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Fusion of multimodal medical images using Daubechies complex wavelet transform – A multiresolution approach

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ABSTRACT

Multimodal medical image fusion is an important task for the retrieval of complementary information from medical images. Shift sensitivity, lack of phase information and poor directionality of real valued wavelet transforms motivated us to use complex wavelet transform for fusion. We have used Daubechies complex wavelet transform (DCxWT) for image fusion which is approximately shift invariant and provides phase information. In the present work, we have proposed a new multimodal medical image fusion using DCxWT at multiple levels which is based on multiresolution principle. The proposed method fuses the complex wavelet coefficients of source images using maximum selection rule. Experiments have been performed over three different sets of multimodal medical images. The proposed fusion method is visually and quantitatively compared with wavelet domain (Dual tree complex wavelet transform (DTCWT), Lifting wavelet transform (LWT), Multiwavelet transform (MWT), Stationary wavelet transform (SWT)) and spatial domain (Principal component analysis (PCA), linear and sharp) image fusion methods. The proposed method is further compared with Contourlet transform (CT) and Nonsubsampled contourlet transform (NSCT) based image fusion methods. For comparison of the proposed method, we have used five fusion metrics, namely entropy, edge strength, standard deviation, fusion factor and fusion symmetry. Comparison results prove that performance of the proposed fusion method is better than any of the above existing fusion methods. Robustness of the proposed method is tested against Gaussian, salt & pepper and speckle noise and the plots of fusion metrics for different noise cases established the superiority of the proposed fusion method.

1. Introduction

Biomedical image processing is a rapidly growing area of research from last two decades. Availability of numerous kinds of biomedical sensors has increased the interest of researchers and scientists in this field. X-ray, ultrasound, magnetic resonance imaging (MRI) and computed tomography (CT) are a few examples of biomedical sensors. These sensors are used for extracting clinical information, which are generally complementary in nature. For example, X-ray is widely used in detecting fractures and abnormalities in bone position, CT is used in tumor and anatomical detection and MRI is used to obtain information among tissues. Similarly, other functional imaging techniques like functional magnetic resonance imaging (fMRI), positron emission tomography (PET), single positron emission computed tomography (SPECT) provide functional and metabolic information. Hence, one can easily conclude that none of these modalities is able to carry all relevant information in a single image. Therefore, multimodal fusion is required to obtain all possible relevant information in a single composite image. Medical image fusion [1] is the process of combining and merging complementary information into a single image from two or more source images which facilitate in more precise diagnosis and better treatment. Fused image provides higher accuracy and reliability by removing redundant information. Some medical applications of image fusion are found in radiology, molecular and brain imaging, oncology, diagnosis of cardiac diseases, neuroradiology and ultrasound [2–10], etc.

There are two basic requirements for image fusion [11,12]. First, fused image should possess all possible relevant information contained in the source images; second, fusion process should not introduce any artifact, noise or unexpected feature in the fused image.

Generally, pyramid and wavelet transforms are used for multiresolution image fusion. A detailed literature review on image fusion can be found in Section 2 (Background and Literature) of this paper. Real valued wavelet transform based fusion methods suffer from shift sensitivity [13] and lack of phase information [14]. Therefore, we have used Daubechies complex wavelet transform (DCxWT) [15] for image fusion, which is approximately shift

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invariant and provides phase information through its imaginary coefficients.

In the present work, we have proposed a new multimodal medical image fusion method using DCxWT which is based on multiresolution principle and performed multilevel fusion over three sets of multimodal medical images using maximum selection scheme. The proposed fusion method is compared with other wavelet domain (Dual tree complex wavelet transform (DTCWT), Lifting wavelet transform (LWT), Stationary wavelet transform (SWT) and Multiwavelet transform (MWT)) and spatial domain (PCA, linear and sharp) image fusion methods. The proposed method is further compared with advanced multiresolution transform (Contourlet transform (CT) and Nonsubsampled contourlet transform (NSCT)) based image fusion [16] methods. The superiority of the proposed fusion method is validated using well known fusion metrics (entropy, edge strength $\left(Q_{AB}^{F}\right)$, standard deviation, fusion factor and fusion symmetry) for normal and noisy cases (Gaussian, salt & pepper and speckle) [17].

Rest of the paper is organized as follows: Image fusion literature is discussed in Section 2. Constructions and properties of DCxWT are described in Section 3. Section 4 explains the proposed fusion method. Experimental results and performance evaluations are given in Sections 5 and 6 respectively. Finally, conclusions of the work are given in Section 7.

2. Background and literature

Image fusion [18] is the process of integrating all relevant and complementary information from different source images into a single composite image without introducing any artifact or noise. Image fusion can be performed at three levels – pixel level [19], feature level [20] and decision level [21]. Pixel level fusion deals with information associated with each pixel and fused image can be obtained from the corresponding pixel values of source images. In feature level fusion, source images are segmented into regions and features like pixel intensities, edges or texture, are used for fusion. Decision level fusion is a high level fusion which is based on statistics, voting, fuzzy logic, prediction and heuristics, etc.

Pixel level fusion is advantageous over the other fusion schemes as it uses original (pixel values) information of images and can be performed both in spatial and transform domains. Spatial domain fusion directly operates on the pixels of the source images. Averaging, principal component analysis (PCA) [22], brovey transform [23] and IHS (Intensity hue saturation) [24] based fusion methods fall under this category. One of the major disadvantages of spatial domain fusion methods is that it introduces spatial distortions in the resultant fused image and does not provide any spectral information. These disadvantages were overcome with the use of transform domain image fusion methods.

In the present work, we are dealing with pixel level transform domain fusion as it is computationally efficient and is more suitable than spatial domain fusion methods. Before fusing images, a proper registration [25] is required. In case of medical imaging, proper alignment of images is highly desired otherwise fusion process could result in mismatched image. Harder tissues like brain can be registered easily whereas for softer tissues, like lung, liver, neck or other organs which have metabolic or shape changing behavior, registration is difficult to perform. So for better fusion result, a good registration algorithm is needed. Discussion of registration techniques is beyond the scope of this paper.

Averaging and weighted averaging are the simplest methods of pixel level image fusion. Perceptual quality of resultant fused image is degraded by applying these fusion strategies. To overcome this problem multiresolution approach [26] has been introduced. Pyramid and wavelet transforms are the most popular multiresolution methods for pixel level fusion. In pyramid transform based image fusion scheme, source images are decomposed into their pyramidal representations followed by application of fusion rules to pyramidal representation. Inverse pyramid transform will give resultant fused image. Laplacian pyramid [27], gradient pyramid [28], contrast pyramid [29], ratio of low pass pyramid [30] are used for image fusion. Pyramid transform based fusion methods suffer from blocking effect [31] in the regions where the input images are significantly different. Also pyramid transform based fusion methods do not provide any directional information and have poor signal to noise ratio. In contrast to pyramid transforms, wavelet transforms have better representation of detailed features of image; hence wavelet domain fusion methods provide better results than pyramid based fusion methods [29].

Discrete wavelet transform (DWT) is the most commonly used wavelet transform for image fusion. It provides spectral as well as increased directional information with three spatial orientations: vertical, horizontal and diagonal. DWT based fusion methods have been applied to a variety of image data sets, such as multifocus, multiview, multimodal, infrared and visible. A simple DWT based medical image fusion, which follows weighted fusion rule, has been introduced by Shangli et al. [32]. Another pixel and region based multiresolution image fusion for MRI and CT image is discussed in [33]. LWT based fusion for T1 and T2 weighted MRI images is proposed in [34]. This method uses wavelet transform modulus maxima criterion and provides better fusion result due to increase in detailed information of images. MWT based medical image fusion [35] has overcome the disadvantages of scalar wavelets and possesses orthogonality, symmetry and smoothness for better image analysis. It provides flexible filtering through which high frequency energy can be transferred into low frequency energy and is beneficial to improve compression ratio.

Real valued wavelet transforms suffer from shift sensitivity, poor directionality and do not provide any phase information [36]. It has been observed that real valued DWT is shift sensitive [13]. This anomaly arises from down sampling in the implementation of real valued DWT. As real valued DWT is implemented with real valued filters, therefore it does not provide any phase information [14]. According to [37], phase information provides description of the amplitude and the local behavior of a function. DTCWT [38] provides shift invariance and better directionality than real valued wavelet transforms. Higher directionality and shift invariance properties of DTCWT make it suitable for image fusion [11,20,39,40]. But DTCWT is not a complex wavelet transform in true sense as it uses real filters. Moreover, it is computationally costly and requires large memory. Therefore, for better phase information and non-redundant representation, an approximate shift-invariant DCxWT [41,42] is proposed and used in different signal processing applications [13,14,36,43,44]. The use of complex filters makes DCxWT, a complex wavelet transform in true sense. Less computational requirements and availability of phase information in DCxWT motivated us to use it in medical image fusion application.

3. Daubechies complex wavelet transform

The basic equation of multiresolution theory is the scaling equation

$$\phi(x) = 2\sum_{k} a_k \phi(2x - k) \quad (1)$$

where a_k are the coefficients. The a_k can be real as well as complex valued and $\sum a_k = 1$.

Daubechies's wavelet bases $\{\psi_{j,k}(t)\}$ in one dimension are defined through the above scaling function and multiresolution analysis of $L^2(R)$ [45]. To provide general solution, Daubechies