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Multimodal medical image fusion using shift invariant shearlet transform

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***Abstract*—This In this paper we propose a new fusion algorithm for multi-modal medical images based on Shearlet transform. It is one of the state-of-the-art Multi-scale Geometric Analysis (MGA) tools. The quality of the fused outcome is determined by the amount of the information captured from the source images, a multi-modal medical image fusion method is developed in the Shift-invariant Shearlet transform (SIST) domain. Firstly, the non-sub sampled pyramid (NSP) is used to decompose an image into low and high-frequency components, and then direction filtering is employed to get the different sub bands and different direction shearlet coefficients. In this, 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 applying inverse SIST.**

***Index Terms*—Medical image, Image fusion, Shift-invariance, Shearlet transform**

1. Introduction:

Medical images such as MRI and PET are very useful in several health care applications such as medical diagnostics, patient health monitoring and drug evaluation. Besides it, various medical imaging modalities become available to support the radiologist representing the information of the different living organs. The magnetic resonance imaging (MRI), computed tomography (CT) and ultra-sound (US) images are named as structural medical images that provide the structural information of the organs. Others are functional medical images such as positron emission tomography (PET) and single photon emission computed tomography (SPECT) that imparts the functional information of anatomy with lower resolution images. The complete and accurate information is not provided by any one single modality of medical imaging. For example, the MR images reflect the soft tissue information and the CT images present the bony structure information. Therefore, there is a requirement to efficient algorithm to integrate both the features in a composite single image. Medical image fusion is a process of merging the complementary and useful redundant information from the multiple source images obtained from the different imaging modalities into a fused single output image that has special clinical meaning. The fused image is suitable for visual perception, analysis and other computer processing tasks.

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 [1] may lead to spectral distortion while the arithmetic combination 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 high pass sub bands, namely, vertical, horizontal and diagonal, capturing only limited directional information. 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 [2]. Yang and Guo proposed a contourlet transform-based medical image fusion method with an improved contrast scheme. Li and Wang introduced the non-subsampled contourlet transform (NSCT) to the fusion of MRI and SPECT with a variable-weight scheme 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 Sub-sampling scheme for the multi-scale partition while the NSCT, the improved version of contourlet transform, is of high time cost.

Shearlet [3] 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 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 sup-ports, unlike the construction of the directional filter banks for contourlet and NSCT [4]. 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.

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 medical image fusion scheme for the subbands of 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.2. 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. Combine high-pass and low-pass coefficients according to the fusion rules.
4. Reconstruct the intensity components of the fused image by the inverse SIST.
5. Reconstruct the fused color image by applying the inverse IHS transform.

2.2. The shift-invariant shearlet transform

In this paper, we will consider a special example of composite wavelets in L2 ($\mathbb{R}^2$) called shearlets. In dimension n = 2, the affine systems with composite dilation are defined as Follows:

$$A_{AS}(\Psi) = \{\Psi_{j,l,k}(x) = |\det A|^{j/2}\Psi(S^l A^j x - k); j, l\epsilon Z, k\epsilon Z^2\}$$

Where $\Psi\epsilon\ L^2(\mathbb{R}^2)$, A, S are both 2 x 2 invertible matrices, and det |S|=1.The elements of this system are called composite wavelet if $A_{AS}(\Psi)$ forms a tight frame for $L^2(\mathbb{R}^2)$ satisfied by:

$$\sum_{j,l,k} \left|\langle f, \Psi_{j,l,k}\rangle\right|^2 = \|f\|^2$$

The shearlet transform [5] is a function of three variables: the scale j, the shear l and the translation k. Let A denote the scaling matrix and S stand for the shear matrix. For each a> 0 and s ∈ $\mathbb{R}$,

$$A=\begin{pmatrix} a & 0 \\ 0 & \sqrt{a} \end{pmatrix} \qquad S=\begin{pmatrix} 1 & s \\ 0 & 1 \end{pmatrix}$$

The former matrix A, controls the scale of the shearlet by applying a fine dilation along the two axes which increasingly elongated the frequency support at fine scales. The latter matrix, which is not expensive, dominates the orientation of the shearlet. The tiling of the frequency and the size of frequency support are illustrated in 1.figfor a particular values of *a* and *s*

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 [6], 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 de-tails can be found in [7]. In frequency domain, each shearlet is supported on a pair of trapezoids, of approximate size 2^{2j} x 2^j, oriented along lines of slope $l2^{-j}$.

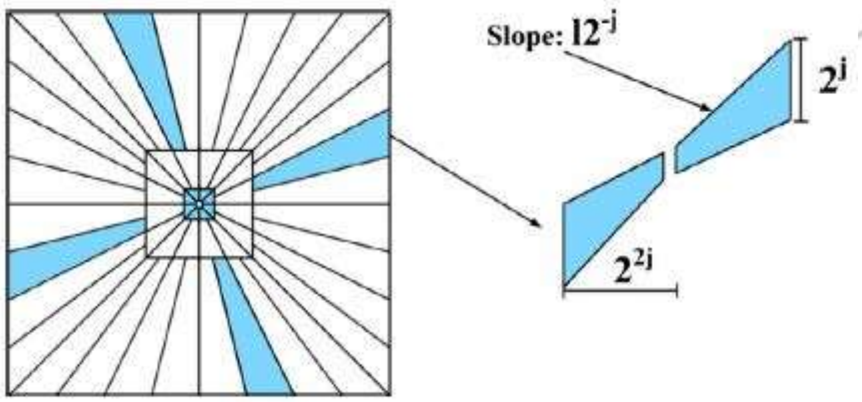


Fig.1: Frequency partition and the support of one shearlet

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 can-not 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} x 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 SIST decomposition process is illustrated in fig.3 the two basic steps are demarcated. In this work, decomposition level by NSP is j= 3 and the sub-band filter adopted is "*maxflat*" in a purpose to be aligned with the compared methods based on SSIT

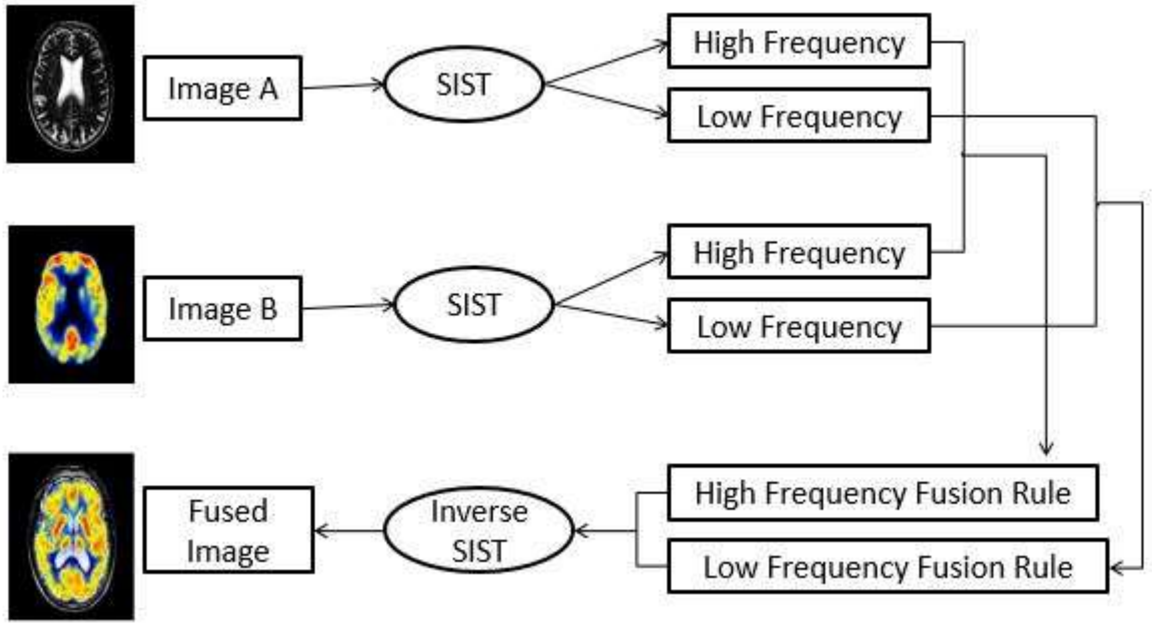


Fig.2: Block diagram of the proposed fusion method

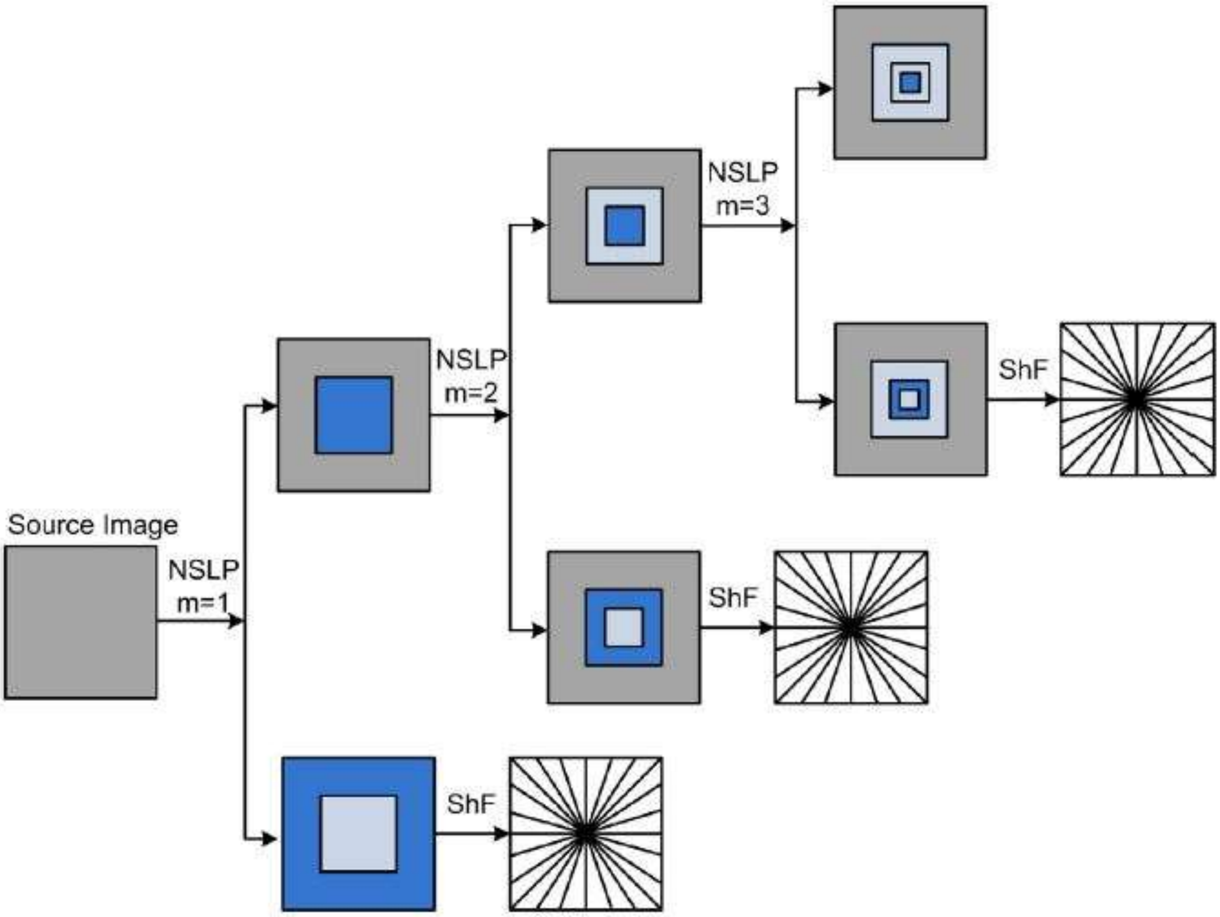


Fig3: Three level multiscale and multidirectional decomposition of SIST

3. The medical image fusion scheme for the sub-bands

3.1. Low frequency fusion rule: Low frequency coefficients of the fused image are conventionally given by the averaging method [7]. However, this technique is only able to contribute with low contrast result. To preserve more contrast, low frequency sub-bands of input images are chosen to be fused using the maximum of the absolute value.

$$LF_F(i,j) = \begin{cases} LF_A(i,j); & |LF_A(i,j)| \geq |LF_B(i,j)| \\ LF_B(i,j); & |LF_A(i,j)| < |LF_B(i,j)| \end{cases}$$

3.2. High frequency fusion rule: Generally, the activity-level measurement is used to express the salience of each high pass coefficient in the MSD-based image fusion methods.

Let $f\mu^{l,k}(i, j)$, $\sigma\mu^{l,k}(i, j)$ denote the probability density function and standard deviation located at (i , j) in the l^{th} sub-band at the k^{th} decomposition level , respectively, μ=A,B

1. Normalize the high pass sub-bands coefficients $C\mu^{l,k}(i,j)$

$$C_\mu^{l,k}(i,j) = \frac{f_\mu\left(C_\mu^{l,k}(i,j)\right) x\ C_\mu^{l,k}(i,j)}{\left|f_\mu\left(C_\mu^{l,k}(i,j)\right)\right|}$$

2. Define a smooth weight factor ω

$$\omega = \begin{cases} \dfrac{f_A\left(C_A^{l,k}(i,j)\right)}{f_B\left(C_B^{l,k}(i,j)\right)}\ ; & f_A\left(C_A^{l,k}(i,j)\right) \leq f_B\left(C_B^{l,k}(i,j)\right) \\ \dfrac{f_B\left(C_B^{l,k}(i,j)\right)}{f_A\left(C_A^{l,k}(i,j)\right)}\ ; & f_A\left(C_A^{l,k}(i,j)\right) > f_B\left(C_B^{l,k}(i,j)\right) \end{cases}$$

3. The fused coefficient located at (i, j) in the l^{th} sub band at the k^{th} decomposition level is computed by

$$C_F^{l,k}(i,j) = \begin{cases} \dfrac{C_A^{l,k}(i,j)\ x\ \sigma_A^{l,k}(i,j) + C_B^{l,k}(i,j)\ x\ \sigma_B^{l,k}(i,j)\ x\ \omega}{\sigma_A^{l,k}(i,j) + \sigma_B^{l,k}(i,j)\ x\ \omega} & \omega \leq 1 \\ \dfrac{C_B^{l,k}(i,j)\ x\ \sigma_B^{l,k}(i,j) + C_A^{l,k}(i,j)\ x\ \sigma_A^{l,k}(i,j)\ x\ \omega}{\sigma_B^{l,k}(i,j) + \sigma_A^{l,k}(i,j)\ x\ \omega} & \omega > 1 \end{cases}$$

4. Experimental Results and comparisons

The implementation is handled in Matlab R2013a on a PC with 2 GHz Core 3 Duo processor and with 4 GB of memory. The proposed fusion method is evaluated on MRI and PET images of the same person and the same part of the body. Furthermore, obtained results are compared quantitatively with contourlet transform based image fusion.

4.1 Evaluation criterion

Visual perception is most of time subjective when providing instinctive comparisons of the fused images due to eyesight level and mental state. As a consequence, several evaluation metrics should be applied in order to provide an objective assessment. These criterions are of two types, metrics based on single image and the others integrating both source and fused images.

Entropy (E): Entropy measures the amount of information in fused image. The larger is the entropy of the fused image denotes the presence of more abundant information. It is defined as follows:

$$H = \sum_i P_i \ \log \frac{1}{P_i}$$

Where, P_i indicates the probability of pixels gray level with the range [0, L-1].

Structural Similarity Index (SSIM): SSIM is a perceptual metric that express the structural similarity between reference and fused image and it values is in [-1 1].so that large value means similarity between source and fused images and the value 1 indicates the identical between two images. It is defined as

$$SSIM\ (I, F) = \frac{(2\mu_F\, \mu_I + C_1)(2\sigma_{FI} + C_2)}{(\mu_F^2 + \mu_I^2 + C_1)(\sigma_I^2 + \sigma_F^2 + C_2)}$$

Where F is the fused image, I is the input image, μ_F and μ_I are respectively the mean intensity of image F and I, σ_I^2 and σ_F^2 denotes the variance of image F and I, σ_{FI} calculates the covariance of F and I and finally, $C_1$and C_2 are constants.

Correlation parameter (CP): CP is a qualitative measure for edge preservation. If one is interested to preserve the edge information while at the same time suppress the noise this parameter is used. It is expressed as

$$CP = \frac{\sum_m \sum_n (A_{mn} - \bar{A})(B_{mn} - \bar{B})}{\sqrt{(\sum_m \sum_n (A_{mn} - \bar{A})^2)(\sum_m \sum_n (B_{mn} - \bar{B})^2)}}$$

Mutual information: MI indicates how much information that input images brings to fused image. Given two input images X**A**, XB and a fused image XF .It is defined as

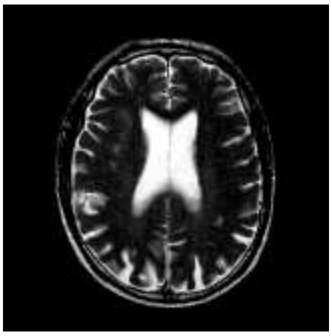
$$MI = I(X_A\ ;\ X_F) + I(X_B\ ;\ X_F)$$

Where,

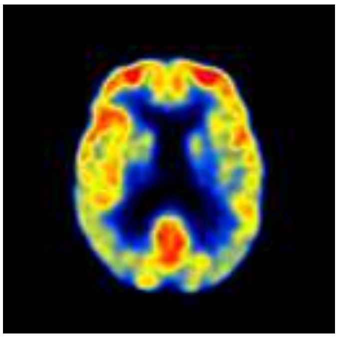
$$I(X_R\ ;\ X_F) = \sum_{u=1}^{L} \sum_{v=1}^{L} h_{R,F}\ (u,v) \log_2 \frac{h_{R,F}(u,v)}{h_R(u) h_F(v)}$$

R denotes a reference image and F is a fused image, where $h_{R,F}(u,v)$ is the joint gray level histogram of X_R and X_F. $h_R(u), h_F(v)$ are the normalized gray level histogram of X_R and X_F respectively.

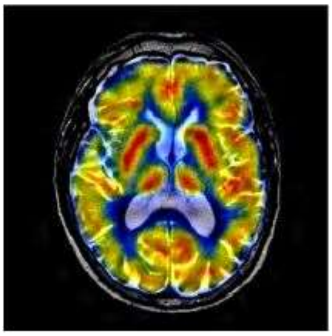
4.2. Simulation result:



(a) MRI



(b) SPECT



(c) Fused Image

Table: Qualitative comparison for the fusion of MRI-PET

parameter	entropy	SSIM	CP	MI
contourlet based image fusion	2.3372	4.3039	0.9123	0.6345
Implemented model(shearlet based)	2.8736	4.8989	0.9955	0.6873

5. Conclusion and future scope

In this paper, a new medical image fusion method is proposed in the SIST domain. The SIST can efficiently capture both of the structural and the functional information contents.

Although the proposed algorithm has shown basically good performance in our experiment, there is still much work to do. Multi-modal medical image fusion will benefit not only the development of multi-scale geo-metric analysis theory but the clinical applications.

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