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Optimal Coefficient Selection For Medical Image Fusion

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ABSTRACT
Medical image fusion is one of the major research fields in image processing. Medical imaging has become a vital component in major clinical applications such as detection/ diagnosis and treatment. Joint analysis of medical data collected from same patient using different modalities is required in many clinical applications. This paper introduces an optimal fusion technique for multiscale-decomposition based fusion of medical images and measuring its performance with existing fusion techniques. This approach incorporates genetic algorithm for optimal coefficient selection and employ various multiscale filters for noise removal. Experiments demonstrate that proposed fusion technique generate better results than existing rules. The performance of proposed system is found to be superior to existing schemes used in this literature.
Keywords:- Genetic algorithm, Medical image fusion, Multiscale decomposition ,Optimal fusion technique

I. INTRODUCTION

Image fusion is defined as a procedure for generating a fused image in which each pixel is determined from a set of pixels in each source image. Many of the today's advanced sensors produce images. Examples include infrared cameras (IR), x-ray imagers, optical cameras and radar imagers. Fusing images from such sensors using the technique termed image fusion. The purpose of image fusion is to generate a single fused image which contains a more accurate and reliable description of the scene than any of the individual source images.

Medical imaging has become a vital component in clinical applications such as diagnosis & treatment planning [1]. Since each imaging modality provides information in a limited domain, many studies prefer joint analysis of medical data collected from the same patient using different modalities. This requirement of joint analysis lead to the introduction of image fusion into the medical field & the development of medical data oriented fusion techniques [2]. For example:-Computed Tomography (CT) and MRI images were fused for neuronavigation in skull base tumor surgery. Fusion of positron emission tomography (PET) and MRI images for hepatic metastasis detection and intracranial tumor diagnosis.

A straightforward multimodal medical image fusion method is to overlay the source images by manipulating their transparency attributes [3] or assigning them to different color channels [4].This overlaying scheme is a fundamental approach in image fusion that uses color to expand the amount of information conveyed in a single image [5]. But this scheme does not enhance the image contrast or make the features more distinguishable.

Image fusion can be performed at three different levels, i.e pixel/data level, feature/attribute level, and symbol/decision level, each of which serves different purposes [6]. Compared with the others, pixel-level fusion directly combines the original information in the source images and is more computationally efficient. According to whether multiscale decomposition (MSD) is used, pixel level fusion methods can be classified as MSD based or non-MSD based. Compared to the latter, MSD-based methods have the advantage of extracting and combining salient features at different scales, and therefore normally produce images with greater information content. The general procedure of MSD-based fusion is illustrated in Fig. 1.

First, the source images are transformed to multiscale representations (MSRs) using MSD. An MSR is a pyramidal structure with successively reduced spatial resolution; it usually contains one approximation level (APX) storing low-pass coefficients and several detail levels (DETs) storing high-pass or bandpass coefficients. Then, a certain fusion rule is applied to merge coefficients at different scales. Finally, an inverse MSD (IMSD) is applied to the fused MSR to generate the final image.

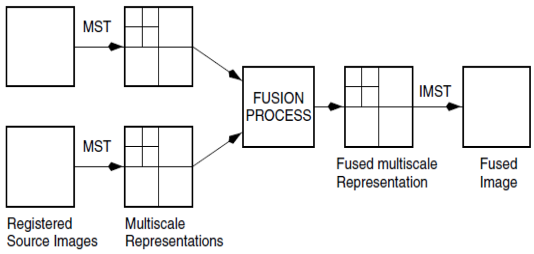

Figure 1: General procedure of MSD –based image fusion

Two directions can be explored in MSD-based fusion to improve fusion quality: advanced MSD schemes and effective fusion rule. Here proposed scheme focus on the latter and introduces an optimal coefficient selection scheme where the membership of each fused coefficient to each source image is calculated.

The rest of the paper is organized as follows. Section II reviews previous methods. Section III presents proposed method. Section IV discusses experimental results. Section V gives conclusion & future work.

II. PREVIOUS WORK

The fundamental image fusion method uses color to expand the amount of information conveyed in a single image. But this scheme does not necessarily enhance the image contrast. The major drawbacks of this approach are:

- It does not enhance the image contrast.
- The image features are not highly distinguishable.
- Fusion results suffer from loss of local contrast.

A. Multiscale Decomposition

The pyramid transforms (PT) and the wavelet transform (WT) are the two categories of MSD schemes that are most commonly employed in image fusion. Among different PT schemes, Laplacian pyramid transform (LPT) [7] is one of the most frequently used. A Laplacian pyramid (LP) is constructed based on its corresponding Gaussian pyramid (GP) by subtracting two adjacent levels [8]. The ratio of low-pass pyramid (RoLP) is also constructed based on GP, but by taking the ratio of two adjacent levels. The gradient pyramid is another type of PT, which is built by applying gradient filters of different orientations to each level of a GP. A standard WT scheme is the discrete WT (DWT), which decomposes a signal into an MSR using scaling (low-pass filtering) and wavelet (high-pass filtering) functions. One drawback of DWT is shift-variance, which tends to cause artifacts along edges in the fused images . Hence, WT schemes that provide shift-invariance, such as dual-tree complex WT (DTCWT) [9] can be employed in image fusion.

B. Fusion Rules

In addition to the MSD scheme, the other key factor affecting fusion results is the fusion rule. A fusion rule is the processing that determines the formation of the fused MSR from the MSRs of the source images.

(a) Simple Image Fusion

Fusion Algorithms mainly perform a very basic operation like pixel selection, addition, subtraction or averaging are: Average Method, Select maximum, Select minimum, PCA. This technique is a basic and straightforward technique and fusion could be achieved by simple averaging corresponding pixels in each input image. Select Maximum/Minimum Method is a selection process if performed here wherein, for every corresponding pixel in the input images, the pixel with maximum/minimum intensity is selected, respectively, and is put in as the resultant pixel of the fused image.

(b) PCA based fusion

In Principal Component Analysis (PCA) is a vector space transform often used to reduce multidimensional data sets to lower dimensions for analysis. It reveals the internal structure of data in an unbiased way. Principal component Analysis is a mathematical tool which transforms a number of correlated variables into a several uncorrelated variables. PCA is widely used in image classification.

(c) Pyramid Decomposition based fusion

Pyramid Fusion Algorithm is a fusion method in the transform domain. Various Pyramid based fusion techniques are FSD Pyramid, Laplacian Pyramid, Ratio-of-low-pass Pyramid, Gradient Pyramid, Morphological Pyramid contrast can be used for the image fusion using different fusion rules. In pyramid approach, pyramid levels obtained from the down sampling of source images are fused at pixel level depending on fusion rules. The fused image is obtained by reconstructing the fused image pyramid. An image pyramid consists of a set of low pass or band pass copies of an image, each copy representing pattern information of a different scale. At every level of fusion using pyramid transform, the pyramid would be half the size of the pyramid in the preceding level and the higher levels will concentrate upon the lower spatial frequencies. The basic idea is to construct the pyramid transform of the fused image from the pyramid transforms of the source images and then the fused image is obtained by taking inverse pyramid transform.

Discrete Wavelet Transform:

The wavelet transform decomposes the image into low-low (LL), low-high (LH), high-low (HL), high-high (HH) spatial frequency bands at different scales. In each level, there are three detail components of high frequency and approximated one of low frequency. The detail components include LH (horizontal information), HL (vertical information) and HH (diagonal information). The approximated component LL describes picture figure. In the first level the frequency components are- LH1, HL1, HH1 and LL1. In the next level LL1 decomposed into LH2, HL2, HH2 and LL2 as shown in Fig. 2.

The DWT fusion method minimizes spectral distortion. DWT provides better signal to noise ratio than pixel based approach.

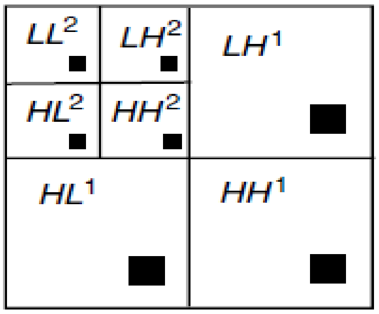

Figure 2: General structure of DWT

III. PROPOSED WORK

In this paper, an optimal cross-scale fusion rule for multiscale-decomposition-based fusion of volumetric medical images is proposed taking into account both intrascale and interscale consistencies. An optimal set of coefficients from the multiscale representations of the source images is determined by effective exploitation of neighborhood information.

The Simple image fusion method does not guarantee to have clear objects from the set of images. The Select Maximum/Minimum method introduces blurring effect which directly effect on the contrast of image. In PCA method fusion may produce spectral degradation. The major drawback of DWT is shift-variance, which tends to cause artifacts along edges in the fused images. Another drawback of DWT is poor directionality.

Hence a standard Wavelet scheme that provides shift-invariance such as Dual-Tree complex Wavelet Transform (DT-CWT) is used in the proposed system. Genetic Algorithm based medical image fusion is performed in the proposed work.

Dual-Tree Complex Wavelet Transform (DT-CWT)

The dual-tree complex wavelet transform (CWT) is a relatively recent enhancement to the discrete wavelet transform (DWT), with important additional properties: It is nearly shift invariant and directionally selective in two and higher dimensions. The multidimensional (M-D) dual-tree CWT is nonseparable but is based on a computationally efficient, separable filter bank (FB).

Genetic Algorithm:

Genetic Algorithms are used for solving optimization problems. Genetic Algorithm is used in the proposed system to select the optimal wavelet coefficient. Genetic algorithm provides the optimized fused image. The major stages of this algorithm include initialization, evaluation and selection as shown in Fig. 3.

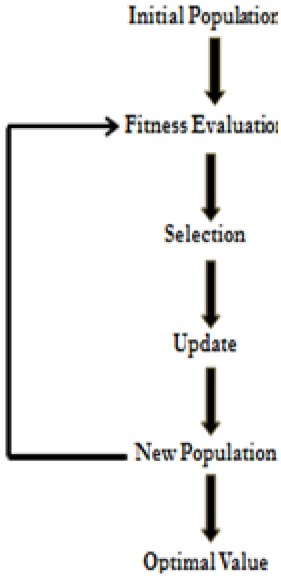

Figure 3: Basic steps of Genetic Algorithm

Firstly choose the weight values as initial population. Evaluate the fitness of each value in the population. Select best values to generate new population. Update the values if required through cross over & mutation to generate new values. Evaluate the fitness of new values. Replace worst values of the population with new values. The process is repeated until an optimal value is reached. The poposed scheme is shown in Fig.4.

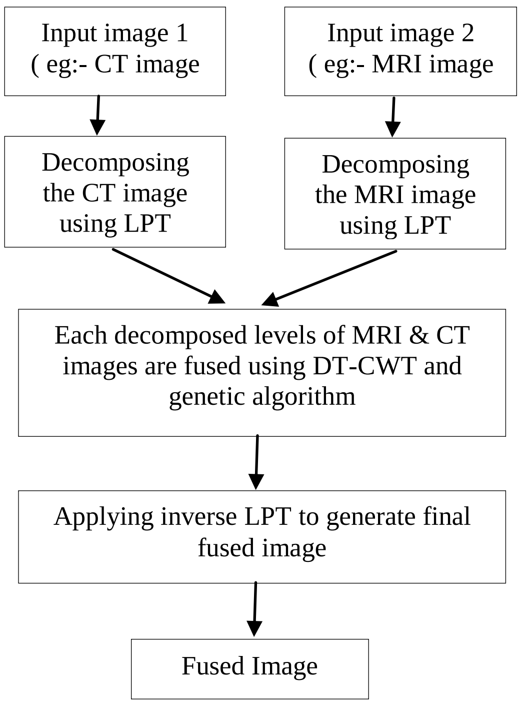

Figure 4: Proposed block diagram

IV. PERFORMANCE EVALUATION

The fused images are evaluated, taking the following parameters into consideration.

(a) ***Peak signal to noise ratio (PSNR)***

It is expressed in logarithmic decibels (dB). Its value will be high when the fused and reference images are similar. Higher value implies better quality of fused image. PSNR can be calculated by using the formula:

$$PSNR = 10\log_{10}\left(\frac{L^2}{MSE}\right)$$

where L is the number of gray levels in the image.

(b) Correlation (CORR)

$$CORR = \frac{2R_{R,F}}{R_R + R_F}$$

(c) Root Mean Square Error (RMSE)

$$RMSE = \sqrt{\frac{1}{NM}\sum_{i=1}^{N}\sum_{j=1}^{M}|R(i,j) - F(i,j)|^2}$$

Table I. The Fusion Methods Performance Measures

Fusion Method	PSNR	CORR	RMSE
Simple average	12.8190	0.8191	0.3753
Select Maximum	9.9581	0.7645	0.5251
PCA	14.8487	0.8465	0.2891
DWT	30.8177	0.8780	0.3332
Proposed Method	64.5303	0.9167	0.1961

V. CONCLUSION & FUTURE WORK

An optimal set of coefficients from multiscale representations of source images are determined by effective exploitation of neighborhood information. Proposed optimal coefficient selection rule provides images with higher quality than existing rules. Genetic algorithm will provide the optimum wavelet coefficient for image fusion. DT-CWT can be incorporated to overcome the lack of translation invariance of the DWT (Discrete Wavelet Transform).Different multiscale filters can be used for noise reduction.

In future an efficient color fusion scheme can be done by utilizing the proposed scheme. Explore the possibility of extending the technique for other imaging modalities. More optimal set of coefficients from the multiscale representations of the source images can be determined .Performing full scale clinical evaluation catered for individual medical applications is also a valuable future work that will facilitate adoption of this technique.

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