

Comparative Analysis of Similarity Measure Performance for Multimodality Image Fusion using DTCWT and SOFM with Various Medical Image Fusion Techniques

C. Karthikeyan^{1*} and B. Ramadoss²

¹Department of CSE, Jawaharlal Nehru Technological University, Hyderabad, India;
ckarthik2k@gmail.com

²Department of Computer Applications, National Institute of Technology, Tiruchirappalli, India;
ramadoss.b5@gmail.com

Abstract

Objectives: In this paper, the performance of similarity measures such as Edge Based Similarity Measure and Structural Similarity Index Measure is evaluated and also compared with the existing medical image fusion techniques. **Materials and Methods:** Multimodality Medical Image fusion is the process of fusing two Medical images obtained from two different sensors for better diagnosis. Medical image fusion combines and merges all relevant and complementary information from multiple source images into single composite image which facilitates more precise diagnosis and better treatment. The fused image should convey a better description of the scene than the individual images. The performance of the fused image is evaluated by various metrics such as Peak Signal to Noise Ratio (PSNR), Entropy, Standard deviation, Edge Based Similarity Measure (EBSM) and Structural Similarity Index Measure (SSIM). This paper proposes a method for fusion of Medical images using Dual Tree Complex Wavelet Transform (DTCWT) and Self Organizing Feature Map (SOFM). **Findings:** The performance of the proposed fusion algorithm is evaluated over pairs of CT and MR images obtained from patients in comparison with existing fusion techniques such as Discrete Wavelet Transform (DWT), Nonsubsampled Contourlet Transform (NSCT) and Fast Discrete Curvelet Transform (FDCT). In this paper, performance is evaluated by using the metric; Edge based Similarity Measure (EBSM), and Structural Similarity Index (SSIM). **Applications / Improvements:** Through the simulation result, as compared with the DWT, FDCT, NSCT and DTCWT fusion methods, it is concluded that the Multimodality image fusion using DTCWT with Robust Second Order First Moment (SOFM) gives better Edge based similarity measure and Structural similarity index measure.

Keywords: Dual Tree Complex Wavelet Transform, Edge Based Similarity Measure, Fuzzy Rules, Structural Similarity Index

1. Introduction

Image fusion combines two or more than two images into a single composite image. Obviously the composite image should give a better composition of the scene than the individual ones. A novel approach of multimodal medical image fusion using wavelet transforms is presented in¹.

An efficient image fusion method using wavelet combined transformation is implemented in² for multi sensor lunar image data. A new information theoretic fusion algorithm combined neural network and fuzzy theory is presented in³⁻⁴. Image fusion method based on non subsampled contour let transform can achieve better fusion performance⁵. This method is complex in fusion algorithm and also lack

*Author for correspondence

of multi resolution feature. An innovative multilevel image fusion algorithm using Fast Discrete Curvelet Transform gives the best fusion result in terms of enhanced visual quality in fused images⁶. But it suffers from multi directional decomposition.

The DWT is the good method for image fusion. DWT and spatial frequency based image fusion algorithm is discussed in⁷. A DWT based multimodal medical image fusion is presented in⁸. DWT has two disadvantages, lack of shift invariance and poor directional selectivity. Dual Tree Complex Wavelet transform overcome the disadvantages of DWT. DTCWT based multimodal medical image fusion is implemented in⁹. In this paper, an efficient approach for medical image fusion based on DTCWT and SOFM is proposed. The importance of Multimodal Medical image fusion is discussed in section 2. The proposed image fusion algorithm is explained in section 3. The experimental results obtained from the proposed fusion technique are discussed in section 4. In section 5, conclusion is made from the results obtained.

2. Medical Image Fusion

Medical imaging has become an important factor in diagnosis, treatment and research. Medical image fusion combines and merges all relevant and complementary information from multiple source images into single composite image. In Medical image fusion, the fusion of images can often lead to additional clinical information not apparent in the separate images. The requirements of Medical image fusion are that the fused image should convey more information than the individual images and should not introduce any artifacts or distortions.

A review about various image fusion algorithms based on Discrete Wavelet Transform (DWT), **Principal Component Analysis (PCA)**, morphological methods, knowledge based methods, neural network based methods and fuzzy logic method and their performances are compared in¹⁰. Fusion rule also plays a vital role in the image fusion. The rules like min rule, max rule, fuzzy rule¹¹ can be applied and are seen in the literature.

3. Multimodality Image Fusion using DTCWT and SOFM

The proposed multimodality image fusion technique is based on the DTCWT and SOFM. The fusion of Multimodal Medical images obtained from different

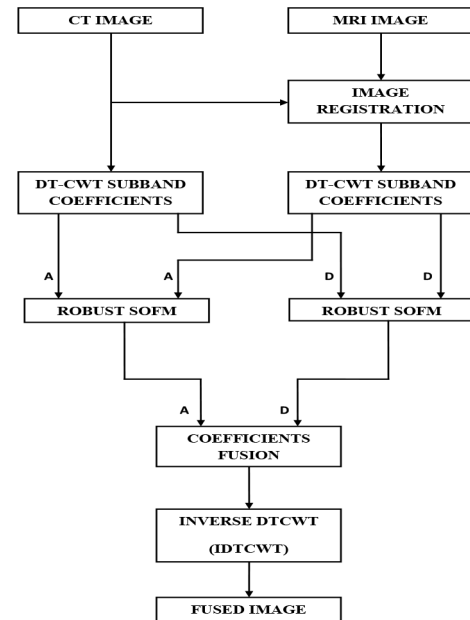


Figure 1. Blockdiagram of the Proposed Image Fusion.

sensors like *Computed Tomography (CT)* and *Magnetic Resonance Imaging (MRI)* has been considered in this work. Many techniques have been proposed in the literature has been studied and reviewed. Proposed method is demonstrated in Figure 1.

Image Registration is the process of establishing spatial correspondence between two or more images of the same scene taken at different times or from different viewpoints or by different sensors. In this work, the intensity based image registration done in MRI to position same coordination.

After image registration, the registered image and the image to be fused are decomposed by using DTCWT at predefined scale¹⁴. The robust SOFM neural network¹² is utilized to recognize and extract the features. This can be done by training and simulating the network for the resultant coefficients (approximation and detailed) of each level of MR and CT images. After decomposition, the proposed method is carried out on each sub band independently.

In order to identify the salient region in each sub-band, clustering¹³ based image thresholding is applied. It assumes that the input image has bi-model histogram and calculates optimum threshold value based on their intra class variance¹⁴. Let us consider A, B are the registered image and the image to be fused respectively. AA and BB are their corresponding threshold image. Then, the fusion

process after thresholding the images for all wavelet coefficients located at pixel position (i,j) :

Input : Registered image (A) and corresponding clustered image (AA), image to be fused (B) and corresponding clustered image (BB)

Output : Fused Image (F)

Rule1 : if $AA_{i,j}$ is true and $Bb_{i,j}$ is false then $Fi,j = Ai,j$

Rule2 : if $Aa_{i,j}$ is false and $Bb_{i,j}$ is true then $Fi,j = Bi,j$

Rule3 : if $Aa_{i,j}$ is true and $Bb_{i,j}$ is true then $Fi,j = \max(Ai,j, Bi,j)$

Rule4 : if $Aa_{i,j}$ is false and $Bb_{i,j}$ is false then $Fi,j = \min(Ai,j, Bi,j)$

Then apply Inverse DTCWT to the fusion result to get the final fused image.

4. Results and Discussions

The performance of the proposed method is evaluated over pairs of CT and MR images obtained from patients in comparison with existing fusion techniques such as DWT, NSCT, FDCT. In this paper, performance is evaluated by using the metric; Edge Based Similarity Measure (EBSM), and Structural Similarity Index (SIM).

4.1 Edge Based Similarity Measure (EBSM)

The edge based similarity measure gives the similarity between the edges transferred in the fusion process.

Mathematically, is defined $Q^{AB/F}$ is defined as

$$Q^{AB/F} = \frac{\sum_{i=1}^M \sum_{j=1}^N [Q_{i,j}^{AF} w_{i,j}^x + Q_{i,j}^{BF} w_{i,j}^y]}{\sum_{i=1}^M \sum_{j=1}^N [w_{i,j}^x + w_{i,j}^y]} \quad (1)$$

Where A , B and F represent the input and fused images respectively.

The definition of Q^{AF} and Q^{BF} are same and given as

$$\begin{aligned} Q_{i,j}^{AF} &= Q_{g,i,j}^{AF} Q_{\alpha,i,j}^{AF}, \\ Q_{i,j}^{BF} &= Q_{g,i,j}^{BF} Q_{\alpha,i,j}^{BF} \end{aligned} \quad (2)$$

where Q_g^{*F} and Q_α^{*F} are the edge strength for images A and B .

It is observed from the Table 1 that the performance of the proposed method outperforms the existing

Table 1. EBSM Performance of the proposed method

| Image Set | Edge based similarity measure | | | | |
|-----------|-------------------------------|--------|--------|--------|------------|
| | DWT | FDCT | NSCT | DTCWT | DTCWT-SOFM |
| 1 | 0.2476 | 0.3643 | 0.4513 | 0.5677 | 0.8136 |
| 2 | 0.2564 | 0.407 | 0.5078 | 0.6151 | 0.8545 |
| 3 | 0.2599 | 0.3704 | 0.4703 | 0.5925 | 0.8241 |
| 4 | 0.2866 | 0.3653 | 0.4555 | 0.5589 | 0.8065 |
| 5 | 0.3271 | 0.3696 | 0.4405 | 0.5265 | 0.7823 |

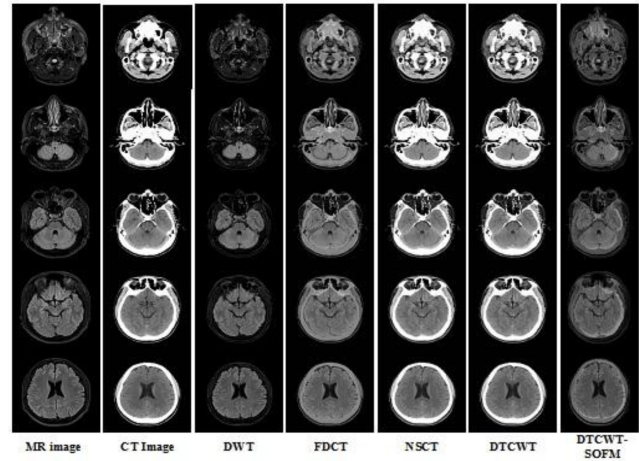


Figure 2. Visual results of the proposed DTCWT-SOFM for five pairs of MRI and CT images in comparison with existing fusion techniques.

methods based on DWT, FDCT, NSCT. The reason for better performance of the proposed fusion method is that the proposed fusion is the mixture of min rule and max rule and the application of these rules are based on the clustering based thresholding approach. Table 1 shows the Comparison on Edge Based Similarity Measure of different methods for Fused Image. Figure 2 shows the visual results of the proposed fusion method for five pairs of images in comparison with existing fusion methods and Figure 3 shows the Chart representation of Comparison on Edge Based Similarity Measure of different methods for Fused Image.

4.2 Structural Similarity Index Measure (SSIM)

The structural similarity index is a method for measuring the similarity between two images using eqn. (3).

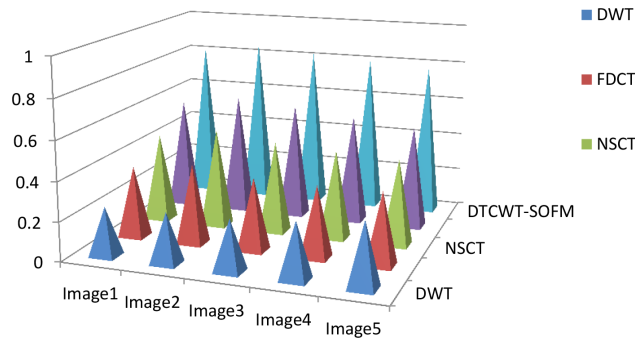


Figure 3. Comparison on Edge Based Similarity Measure (EBSM) of different techniques for Fused Image.

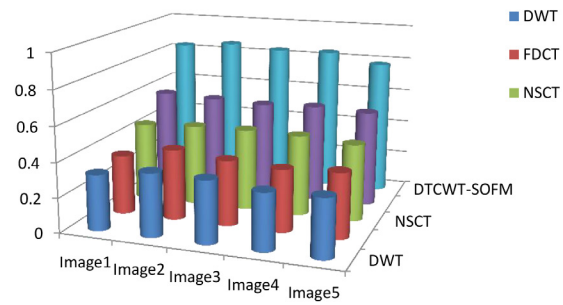


Figure 4. Comparison on Structural Similarity Index Measure (SSIM) of different techniques for Fused Image.

Table 2. Performance evaluation of SSIM using DTCWT-SOFM and Fuzzy rule based fusion method

| Image Set | Structural Similarity Index Measure (SSIM) | | | | |
|-----------|--|-------|-------|-------|------------|
| | DWT | FDCT | NSCT | DTCWT | DTCWT-SOFM |
| 1 | 0.321 | 0.343 | 0.451 | 0.577 | 0.831 |
| 2 | 0.364 | 0.407 | 0.467 | 0.566 | 0.857 |
| 3 | 0.359 | 0.377 | 0.472 | 0.555 | 0.835 |
| 4 | 0.327 | 0.359 | 0.467 | 0.567 | 0.839 |
| 5 | 0.336 | 0.375 | 0.445 | 0.555 | 0.783 |

$$SSIM(x, y) = \frac{(2\mu_x\mu_y + c_1)(2\sigma_{xy} + c_2)}{(\mu_x^2 + \mu_y^2 + c_1)(\sigma_x^2 + \sigma_y^2 + c_2)} \quad (3)$$

with

μ_x the average of x ; μ_y the average of y ; σ_x^2 the variance of x ; σ_y^2 the variance of y ; σ_{xy} the covariance of x and y ;

Table 2 shows the Comparison on Structural Similarity Index Measure of different methods for Fused Image. It is observed from the Table 2 that the performance of the proposed fusion algorithm outperforms the existing algorithms based on DWT, FDCT, NSCT and DTCWT. The reason for better performance of the proposed fusion method is that the proposed fusion is the mixture of min rule and max rule and the application of these rules are based on the clustering based thresholding approach. Table 2 shows the Comparison on Structural Similarity Index Measure of different methods for Fused Image. Figure 4 shows the Chart representation of Comparison on Structural Similarity Index Measure of different methods for Fused Image.

Table 3. Percentage of improvement on EBSM and SSIM for DWT vs. proposed method

| Metrics | Image Set | DWT | Proposed DTCWT-SOFM | % of improvement |
|-------------------------------------|-----------|--------|---------------------|------------------|
| Edge based similarity measure | 1 | 0.2476 | 0.8136 | 228.59 |
| | 2 | 0.2564 | 0.8545 | 233.27 |
| | 3 | 0.2599 | 0.8241 | 217.08 |
| | 4 | 0.2866 | 0.8065 | 181.40 |
| | 5 | 0.3271 | 0.7823 | 139.16 |
| Structural Similarity Index Measure | 1 | 0.321 | 0.831 | 158.88 |
| | 2 | 0.364 | 0.857 | 135.44 |
| | 3 | 0.359 | 0.835 | 132.59 |
| | 4 | 0.327 | 0.839 | 156.57 |
| | 5 | 0.336 | 0.783 | 133.04 |

4.3 Comparative Analysis

The proposed image fusion method using DTCWT with SOFM is quantitatively and qualitatively compared in terms of EBSM, SSIM and image quality with four other existing state of the art methods for image fusion. Table 3 – Table 6 shows the percentage of improvement for EBSM and SSIM between proposed multimodality image fusion using DTCWT with SOFM and existing state of the art methods; DWT, FDCT, NSCT and DTCWT.

Table 3 gives the percentage of improvement on EBSM and SSIM between proposed multimodality image fusion and DWT. From Table 3, the simulation results show that the proposed DTCWT and SOFM method has achieved maximum edge based similarity measure of 0.8545 and structural similarity index measure of 0.831 whereas the existing DWT method with maximum Edge

Table 4. Percentage of improvement on EBSM and SSIM for FDCT vs. Proposed Method

| Metrics | Image Set | FDCT | Proposed DTCWT-SOFM | % of improvement |
|-------------------------------------|-----------|--------|---------------------|------------------|
| Edge based similarity measure | 1 | 0.3643 | 0.8136 | 123.33 |
| | 2 | 0.407 | 0.8545 | 109.95 |
| | 3 | 0.3704 | 0.8241 | 122.49 |
| | 4 | 0.3653 | 0.8065 | 120.78 |
| | 5 | 0.3696 | 0.7823 | 111.66 |
| Structural Similarity Index Measure | 1 | 0.343 | 0.831 | 142.27 |
| | 2 | 0.407 | 0.857 | 110.57 |
| | 3 | 0.377 | 0.835 | 121.49 |
| | 4 | 0.359 | 0.839 | 133.70 |
| | 5 | 0.375 | 0.783 | 108.80 |

based similarity measure of 0.2564 and structural similarity index measure of 0.321. Thus there is an improvement of 233.27% in edge based similarity measure and 158.88% in structural similarity index measure.

Table 4 gives the percentage of improvement on EBSM and SSIM between proposed multimodality image fusion method and FDCT.

From Table 4, the simulation results show that the proposed DTCWT and SOFM method has achieved maximum edge based similarity measure of 0.8136 and structural similarity index measure of 0.831 whereas the existing FDCT method with maximum Edge based similarity measure of 0.3643 and structural similarity index measure of 0.343. Thus there is an improvement of 123.33 in edge based similarity measure and 142.27% in structural similarity index measure.

Table 5 gives the percentage of improvement on EBSM and SSIM between proposed technique and NSCT. From Table 5, the simulation results show that the proposed DTCWT and SOFM method has achieved maximum edge based similarity measure of 0.8136 and structural similarity index measure of 0.831 whereas the existing NSCT method with maximum Edge based similarity measure of 0.4513 and structural similarity index measure of 0.451. Thus there is an improvement of 80.28 in edge based similarity measure and 84.26% in structural similarity index measure.

Table 6 gives the percentage of improvement on EBSM and SSIM between proposed multimodality image fusion method and DTCWT. From Table 6, the simulation

Table 5. Percentage of improvement on EBSM and SSIM for NSCT vs. Proposed Method

| Metrics | Image Set | NSCT | Proposed DTCWT-SOFM | % of improvement |
|-------------------------------------|-----------|--------|---------------------|------------------|
| Edge based similarity measure | 1 | 0.4513 | 0.8136 | 80.28 |
| | 2 | 0.5078 | 0.8545 | 68.27 |
| | 3 | 0.4703 | 0.8241 | 75.23 |
| | 4 | 0.4555 | 0.8065 | 77.06 |
| | 5 | 0.4405 | 0.7823 | 77.59 |
| Structural Similarity Index Measure | 1 | 0.451 | 0.831 | 84.26 |
| | 2 | 0.467 | 0.857 | 83.51 |
| | 3 | 0.472 | 0.835 | 76.91 |
| | 4 | 0.467 | 0.839 | 79.66 |
| | 5 | 0.445 | 0.783 | 75.96 |

Table 6. Percentage of improvement on EBSM and SSIM for DTCWT vs. Proposed Method

| Metrics | Image Set | DTCWT | Proposed DTCWT-SOFM | % of improvement |
|-------------------------------------|-----------|--------|---------------------|------------------|
| Edge based similarity measure | 1 | 0.5677 | 0.8136 | 43.32 |
| | 2 | 0.6151 | 0.8545 | 38.92 |
| | 3 | 0.5925 | 0.8241 | 39.09 |
| | 4 | 0.5589 | 0.8065 | 44.30 |
| | 5 | 0.5265 | 0.7823 | 48.58 |
| Structural Similarity Index Measure | 1 | 0.577 | 0.831 | 44.02 |
| | 2 | 0.566 | 0.857 | 51.41 |
| | 3 | 0.555 | 0.835 | 50.45 |
| | 4 | 0.567 | 0.839 | 47.97 |
| | 5 | 0.555 | 0.783 | 41.08 |

results show that the proposed DTCWT-SOFM method has achieved maximum edge based similarity measure of 0.8136 and structural similarity index measure of 0.857 whereas the existing DTCWT method with maximum Edge based similarity measure of 0.5265 and structural similarity index measure of 0.566. Thus there is an improvement of 48.58% in edge based similarity measure and 51.41% in structural similarity index measure.

5. Conclusion

In Medical image processing applications, specifically in MRI and CT images, the edge preserve is an important criterion in complementary details of input images.

This work investigates the proposed Neural Network based nonlinear medical image fusion algorithm based on DTCWT with Robust SOFM. This allows us to fuse two modalities, CT and MR images to visually assess the details on a single image. The steps involved in the proposed fusion algorithm are image registration, DTCWT decomposition, Robust SOFM, image fusion and reconstruction to obtain the fused image. The Similarity Measure performance is evaluated by using Edge Based Similarity Measure and Structural Similarity Index Measure. The simulation results show that the proposed method has achieved maximum Edge based similarity measure and Structural Similarity Index Measure values. Hence the fused image provides better diagnosis without artifacts. Through the simulation result, as compared with the DWT, FDCT, NSCT and DTCWT fusion methods, it is concluded that the Multimodality image fusion using DTCWT with Robust SOFM gives better Edge based similarity measure and Structural similarity index measure.

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