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Research paper

Multi-modality medical image fusion based on image decomposition framework and nonsubsampled shearlet transform

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ABSTRACT

Medical image fusion increases accuracy of clinical diagnosis and analysis through integrating complementary information of multi-modality medical images. A novel multi-modality medical image fusion algorithm exploiting a moving frame based decomposition framework (MFDF) and the nonsubsampled shearlet transform (NSST) is proposed. The MFDF is applied to decompose source images into texture components and approximation components. Maximum selection fusion rule is employed to fuse texture components aimed at transferring salient gradient information to the fused image. The approximate components are merged using NSST. Finally, a components synthesis process is adopted to produce the fused image. Experimental results verify that the proposed method achieves better performance than other compared state-of-art methods in both visual effects and objective criteria.

1. Introduction

The modern medical imaging technologies provide diversified modalities such as computed tomography (CT), magnetic resonance imaging (MRI), single-photon emission computed tomography (SPECT) and etc., to ensure accuracy of clinical diagnosis. Medical image fusion automatically combines complementary information from multiple source images into single informative one, which helps to improve location precision and make unbiased decisions [1]. With the growing appeal of this huge potential research field, various kinds of multi-modality medical image fusion methods have been proposed [2–6].

The mainstream image fusion methods adopt multi-scale decomposition to capture salient features of source images. Generally, the decomposition procedure is completed with multi-scale transform (MST) tools such as multi-scale pyramid transform [7,8], discrete wavelet transform (DWT) [9], stationary wavelet transform (SWT) [10], dual tree complex wavelet transform (DTCWT) [11,12], nonsubsampled contourlet transform (NSCT) [13,14], nonsubsampled shearlet transform (NSST) [15,16], and so on. Among all the prevalent MST tools, the NSST possesses fine characteristics of shift-invariant, high directional sensitivity and relatively lower computational complexity, which makes it an excellent MST tool for medical image fusion. Current contribution of recently proposed NSST based image fusion methods mainly lies in formulating efficient fusion rules. Liu et al. used morphological component analysis to fuse decomposed low-frequency subbands by NSST [17]. For the fusion of low-frequency and high-frequency subbands, fusion rules are respectively formulated based on sum of variation in square and two different features in Ganasala's method [18]. Yin et al. used singular value decomposition method to estimate structure information of image while fusing low-frequency subbands [5]. Considering the dependence of NSST coefficients, a contextual statistical similarity based fusion method is proposed in [19]. Kong proposed a concise and effective improved pulse-coupled neural network to fuse NSST coefficients and obtain good fusion results [20]. In order to avoid blur and contrast reduction of the fused image, feature-motivated adaptive PCNN is proposed to fuse subbands decomposed with NSST [21]. In addition, NSST based medical fusion method is applied to evaluate six color models in the fusion of functional and anatomical images [22].

The conventional fusion methods based on NSST are directly decomposed the source images. Although NSST with suitable fusion rules may achieve good fusion results, utilizing one transform cannot fully capture salient features especially for edge and textures contained in source images. Recently, a moving frame based decomposition framework (MFDF) is proposed to encode local geometry of an image [23]. By using MFDF, an image can be decomposed into a texture component J_1 containing texture and edge features and an approximate component J_3 similar to source image. The MFDF can be used to separate edge information from source images, which is helpful in transferring more salient edge features

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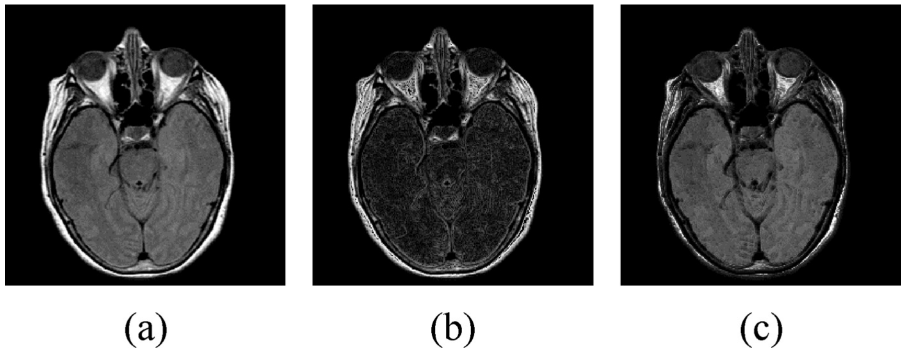

Fig. 1. The decomposition example: (a) an MRI image, (b) component J_1, (c) component J_3.

into the fused image. The separated approximate image including detail information can be extracted using NSST. Through formulating appropriate rules, more information will be transferred from source images into fused image. Out of the above considerations and transfer more edge and texture features of the source image into the fused image, a novel medical image fusion method combining the MFDF and NSST is proposed in this paper. Each source image is firstly decomposed into J_1 and J_3 components using MFDF. As J_1 components mainly maintain edges and textures information, so maximum selection fusion rule is employed to get the fused J_1. Since many significance features are still contained in J_3 components, NSST is used to further decompose the J_3 component to capture and transfer more salient features into the fused image. The average fusion rule and sum-modified-Laplacian (SML) fusion strategy are respectively applied in the fusion of decomposed low-frequency and high frequency subbands of NSST decomposed components. The final fusion result is obtained through synthesising fused J_1 and J_3 components. Experimental results demonstrate that the proposed method achieves a remarkable superiority in both visual effects and objective criteria.

2. Basic theory

2.1. Image decomposition framework

The literature [23] introduces an image decomposition model named as MFDF. It uses a moving frame that encodes local geometry information including gradient's direction and level lines. For an image I, the orthonormal moving frame ($\mathbf{Z_1}$,$\mathbf{Z_2}$, $\mathbf{N}$) is constructed by the following formulas,

$$\mathbf{Z_i} = \frac{d\psi(z_i)}{\|d\psi(z_i)\|_2}, i = 1, 2 \tag{1}$$

$$\psi : (x, y) \mapsto (x, y, \mu I(x, y)) \tag{2}$$

where $z_1 = \left(\mu I_x, \mu I_y\right)^{\mathrm{T}}$ and $z_2 = \left(-\mu I_y, \mu I_x\right)^{\mathrm{T}}$ respectively denotes the gradient and level lines of scaled version $\mu I(\mu \in [0, 1])$ of image I. The unit normal $\mathbf{N}$ is orthogonal with $\mathbf{Z}_1$ and $\mathbf{Z}_2$. The columns of $\mathbf{Z}_1$, $\mathbf{Z}_2$ and $\mathbf{N}$ constitute a matrix $\mathbf{D}$ as follows,

$$\mathbf{D} = \begin{pmatrix} \dfrac{I_x}{|\nabla I|\sqrt{\left(1+\mu^2|\nabla I|^2\right)}} & \dfrac{-I_y}{|\nabla I|} & \dfrac{-\mu I_x}{\sqrt{\left(1+\mu^2|\nabla I|^2\right)}} \\ \dfrac{I_y}{|\nabla I|\sqrt{\left(1+\mu^2|\nabla I|^2\right)}} & \dfrac{I_x}{|\nabla I|} & \dfrac{-\mu I_y}{\sqrt{\left(1+\mu^2|\nabla I|^2\right)}} \\ \dfrac{\mu|\nabla I|}{\sqrt{\left(1+\mu^2|\nabla I|^2\right)}} & 0 & \dfrac{1}{\sqrt{\left(1+\mu^2|\nabla I|^2\right)}} \end{pmatrix} \tag{3}$$

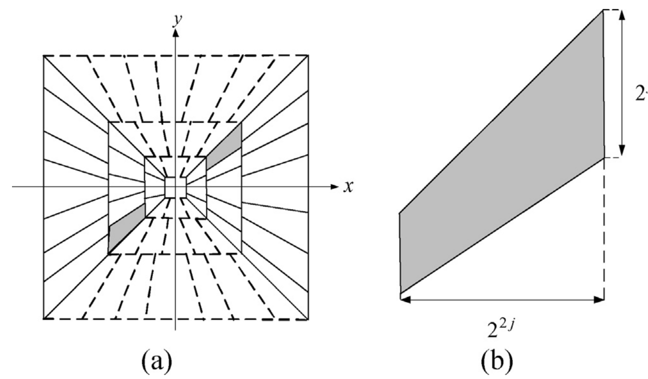

Fig. 2. The (a) frequency plane and (b) frequency support of the frequency partition of NSST [24].

By using the inverse matrix of $\mathbf{D}$, the image I can be decomposed into three components (J_1, J_2, J_3) and decomposition can be expressed as

$$\begin{pmatrix} J_1 \\ J_2 \\ J_3 \end{pmatrix} = \mathbf{D}^{-1} \begin{pmatrix} 0 \\ 0 \\ I \end{pmatrix}. \tag{4}$$

As Eq. (4) indicates that the component J_2 is always $\mathbf{0}$. The decomposed texture component J_1 mainly contains edges and textures, and the approximate component J_3 is the difference between the original image and its gradient's norm. Fig. 1 shows decomposition results of an MRI image, where the parameter μ is set to 0.05.

2.2. Nonsubsampled shearlet transform

As a multi-scale geometric analysis tool, the NSST has shift-invariance property and anisotropic direction selectivity. Compared to the discrete wavelet transform which is only good at capturing point-wise singularities, the NSST is a true 2-D sparse representation tool for its excellent performance in detecting linear singularities. The NSST uses nonsubsampled Laplacian pyramid filter to implement multi-scale partition and shearing filters to complete directional localization. Besides the shift-invariance and flexible directional selectivity, it has higher computational efficiency than NSCT. A schematic diagram of frequency partition of NSST is shown in Fig. 2, from which we can see that the support is a pair of trapezoids with size $2^{2j} \times 2^j$. More details about NSST can be found in literature [24].