# Multimodal Medical Image Fusion using Redundant Discrete Wavelet Transform

Richa Singh, Mayank Vatsa, Afzel Noore
West Virginia University, Morgantown, WV, USA
{richas, mayankv, noore}@csee.wvu.edu

## Abstract

*Medical image fusion has revolutionized medical analysis by improving the precision and performance of computer assisted diagnosis. In this research, a fusion algorithm is proposed to combine pairs of multispectral magnetic resonance imaging such as T1, T2 and Proton Density brain images. The proposed algorithm utilizes different features of Redundant Discrete Wavelet Transform, mutual information based non-linear registration and entropy information to improve performance. Experiments on the BrainWeb database show that the proposed fusion algorithm preserves both edge and component information, and provides improved performance compared to existing Discrete Wavelet Transform based fusion algorithms.*

## 1. Introduction

Computer assisted diagnoses and therapy strongly depend on image processing methods and are of increasing importance in modern medicine and health care. Over the past decade, research in processing and analysis of medical data has begun to flourish. Sophisticated imaging techniques such as MRI and CT scanning provide abundant information that are useful for diagnosis. These advancements have driven the need for algorithm development which in turn has provided a major impetus for new algorithms in signal and image processing. Typically, the field of medical image analysis is divided into six categories:

- **Post-acquisition**: Preprocessing techniques such as denoising and restoration are used to restore the images so that they can be used for diagnosis.
- **Segmentation**: Images such as brain MRI or abdomen CT scan contain multiple features (organs). Delineating features of interest is important for analysis and accurate diagnosis.
- **Registration**: In computer assisted surgery, it is required to register or align the captured image with a model or a previously captured image.
- **Computation**: Physical quantity derivation and other computation such as fusion and compression are also required in several computer assisted therapy.
- **Visualization**: It is important to display medical images on screen so that a medical professional can diagnose diseases.
- **Security**: Personal medical health-care information is very sensitive and it is very important to secure it using techniques such as watermarking so that only legitimate user can access it and also accurately associate with the medical record wit the correct patient.

An important research issue in medical image processing, specifically in information computation, is fusion of multimodal information [5, 7, 8, 9, 10, 11]. Medical images from different modalities often provide complementary information. Several diagnostic cases require integration of complementary information for better analysis. Fusion of multimodal medical images can provide a single composite image that is dependable for improved analysis and diagnosis. Existing algorithms generally use Discrete Wavelet Transform (DWT) [3] for multimodal medical image fusion [5, 7, 8, 11] because DWT preserves different frequency information in stable form and allows good localization both in time and spatial frequency domain. However, one of the major drawbacks of DWT is that the transformation does not provide shift invariance. This causes a major change in the wavelet coefficients of the image even for minor shifts in the input image. In medical imaging, it is important to know and preserve the exact location of these information; but shift variance may lead to inaccuracies. For example, in medical image fusion we need to preserve edge information, but DWT based fusion may produce specularities along the edges.

Redundant discrete wavelet transform (RDWT) [3, 4], another variant of wavelet transform, is used to overcome the shift variance problem of DWT. It has been applied in different signal processing applications but it is not well researched in the field of medical image fusion. RDWT can be considered as an approximation to DWT that removes the down-sampling operation from traditional critically sampled DWT, produces an over-complete representation, and provides noise per-subband relationship [4]. The shift variant characteristic of DWT arises from the use of down-sampling whereas RDWT is shift invariant because the spatial sampling rate is fixed across scale. Similar to DWT, RDWT and Inverse RDWT (IRDWT) of a two dimensional image or three dimensional volume data is obtained by computing each dimension separately where detailed and approximation bands are of the same size as the input image/data [1].

The main objective of this research is to investigate the utility of RDWT in medical image fusion. Specifically, we introduce RDWT based image fusion algorithm to fuse properties of medical images of different modalities such as brain proton density (PD) and T1 brain images. The proposed algorithms utilize properties of RDWT such as shift invariance and noise per-subband relationship along with other techniques such as mutual information based non-linear registration and entropy features for improved performance. Experimental results on the BrainWeb database show the usefulness of this member of the wavelet family and clearly indicate its potential in medical image fusion.

## 2 Fusion of Multimodal Brain Images using RDWT

Medical images captured at different time instances can have variations due to geometric deformations. To optimally fuse two 2D/3D medical images (e.g. T1 and T2 brain images), we first need to minimize linear and non-linear differences between them using registration technique. Medical image registration is about determining geometrical transformation that aligns points in one medical data set with corresponding points in another data set [6]. We first propose mutual information based non-linear registration algorithm for registering multimodal medical images. Mutual information is a concept from information theory in which statistical dependence is measured between two random variables. Registration algorithm of medical images is described as follows[2]:

Let $\bar{I}_1$ and $\bar{I}_2$ be the input multimodal brain images for registration. Mutual information between the two images can be represented as,

$$M(\bar{I}_1, \bar{I}_2) = H(\bar{I}_1) + H(\bar{I}_2) - H(\bar{I}_1, \bar{I}_2) \quad (1)$$

$H(\cdot)$ is the entropy of the image and $H(\bar{I}_1, \bar{I}_2)$ is the joint entropy. Registering $\bar{I}_1$ with respect to $\bar{I}_2$ requires maximization of mutual information between $\bar{I}_2$ and $\bar{I}_1$, thus maximizing the entropy $H(\bar{I}_1)$ and $H(\bar{I}_2)$, and minimizing the joint entropy $H(\bar{I}_1, \bar{I}_2)$. Further, normalized mutual information [2] can be written as,

$$NM(\bar{I}_1, \bar{I}_2) = \frac{H(\bar{I}_1) + H(\bar{I}_2)}{H(\bar{I}_1, \bar{I}_2)} \quad (2)$$

The registration is performed on a transformation space, $S$, such that

$$S = \begin{bmatrix} a & b & 0 \\ c & d & 0 \\ e & f & 1 \end{bmatrix} \quad (3)$$

where, $a, b, c, d$ are shear, scale, and rotation parameters, and $e, f$ are the translation parameters. Using the normalized mutual information, we define a search strategy to find the transformation parameters, $S^*$, by exploring the search space, $S$.

$$S^* = arg\ max_{\{S\}}\{NM(\bar{I}_2,\ S(\bar{I}_1))\} \quad (4)$$

Multimodal images $\bar{I}_1$ and $\bar{I}_2$ are registered using the transformation parameters $S^*$. To account for both linear and non-linear variations, first the global transformation is applied followed by the local registration. Global transformation is performed by applying the normalized mutual information registration approach globally on the image to minimize the global variations due to shear, scale, rotation, and translation. Local transformation is then performed on the globally registered images by applying the same registration technique in blocks of size $16 \times 16$. This local registration compensates for the non-linear variations in features. Figure 1 shows examples of the registration algorithm in which two brain images are registered.

Once the images are registered, multimodal image fusion can be effectively performed. Let $I_1$ and $I_2$ be the registered brain images of different modalities. Three levels of RDWT decomposition is applied on both the images to obtain the detail and approximation wavelet bands. Let $I_1^a$, $I_1^v$, $I_1^d$, and $I_1^h$ be the RDWT subbands from $I_1$ and $I_2^a$, $I_2^v$, $I_2^d$, and $I_2^h$ be the corresponding RDWT subbands from $I_2$ image. To preserve the features from both the images, coefficients from approximation band of $I_1$ and $I_2$ are averaged,

$$I_F^a = mean(I_1^a, I_2^a) \quad (5)$$

where $I_F^a$ is the approximation band of the fused image. For the three detailed subbands, each band is divided into blocks of size 3 x 3 and the entropy of each block is calculated using Equation 6.

$$e_i^{jk} = ln\sqrt{\left(\frac{\mu_i^{jk} - \sum_{x,y=1}^{3,3} I_i^{jk}(x,y)}{\sigma_i^{jk}}\right)^2 / m^2} \quad (6)$$

[1] Mathematical details of RDWT can be obtained from [3] and [4]. For the proposed algorithm, we use DB9/7 mother wavelet.

[2] Without loss of generality, the 2D registration algorithm can also be used for 3D medical data.

where $j\,(= v, d, h)$ denotes the subbands, $m = 3$ (size of each block), $k$ represents the block number, and $i\,(= 1, 2)$ is used to differentiate the two multimodal images $I_1$ and $I_2$. $\mu_i^{jk}$ and $\sigma_i^{jk}$ are the mean and standard deviation of the RDWT coefficients of the $k^{th}$ block of $j^{th}$ subband from $i^{th}$ image respectively. Using the entropy values, the detail subbands for the fused image $I_F^v$, $I_F^d$, and $I_F^h$ are generated using Equation 7. For fused image block $I_F^{jk}$, RDWT coefficients from $I_1$ is selected if the entropy of block from $I_1$ image is greater than the corresponding block from the $I_2$ image, otherwise $I_2^{jk}$ is selected.

$$I_F^{jk} = \begin{cases} I_1^{jk}, & if \quad (e_1^{jk}) > (e_2^{jk}) \\ I_2^{jk}, & otherwise \end{cases} \tag{7}$$

Finally, IRDWT is applied on the four fused subbands to generate the fused medical image $I_F$.

$$I_F = IRDWT(I_F^a, I_F^v, I_F^d, I_F^h) \tag{8}$$

### 2.1 Experimental Results

To evaluate the performance of the proposed fusion algorithm, we fuse the brain data of three different modalities. 3D images are obtained from the BrainWeb database [1]. We fuse T1 image with PD image, T1 image with T2 image, and T2 image with PD image. Performance is also compared with the DWT based medical image fusion algorithms [5, 7, 8, 11]. To quantitatively compare the performance with existing fusion algorithms, normalized mutual information based performance metric is defined. Let $NM_{FI_1}$ be the normalized mutual information between the fused image and $I_1$ and $NM_{FI_2}$ be the normalized mutual information between fused image and $I_2$. The performance metric is defined as $NM_F = \frac{NM_{FI_1} + NM_{FI_2}}{2}$. Higher values of $NM_F$ shows that the images are well fused.

Using all the BrainWeb samples, average value of $NM_F$ pertaining to the proposed algorithm is 0.79 whereas existing algorithms yield $NM_F$ values in the range of 0.41 to 0.63. Among existing algorithms, DWT fusion algorithm proposed by Guihong *et al.* [5] provides the best $NM_F$ values of 0.63. Figures 2, 3, and 4 show the visual results of the proposed fusion algorithm and comparison with DWT based fusion algorithm [5]. These figures clearly show that the proposed algorithm outperforms DWT based approach and preserves the multimodal information. With DWT fusion, edges are blurred due to shrinking effect and shift variance whereas RDWT fused images provide clear representation at both edges and non-edge regions. Furthermore, visual results were shown to eminent medical professionals and they asserted that the proposed RDWT based algorithm provides better information for medical diagnosis compared to DWT based algorithm. Finally, the average time required for multimodal 3D medical image fusion using the proposed algorithm is 4.49 seconds which shows that the proposed algorithm can be efficiently used for real time applications.

## 3 Conclusion

A novel medical image fusion algorithm is proposed that incorporates properties of RDWT decomposition, normalized mutual information based non-linear registration, and entropy based information selection. The algorithm is evaluated on the BrainWeb database and experimental results showed that the proposed algorithm conserves important edge and spectral information without much of spatial distortion. In future, we plan to extend the proposed algorithm by incorporating learning techniques such as support vector machine and evaluate the performance with other medical images.

## 4. Acknowledgment

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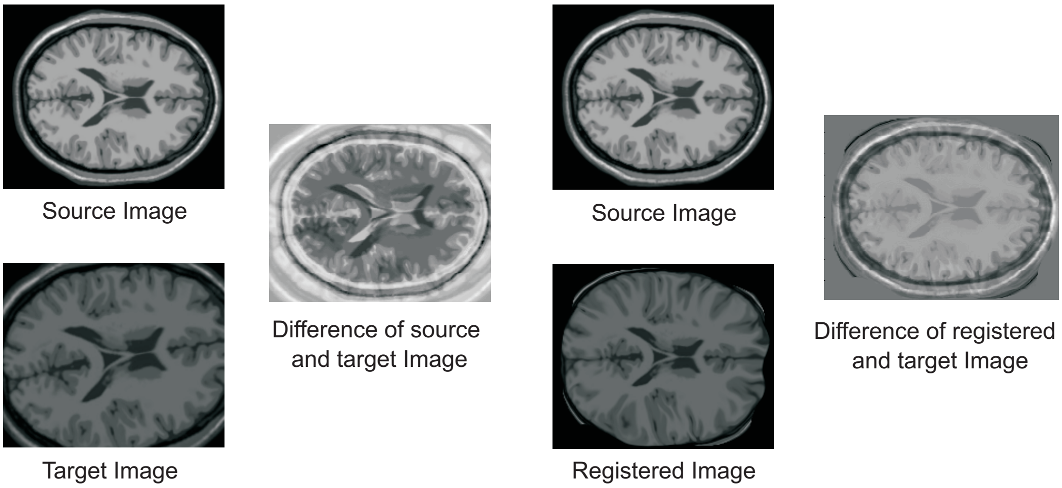


**Figure 1. Example of multimodal brain image registration.**

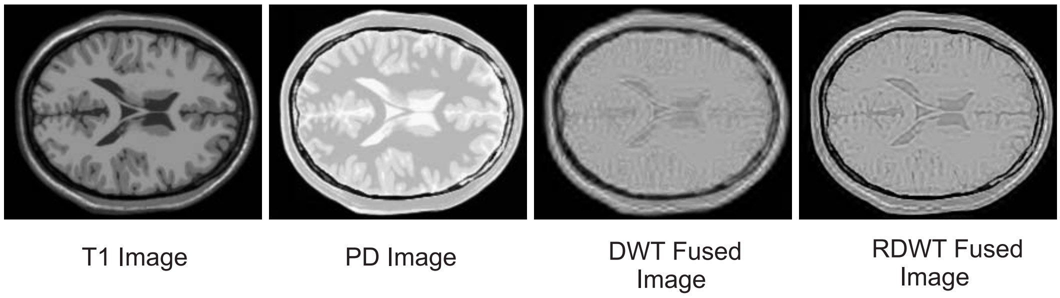


**Figure 2. Fusion of T1 and PD images using the proposed RDWT fusion algorithm.**

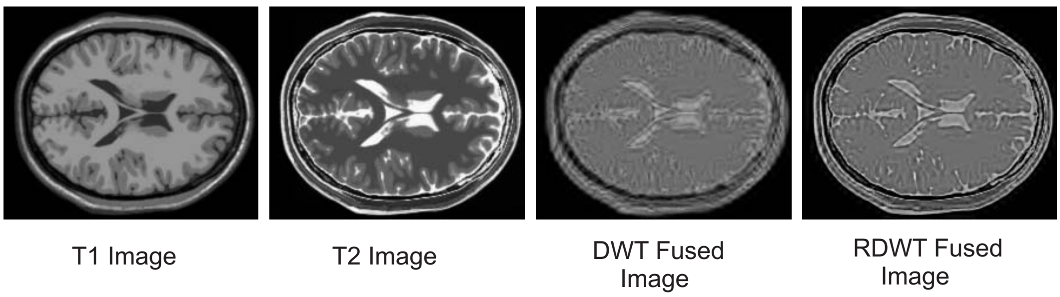


**Figure 3. Fusion of T1 and T2 images using DWT and RDWT fusion algorithms.**

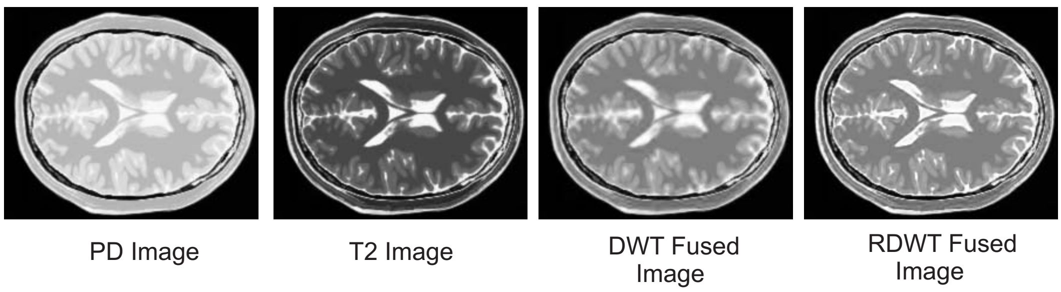


**Figure 4. Fusion of T2 and PD images using DWT and RDWT fusion algorithms.**