ADVANCED MULTIMODALITY IMAGE FUSION TECHNIQUE USING DDWT AND PSO

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Abstract— Image fusion is a process where multiple images (more than one) from different or same source are combined to form a single resultant fused image. This fused image is more productive, informative, descriptive and qualitative as compared to its original input images or than individual images. The fusion technique in medical images is useful for resourceful disease diagnosis purpose and robot surgery for doctors. This paper illustrates multimodality medical image fusion techniques and their results assessed with various quantitative metrics. Firstly two registered images CT and MRI-T2 are taken as input.

In this paper, a multimodal image fusion algorithm based on Dual tree discrete wavelet transform and particle swarm optimization (PSO) is proposed. Firstly, the source images are divided into low-frequency coefficients and high-frequency coefficients by the dual-tree discrete wavelet transform (DDWT). The low-frequency coefficients are fused by weighted average method based on regions, and PSO is used to determine to obtain proper fusion weight parameter from high-frequency coefficients from segmented images by DDWT. Also PSO is used to determine α parameter called scalar weight. Finally, the fused image is reconstructed by the inverse DDWT.

Index Terms: DDWT, PSO, Image fusion, Quantitative Metrics.

I. INTRODUCTION

Medical imaging field require highly productive, descriptive, informative image with high resolution and having high information content with respect bones, tissues and visualization for Necessary disease diagnosis for doctors and experts. This is impossible using single modality medical Images as X-ray computed tomography (CT) is best suited only for recognizing bones structure, where as MRI giving better information about the soft tissues. In reality we require corresponding information from different modalities for correctly diagnosis of disease of patient. For the same reason, Medical image fusion is the only promising technique which is successful to attract researchers, scientist to guide the doctors by producing high quality fused images and by extracting suitable information from a variety of modalities say CT, MRI, SPET, PET etc. In the area of medical image fusion, there are various fusion techniques, but these techniques have certain limitations [2]. For example, Wavelet transform is famous technique but suffers from Shift variance and additive noise which can be reduced by Using DDWT (Dual Tree Discrete Wavelet Transform). Thus multimodality medical image fusion has emerged as a promising research area in the recent years.

Image fusion basically aims at extracting and combining information from the source images on pixel basis thus resulting a more precise and complete information about an object. The actual fusion process can be carried out at several levels. Under this, in the pixel-level image fusion the fused images provided all relevant information present in original images with no artifacts or inconsistencies.

The pixel-level image fusion was classified into two type one as spatial domain fusions and second as transform domain fusion. Spatial domain fusion is directly applied on the source images which results in reduce the signal to-noise ratio of the resultant image with simple averaging technique but causes spatial distortion in the resulting fused image. Improvement in fused image is carried out by using PSO (Particle Swarm Optimization) a population based algorithm inspired by natural behaviors of bird flocking, Ant colony etc.PSO gives optimal fused image also it is used to select proper scalar weight from high-coefficient intensities pixel from decomposed source images [11]. The quality of fused image is assessed by quantitative metrics like Entropy (EN), Root Mean Square Error (RMSE), Mutual Information (MI), and Peak Signal to Noise Ratio (PSNR) and Signal to Noise Ratio (SNR).

II. Literature Survey

The traditional Wavelet transform (WT) is based on Mallat algorithm. Basically wavelets transform carries out in three steps: 1) Decomposition of registered input images in to high and low frequency sub-bands, 2) To obtain new image, combination of approximate (low frequency part) and detail (high frequency part) is done and lastly 3) inverse wavelet transform is applied to construct fused image. The traditional wavelet is complex and it requires more storage space for read and writes an operation which is not suitable for real time applications [4]. The second generation of wavelet transform is called as Lifting Wavelet transforms (LWT) algorithm proposed in [10].It reduces the running time and storage space of image fusion. Lifting scheme consists of three phases: Split phase,2)Prediction phase and3)Update phase. Reconstruction of the image in LWT is also having three phases: Anti-update phase, Anti-Prediction phase and Merger phase which is opposite process of decomposition [10]. In LWT algorithm, first approximation coefficients and detail coefficients are computed by applying LWT, feature selection rule is applied on wavelet coefficients to obtain fused coefficients groups and finally the inverse LWT (ILWT) is applied to obtain fused image.

Discrete Wavelet Transform proposed in [7] frequently apply two channel filter bank out of which low pass band at the lowest resolution and high pass band at each step iteratively. In this Wavelet environment, firstly the K-level decomposition based on WT is performed on registered source images. K level decomposition consist of one low frequency band and 3K high frequency bands, then fused coefficients are obtained and lastly inverse DWT is carried out to get the fused image. The DWT gives better fused image with less computational cost and no loss of information.

III. Implementation Details

DDWT Algorithm:

It stands for Dual Tree Discrete Wavelet Transform. DDWT proposed by Kingsbury is only potential tools with the following advantages: direction selectivity, limited redundancy, and shift invariance. It is a complex transform whose wavelet function is restrained to have single-sided spectrum. Either the real part or the imaginary part can be used as a individual transform since both guarantee perfect reconstruction. Thus, DDWT is an over complete transform with redundancy of $2m$:1 for m-dimensional signals. Only the real part of DDWT is taken in coding applications to reduce the introduced redundancy. For example, the resulting repeated information will be reduced to 2:1 from 4:1 i.e. by twice for 2-D case. The real part of DDWT is simply referred to as DDWT hereafter, unless otherwise stated. The implementation of 2-D DDWT follows two steps procedure. Firstly, an input image is divided up to a desired level by two separable 2-D DWT braches, branch *a* and branch *b*, whose filters are purposely designed to meet the Hilbert pair requirements. Thus six high-pass sub bands are generated: *HL*a, *LH*a, *HH*a, *HL*b, *LH*b, and *HH*b, at each level. Secondly, every two corresponding sub bands which have the same pass-bands are linearly combined by either averaging method or differencing method. We have result, sub bands of 2-D DDWT at each level are obtained as $(HL_a + HL_b)/2$, $(HL_a - HL_b)/2$, $(LH_a + LH_b)/2$, $(LH_a - LH_b)/2$, $(HH_a + HH_b)/2$, $(HH_a + HH_b)/2$ [5].

PSO Algorithm:

PSO stands for Particle Swarm Optimization is a population based optimization algorithm exhibits natural behaviors of animal such as bird flocking, Ant colony etc. which is useful to find scalar weight (α parameter).

The processing steps of PSO are given as follows.

Step 1: Set off the population. Each particle has its own random velocity and position.
Step 2: Determine the fitness function value of each particle.
Step 3: Find the best position of each particle by its own experience.
Step 4: Find the position of the best particle.
Step 5: Update the velocity and position of each particle by following equation no. (1) And equation no. (2).

$$V^d_i\,(t+1) = \omega.(t) + c1.r1(t).(p^d_i(t)-x^d_i(t)) + c2.r2\,(t).(p^d_g(t)-x^d_i(t)) \quad (1)$$

$$x^d_i(t+1)=x^d_i(t)+V^d_i(t+1) \quad (2)$$

Where t = iteration counter, ω = is the inertia weight controlling the impact of the previous velocity,c1 and c2 = learning constant , r1 and r2=random variables in the range[0,1],p_i=best position of particle i, p_g=best position of all particles within iteration t.
Step 6: Stop if the current approximate solution can be accepted or the stopping criterion is satisfied. Otherwise, jump to Step 2 [11].

Proposed fusion method model:

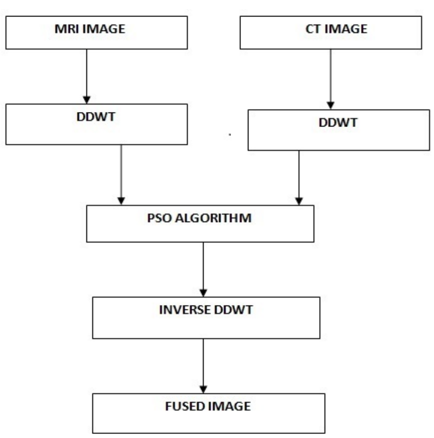


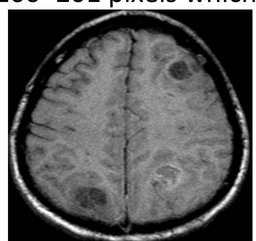
Fig.1. Proposed fusion method Design

This proposed fusion method accepts two input images of different modality say CT and MRI. Then those input images are decomposed into high sub band and low sub band respectively using DDWT algorithm and high coefficient are selected using either averaging method and PSO is used to find scalar weight to find optimal coefficient for fused image. Finally inverse DDWT is performed to get resultant fused image.

IV. Results

Dataset description:

This section describes different modality input images for experimental or demonstration purpose. Images of modality like MRI considered for fusion process one is MRI-T1 and MRI-T2 of which are gray scale images. Both input images are having GIF format and of size 9.06KB and 9.36KB respectively. Also images have dimensions of 169×204 pixels and 166×201 pixels which are registered images.



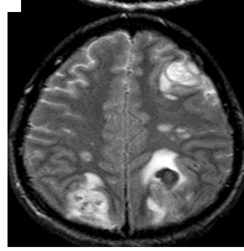
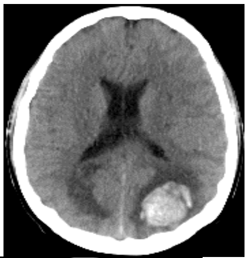


Fig.2.MRI-T1.gif
Fig.3.MRI-T2.gif

Similarly gray scale images of CT and CT-1 modality can be used for same process with size of 9.79KB and 6.89KB respectively with dimensions of 177×228 pixels and 164×207 pixels.



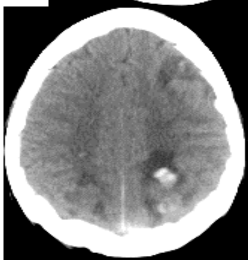


Fig.4. CT.gif
Fig.5.CT-1.gif

Result Description:

This section briefly describes several quantitative measure for visual as well quality evaluation of resultant fused image. The visual analysis alone cannot be only the criteria for quality evaluation.

1. Peak signal to noise ratio (PSNR): PSNR is defined as the ratio between the signal and the noise. PSNR is computed as[2]

$$PSNR=20\log_{10[L}{}^{2}/1(m\times n)\sum_{i=1}^{m}\sum_{j=1}^{n}[R(i,j)-(i,j)]^{2}] \qquad (3)$$

A higher value of PSNR gives better fusion results.

2. Signal to Noise Ratio (SNR): It is defined as the ratio of mean pixel value to that of standard deviation of the corresponding pixel values. It gives the contrast information of the image Higher value of SNR indicates more contrast.[2]

$$SNR=Mean/StandardDeviation \qquad (4)$$

3. Overall cross entropy (OCE): OCE measure difference between the input images and the fused image. Lower the value better is the fusion results obtained. It is given as[2]

$$OCE(I_{A},I_{B},F)=(CE(I_{A},F)+CE(I_{B},F))/2 \qquad (5)$$

4. Root Mean Square Error (RMSE): RMSE value is calculated between the reconstructed image and original image for every fusion performed and present resulting error as a percentage of the mean intensity of the original image [6].

$$RMSE=\sqrt{(1/(M/N))}[\sum X\sum Y(I_{true(x,y)-used(x,y)})] \qquad (6)$$

5. Entropy (EN): Entropy is often calculated to measure the information content of the image. A higher value of entropy display better fusion results. The entropy of an image is calculated using the formulae:[9]

$$EN=-\sum_{i=0}^{L-1}p_i\log_2 p_i \qquad (7)$$

From above qualitative measure we can predict expected result will be as follows: Exiting result and Expected results are provided by considering dataset images of Brain say MRI-T1.gif and CT.gif

TABLE I
EXPECTED RESULTS

Quality Measure	Exiting Result	Expected result with proposed model
PSNR	47.6414	>47.6414
SNR	0.4576	>0.4576
OCE	1.0705	<1.0705
RMSE	5.6665	<5.6665
EN	6.6090	>6.6090

V. CONCLUSION AND FUTURE SCOPE

In our paper new technique of multimodality image fusion which combines the DDWT and PSO is presented. Our proposed method will give outperformed result using DDWT and PSO. Also proposed system overcome shift invarience effect and ensures better quality fused image. Also researcher has scope to develop more reliable fusion technique using Multifocus images or Multiresolution images for motion picture and in scene mixing as well as we can extend our research for 3D image fusion.

VI. Acknowledgement

I would like to thank my colleagues to solve many queries that I had taken to them. In particular, I would like to thank my guide Prof. Ritesh Thakur for supporting my work.

VII. Reference

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