Wavelet and Bioinspired Algorithms Based Medical Image Fusion

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Abstract- The process of creating a single image from two medical images of various modalities is known as medical image fusion.The technique is accomplished by using some computer aided programming and signal processing tools. Wavelet transform is 0ne such signal processing tool we are using here. The Bayesian model is proposed for fusion of different image coefficients along with its effort of its optimization by using some bioinspired computing algorithms like genetic algorithm, bird swarm algorithm (BSA) and using fractional theory concept with BSA.Our proposed work based on Haar wavelet and fractional BSA provides better results over few other reviewed work like cascading two transforms at two levels and fusion scheme based on optimization inspired by whales swarm.The proposed scheme is applied on MRI images from two different Brain tumor data sets popularly named as Brats data sets. The same strategy is also implemented by optimizing Bayesian model by genetic algorithm(GA).The performance of this method is also found satisfactory and leads to prove a new scheme in this domain.

Keywords: Image Fusion, Wavelet Transform, Genetic

I. INTRODUCTION

This in medical imaging image fusion has proved an unavoidable technique from a last decade. In computerized aided surgery the exact location of interest in human body must be visually clear and focused[1]. This aim can be achieved by using the image fusion technique to an extent. In image processing a number of such efforts in the direction of image fusion has been proposed by a number of researchers. In transform domain almost every image fusion (IF) method involves two part of IF that is image decomposition and reconstruction by using an appropriate transform [2]. The another part is using any fusion rule for fusing the coefficients extracted at decomposition level[3]. The quality of image fusion can be greatly effected by using any of salient method at any part of fusion that either at image decomposition or at fusion rule[4]. Wavelet transform(WT) and its generations like discrete wavelet (DWT),Static wavelet (SWT), Lifting wavelet(LWT), contourlet transform (CT), Curvelet transform(CVT), Shearlet Transform(ST) are few renown transforms having suitable properties for images like multiresolution, orthogonality, sparsity and highly re - constructible[5]. The features of an medical image is present in the form of picture elements (pixels) .The appropriate use of a transform extracts the suitable feature information from a medical image like patch, edge, tumor etc in the form of frequency components containing the varying level of frequency ,means low and high[6]. Mainly four types of such coefficients are generated by any transform containing the information of image in its horizontal ,vertical ,diagonally direction [7].Also one coefficient provides the approximation of whole image called approximation coefficient. While the others are called horizontal coefficient, vertical coefficient and diagonal coefficient[8]. In our work we are using DWT and LWT for image decompositions [9],[10],[11].

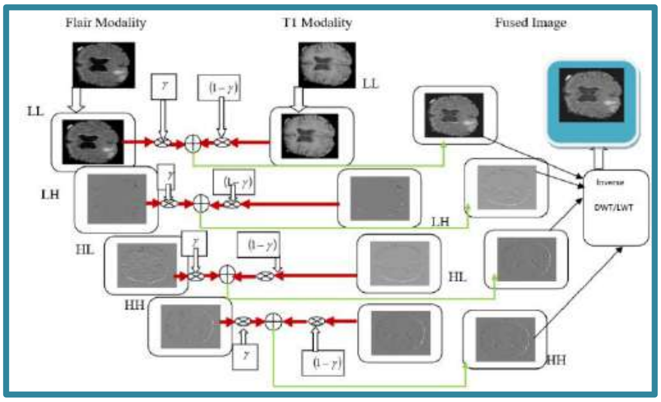


Fig. 1 Basic Fusion Scheme

II. LITERATURE REVIEW

From the last decade an ample number of researches has been done in the area of medical image fusion [12],[13],[14], [15].Patil et al.[16] proposed an fusion strategy employing Whale optimisation algorithm[17]. This method found to be excellent , but failed to the Bayesian theory[18],[19]. Durga Prasad and Dhuli [20] proposed an IF technique of anisotropic diffusion. Vikrant Bhateja et al.[21] proposed the Stationary Wavelet Transform (SWT) and Non Sub-sampled Contourlet Transform (NSCT) cascading method of image fusion based on PCA rule, it minimized the redundancy. But the non-directionality of the SWT coefficients was observed. An excellent fusion method was proposed by Gaurav Bhatnagar et al. [10] which increased the color information with least storage cost, but this technique is highly affected by the coefficients of high frequency. Sudipta Majumdar and Jayant Bharadwaj [6] proposed a scheme using Haar lifting wavelet transform with easy implementation and low computational complexity. But this method failed a little for the perfect reconstruction. Sneha Singh et al. proposed a method of sum modified cascade fusion. Although this method shows higher performance but poor visualization of the fused images is the main drawback Bhardwaj et al. presented a superb approach to medical picture fusion.The same authors have offered a couple additional superb picture fusion techniques based on the bird swarm algorithm and wavelet transform [2], [3].The authors also proposed techniques based on BSA, genetic algorithms, and other DWT variants [4], [5].

III. PROPOSED METHODOLOGY

The research methods we are proposing consist of basic wavelet transform in discrete form and Bayesian model to fuse the coefficients obtained. Three different schemes we are proposing .One is basic DWT and LWT based image fusion. Second one is again WT but with bird swarm optimized Bayesian fusion model .Third method is again a bioinspired one method based on genetic algorithm. To assess the effectiveness of the suggested method, values for mutual information, PSNR, and RMSE are computed. The fused original image and the source images are utilized to calculate PSNR, a metric that indicates the quality of the fused medical image. where the image size is represented by Bƻ B and ^{5}max specifies the maximum pixel energy. The image's fused pixel value is 2, while the original pixel value is shown as 1. In particular, the maximum energy of 255 is thought to be acquired by each individual pixel.

RMSE: The effective approach provides the lowest RMSE, which is a measure of error that quantifies the difference between the intended output and the fused image. Mutual information is the quantity of information that is passed from the original photos to the final image that is produced by fusing the original images. A good fusion scheme must have the highest possible.

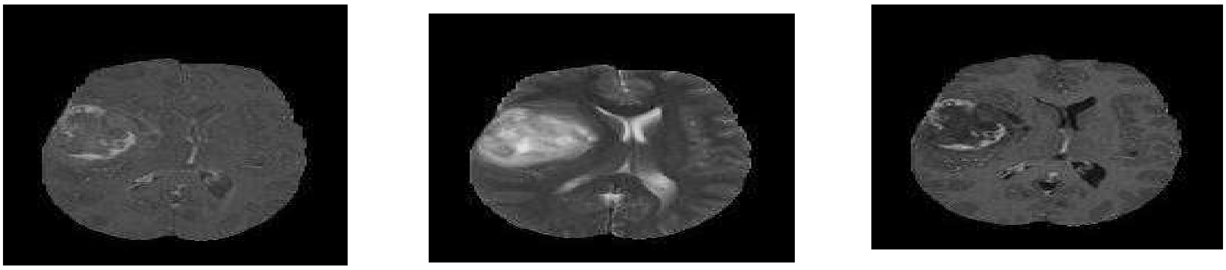


Fig. 2 Medical images, a) Fused image, b) T1C image, c) T2 image

IV. RESULT AND DISCUSSION

This section presents the experimental results, Figure 2 and Figure 3 shows the experimental results using the dataset 2. Figure 2 (a) shows the original image referring the T1C modality and figure 2 (b) corresponds to the T2 modality. The fused medical image using the proposed Fractional- BSA-based Bayesian Fusion is presented in figure 2 (c). Similarly, Figure 3 (a) is the original image with Flair modality, Figure 3 (b) is the original image with T2 modality, and Figure 3 (c) is the fused image using the proposed Fractional-BSA-based Bayesian Fusion.The experimental results are shown in this section. Figures 2 and 3 use dataset 2 to illustrate the experimental outcomes. Figure 2 (b) represents the T2 modality, while Figure 2 (a) displays the original image referring to the T1C modality. Figure 2 (c) displays the fused medical image created by the suggested Fractional-BSA-based Bayesian Fusion. The original image with Flair modality is shown in Figure 3 (a), the original image with T2 modality is shown in Figure 3 (b), and the fused image utilizing the suggested Fractional-BSA-based Bayesian Fusion is shown in Figure 3 (c). We contrast three approaches to medical picture fusion with the suggested BSA method .The first is the holoentropy-whale fusion (HW Fusion) approach [16], which shares the intelligent estimation behaviour of whale fish and is likewise based on a bioinspired optimization algorithm. The second technique is essentially a cascaded framework of non-sub-sampled contourlet transform (NSCT) and stationary wavelet transform (SWT) [8], while the third method is a straightforward system of image fusion based on non-sub sampled contourlet transform (NSCT) [15].Below is a detailed examination of the suggested approach based on dataset-1's performance indicators. Based on the percentage of data, Figure 3 displays the performance analysis of the suggested fractional-BSA Bayesian fusion. The performance analysis based on the mutual knowledge is highlighted in Figure 4a). The fractional-BSA Bayesian fusion approach obtained mutual information of 1.4267, 1.5050, 1.4214, and 1.5028 for iteration numbers of 50, 100, 150, and 200 when the multimodality Flair and T1 is utilized. The performance analysis based on the PSNR is highlighted in Figure 3b). Fractional-BSA Bayesian fusion obtained PSNRs of 35.4480 dB, 38.3020 dB, 35.2898 dB, and 38.5553 dB for iterations 50, 100, 150, and 200 when multimodality, Flair, and T1 are utilized. The performance analysis based on the RMSE is highlighted in Figure 3c). The fractional-BSA Bayesian fusion approach obtained the RMSE of 9.6233, 10.3228, 10.6891, and 9.8398 for the iteration when the multimodality, Flair, and T1 were utilized. The mutual information (MI), RMSE, and PSNR obtained from various fusion procedures for different modalities fusion are shown in tables no. 1 through no. 3 below.

Table No 1 Comparative values of MI

Modalities	DWT-BSA Bayesian	DWT-Fractional BSA Bayesian	DWT-GA Bayesian	LWT-Fractional BSA Bayesian
Flair_T1	1.5130	1.6266	1.3966	**1.6566**
Flair_T1C	1.5325	1.5650	1.4050	**1.5950**
Flair_T2	1.4537	1.4991	1.4491	**1.4991**
T1_T1C	1.5072	1.5664	1.4964	**1.6564**
T1_T2	1.5174	1.5866	1.5066	**1.6166**
T1C_T2	1.5167	1.5265	1.4965	**1.5965**

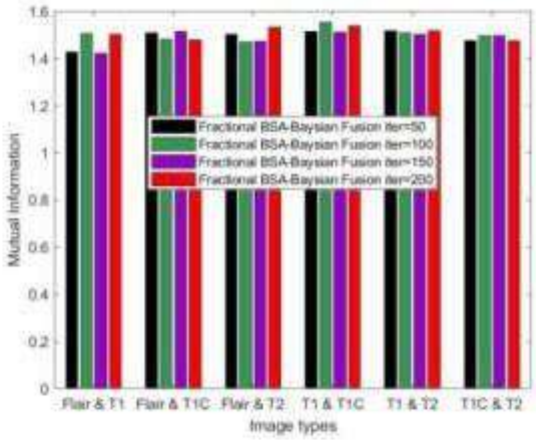
Table No 2 Comparative values of RMSE

Modalities	DWT-BSA Bayesian	DWT-Fractional BSA Bayesian	DWT-GA Bayesian	LWT-Fractional BSA Bayesian
Flair_T1	5.9324	5.484	6.1234	**4.1123**
Flair_T1C	6.2324	5.984	6.0123	**4.1423**
Flair_T2	6.1324	5.884	6.7635	**4.8123**
T1_T1C	6.3324	5.784	6.1234	**4.6123**
T1_T2	6.1224	5.984	6.6754	**4.7123**
T1C_T2	5.9324	5.184	6.1237	**4.1123**

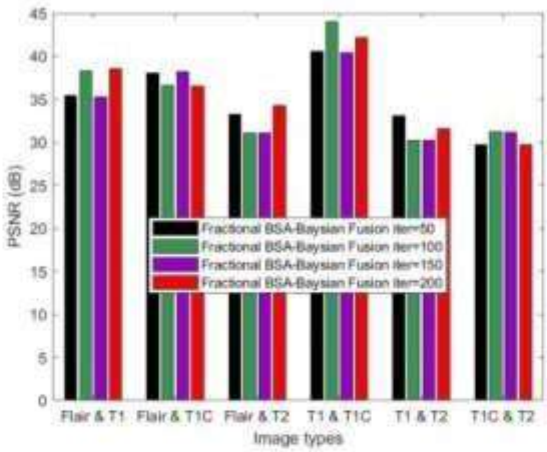
Table No 3 Comparative values of PSNR

Modalities	DWT-BSA Bayesian	DWT-Fractional BSA Bayesian	DWT-GA Bayesian	LWT-Fractional BSA Bayesian
Flair_T1	42.99121	44.0312	38.07441	**46.41313**
Flair_T1C	42.39121	44.39749	39.92449	**46.00754**
Flair_T2	42.49121	44.08698	37.42706	**46.73591**
T1_T1C	42.39121	44.88477	38.89037	**46.08573**
T1_T2	42.69121	43.85007	39.5642	**46.26442**
T1C_T2	42.32121	44.1267	41.21912	**46.78641**

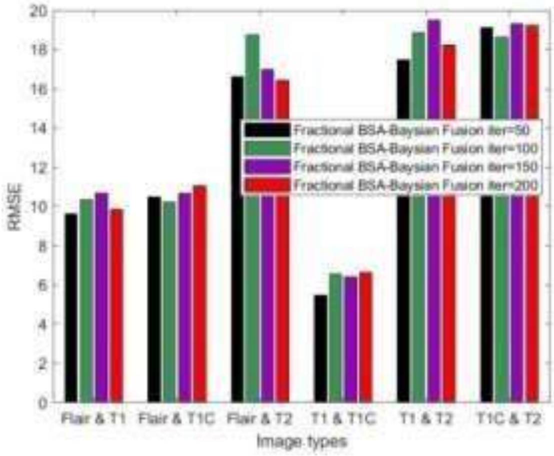
The preceding tables can also be used to perform a quantitative study of MI, PSNR, and RMSE, as shown in figures 3(a) to 3(c) below.



(a)



(b)



(c)

Fig.3. Performance of proposed method a) Mutual Information, b) PSNR, c) RMSE

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