type-2 fuzzy concept is proposed.

A type-2 fuzzy logic system can be defined as in (1).

$$A = \{((x,u), \mu_A(x,u)) | \forall_x \in X, \forall_u \in J_x \subseteq [0,1]\} \qquad (1)$$

Where symbol A represents the type-2 fuzzy set and $\mu_A(x, u)$ represents its type-2 membership function with $0 \le \mu_A(x, u) \le 1$. $J_x$denotes the primary membership function and $\mu_A(x', u)$denotes the secondary membership function when x=x'.

Using the skeleton of type-1 fuzzy membership function type-2 fuzzy set are constructed and footprint of uncertainty (FOU) present with the created type-2 fuzzy set as shown in below Fig.2.

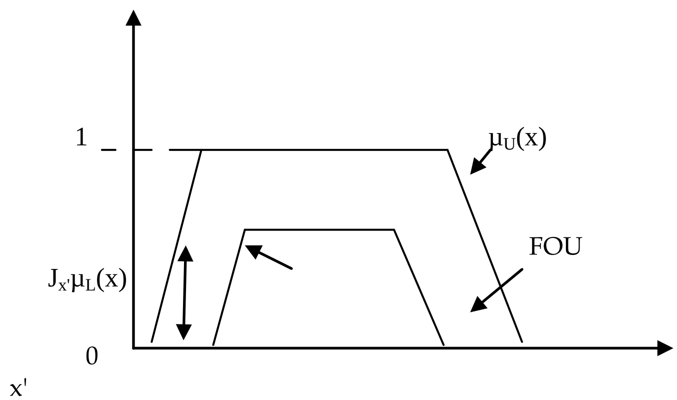

Fig.2. A type-2 fuzzy logic membership function

Type-1 fuzzy set $\mu_L(x)$ and $\mu_U(x)$. And the area between $\mu_L(x)$ and $\mu_U(x)$ is referred to as FOU. The schematic diagram of T2FIS is shown in Fig.3.

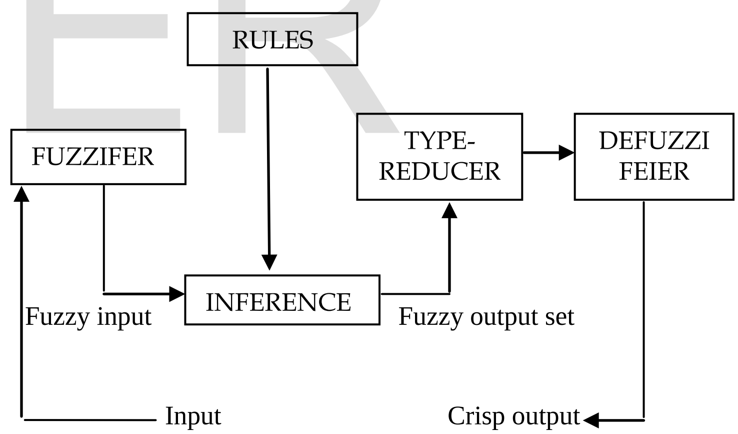

Fig. 3.Type-2 fuzzy logic system

The steps involved in the type-2 fuzzy logic system are mentioned below.

- Determining fuzzy rule set (generally if-then instruction) according to which fusion process is to be handled.
- Fuzzification: Type-2 membership functions are applied to input information to get a degree of truth for each rule premise from the actual values of input. So thereby inputs information is translated to type-2 fuzzy sets.
- Inference: Rules need to be combined to map input type-2 fuzzy set to output type-2 fuzzy set this is done

by an inference engine.

- Type–reduction: In this step translation of output from inference engine that is type-2 fuzzy set to type-1 fuzzy set is carried out.
- Defuzzification: In the last step the fuzzy output set is converted to a crisp number.

3 Proposed Methodology

The proposed novel fusion method DWT-Type 2 fuzzy comprises three steps: Decomposition, Fusion, and Reconstruction. The block diagram of the proposed DWT- Type 2 fuzzy method based image fusion is shown in Fig.4.

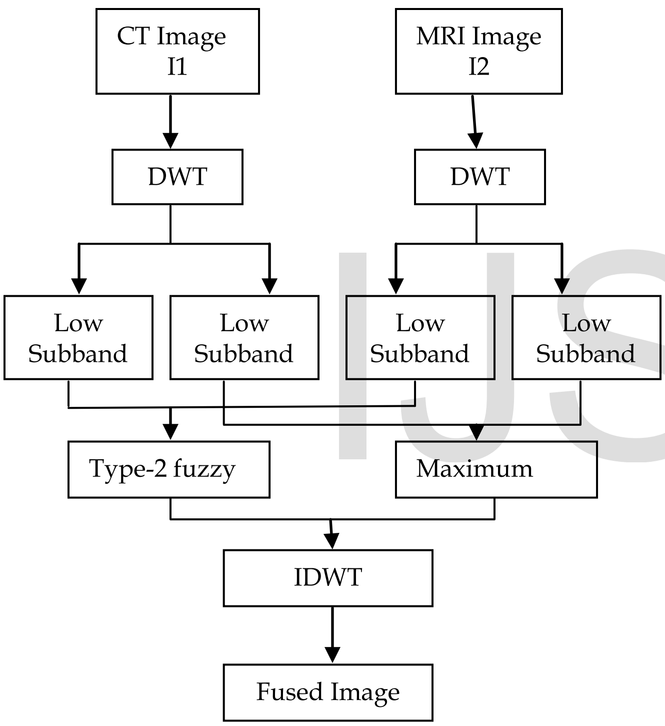

Fig. 4. Diagram of proposed DWT-Type 2 fuzzy based image fusion

The steps involved in the proposed method are as follows.

1. Read the two input images CT and MRI as I_1 and I_2.
2. Check the size of the source images if both are equal than proceed to step-3 otherwise reshape them to make equal size images.
3. Decompose I_1 and I_2 source images using DWT.
4. Four sub-images are obtained; approximate, horizontal, vertical and diagonal sub-images.
5. Approximate sub-image are fused using type-2 fuzzy and maximum rule is applied on other sub-images
6. At the end inverse, a discrete wavelet transform is applied on the fused components to obtain a reconstructed fused image.

3.1 Decomposition

In the proposed method a DWT decomposition technique is employed to decompose the source images. The DWT based decomposition provides the knowledge of both location and frequency. DWT gives detailed High-level sub-band and low-level sub-band. The decomposition procedure is defined as,

$$[CA_1, CH_1, CV_1, CD_1] = dwt2(I_1)$$

$$[CA_2, CH_2, CV_2, CD_2] = dwt2(I_2)$$

Where I_1 and I_2 are CT and MRI images respectively. CA_1 and CA_2 are low-level sub-band images with approximate information. Remaining sub-band images are horizontal, vertical and diagonal information of source images.

3.2 Fusion

A type-2 fuzzy set is used in mathematics to address the uncertainty problem. The low-level sub-band images obtained after decomposition of CT and MRI source images are categorized into a corresponding fuzzy set based on defined membership function. These fuzzy sets are then evaluated for the maximum fuzzy for the fusion process of an approximate component of source images.

The high-level sub-bands like horizontal, vertical and diagonal sub-band images are fused using the maximum filter. Each detail sub-band image of the CT image is fused with its corresponding detailed sub-band image component of MRI image. The three detailed sub-band images of fused image are obtained by following steps.

$$CH_f = \max(CH_1 + CH_2)$$

$$CV_f = \max(CV_1 + CV_2)$$

$$CD_f = \max(CD_1 + CD_2)$$

Where CH_f, CV_f, CD_f are the detailed sub-images of a fused image and CA_f is approximate sub-image of the fused image obtained from the type-2 fuzzy system.

3.3 Reconstruction

The four sub-images approximate, horizontal, vertical and diagonal images are fused according to the fusion algorithms. In the end, IDWT is performed on the sub-images to get the reconstructed fused image and is obtained by the following step.

$$I_F = idwt2(CA_1, CH_1, CV_1, CD_1)$$

Where I_F is the fused image of CT and MRI source images.

4 Results and Discussion

In this section analysis of proposed DWT-Type2 fuzzy image fusion method is discussed and results are compared with already existing image fusion methods. For performance evaluation, CT and MRI images are taken from Harvard University website.

4.1 Performance evaluation metrics

4.1.1reference image based

If reference image is provided for the input dataset, fusion quality could be measured using the following evaluation metrics.

A) Root mean square error (RMSE)

RMSE calculate the per pixel change due to processing in the fused image I_F and reference image I_R is shown in (2).

$$RMSE = \sqrt{\frac{1}{MN}\sum_{i=1}^{M}\sum_{j=1}^{N}(I_R(i,j) - I_F(i,j))^2} \qquad (2)$$

For better fusion quality the RMSE ahould be minimum.

B) Mean absolute error (MAE)

MAE equation (3) calculates the analogous pixel mean absolute error in reference I_R and the fused image I_F.

$$MAE = \frac{1}{MN}\sum_{i=1}^{M}\sum_{j=1}^{N}|I_R(i,j) - I_F(i,j)| \qquad (3)$$

For better fusion quality of an image, this metric should be minimum.

C) Signal to noise ratio (SNR)

SNR equation (4) is used to measure the ratio between image information andnoise of the fused image.

$$SNR = 20log_{10}\left[\frac{\sum_{i=1}^{M}\sum_{j=1}^{N}(I_R(i,j))^2}{\sum_{i=1}^{M}\sum_{j=1}^{N}(I_R(i,j)-I_F(i,j))^2}\right] \quad (4)$$

For better fusion quality of image this metric should be maximum that is noise level is less in fused image.

D) Percentage fit error (PFE)

PFE equation (5) calculates the ratio of the norm. That is a norm of divergence between the analogous pixel of I_R and I_F images to a norm of the I_R image. If the I_R and I_F are similar than this metric is zero otherwise it increases as fused image deviates from the reference image.

$$\text{PFE} = \frac{norm(I_R - I_F)}{norm(I_R)} * 100 \qquad (5)$$

Where normoperator estimates the largest singular value.

E) Peak signal to noise ratio (PSNR)

If the I_F and I_R images are alike the PSNR will be high. Higherthe PSNR value image fusion is better and PSNR equation is given in (6) .

$$PSNR = 20\ log_{10}\left[\frac{L^2}{\frac{1}{MN}\sum_{i=1}^{M}\sum_{j=1}^{N}(I_R(i,j)-I_F(i,j))^2}\right] \qquad (6)$$

Where L is the number of gray levels in the image.

F) Correlation (CORR)

The correlation equation (7) metric measures the similarity in small size structures between the original source image and the fused images. For better fusion, an idle value is one.

$$\text{CORR} = \frac{2C_{RF}}{C_R + C_F} \qquad (7)$$

Where

$$C_R = \sum_{i=1}^{M}\sum_{j=1}^{N} I_R(i,j)^2$$

$$C_F = \sum_{i=1}^{M}\sum_{j=1}^{N} I_F(i,j)^2$$

$$C_{RF} = \sum_{i=1}^{M}\sum_{j=1}^{N} I_R(i,j)I_F(i,j)$$

4. 1. 2 Without reference image based

If the reference image is not provided for dataset the below metrics could be used to test the fusion quality.

A) standard deviation (SD)

SD equation (8) evaluates the contrast level in the I_F. An image with greater standard deviation has high contrast.

$$\text{SD} = \sqrt{\frac{1}{MN}\sum_{i=1}^{M}\sum_{j=1}^{N}(I_F(i,j) - m)^2} \qquad (8)$$

Where equation (9) represents m, is the mean pixel value of fused image I_F and given as,

$$\text{m} = \frac{1}{MN}\sum_{i=1}^{M}\sum_{j=1}^{N} I_F(i,j) \qquad (9)$$

B) Entropy

It measures the data content of the fused image. Image with maximumdata would have maximum entropyand is given by equation (10).

$$\text{H} = -\sum Plog_2 P \qquad (10)$$

Where P indicates the probability of the pixel values.

C) Spatial frequency (SF)

The entire activity level in the fused image is indicated by frequency in the spatial domain, an expected value for the metric is maximum and is given by (11) .

$$\mathrm{SF} = \sqrt{RF^2 + CF^2} \tag{11}$$

$$\mathrm{RF} = \sqrt{\frac{1}{MN}\sum_{x=1}^{M}\sum_{y=2}^{N}(I_F(x,y) - I_F(x,y-1))^2}$$

$$\mathrm{CF} = \sqrt{\frac{1}{MN}\sum_{x=2}^{M}\sum_{y=1}^{N}(I_F(x,y) - I_F(x-1,y))^2}$$

Where RF component is row frequency and CF component is the Column frequency.

In figure 5 and 6 source images CT and MRI are shown. Figure 7 and 8 depict the decomposed image of MRI and CT source images, and figure 9 to 15 shows the fused images using minimum, average, maximum, DWT, Type-1 fuzzy, DWT-Type1 fuzzy and proposed DWT-Type2 fuzzy respectively.

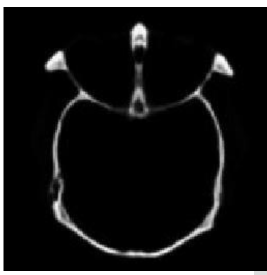
Fig.5. CT image

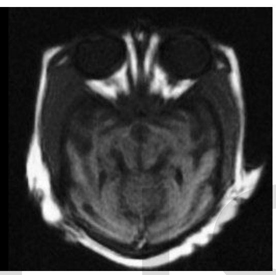
Fig.6. MRI image

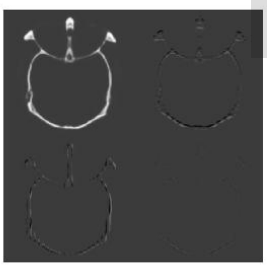
Fig.7. Decomposition of CT using DWT

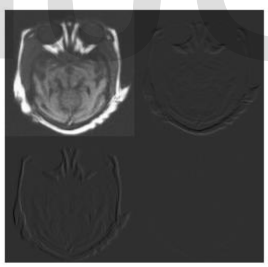
Fig.8.Decoposition of MRI using DWT

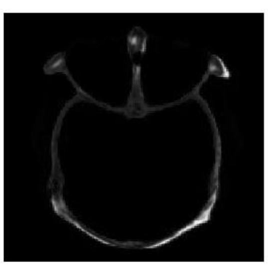
Fig.9. Minimum method

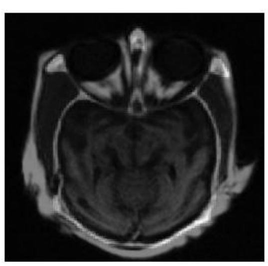
Fig.10.averaging method

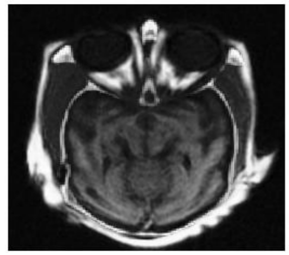
Fig.11.maximum method

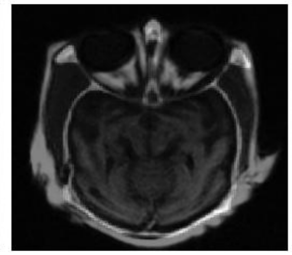
Fig.12.DWT method

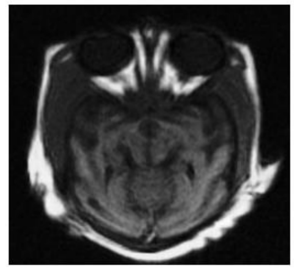
Fig.12. PCA method

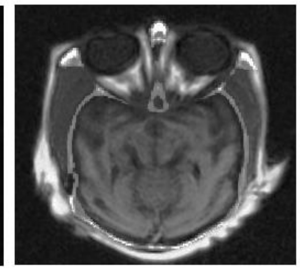
Fig.13.Type-1 fuzzy

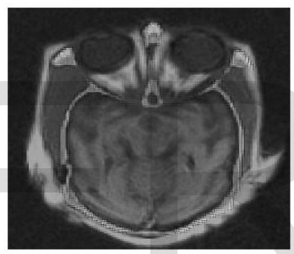
Fig.14.DWT-Type1 fuzzy

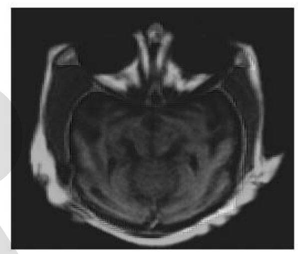
Fig.15.DWT-Type2 fuzzy

For various image fusion methods we computed the performance evaluation metrics and are tabulated in the Table 1.

Methodology	Entropy	Standared deviation	Spatial frequency
Minimum	2.0906	17.5907	9.2395
Average	6.8981	34.7432	10.9025
Maximum	6.7582	61.2556	19.3240
PCA	8.4271	54.1163	13.6975
DWT	8.6800	34.7332	10.9025
Type-1 fuzzy	7.3378	46.9703	15.6294
DWT-Type1	12.4103	36.5100	18.0432
DWT-Type2	11.8008	51.4507	19.6067

TABLE.1. COMPARITIVE ANALYSIS FOR DIFFERENT IMAGE FUSION METHODS.

4 DWTCONCLUSION

In this paper we have proposed a image fusion technique using DWT and Type-2 fuzzy logic system for medical images.

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Here a DWT decomposition is used to extract the low-frequency and high-frequency sub-bands of source images. For fusion of low-level and high-level sub-bands Type-2 fuzzy logic and maximum fusion rules are applied respectively. Using Type-2 fuzzy logic on low-level sub-band most prominent feature with highest degree of certainty is achieved. Then at the end fused images are reconstructed using IDWT.And for different methods performance metrics are evaluated. The proposed DWT-Type2 fuzzy technique provides better results in all metrics and is tabulated in table.1. In addition the proposed DWT-Type2 fuzzy method provides improved clinical perspective for disease diagnosis and surgery. In future high ended decomposition techniques are applied on source images to get better results.

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