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Full Length Article

Multi-modal medical image fusion using the inter-scale and intra-scale dependencies between image shift-invariant shearlet coefficients

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ABSTRACT

For the quality of the fused outcome is determined by the amount of the information captured from the source images, thus, a multi-modal medical image fusion method is developed in the shift-invariant shearlet transform (SIST) domain. The two-state Hidden Markov Tree (HMT) model is extended into the SIST domain to describe the dependent relationships of the SIST coefficients of the cross-scale and inter-subbands. Base on the model, we explain why the conventional Average–Maximum fusion scheme is not the best rule for medical image fusion, and therefore a new scheme is developed, where the probability density function and standard deviation of the SIST coefficients are employed to calculate the fused coefficients. Finally, the fused image is obtained by directly applying the inverse SIST. Integrating the SIST and the HMT model, more spatial feature information of the singularities and more functional information contents can be preserved and transferred into the fused results. Visual and statistical analyses demonstrate that the fusion quality can be significantly improved over that of five typical methods in terms of entropy and mutual information, edge information, standard deviation, peak signal to noise and structural similarity. Besides, color distortion can be suppressed to a great extent, providing a better visual sense.

1. Introduction

Multi-modal medical image fusion, an easy access for physicians to understand the lesion by reading images of different modalities, has been emerging as a new and promising research area due to the increasing demands in clinical applications. For example, combined MRI/CT imaging can concurrently visualize anatomical and physiological characteristics of the human body for diagnosis and treatment planning [1]. In oncology, the combined PET/CT imaging is helpful to view the tumor activity, allowing physicians to better understand the effects of cancer treatment [2].

Nowadays, multi-scale decomposition (MSD)-based medical image methods have been widely discussed because of their advantages over the other fusion techniques. For example, Intensity–Hue–Saturation (IHS) transform-based methods [3] may lead to spectral distortion while the arithmetic combination [4] will lose original details as a result of the low-contrast of the fused image. One core problem for MSD-based method is the choice of MSD tool. As well known, two dimensional (2-D) separable wavelets decompose images into only three directional highpass subbands, namely, vertical, horizontal and diagonal, capturing only limited directional information [5]. In order to overcome the limitations of the traditional wavelets, some novel multi-scale geometric analysis (MGA) tools have been introduced into medical image fusion. For example, Ali et al. proposed a curvelet transform (CVT) based-method for the combination of CT and MRI [6]. Yang and Guo proposed a contourlet transform-based medical image fusion method with an improved contrast scheme [7]. Li and Wang introduced the non-subsampled contourlet transform (NSCT) to the fusion of MRI and SPECT with a variable-weight scheme [8], etc. Quite good results have been reported in these lectures as the source images can be decomposed into any power of two number of directions in each scale, capturing more directional information than that of the wavelets. With respect to the CVT, however, its implements are not built directly in the discrete domain and it does not provide a multi-resolution representation of the geometry. As for the contourlet transform, the shift-invariance is lost as a result of the subsampling scheme for the multi-scale partition while the NSCT, the improved version of contourlet transform, is of high time cost.

Shearlet [9] is one of the state-of-the-art MGA tools. From the point of view of approximation theory, the shearlets form a tight frame of well localized waveforms at various scales and directions, which are the true 2-D sparse representation for images with edges. Different from the CVT, the shearlets can be studied within

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the framework of generalized multi-resolution analysis with directional subdivision schemes. Compared to the contourlet and NSCT, an advantage of the shearlet is that there are no restrictions on the number of directions for the shearing, as well as the size of the supports, unlike the construction of the directional filter banks for contourlet and NSCT in [10,11]. In addition, the inversion of the discrete shearlet transform only requires a summation of the shearing filters rather than inverting a directional filter bank, which results in an implementation that is more efficient computationally. So far, shearlet has been applied in the fusion of remote sensing images [12,13]. However, the shearlet transform used in [12,13] is implemented by the sub-sampling scheme, which can bring about pseudo-Gibbs phenomena in the singularities of the images.

Another core problem for the MSD-based image fusion method is the choice of the fusion schemes. The generic Average–Maximum fusion scheme, meaning the fused low-frequency coefficients are the average of the corresponding coefficients of the source images and the high-frequency coefficients are computed by the approach of choosing absolute maximum or energy maximum in a sliding window, has been popularly employed, such as [5,12,13]. Artificial Neural Network is another popular fusion scheme. For example, Yang and Wang employed Pulse Coupled Neural Network and a new contourlet packet for the image fusion in [14]; Jiang and Tian proposed an improved Self-Generating Neural Network scheme in [15]. In these schemes, the fused images are determined by the clustering results of the coefficients. The schemes mentioned above, however, are all based on the same assumption that all the coefficients in different subbands are statistically independent. Therefore, all the operations are only implemented in the intra-subbands, which means only separate coefficient or a small neighborhood of current coefficient is considered. Important dependency information existing in the coefficients of the inter-subbands and the cross-scale has been lost.

In fact, some famous statistical models have been successfully proposed to describe the dependencies for the coefficients of the inter-subbands and cross-scale in the MSD domain, such as the Hidden Markov Tree (HMT) model in the wavelet domain [16] and the contourlet domain [17]. According to our study, there is also strong dependencies between the coefficients of inter-subbands and cross-scale in the SIST domain. To make full use of the advantages of the SIST and the dependencies of the SIST coefficients, a SIST-based multi-modal medical image fusion method is developed in this paper. The distinguishing characteristics of our work are as follows.

(1) Different from the sub-sampling scheme of the ST, SIST is implemented by the non-subsampled pyramid filter scheme and shift invariant shearing filters, by which the pseudo-Gibbs phenomenon can be suppressed efficiently as a result of replacing the sub-sampling scheme with convolutions.
(2) The dependencies of the SIST coefficients have been studied and the two-state HMT model is extended to the SIST domain to describe the statistical relationships. Thanks to the model, more important dependency information in the cross-scale and inter-subbands can be captured from the source images. Besides, the common Average–Maximum scheme is quantitatively shown why not the best fusion rule.
(3) To employ the dependency information in the cross-scale and inter-subbands, a new fusion scheme is developed. In the two state HMT model, states 0 and 1 correspond to the edges and the smooth region of the images. Besides, the SIST coefficients can be only determined by their probability density functions. Therefore, the full use of the probability density function and the standard deviation of the SIST coefficients are made to calculate the fused coefficients in the developed scheme. Compared to the Average–Maximum scheme, more information from the source images can be transferred into the fused images.

The remainder of this paper is organized as follows: the main framework of the proposed method and the superiorities of the SIST are illustrated in Section 2. In Section 3, the HMT model to describe the statistical dependencies of the SIST coefficients and the proposed fusion scheme are presented in detail. Experimental results are shown in Section 4. Finally, the whole paper is concluded in Section 5.

2. The SIST based medical image fusion method

2.1. The framework of the SIST based fusion algorithm

Throughout this paper, let A, B denote the source images and F denote the fused images. Without loss of generality, the whole framework of the proposed method is shown by Fig. 1. The procedure of the algorithm can be summarized as follows.

(1) Calculate the intensity components of the source images by the IHS transform.
(2) Decompose the intensity components into low-pass and high-pass subbands via SIST.
(3) Train the high-pass subbands coefficients using the two-state HMT model.
(4) Combine high-pass and low-pass coefficients according to the fusion rules.
(5) Reconstruct the intensity components of the fused image by the inverse SIST.
(6) Reconstruct the fused color image by applying the inverse IHS transform.

2.2. The shift-invariant shearlet transform

The SIST can be completed by two steps: multi-scale partition and directional localization. In the multi-scale partition, the shift-invariance which means less sensitivity to the image shift can be achieved by the non-subsampled pyramid filter scheme [11], in which the Gibbs phenomenon is suppressed to a great extent as a result of replacing down-samplers with convolutions. In the directional localization, the frequency plane is decomposed into a low-frequency subband and several trapezoidal high-frequency subbands by the shift-invariant shearing filters. The introduction for the process of SIST is not the main focus in this paper, more details can be found in [18]. In frequency domain, each shearlet is supported on a pair of trapezoids, of approximate size $2^{2j} \times 2^{j}$, oriented along lines of slope $l2^{-j}$. The frequency partition of one image is shown in Fig. 2.

An efficient multi-scale image representation is one of the foundations for multi-modal medical image fusion. According to the theory of wavelets, the support of one wavelet is a square. When wavelet is used to represent the multi-dimensional features, such as contours, non-zero coefficients increase exponentially and cannot be neglected for their large amplitude, demonstrating the directional sensitivity is lost. Therefore, wavelet cannot be considered as the true sparse representation. On the other hand, each shearlet is supported on a pair of trapezoids, of approximate size $2^{2j} \times 2^{j}$, oriented along lines of slope $l2^{-j}$, where l is an integer. When the scale j increases, the slope of the orientation changes accordingly, which means shearlet has strong selectivity of anisotropic directionality. The basis functions of 2-D tensor-product wavelets and the shearlets are shown in Fig. 3a and b, respectively. Lacking of directionality, wavelets are only good at catching point