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Multi-Modality Medical Image Fusion using Discrete Wavelet Transform

Bhavana. V[a], Krishnappa. H.K[b]

[a]*Amrita Vishwa Vidyapeetham, Amrita School of Engineering, Bengaluru Campus, Bengaluru-35, India*
[b]*R.V. College of Engineering, Bengaluru-59, India*

Abstract

Diagnosis and treatment of ailments require that precise information be obtained through various modalities of medical images such as Computed Tomography (CT), Positron Emission Tomography (PET), and Magnetic Resonance Imaging (MRI) etc. Often these techniques give some information regarding the ailment which is incomplete and ambiguous. In this scenario, image fusion gains utmost importance as the overall quality of scans can be improved. Thus, fusing various multi – modality medical images into a distinct image with more detailed anatomical information and high spectral information is highly desired in clinical diagnosis. In this work, MRI and PET images are preprocessed along with enhancing the quality of the input images which are degraded and non-readable due to various factors by using spatial filtering techniques like Gaussian filters. The enhanced image is then fused based on Discrete Wavelet Transform (DWT) for brain regions with different activity levels. The system showed around 80-90% more accurate results with reduced color distortion and without losing any anatomical information in comparison with the existing techniques in terms of performance indices including Average Gradient (AG) and Spectral Discrepancy (SD), when tested on three datasets - normal axial, normal coronal and Alzheimer's brain disease images.

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Keywords: Multi-modal medical images; discrete wavelet transform; image fusion;

* Bhavana. V. Tel.: +91-9986547944; fax: +91-80-28440092.
v_bhavana@blr.amrita.edu

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1. Introduction

In medical field, both the qualities of spectral and spatial data in a solitary image is highly desired by the doctors (radiologists) for various purposes like researches, monitoring, accurate diseases diagnosing and also for treatment process. Using single modality image, it is quiet difficult to obtain information of this type since, Computed Tomography (CT) images are most popular for showing bone structures and lacks in providing information about the tissues; at the same time, Magnetic Resonance Imaging (MRI) provides soft tissue information and lacks in boundary information, Positron Emission Tomography (PET) image reveals actual information of flow of blood. Thus, every single modality image has its own drawbacks in providing needed information because each image is captured with different radiation power. In order to overcome this it is highly required to obtain information from multiple modalities which is used for clinical diagnosis. In this situation, fusion is a technique used to combine multimodality medical images such as CT, MRI, PET etc. Image fusion technique integrates suitable information from various modalities of input images into a fused distinct image where the resultant image provides better inventive information in comparison with the input images which are used for fusion[1]. This fused information of image is used in many fields such as Medicine, Agriculture, Aeronautics, Law Enforcement etc. Many methods for fusing MRI and PET images have already been existed. The IHS substitution method can obtain fused images with rich anatomical structural information. However, it has a serious side effect of color distortion. Several multi-resolution based methods were proposed to generate fused images with less color distortion but having the problem of missing detailed structural information.

2. Review of Existing Fusion Techniques

Various literature reviews has been done on the existing image fusion[2] techniques. In many medical applications, image fusion is the most significant tool for the interpretation of the quality of images and the data acquired through this is either functional or having high spatial resolution. Usually, MRI image shows structural information of the brain without any functional data, where as PET image describes functional information of the brain but with low spatial resolution. Therefore, image fusion is conceded to improve functional image’s spatial resolution through which original functional characteristics is preserved[1] with no spatial distortion. A technique for fusing PET- MRI image using wavelet and spatial frequency method is proposed which eliminate the influence of image imbalance[3]. This method reduced blur effect, improved the clarity which is useful for clinical diagnosis. The result analysis indicated that suggested system is comparatively better than the conventional algorithm based on PCA in terms of good visual & quantitative fusion results. Based on DWT, two algorithms namely pixel averaging & maximum pixel replacement approach[4] with very good fusion results is proposed which eliminates the drawbacks of PCA technique. Many medical applications use multimodal medical image fusion for the repossession of corresponding data from medical images. A new algorithm based on Daubechies transform coefficients[5] for fusion is proposed and is compared using region segmentation and spatial frequency method. This work also compared the performance evaluation metrics such as entropy, standard deviation and fusion factor between input images and output images.

Medical multimodal image fusion is an important method of medical imaging to obtain information from different multimodalities of medical images. An innovative multimodal medical image fusion method by means of Daubechies complex wavelet transform using mixed fusion scheme[6] is explained here. Image fusion is performed using spatial or transform domain methods. A scheme for image fusion which is helpful for determining average information of image is described. The proposed scheme is based on energy which gives better fusion results. Images that are obtained by combining magnetic resonance imaging and computed tomography images helps the doctor in analyzing more information and helps in testing clinically[7]. In many fields we have been using technologies for integrating the PET and CT images that helps in perfect fusion. The fusion image has the advantage of locating the pathological changes using the characteristics of computed tomography and has the ability in detecting the pathological changes using characteristics of PET. The fusion equipments that authors used in this machine are very expensive. Fused image detects and locates the changes in the nature of the disease, especially changes in body tissues and organs[8]. An approach regarding low and high activity regions of wavelet transform of brain is illustrated which can generate proficient fusion result by slightly changing the gray matter (GM) anatomical structural information and then patching white matter (WM) spectral information[9], followed by wavelet decomposition and gray-level fusion. A novel adjustment for the pixel intensity in the non-white matter area of high-activity region in the gray-level fused image will bring more anatomical structural information into the final color fused image. Spectral information patching in the white matter area of high-activity region will preserve more color information from PET image for the white-matter area.

3. Proposed Method

The block diagram of the proposed method is shown in Fig.1. As shown in Figure, PET and MR images are taken as its input for pre-processing and enhancement. PET image is firstly decomposed into its Intensity Hue Saturation (IHS) transform and thus the information of high activity region is differentiated from the low activity region of PET image by making use of “hue angle” obtained from the IHS transform. Pre-processing stage involves removal of noise and enhancing the input images using Gaussian filter. Filtering is used mainly to smoothen or sharpen the input images. High activity and low activity regions of PET image carries more anatomical and spectral information, respectively. Hence both the high activity and low activity regions are decomposed by applying 4-level DWT transform to obtain high and low frequency coefficients. Then we combine high frequency coefficients of PET and MR images using averaging method and perform the inverse DWT to obtain the fused result for the fused high frequency output. Similarly by combining low frequency coefficients of PET and MR images into a complete set of wavelet coefficients and performing the inverse DWT, we can obtain the fused result for the low activity region. In order to get better structural information, Fuzzy - c means clustering is used and to avoid color distortion, color-patching is also done. Finally fused image is extracted and displayed with less color distortion and without losing any structural information.

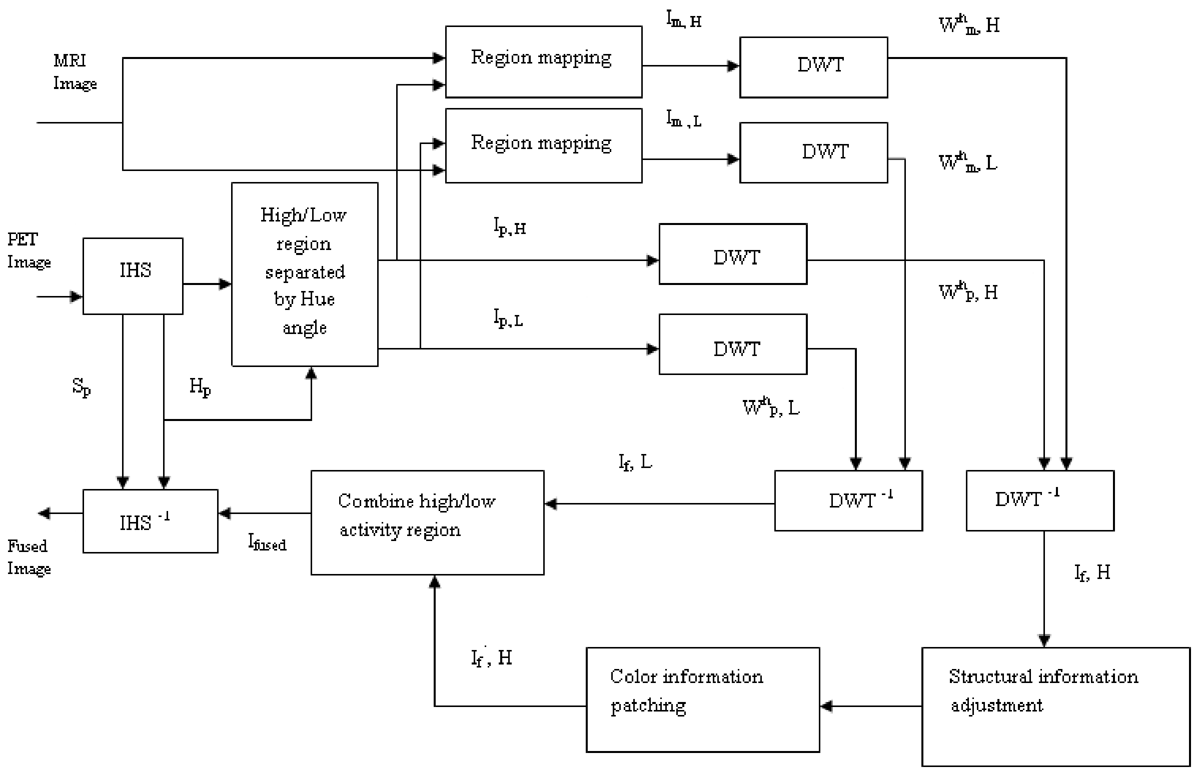

Fig.1 Block diagram of proposed method

Let Rw be the WM area which can be segmented by FCM[8] (Fuzzy c-means algorithm) as shown in Figure 2.7. $B(x, y)$ is a 7 × 7 window centered at (x, y). $D_{avg}(x, y)$ is the average difference between the pixel's intensity of the I-component of the original PET image and the pixel's intensity of the gray-level fused image for all WM pixels within window $B(x, y)$.

That is

$$D_{avg}(x,y) = \frac{\sum_{(m,n)\in R_W \cap B(x,y)} (I_{p,H}(m,n) - I_{f,H}(m,n))}{|R_W \cap B(x,y)|} \tag{1}$$

As mentioned before, the pixel intensity in I_f,H is higher (brighter) than the pixel intensity in I_p,H. Therefore, the value $D_{avg}(x, y)$ in (1) is always negative. So we can lower down the intensity level for each non-WM pixel of the high-activity region in I-component fused image I_f,H using (2.1), where the percentage w is set to 50% or 70% in our implementation.

$$I_{f,H}(x,y) \leftarrow I_{f,H}(x,y) + w \times D_{avg}(x,y) \tag{2}$$

On the other hand, for each pixel in the WM area of the high-activity region of I-component fused image, we replace $I_f,H(x, y)$ by $I_{p,}H(x, y)$ to keep less color distortion. We use I'_f,H to represent the high-activity region of the gray-level fused image after intensity adjustment by using (2.1) and spectral patching by using (2). Now we can combine I_f,L to form a new gray-level image I_{fused} as the I-component of the finally fused image. By taking I_{fused}, Sp (saturation-component of PET image), and H_p (hue-component of PET image) as the inputs for inverse IHS transform, we can obtain a finally fused image for PET and MRI images.

4. Experimental Results and Discussion

The verified application has been experimented with various inputs and the results are analyzed for its performance and accuracy. Metrics are the various measures which facilitate the qualification of some particular characteristics. The metrics used to evaluate this work are: (i) Mean Square Error (MSE): MSE is broadly used to compute the extent of image misrepresentation as it can characterize the entire gray-value error enclosed in the complete image. The lesser the estimation of MSE, the picture will be of lesser noise content. (ii) Peak Signal to Noise Ratio (PSNR): PSNR is likewise used to figure the degree of image misrepresentation on. The image will be having lesser noise content if the value of its PSNR is larger. (iii) Average Gradient (AG): The spatial resolution of an image is determined with the help of AG. The larger the value of AG is, the fused image will be of higher spatial resolution. (iv) Spectral Discrepancy (SD): The spectral quality of a fused image is obtained using SD. If there is a small discrepancy, then the fusion result is acceptable. The experimental dataset consists of PET and MRI images for pre processing and fusion from the website www.med.harvard.edu. A total of 3 set of brain diseases like PET Normal Axial, PET Normal Coronal, PET Alzheimer, MRI Normal Axial, MRI Normal Coronal and MRI Alzheimer constitute the experimental dataset for fusion as shown in Fig.2.

In this study, four metrics are used for objective assessments such as PSNR, MSE, SD and AG; where w is the weight percentage corresponding to fuzzy c means algorithm for clustering (set as 70% and 50% for the cases given in Tables 1, 2, 3 and 4).

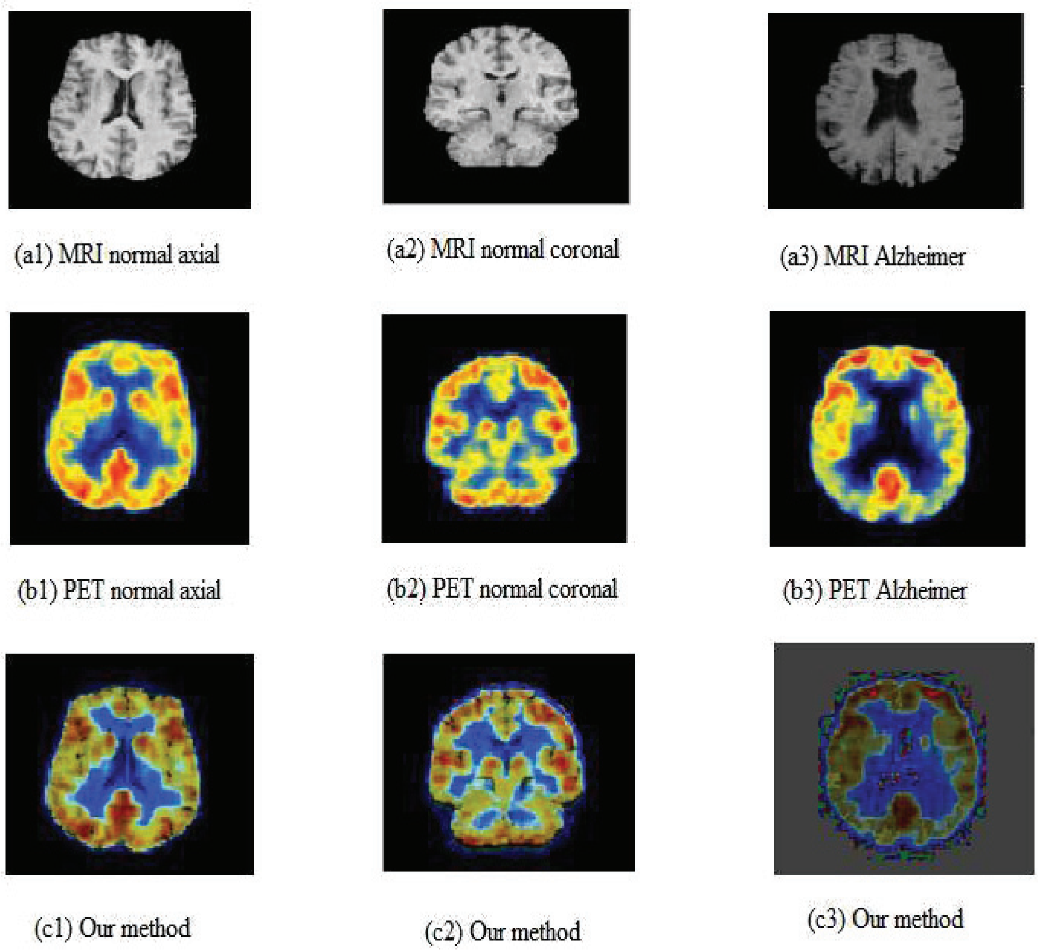

Fig.2 Comparison of fused output with the input MRI and PET images for Normal Axial, Normal Coronal and Alzheimer's brain diseases

4.1 Tables

Table 1 and 2 shows the performance analysis based on mean square error (MSE) and peak signal to noise ratio (PSNR) for the fused image. Table 3 and 4 shows the performance comparison between IHS+RIM method and our method in terms of performance indices.

Table 1. Performance Analysis Based on Mean Square Error for the Fused Image

	Dataset – 1	Dataset - 2	Dataset -2
Proposed Method (w = 0.5)	0.02819	0.11529	0.10509
Proposed Method (w = 0.7)	0.1911	0.18589	0.19144

Table 2. Performance Analysis Based on Peak Signal to Noise Ratio for the Fused Image

	Dataset – 1	Dataset - 2	Dataset -2
Proposed Method (w = 0.5)	63.6424	57.5131	58.0621
Proposed Method (w = 0.7)	55.3184	55.4383	55.3104

Table 3. Performance Comparison Based on Spectral Discrepancy between Fused Image and PET Images

Fusion method	Dataset -1	Dataset -2	Dataset-3
IHS + RIM method	8.23	7.9031	6.0118
Proposed Method (w = 0.5)	8.116	4.9116	2.3371
Proposed Method (w = 0.7)	2.2966	2.63	0.38082

Table 4. Performance Comparison Based on Average Gradient between Fused Image and MRI Images

Fusion method	Dataset -1	Dataset -2	Dataset-3
IHS + RIM method	5.3603	5.2927	5.0353
Proposed Method (w = 0.5)	5.6237	5.4715	6.7541
Proposed Method (w = 0.7)	6.8573	7.9881	10.5855

Experimental results demonstrated that fused results for PET and MRI normal axial, PET and MRI normal coronal and PET and MRI Alzheimer's disease brain images have less color distortion and richer anatomical structural information than those obtained from the existing method visually and quantitatively and by using adaptive histogram equalization in the fused image, high contrast is also achieved. The system showed promising results when tested on three datasets - normal axial, normal coronal and Alzheimer's brain disease images. For fusion, experimental results indicated around 80-90% more accurate results with reduced color distortion and without losing any anatomical information in comparison with the existing techniques in terms of performance indices including Average Gradient (AG) and Spectral Discrepancy (SD).

5. Conclusion and Future Scope

In this paper, we proposed a new fusion method for fusing PET and MRI brain images based on discrete wavelet transform with less color distortion and without losing any anatomical information. The proposed method is different from regular simple DWT fusion method in that our method performs wavelet decomposition with four levels for low- and high-activity regions, respectively, in the PET and MRI brain images. Experiments demonstrated that our fused results for normal axial, normal coronal and Alzheimer's disease brain images have less color distortion and richer anatomical structural information than those obtained from the other existing fusion techniques.

Also, the comparison based on performance metrics illustrates that this method of image fusion gives promising results. The research can be further extended by using other multi-modality medical images with color and gray scale information and using an integration of complex wavelets and contourlets for fusion to preserve the edge information.

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