Fuzzy Whale Fusion model for MRI multimodal image fusion

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Abstract : Medical treatment and diagnosis require information from several modalities of images like MRI, CT and so on. The image fusion schemes provide combined information of these images. This paper proposes a hybrid algorithm using fuzzy concept and novel P-Whale algorithm, called Fuzzy Whale Fusion, for the fusion of MRI multimodal images. Two multimodal images from MRI (T1, T1C, T2, FLAIR) are considered as the source images, which are fed as inputs to the wavelet transform. The proposed P-Whale approach combines Whale Optimization Algorithm (WOA) and Particle Swarm Optimization (PSO) for the effective selection of whale fusion factors. The performance of Fuzzy Whale Fusion model is compared with the existing strategies using Mutual Information (MI), Peak Signal-to-Noise Ratio (PSNR), and Root Mean Squared Error (RMSE), as the evaluation metrics

I.INTRODUCTION

Medical image fusion is an emerging field that produces a single image having relevant information of original images by incorporating information taken from two or more images of varying modality without generating any noise or artefact [10]. The fused image can describe the view much better than any individual image.

MRI is used commonly for the recognition of tumor region and bone structure, in medical image processing and analysis [2]. MRI images have different modalities that contain complementaryinformation. This complementary information is transformed into a single image for quick and accurate diagnosis. The fusion techniques for MRI images mostly deal with wavelet transformation. In wavelet transform technique [7], the image is decomposed into a sequence of sub-band images having varying resolutions, directional characteristics, and frequencies.

This paper aims to design a fusion method for MRI multimodal images using a hybrid technique, Fuzzy Whale Fusion, obtained by the combined effect of fuzzy weighted fusion formula and P-Whale optimizer.

II.RESEARCH GAPS AND CHALLENGES

Numerous research contributions have been made in the literature to deal with the issue in the fusion of MRI multimodal images. In [1], a pre-processing MRI and Positron Emission Tomography (PET) has been adopted to enhance the quality of the images. However, this method failed to consider multi-modality medical images. On the other hand, the Genetic Algorithm (GA) [2] has known for its efficiency and supports multi-objective. In spite of that no guarantee of finding global maxima and it takes time for convergence. In [3] multispectral MRI image has been developed to enhance the visualization of pathological and anatomical information. Again, it requires consistent scanner performance and a high degree of quality control. In addition, the multimodal fusion approach [4] exploits the correlation between multiple features from different modalities. Nevertheless, the synchronization between features is more complex due to their different modalities and non-linearity. In [5], the multimodal medical image fusion increases the visual quality of the images and decreases the image artifacts and noise. However, it suffers from less spatial resolution. The principal component averaging based on DWT used in [6] reduces complexity in images, but the covariance matrix is difficult to be evaluated accurately. Moreover, the PSO and GA used in [15] [16] [17] provides easy handling of an unknown characteristic of the system and good convergence rate. Conversely, it suffers from limited real-time performance and high dependence on algorithm parameters. Some of the challenges noticed in image fusion, are as follows,

The selection of fusion rule is very crucial.

Even though image fusion at pixel-level is simple and easy for the implementation, it results in information loss and blurring of edges that degrades the quality of fused image.

Another challenge in image fusion [11] is deciding how to integrate the information from images of different modalities to obtain a single composite image with all the relevant information of source images without any artifact.

A PROPOSED MULTIMODAL IMAGE FUSION APPROACH USING HYBRID FUZZY AND P-WHALE BASED ALGORITHM

Fuzzy W hale Fusion algorithm considers two MRI images that are applied to a two-level wavelet transform, where the images are converted into four bands, namely Low-Low (LL), Low-High (LH), High-Low (HL) and High-High (HH), respectively. The fused image is obtained by fusing the corresponding wavelet coefficients of the images with a weighted function that utilizes fuzzy fusion and whale fusion factors. The fuzzy approach determines the fuzzy fusion factor effectively by estimating the distance between the wavelet coefficients of both the images. Meanwhile, the proposed P-Whale technique computes the factor by the optimal selection of coefficients. Finally, the coefficients for the fused image can be obtained by averaging the two factors. Taking inverse transform, the fused image for the MRI multimodal source images can be obtained. The block diagram of the proposed technique of multimodal image fusion is demonstrated in figure 1.

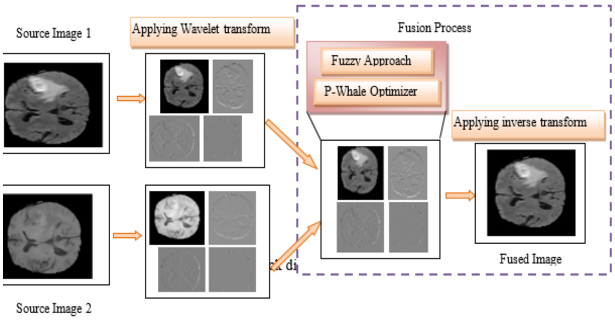


Figure 1. Block diagram of proposed FWFusion algorithm

Applying wavelet transform for the twosource images

In this part, the two-level wavelet transform [13] designed for the fusion of images is explained in detail. Wavelet transform, which is an extension of Fourier Transform (FT), is used due to its effectiveness in blocking artifacts during the process. It decomposes the images into two frequency components, low and high, by undergoing two processes; such as filtering and downsampling. The low-frequency component in wavelet transform is an approximation, whereas, the later contains detailed information. In two-level transform, these two frequency components are further decomposed into four subbands, LL, LH, HL, and HH. These frequency components are sensitive to frequencies, such that LH, HL, and HH correspond to the frequencies in vertical, horizontal and diagonal directions, respectively.

Let $I(x,y)$ be the input image filtered using a Low Pass Filter (LPF) to produce a coefficient matrix $I^{L}(x,y)$ and through a High Pass Filter (HPF), to create $I^{H}(x,y)$, after downsampling by a scaling factor 2. The low and the high-frequency components generated using wavelet transform is given as,

$$I^{L}(x,y)=\sum_{i=-N}^{N}\sum_{j=-N}^{N}\left[I(x,y)*L(x-i,y-j)\right] \tag{1}$$

$$I^{H}(x,y)=\sum_{i=-N}^{N}\sum_{j=-N}^{N}\left[I(x,y)*H(x-i,y-j)\right] \tag{2}$$

where, $L(x-i,y-j)$ is the filter function of LPF, $H(x-i,y-j)$ is the HPF function, N is the number of pixels in the image and $*$ is the convolution operator.

At the second level, the coefficient matrices are filtered and down sampled to form the subbands as under, $I^{LL}(x,y)$, $I^{LH}(x,y)$, $I^{HL}(x,y)$ and $I^{HH}(x,y)$. These four wavelet coefficients can be formulated as,

$$I^{LL}(x,y)=\sum_{i=-N}^{N}\sum_{j=-N}^{N}\left[I^{L}(x,y)*L(x-i,y-i)\right] \tag{3}$$

$$I^{LH}(x,y)=\sum_{i=-N}^{N}\sum_{j=-N}^{N}\left[I^{L}(x,y)*H(x-i,y-i)\right] \tag{4}$$

where, $I^{L}(x,y)$ is the low-frequency component obtained at level 1. Similarly, the subbands obtained from the high-frequency component can be formulated. $I^{LL}(x,y)$ represents the approximation of input image $I(x,y)$, whereas, the remaining subbands contain detailed information.

Generation of whale fusion factor using the Proposed P-Whale Algorithm

In this section, contribution of selecting whale fusion factor is presented using the proposed P-Whale algorithm. P-Whale is an optimization algorithm that modifies WOA by the integration of PSO in the update rule to improve the search process and thereby, enhance the performance of the algorithm. WOA [12] is a meta-heuristic algorithm that solves optimization problems inspired by the physical behavior of humpback whales, encircling prey, bubble-net attack mechanism and search for prey. In the position update of WOA, the update rule of PSO is adopted and thus, determines a suitable whale fusion factor for each subband. For the optimal selection of the factor, a multi-objective fitness function is formulated utilizing three objectives based on statistical evidence, visual evidence, and error estimate. A detailed description of the proposed algorithm to determine the whale fusion factor for the medical image fusion is illustrated using the solution encoding, fitness function formulation, and the algorithm.

P-Whale Algorithm

This section presents the proposed P-Whale algorithm employed for the selection of whale fusion factor. The algorithm is designed by hybridizing WOA with another optimization approach, PSO, to boost up the performance of WOA solving optimization problems.

The function that decides the strength or the quality of the solution is the fitness function. is formulated as given below,

$$F_N = \frac{1}{3}\left[f_S + f_V + f_E\right] \tag{5}$$

where, f_S is the fitness providing statistical evidence, f_V is the fitness regarding visual evidence and f_E is the fitness for the error estimationThe selection of fusion factors for each subband is based on a fitness function that considers three objectives, like MI, PSNR, and RMSE. The procedure involved in the proposed P-Whale algorithm is described using the steps as follows,

I. Population Initialization

The algorithm starts with the random initialization of a whale population of dimension N, represented as,

$$U = \{U_1, U_2, \ldots, U_N\}; 1 \le i \le N \tag{6}$$

where, U represents the ithsolution of size Rin the population U.

II. Fitness Evaluation

After the initialization of population, the fitness of the solutions in the population is evaluated using the fitness function

III. Position Update

The position update of the P-Whale algorithm follows the encircling prey model of WOA.

IV. Finding best candidate solution

Once the positions of the solutions are updated, the fitness values are computed using equation (5).

V. Termination

The steps from I to IV are repeated until a termination condition is reached.

III.RESULTS AND DISCUSSION

This section demonstrates the results of the proposed Fuzzy Whale Fusion algorithm used for the fusion of multimodal MRI images. Moreover, a comparative analysis is performed by comparing the performance of the proposed approach with existing algorithms and the results are also illustrated.

Parametric Values: The values assigned to the parameters used in the Fuzzy Whale Fusion approach are as follows: size of the population N=10, membership function parameters: p=1073, r=2047, and s=2147.

Dataset Description:The database considered for the experimentation is Multimodal BRAin Tumor image Segmentation (BRATS) MRI [14], which consists of training dataset in Virtual Skeleton Database (VSD). The dataset consists of data from BRATS 2012 and BRATS 2013 and NIH Cancer Imaging Archive, developed as part of BRATS 2014 and BRATS 2015. Each dataset is comprised of T1 MRI, T1 contrast-enhanced MRI, T2 MRI and T2 FLAIR MRI volumes.

A. Evaluation Metrics

The metrics used for the performance evaluation of image fusion are MI and RMSE, which are defined in section 3.4.2. These measures are computed by taking the average of those measured between source image 1 and fused image and between source image 2 and fused image, as given below,

$$MI = \frac{1}{2}\left[MI\left[I_1(x,y), I_F(x,y)\right] + MI\left[I_2(x,y), I_F(x,y)\right]\right]$$

$$PSNR = \frac{1}{2}\left[PSNR\left[I_1(x,y), I_F(x,y)\right] + PSNR\left[I_2(x,y), I_F(x,y)\right]\right]$$

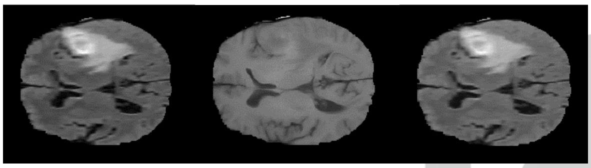
$$RMSE = \frac{1}{2}\left[RMSE\left[I_1(x,y), I_F(x,y)\right] + RMSE\left[I_2(x,y), I_F(x,y)\right]\right]$$

B. Methods employed for comparison

The methods that are used in the comparative analysis to compare the performance are i) Wavelet+ Average [6] ii) Wavelet+ Fuzzy+ WOA (Applied WOA in the proposed fusion process instead of the P-Whale algorithm) and iii) Wavelet+ Fuzzy+ GA [2]. In [6], by performing an average of principal components, the image fusion was done, whereas in [2], GA was used for the estimation of weights in the fusion process.

C. Experimental Results

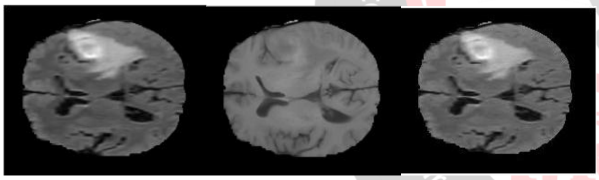
The experimental results of the proposed approach of multimodal MRI image fusion are illustrated in this section. The results of fusion using two multimodal images, T1 and FLAIR, from the BRATS database in two wavelet transforms, Daubechies 1 (db1) wavelet and Haar wavelet transform, are presented here. In figure 2, the results of image fusion performed using db1 wavelet transform is depicted in the two MRI images of different modalities. Figures 2.a and 2.b show the MRI images of T1 and FLAIR, which are the source images to be fused. In figure 2.c, the resulting fusion image obtained using db1 wavelet transform with the proposed FWFusion approach that utilizes the fusion process based on fuzzy and whale fusion factors is given.



(a) T1 (Source Image)(b) FLAIR (Source Image 2)(c) Fused Image

Figure 2. Fusion result using db1 wavelet transform

Figure 3 shows the fusion of two multimodal images that are fused using Haar wavelet transform. The source MRI images T1 and FLAIR that are to be fused are pictured out in Figures 3.a and 3.b. In figure 3.c, the image fusion result provided by the Haar wavelet with the proposed Fuzzy Whale Fusion approach is depicted. From the results shown in figures 2.c and 3.c, using the two wavelet transforms with the proposed algorithm, it is observed that better results of fusion can be obtained with all the informative contents of the source images shown.



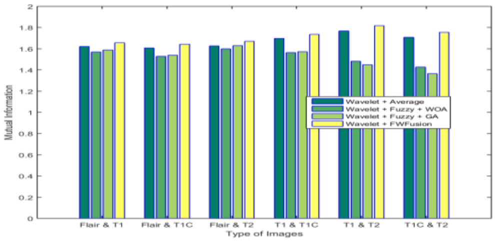
(a) T1 (Source Image 1) (b) FLAIR (Source Image 2)(c) Fused Image

Figure 3. Fusion result using Haar wavelet transform

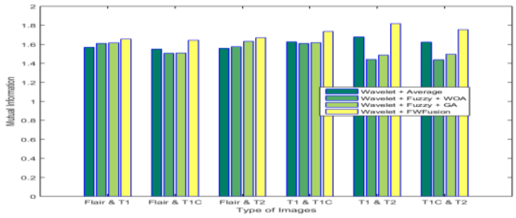
D. Performance Analysis

I. Analysis based on MI

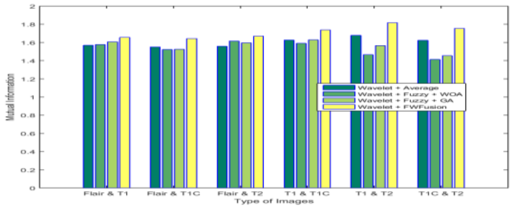
Higher the MI, greater is the performance. In figure 4.a, the MI analysis results using db2 wavelet in Wavelet+Average, Wavelet+Fuzzy+WOA, Wavelet+Fuzzy+GA and Wavelet+FWFusion with different modality MRI images are presented. For the fusion made using FLAIR and T1 images, the MI measured using Wavelet+Average, Wavelet+Fuzzy+WOA, Wavelet+Fuzzy+GA, and Wavelet+FWFusion, is 1.5701, 1.6115, 1.6169 and 1.6564, respectively. The proposed Wavelet+FWFusion method has the maximum value of 1.8187, for the fusion using T1 and T2 images, whereas the maximum MRI obtained in the existing Wavelet+Average is just 1.6785. The results of analysis based on MI using Haar wavelet is depicted in figure 4.b, where the maximum MRI provided by the proposed method is 1.8188, for the fusion made using T1 and T2 images. With the same images, MI calculated in Wavelet+Average, Wavelet+Fuzzy+WOA, and Wavelet+Fuzzy+GA is 1.7684, 1.4822, and 1.4487. Figure 4.c depicts the comparative analysis chart based on MI using coif1 wavelet. When the images FLAIR and T1 are fused, MI obtained using the existing methods, Wavelet+Average, Wavelet+Fuzzy+WOA, and Wavelet+Fuzzy+GA is 1.5950, 1.6007, and 1.5907, while the proposed Wavelet+FWFusion has 1.6577 as the MI. Maximum MI is produced when the fusion is made using T1 and T2 images with a value 1.8187 in Wavelet+FWFusion. MI analysis result obtained using sym2 wavelet is depicted in figure 4.d with the multimodal images FLAIR, T1, T2 and T1C. In this case too, maximum MI is observed for the fusion made using T1 and T2 images. The maximum value attained with this fused image using Wavelet+Average, Wavelet+Fuzzy+WOA,Wavelet+Fuzzy+GA and Wavelet+FWFusion is 1.6785, 1.4662, 1.5662, and 1.8187 respectively



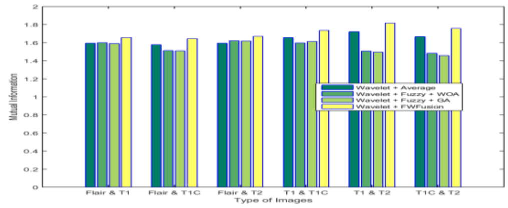
(a) db2 wavelet



(b) Haar wavelet



(c) coif1 wavelet

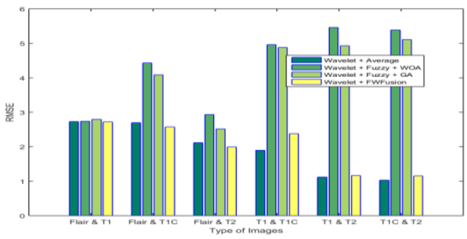


(d) sym2 wavelet

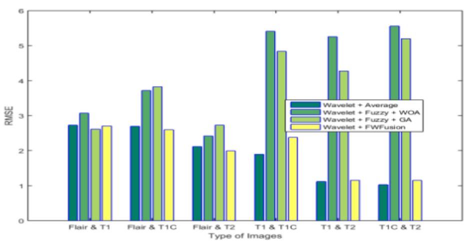
Figure 4. Performance Analysis based on MI

IV. ANALYSIS BASED ON RMSE

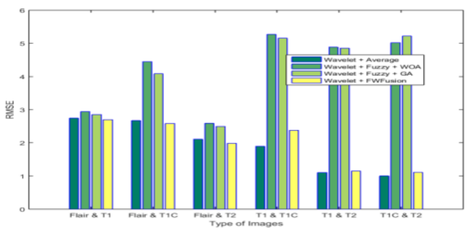
The comparative analysis results based on RMSE performed using the wavelets, db2, Haar, coif1 and sym2, in the four comparative approaches is demonstrated in figure 5, using six combinations of fused images. An effective algorithm requires minimum RMSE for the performance improvement. In figure 5.a, the RMSE analysis chart using db2 wavelet is shown. When the images FLAIR and T2 are fused, the RMSE value attained by the techniques Wavelet+Average, Wavelet+Fuzzy+WOA, Wavelet+Fuzzy+GA and Wavelet+FWFusion are 2.1167, 2.9339, 2.5169, and 1.9936, respectively. Figure 5.b presents the RMSE analysis performed in the four approaches using Haar transform. The minimum RMSE provided using Wavelet+Average, Wavelet+Fuzzy+WOA, and Wavelet+Fuzzy+GA is 1.1579, 5.3770, and 5.4939, while Wavelet+FWFusion has 1.1455 as the minimum RMSE for the combination of images T1 and T2. The analysis based on RMSE using coif1 wavelet is pictured out in figure 5.c, where the minimum RMSE produced using the proposed Wavelet+FWFusion method is 1.1135, which is slightly more than the existing Wavelet+Average that has a value 1.0031 for the fusion of T1C and T2 images. However, for most of the other combinations, Wavelet+FWFusion has the least RMSE. In figure 5.d, the RMSE analysis graph using sym2 wavelet is shown. The RMSE value obtained when the images FLAIR and T2 are fused is 2.11675, 2.4224, 2.7295, and 1.9922 using the methods, Wavelet+Average, Wavelet+Fuzzy+WOA, Wavelet+Fuzzy+GA and Wavelet+FWFusion, respectively. For the combinations T1&T1C, T1&T2 and T1C&T2, the RMSE value of the proposed approach tends to be increasing a little than in the existing Wavelet+Average, which is negligible, since the proposed approach has better performance for the other combinations. Moreover, when the performance of proposed Wavelet+FWFusion is compared with Wavelet+Fuzzy+WOA and Wavelet+Fuzzy+GA, the proposed approach has attained better results.



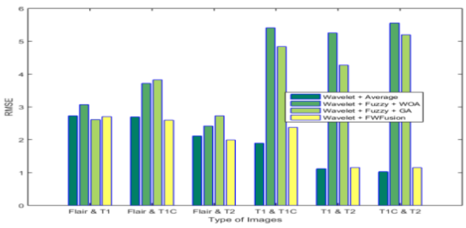
(a) db2 wavelet



(b) Haar wavelet



(c) coif1 wavelet



(d) sym2 wavelet

Figure 5. Performance Analysis based on RMSE

V.DISCUSSION:

From the overall comparative analysis result demonstrated above, a discussion is made regarding the three evaluation metrics, such as MI and RMSE. Based on these two metrics, the performance of the proposed method is compared with the existing methods. The MI metric is exploits to measure the degree of dependence of two images. In addition, the RMSE exploits to compare the image compression quality. In addition, an effective algorithm needs maximum MI as well as minimum RMSE. Table 1 presents the performance comparison carried out in fusion using different combinations of multimodal images by computing the mean performance for the evaluation.

Table 1. Mean Performance Comparison

Methods	MI	RMSE
Wavelet+Average	*1.6276*	*1.936*
Wavelet+Fuzzy+WOA	*1.5359*	*4.3072*
Wavelet+Fuzzy+GA	*1.5488*	*4.1455*
Wavelet+FWFusion	***1.5914***	***1.9***

VI.CONCLUSION

In this paper, a novel algorithm designed using fuzzy and P-Whale algorithm is presented for the fusion of MRI multimodal images. Two multimodal images taken from MRI (T1, T1C, T2, FLAIR) Moreover, an optimization approach, P-Whale, is designed by modifying WOA using PSO, for the optimal selection of whale fusion factor. For the effective determination of fusion factors, a fitness function is formulated considering MI and RMSE, which provides statistical evidence, visual evidence, and error estimate. The performance of the proposed method is compared with three existing methods of fusion, such as Wavelet+Average, Wavelet+Fuzzy+WOA, and Wavelet+Fuzzy+GA, using the metrics, MI and RMSE. From the mean evaluation, the proposed fusion scheme could attain MI of 1.5914, RMSE of 1.9, while the existing Wavelet+Average had only 1.6276and 1.9362, as the best values of MIand RMSE,. Hence, it can be concluded that the proposed algorithm performs better than the existing fusion techniques.

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