

An Improved Image Fusion and Segmentation using FLICM with GA for Medical Diagnosis

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Abstract

Background: Medical image fusion has become a common term used in medical diagnostics and treatment. Now a day's numerous wavelet transform based fusion methods proposed for overcoming the spectral distortion in the conventional fusion techniques such as PCA and IHS. DWT based image fusion process has the spatial distortion and lack of information. So selecting suitable wavelet transform for fusion is an important task. **Method:** In the proposed system, Dual tree Discrete Wavelet transform based Fusion and GA based FLICM segmentation is proposed. First, two different types of medical images-MRI and CT are decomposed by Dual tree Discrete Wavelet Transform (DDWT). Next, DDWT coefficients from two input images are fused pixel-by pixel by choosing the average of the approximation coefficients. **Findings:** Genetic algorithm is applied for the fused image in order to generate the optimal cluster centers of its own. From the clusters the affected portion cells are identified using FLICM segmentation process. **Improvements:** The performance of the proposed method is tested for various medical images and the results are analyzed. The fusion results shows DDWT based fusion technique provides around 5db improved PSNR performance when compared to the DWT based fusion. The GA optimizer based FLICM segmentation technique reduces the computation time. For various medical images the segmentation time is approximately reduced as half when compared to the FLICM segmentation technique without GA.

Keywords: DDWT, FLICM, Genetic Algorithm, Image Fusion, Medical Diagnosis, Wavelet Transform

1. Introduction

Image fusion takes an important role in the diagnosis and treatments and especially for the cancer patient treatment. Image fusion process combines two images into a single image in such a way that the combined image has maximum information content than the input images¹. Multiple modalities images are fused to improve the clinical accuracy of decisions. For example, CT images are used to determine hard bone information while MRI images are typically used to visualize soft tissue information.

Fusion methods classification in spatial domain and Frequency domain is discussed²

Image fusion is done in different levels as³

- Pixel level,
- Feature level,
- Decision level.

Pixel level based image fusion is used to produce a new image with higher information for clinical purpose⁴ introduced that, pixel-level method works either in the spatial domain or in the transform domain. Pixel level fusion works directly on the pixels obtained at imaging sensor outputs. Feature level fusion algorithms operate on features extracted from the source images.

Features can be extracted from simultaneous processing of input images or from calculating separately from each input image⁵. Object detection and classification outputs are used as inputs to decision level fusion algorithm for data integration.

Both feature level and decision level image fusion may result in inaccurate and incomplete transfer of information. In pixel level fusion, it is wise to use arithmetic operations directly for pixel values in spatial domain⁵.

Transform Domain Fusion is chosen in the proposed work since spatial domain process provides low peak to signal ratio and introduces spectral distortion, resulting in degradation of the fused image. Wavelet transform based fusion technique comprises both spatial and spectral quality^{6,7}. In general, from higher resolution images, higher information can be extracted along with the spatial quality.

Multispectral image fusion techniques are discussed in^{8,9}. GA is used in image processing for segmentation and clustering. GA based clustering is not suitable for real time applications. But for off line processing, it is efficient¹⁰.

Fuzzy clustering algorithm is the process of organizing objects into groups whose members are similar in some way. Fuzzy Local Information C- Means algorithm (FLICM) is the improved version of FCM (Fuzzy C Means) algorithm implemented on the fused image for segmentation for identifying tumors easily and effectively. FLICM incorporates the local spatial information and gray level information in novel fuzzy way. In this work, FLICM algorithm is used for the process of segmentation and finds the cluster centre in optimum manner with GA even though the images are influenced by noise.

The paper is organized as follows. First the basic fusion process using DWT is explained. Next the fusion using DDWT and segmentation using GA based FLICM Technique is described in section 3. Section 4 analyzes the performance of the proposed system and conclusion is in section 5.

2. Fusion Process using DWT and DDWT

The Discrete Wavelet Transform (DWT) of image produces a non-redundant image representation, which provides better spatial and spectral localization of image formation, compared with other multi scale representations such as Principal Component Analysis, Intensity Hue Saturation¹¹. The fusion process based on wavelet DWT and DDWT are discussed in¹² and various image fusion techniques are discussed in¹³.

The limitations in the DWT based fusion are eliminated in the proposed work with increased Peak signal to noise ratio without spectral and spatial distortion using DDWT combined with FLICM clustering technique¹³. The Proposed work, the performance is improved by adding GA optimizer. GA optimizer is used select optimum clusters for segmentation. The proposed technique modules are shown in Figure 1 and is explained in the following section.

2.1 Description

Array of similar images with different information is taken and fused into a single image. So that it provides more accuracy and information than the input images. The input images may be in different formats and in different size. So the input images should be organized into a standard image of size (512*512). For easy computation and to extract information, the image has to be converted into a gray scaled image from color image. Histogram Normalization provides tonal distribution of the entire image. This helps to notify the minute changes in the intensity values.

Then using DDWT the preprocessed image is decomposed into sub bands. The sub bands are analyzed and using suitable fusion rule, a set of sub bands are selected for fusion process. The fused sub bands are then subjected to inverse DDWT and the fused image is obtained. From the Fused image, using GA and FLICM technique, the affected portions in the image are segmented.

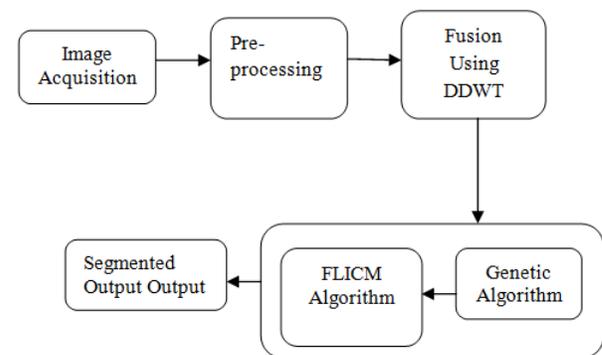


Figure 1. Block diagram of the modules involved in image fusion process.

2.2 DDWT (Dual Tree Discrete Wavelet Transform)

The Dual-tree Discrete Wavelet Transform (DDWT)

calculates the complex transform of image using two separate DWT decompositions (tree a and tree b) are shown in Figure 2. If the filters used in one are specifically designed different from those in the other it is possible for one DWT to produce the real coefficients and the other the imaginary. DWT filtering can be obtained by first applying the 1D DWT row-wise (to produce L and sub bands in each row) and then 1D DWT in column-wise. In the first level of decomposition, four sub bands LL, LH, HL and HH are obtained. The LL sub-band represents an approximation of the original image and other three sub-bands HL, LH, and HH contain higher frequency detail information.

To improve the performance of DDWT, the suitable values of scaling and wavelet functions are selected for the filters used in the two trees. The scaling and wavelet functions of the one tree $\{g_0, h_0\}$ is approximate Hilbert transform value of the other tree's scaling and wavelet function $\{g_1, h_1\}$. So the complex-valued scaling function and wavelet formed from the two trees are approximately analytic. Therefore the Dual Tree DWT has less shift variant and more directional selectivity than the DWT. But due to its expansive nature, it produces M number of coefficients for N number of samples where $M > N$. It has 2^d redundancy factor for d -dimensional data.

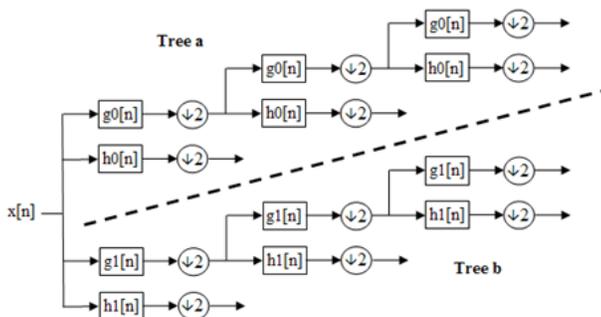


Figure 2. 3-level DDWT Decomposition.

Fused image is subjected to GA for generating optimal cluster centers of its own followed by FLICM segmentation algorithm which is used to segment the fused image for medical diagnosis and to find out the tumors easily. Basic components of GA is discussed in the following section.

3. GA based Clustering and FLICM Segmentation

Genetic Algorithm is one of the simplest and most popular

evolutionary algorithm¹⁴. GA makes use of simplest representation, reproduction and diversity mechanism. Optimization with GA is performed through natural exchange of genetic material between parents. Offspring's are formed from parent genes. Fitness of offspring's is evaluated. The fittest individuals are allowed to breed only. GA's are being used in different applications such as function optimization, system identification and control, Image processing, parameter optimization of controllers, Multi objective optimization, etc.

3.1 GA in Segmentation Phase

GA in segmentation and clustering: GA is used to improve the performance of FLICM segmentation technique. For the segmentation, initially optimum number of clusters is generated using GA.

GA uses rank selection, single-point crossover, and mutation for its operation. Numerical rank is allotted for each individual based on its fitness value and higher ranked individuals more likely to be selected to produce offspring. Fixed-length individuals are used here, and single-point crossover is implemented (with probability 1 per pair of parents) by swapping same length segments of genes between two individuals. For each pair, a single crossover point is chosen randomly with uniform probability over genes in the chromosome. Mutation is performed by randomly changing the value of a gene based on ranges.

To calculate G fitness value, two binary images are generated corresponding to the human-drawn contour and the contour derived from an evolved individual: in each, the pixels inside the segmenting contour are set to 1 and outside are set to 0. H as the Hamming distance between these two binary images i.e., the number of pixels that are classified differently in the evolved individual's segmentation from corresponding pixels in the manually segmented binary image. The goodness of fit is numerically defined as¹⁵

$$G = (1 - (H/N))1000 \quad (1)$$

Where N is the total number of pixels in the image. A score of 1000 represents a perfect match with the training data.

$$F = 500(A + (1 - B)) \quad (2)$$

A denotes the detection rate: i.e., the fraction of pixels inside the segmenting contour that are labeled “True” (i.e., texturally similar to the prostate). B denotes the false alarm rate: the fraction of pixels outside the segmenting contour that are labeled “True”. An increase in fitness means that more pixels inside (and fewer pixels outside) the contour are labeled as “True”. A fitness score of 1000, therefore, represents a perfect segmentation result.

3.2 FLICM Technique

M. S. Yang explained fuzzy based clustering in¹⁶. Fuzzy Local Information C- Means algorithm (FLICM) is the improved version of FCM (Fuzzy C Means) algorithm. FLICM incorporates the local spatial information and gray level information in novel fuzzy way. This algorithm is successfully used for the process of segmentation even though the images are influenced by noise. The traditional FCM process handles three important operations

Generation of Cluster center ‘Cc’,

- Generation of Membership function ‘Mf’ using current Cc,
- Generation of Objective function ‘Obf’ using current Mf and Cc.

These processes will be handled iteratively by choosing initial random membership function. Since FLICM is from FCM family it shares the same type of methodology of calculating Cc, Mf, Obf as FCM. But the process which makes FLICM more superior than FCM is additional inclusion of Fuzzy factor G. To avoid the distortion due to noise during clustering process it has to be found, which pixel is a noisy one at the same time denoising process does not affect the image details. The influence of the neighbor pixels will exponentially increase the miss and false hit ratio. This is the main reason for using this Fuzzy factor G. Also this G is very much helpful in reducing number of iteration in mining process and to preserve robustness;

Fuzzy factor G_{ki} is defined as

$$G_{ki} = \sum_{j \in N_i} \frac{1}{d} (1 - Mf_{kj})^2 \|x_j - Cc_k\|^2, i \neq j \quad (3)$$

Where,

Mf - membership Function

x - Image pixels in vector form

d - distance between Cc and x

FCM frame work which used for FLICM is

$$Obf(I) = \sum_{i=1}^N \sum_{k=1}^c [Mf^m \|x_i - Cc_{jk}\|^2 + G_{ki}] \quad (4)$$

Where,

I - Iteration Number

m - fuzzification parameter

Whereas, Membership function and Cluster center are obtained by

$$Mf(I) = \frac{1}{\sum_{j=1}^c \left(\frac{\|x_i - Cc_{jk}\|^2 + G_{ki}}{\|x_i - Cc_{ji}\|^2 + G_{ii}} \right)^{\frac{1}{m-1}}} \quad (5)$$

$$Cc(I) = \frac{\sum_{i=1}^N Mf^m x_i}{\sum_{i=1}^N Mf^m}$$

Algorithm for FLICM is as follows

Step 1: Initialize a) No of Clusters ‘c’ need to process using GA, b) Fuzzification factor ‘m’

c) Stopping Condition ‘Sc’, which define where the process has to be convergence.

Step 2: Form an initial membership function Mf_{int} in a randomized manner.

Step 3: Set a loop for iteration let it be ‘I’

Step 4: Calculate Cluster center Cc using Mf_{int} for the first iteration else use current Mf by equation (3.18)

Step 5: Calculate Fuzzy factor G_{ki} using Cc and the same Mf which is used for the calculation of current Cc using equation (3.15)

Step 6: Now a new Membership function Mf is formed using current Cc and G_{ki} using equation (3.17)

Step 7: Calculate the Objective function Obf to find the convergence condition using equation (3.16)

Step 8: End of the iteration Stage:

Check if $((Obf(I - 1) - Obf(I) < Sc)$

if condition is satisfied when stop the iteration

(since the clustering process is converged)

else increment the iteration to 1

i.e $I = I + 1$ then

go to step 4 and repeat the process

FLICM clustering algorithm is used to segment the fused medical image. From the segmented classes, tumors can be easily identified. FLICM algorithm along with GA is used for finding optimized solution in segmentation phase.

4. Examples and Results

The given input images of multiple modalities (CT and MRI) are converted into standard size of 512*512. The preprocessing operations like gray scale conversion, histogram equalization and registration are done for all the images. Registration has to be done so that images with information located in different places will be considered and will be taken as that of the same input image. The images are subjected to DDWT decomposition of level 2. Array of similar images with different information is taken and fused into a single image. The fused image is subjected to FLICM segmentation process combined with GA clustering.

4.1 Examples: Medical Images Fusion and Segmented Outputs

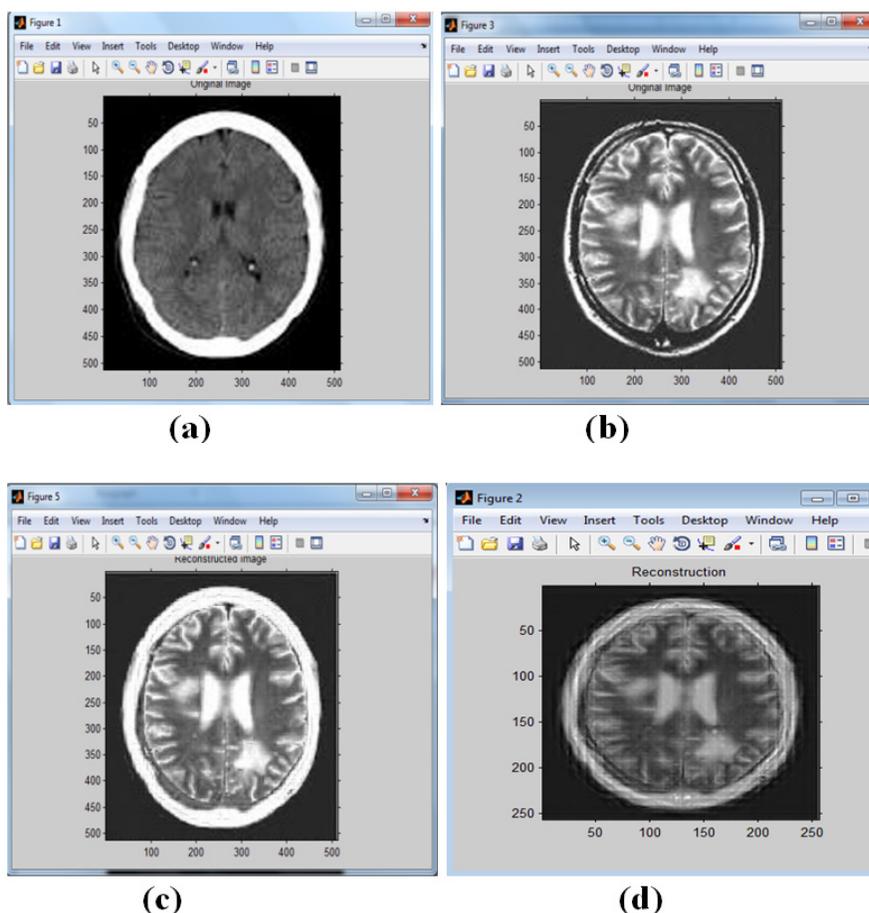
Fusion of images from different modalities such as MR image and CT image is done in example 1. Magnetic resonance image and Computed tomography image is

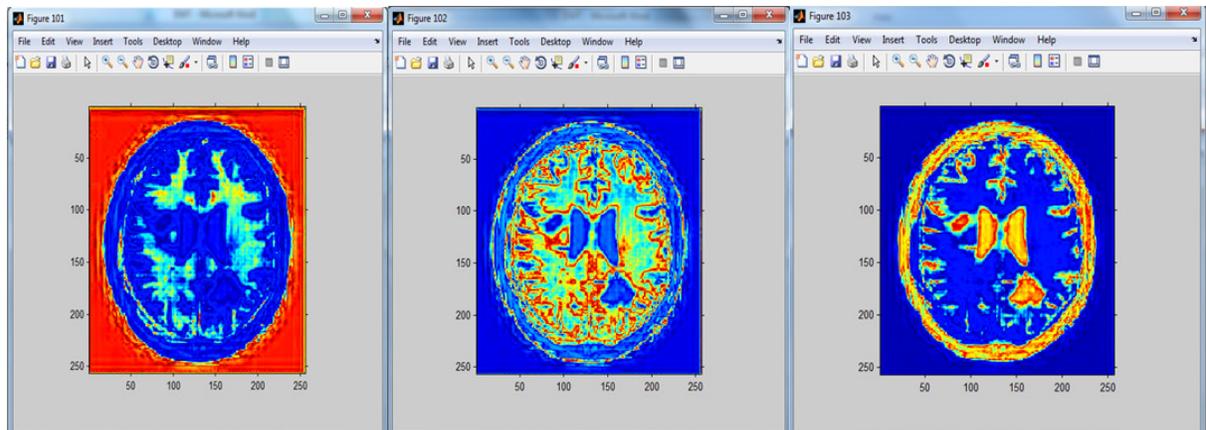
shown in Figure 3a to Figure 3e are fused together and segmentation using FLICM with GA is shown in order to diagnosis the tumors present in the human body and to provide treatment required, which will make doctors diagnosis work easier. Comparison of DWT and DDWT method for medical image is also done and tabulated in Table 1. DDWT fused image provides best segmentation output than DWT based fusion image.

The same process is done for example 2, example 3 and example 4. The input images and output images after fusion and segmented outputs are shown in Figures 4a, 4b, 5a, 5b 6a, 6b and 7a, 7b respectively. The performance of the DDWT based fusion is shown in Tables 1, 2, 3 and 4 respectively.

Table 1. Fusion Result for Medical Image-1

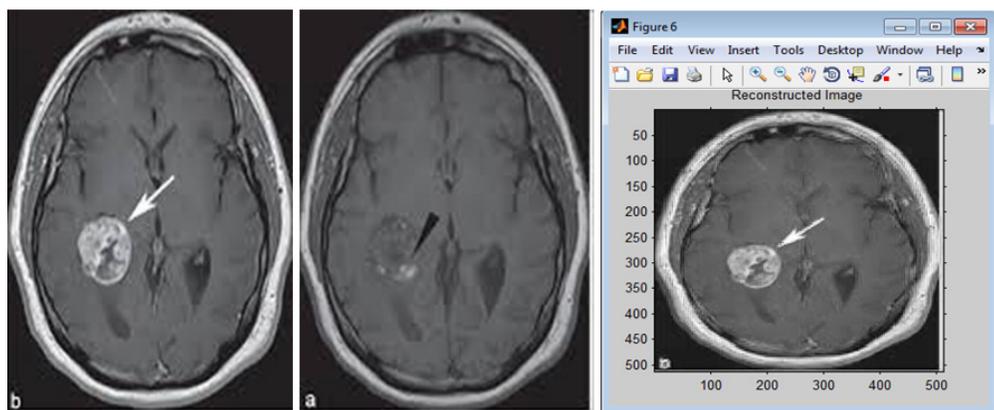
Medical Images (CT and MRI)	Fusion Techniques	PSNR(dB)	RMSE
	DWT	27.6	13.33
	DDWT	32.09	9.5447



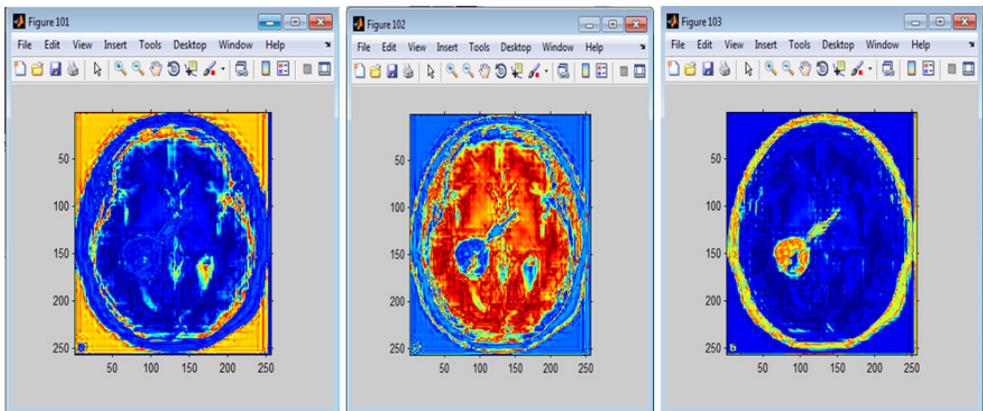


(e)

Figure 3. Fused image Medical image -1. (a) MR Image (b) CT Image. (c) Fusion using DWT (d) Fusion using DDWT (e) Segmented Image based on 3 Cluster Centers: Medical Image-1

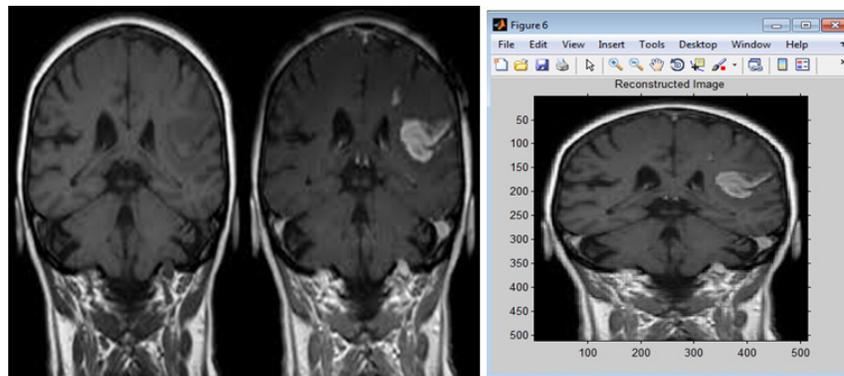


(a)

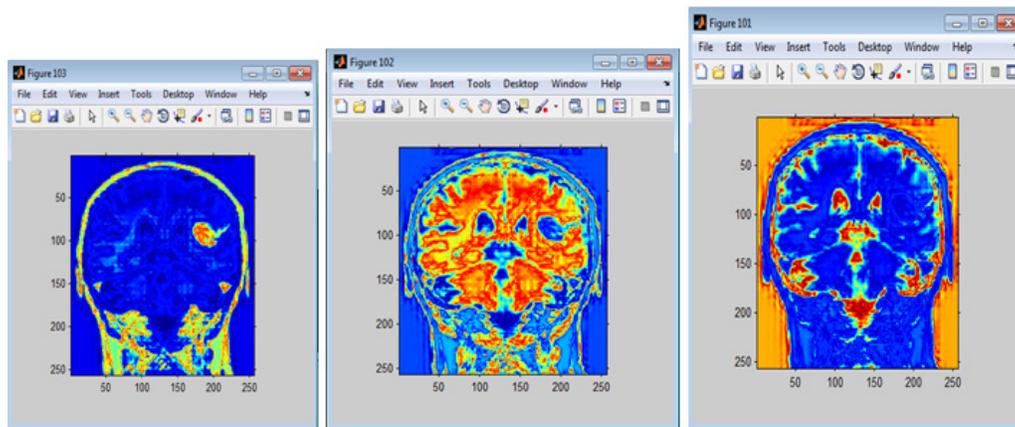


(b)

Figure 4. (a) MRI and CT Scanned Image Fused Image-2 (b) Segmented image based on 3 cluster centers Medical Image-2.



(a)



(b)

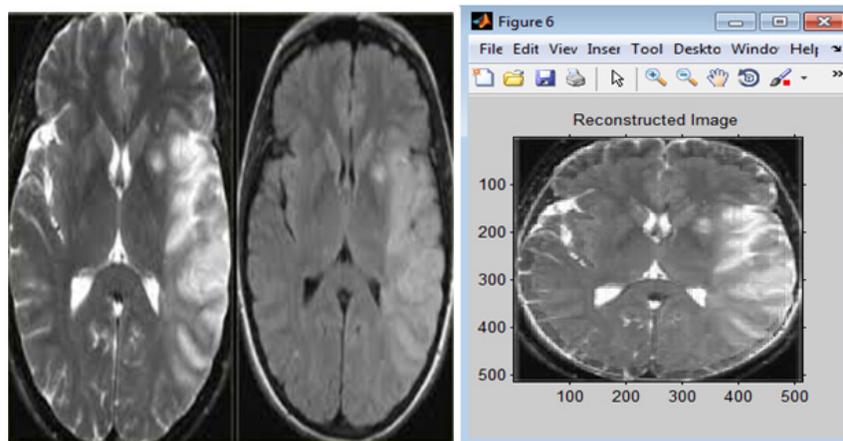
Figure 5. (a) MRI and CT Scanned Image Fused Medical Image-3 (b) Segmented image based on 3 cluster centers: Medical Image-3.

Table 2. Fusion Result for Medical Image-2

Medical Images (CT and MRI)	Fusion Techniques	PSNR(dB)	RMSE
	DWT	25.97	12.03
	DDWT	31.577	8.51

Table 3. Fusion Result for Medical Image-3

Medical Images (CT and MRI)	Fusion Techniques	PSNR (dB)	RMSE
	DWT	27.9	11.84
	DDWT	32.35	8.32



(a)

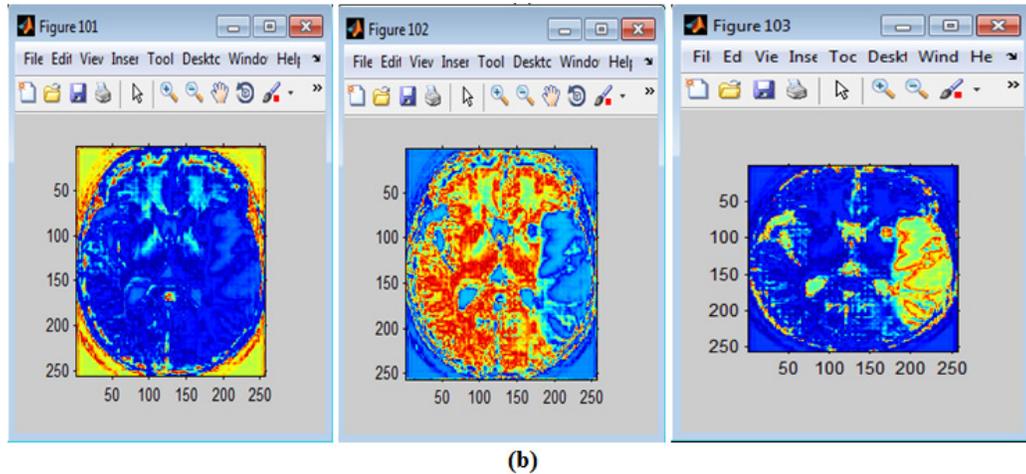


Figure 6. (a) MRI and CT Scanned Image Fused Medical Image-4 (b) Segmented Image Based On 3 Cluster Centers: Medical Image-4.

Table 4. Fusion Result for Medical Image-4

Medical Images (CT and MRI)	Fusion Techniques	PSNR (dB)	RMSE
	DWT	25.6297	13.33
	DDWT	30.577	9.5447

4.2 GA Optimization.

The image to be segmented is given to GA optimizer, where optimal cluster centre of its own is created and the plot is shown in Figure 7 and Figure 8 for given number of cluster for the Medical Image-1 and Medical Image-2. Comparison of number of iteration and time taken for each iteration with and without Genetic Algorithm for all medical images are tabulated in Tables 5, 6, 7, 8 respectively.

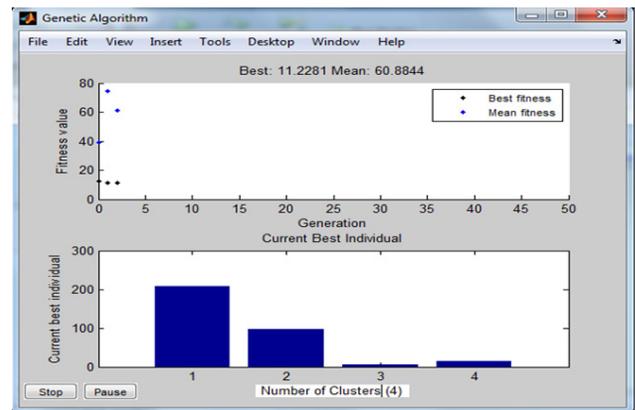


Figure 8. GA optimizer for Medical Image-2.

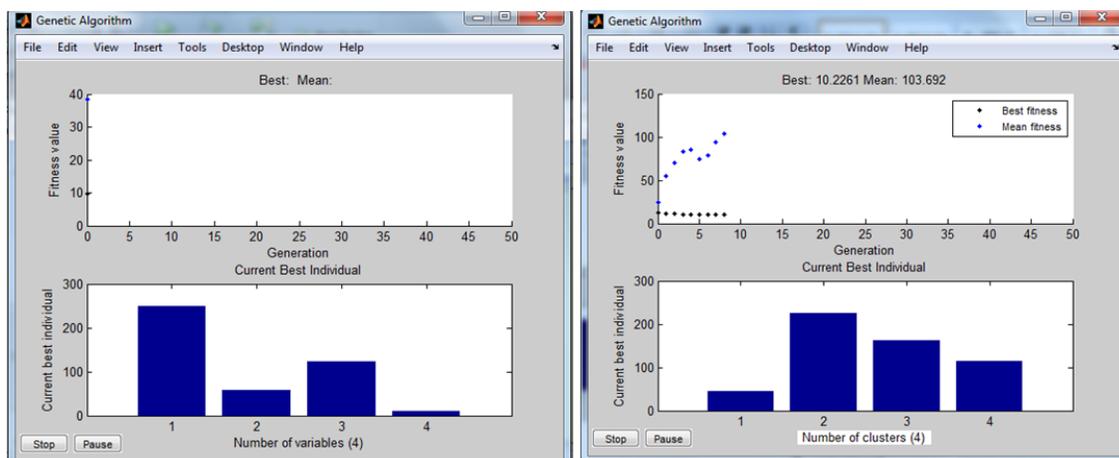


Figure 7. MGA optimizer for medical image-1.



Figure 9. GA optimizer for medical image-3.

The fused image is allowed to GA optimizer in order to calculate the optimum Cluster centre of its own and the plot is shown in Figure 9 and Figure 10 for the Medical image-3 and Medical Image-4. Number of cluster center for the medical image is chosen as 4. For the medical images of given inputs, 4 cluster centers are well enough to calculate the optimum weights without much time and computational complexity.

PSNR performance of various medical images using DWT and DDWT technique is plotted and is shown in Figure 11. Computation time for all the medical images with and without GA is plotted and is shown in Figure 12.

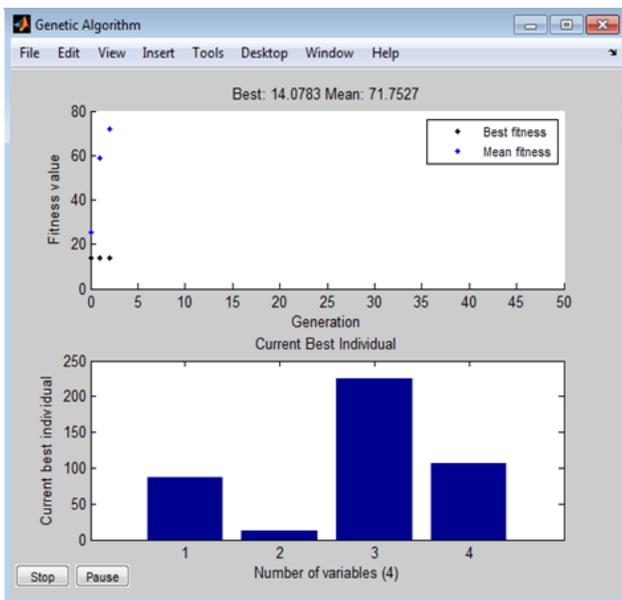


Figure 10. GA optimizer for medical image-4.

Table 5. Performance of Segmentation with and without GA for Medical Image-1

DDWT Technique	Segmentation	Number of iterations	Total Execution Time
Medical Image-1	Without GA	17	30.6 sec
	With GA	13	16.3 sec

Table 6. Performance of Segmentation with and without GA for Medical Image-2

DDWT Technique	Segmentation	Number of iterations	Total Execution Time
Medical Image-2	Without GA	18	31.4 sec
	With GA	13	16.51 sec

Table 7. Performance of Segmentation with and without GA for Medical Image-3

DDWT Technique	Segmentation	Number of iterations	Total Execution Time
Medical Image-3	Without GA	21	36.288 sec
	With GA	15	19.095 sec

Table 8. Performance of Segmentation with and without GA for Medical Image-4

DDWT Technique	Segmentation	Number of iterations	Total Execution Time
Medical Image-4	Without GA	24	42.96 sec
	With GA	16	20.8 sec

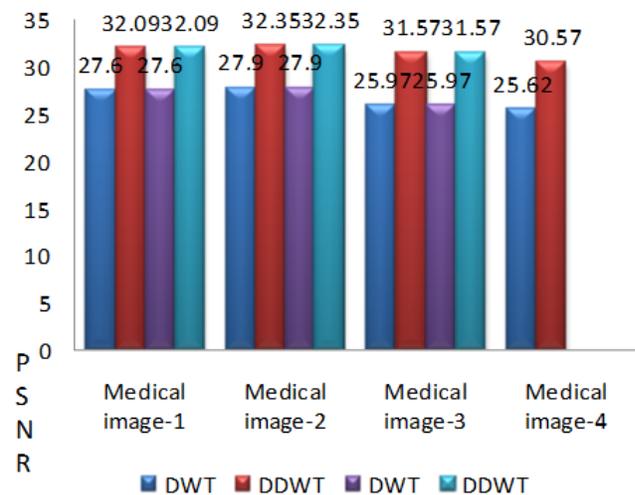


Figure 11. PSNR performance of various medical images Using DWT and DDWT techniques.

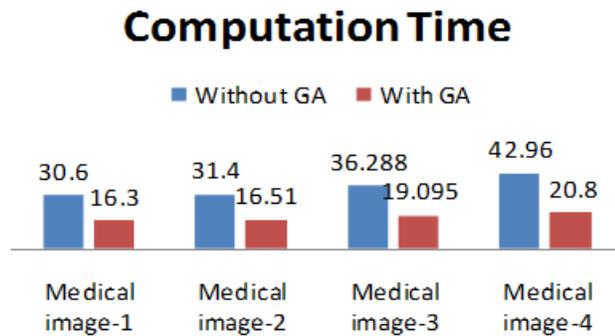


Figure 12. Computation Time for medical images with and without GA in seconds.

5. Conclusion

In this paper, Dual tree discrete wavelet transform based image fusion technique with FLICM segmentation with GA is applied for medical diagnosis applications. Different types of medical images are considered for Image fusion and the segmented output from the fused image provides better solution for the medical diagnosis and treatment. The proposed technique is enhanced by incorporating the position information of various organs in the body. The relative position of the various organs, if incorporated, can be used for initial placement of the segmenting curve (which is random at present). This has the potential to significantly improve the segmentation results. This work can also be extended to 3D segmentation by analyzing 3D pose of an object. The work can be used to evolve a surface instead of a curve in a 3-D domain. Thus information from all the slices of a medical image can be used simultaneously for 3-D segmentation.

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