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Fusion of Medical Image using STSVD

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ABSTRACT

The process of uniting medical images which are taken from different types of images to make them as one image is a Medical Image Fusion. This is performed to increase the image information content and also to reduce the randomness and redundancy which is used for clinical applicability. In this paper a new method called Shearlet Transform (ST) is applied on image by using the Singular Value Decomposition (SVD) to improve the information content of the images. Here two different images Positron Emission Tomography (PET) and Magnetic Resonance Imaging (MRI) are taken for fusing. Initially the ST is applied on the two input images, then for low frequency coefficients the SVD method is applied for fusing purpose and for high frequency coefficients different method is applied. Then fuse the low and high frequency coefficients. Then the Inverse Shearlet Transform (IST) is applied to rebuild the fused image. To carry out the experiments three benchmark images are used and are compared with the progressive techniques. The results show that the proposed method exceeds many progressive techniques.

Keywords: Magnetic Resonance Imaging, Positron Emission Tomography, Medical Image Fusion, Singular Value Decomposition, Shearlet Transform, Inverse Shearlet Transform.

1. INTRODUCTION

Fusing the image is a significant work in many image analysis processes where the images are taken from different generators. The fusion of images is done because to fuse the information into a single image from the information of different types of images [11]. These different types of images which are going to use as the source images are taken from different types of sensors and of varying timings whose physical feature are of different. Because of different features present in the images it is needed to fuse the images to get the exact information which is helpful for both the machine and human sensing. Nowadays there are many techniques has been developed to fuse the medical images of different types [13]. Fusion types are of two: Transform Domain (TD) and Spatial Domain (SD).

The basic method used for fusing the images is averaging the Principal Components Analysis (PCA) which comes under the SD method but it has a limitation that it suffers from reducing contrast and the sharpness [14]. But the pixel based method solves this contrast problem, in this method each pixel value in image is replaced by setting the threshold value. But this method measures inaccurately which reduces the performance of the fusion method. This is solved by the region based method. But in region based method the quality of the image is reduced as because of the artifacts come at edges.

Another method used for fusing is the Wavelet Transform (WT) which comes under TD approach [6], [9]. The WT is developed as a big multi-resolution system; this method permits changes in time extension but in shape. It has many features like sparse representation and multi-scale features of the function [2], [12], [17]. But it cannot handle more number of frequency coefficients so to overcome this many methods have attached to the WT such as ridgelet method [3], [4], curvelet method [3] and contourlet method.

Recently ST has been developed by many authors through affine system which is helpful in analysis and synthesis of an image. And another method is the SVD which retrieves the features from the image which is used by many authors for many purposes like in image registration, in face recognition, image fusion and in resolution problems [1], [5]. In this paper a new method is proposed to fuse the images by fusing SVD and ST. The experiments are conducted on three set of images and the proposed method is compared with the existing methods like Discrete Wavelet Transform (DWT), Non-Subsampled Contourlet Transform (NSCT) and Curvelet Transform (CVT). The results show that the proposed method exceeds the existing methods.

The paper is organized as follows: Section 2 gives brief description of ST and SVD, Section 3 presents the proposed method, the experimental results are illustrated in Section 4 and Section 5 gives the conclusion of the work

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2. SHEARLET TRANSFORMS

The ST is used to encode the features which are varying in direction in many problems. Its primary steps are localization in directions and decomposition is done in multiple scales [4]. There are two types of ST: continuous and discrete which are defined as follows with the fixed resolution level j.

2.1. Continuous Shearlet Transform

It is defined as the affine systems which are grouped with the complex dilations which are of the form:

$$Sh_{PQ}(\psi) = \left\{\psi_{a,b,c}(x) = |\det P|^{a/2}\psi\left(Q^b P^a X - c\right); a,b \in Z, c \in Z^2\right\} \quad (1)$$

Where a represents scale, b is orientation, c is cone for 2 dimensions, P and Q are 2×2 invertible matrices. For the function $fn \in L^2(\mathcal{R}^2)$, is as follows:

$$\sum_{a,b,c} \left|\langle fn, \psi_{a,b,c}\rangle\right|^2 = \left||fn|\right|^2 \quad (2)$$

For the function $fn \in L^2(\mathcal{R}^2)$, tight frame is formed by the $Sh_{PQ}(\psi)$. The matrix P^a is related with scale transform and the matrix Q^b related with the orientation like shear and rotation.

The continuous ST is of the form:

$$\psi_{a,b,c}(x) = a^{-3/4}\psi\left(B_b^{-1}A_a^{-1}(x-c)\right) \quad (3)$$

Where $A_a = \begin{pmatrix} a & 0 \\ 0 & \sqrt{a} \end{pmatrix}$, $B_b = \begin{pmatrix} 1 & b \\ 0 & 1 \end{pmatrix}$, $\psi \in L^2(\mathcal{R}^2)$, which should satisfy the following conditions:

1) $\hat{\psi}(\xi) = \hat{\psi}(\xi_1, \xi_2) = \hat{\psi}_1(\xi_1)\hat{\psi}_2(\xi_2/\xi_1)$;

2) $\hat{\psi}_1 \in C^\infty(\mathcal{R})$ supp $\psi_1 \subset [-2, -1/2] \cup [1/2, 2]$;

3) $\hat{\psi}_2 \in C^\infty(\mathcal{R})$ supp $\psi_2 \subset [-1, -1], \hat{\psi}_2 > 0$, But $\left||\psi_2|\right| = 1$

where ψ_1 is a continuous WT, in $\psi_{a,b,c}$ $a, b \in \mathcal{R}$, and $c \in \mathcal{R}^2$, for any function $fn \in L^2(\mathcal{R}^2)$, for different scales of wavelets. Usually, the values of a = 4 and b = 1.

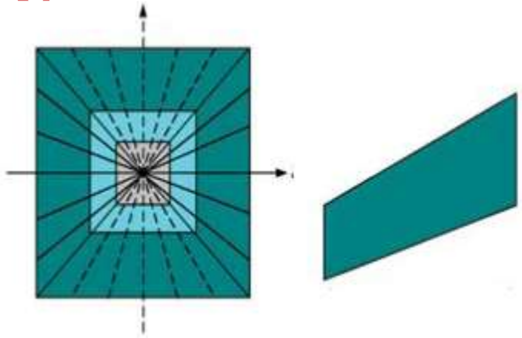


Fig 1: Frequency tiling by the Shearlet: (a) The frequency plane $\mathcal{R}^2$ is tiled, (b) The frequency size.

2.2. Discrete Shearlet Transform

There are two steps in discrete shearlet transform: they are directional localization and dividing in different scales. The decomposition of shearlet is shown in Figure 1.

Let for any scale j, the function $fn \in L(Z_n^2)$. Initially for decomposing an image the Laplacian pyramid is applied. Let consider the image as f_a^j, when Laplacian pyramid is applied on image then it is decomposed into low frequency f_l^j and high frequency f_h^j. If another division is needed then the Laplacian pyramid is applied on low frequency f_l^j. Then for reconstructing these frequencies into images the inverse fast Fourier Transform is applied.

2.3. Singular Value Decomposition

It is a method which is used to extract the features from the image. When SVD is applied on a matrix it is decomposed into three matrices, where two are singular matrices and one is diagonal matrix [5]. The singular value gives description of the images like scale invariance, feature stability etc. The SVD of the matrix I of size i x j is as follows:

$$I = U_I \Sigma_I V_I^T \tag{4}$$

where $\mathbf{U_I}$ is the matrix with dimension i x i whose columns are called as left singular vectors, $\mathbf{V_I^T}$ is the matrix with dimension j x j whose rows are called as right singular vectors, and $\mathbf{\Sigma_I}$ is the matrix with dimension i x j whose diagonal elements are called as singular values. The diagonal elements are arranged in decreasing order; the highest value is at the top left.

3. PROPOSED FUSION METHOD

A new fusion method is proposed in this paper named as STSVD to use the advantage of ST that is inter-scale sub-band. The proposed method is divided into two parts which are as low and the high frequency coefficients. The SVD is used by low frequency coefficients; after SVD is applied the max method is used to fuse the low frequencies. The high frequencies are fused by deriving the same and the different levels of high sub-bands. The proposed system structure is shown in Figure 1.

3.1. Computing the Low Frequency sub-band coefficients

The ST is applied on the original image which is divided into low and high frequencies. Then the SVD method is applied on the low frequency coefficients. But before the SVD method the covariance matrix is found for the low sub-bands of two input images as follows:

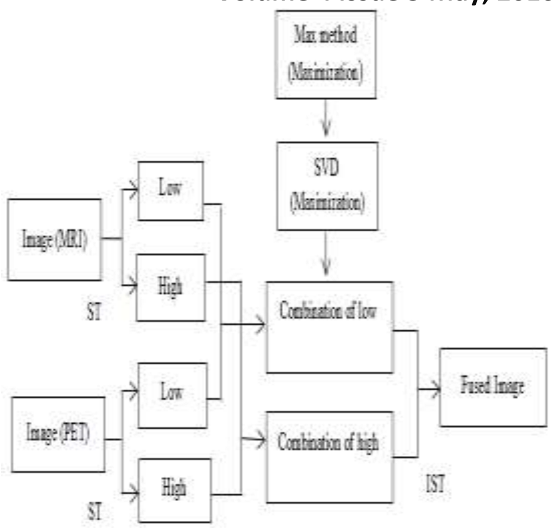


Fig 2: The structure of the proposed system.

Let L_p (m, n) denote the low sub-band located at (m, n), p = A, B. The covariance matrix C (m, n) for low frequency coefficients is C (m, n) = **Covariance** (L_A (m, n), L_B (m, n)). Then apply SVD on that matrix as SVD (C (m, n)) whose output is [U, D, V], then normalize the U and V matrices as follows:

1) If V (m, m) ≥ V (m+1, m+1), then m[th] column of matrices U, V are normalized.
2) Otherwise (m + 1)[th] column of matrices U, V are normalized.

For m = 1,

$$L_z = (U(:,m) + V(:,m)) / (\sum_{m=1}^{x} (U(:,m) + V(:,m)) \tag{5}$$

$$L_z = (U(:,m+1) + V(:,m+1)) / \sum_{m=1}^{x} (U(:,m+1) + V(:,m+1)) \tag{6}$$

where x is the last value of the row of the matrix. Then

$$a = \left[L_z(:,m) \Big/ \left((r * c) \sum L_A \right) \right] \tag{7}$$

$$b = \left[L_z(:,m+1) / ((r * c) \sum L_B) \right] \tag{8}$$

where r is the rows and c is the columns.

$$q = \sqrt{1 + a^2 + b^2} \tag{9}$$

Then the fused low-pass coefficients are obtained as follows:

$$L_F(m,n) = \begin{cases} L_A(m,n) * q \text{ if } L_A(m,n) \geq L_B(m,n) \\ L_B(m,n) * q \text{ if } L_B(m,n) > L_A(m,n) \end{cases} \quad (10)$$

3.2. Computing the High frequency sub-band coefficients

The edges and corners of the image is obtained from the high frequency coefficients of the ST. The fused coefficients are calculated as follows:

Let $H_p^{k,l}(m,n)$ be the high frequency coefficient at the location (m, n) in the kth sub-band at the lth level, p = A, B.

Let $S_{p,h}$ be the summation of the sub-bands $H_p^{k,l}$ and $H_p^{m,l}$ in the same level l call as horizontal sub-bands, which is calculated for each level as follows:

$$S_{p,h} = \sum_{k=1}^{K} (H_p^{k,l}, H_p^{k,l}) \quad (11)$$

Similarly, $S_{p,v}$ be the sum of $H_p^{k,l}$ and $H_r^{m,n}$ in different level call as vertical sub-band, which is calculated as:

$$S_{p,v} = \sum_{k,m=1}^{L} \sum_{l,n=1}^{K} (H_p^{k,l}, H_p^{m,n}) \quad (12)$$

Finally, compute the new coefficients $H_{p,new}^{k,l}$ as follows:

$$H_{p,new}^{k,l} = H_p^{k,l} \times \sqrt{1 + S_{p,h}^2 * S_{p,v}^2} \quad (13)$$

Then calculate the fused coefficients $H_F^{k,l}(m,n)$ as follows:

$$H_F(m,n) = \begin{cases} H_{A,new}^{k,l}(m,n), \text{if } H_{A,new}^{k,l} \geq H_{B,new}^{k,l} \\ H_{B,new}^{k,l}(m,n), \text{else } H_{B,new}^{k,l} > H_{A,new}^{k,l} \end{cases} \quad (14)$$

Proposed STSVD Algorithm

Input: A and B are the source images which needs to be registered.
Output: Image which is fused.

Step 1: Using ST decompose A and B.
Step 2: Compute low frequency coefficients using the equations 5 to 10.
Step 3: Compute high frequency coefficients using the equations 11 to 14.
Step 4: Then the selected high and low frequency coefficients are fused.
Step 5: Apply IST to reconstruct the image.
Step 6: Fused image is displayed.

4. EXPERIMENTAL RESULTS

The experiments are conducted on three set of images and the proposed method is compared with existing systems i.e. DWT [7], [10], [18], NSCT [8], [16] and CVT [15]. The experiment is executed in MATLAB R2013b. The image size selected is 256 x 256 to fusion process.

4.1. Data set 1

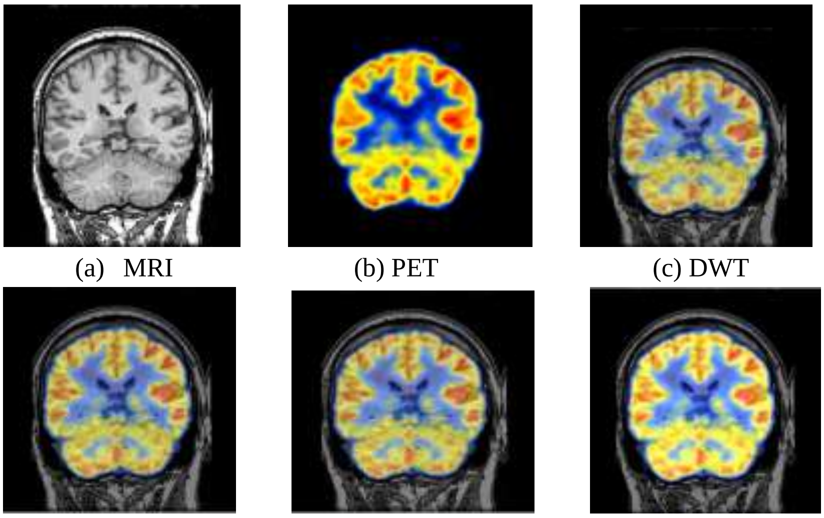
The MRI and PET images are shown in Figure 3(a) and Figure 3(b) respectively. Figure 3(f) is the output image of the proposed method. The existing methods DWT, NSCT and CVT outputs are shown in Figure 3(c), Figure 3(d) and Figure 3(e) respectively.

4.2. Data set 2

The MRI and PET images are shown in Figure 4(a) and Figure 4(b) respectively. Figure 4(f) is the output image of the proposed method. The existing methods DWT, NSCT and CVT outputs are shown in Figure 4(c), Figure 4(d) and Figure 4(e) respectively.

4.3. Data set 3

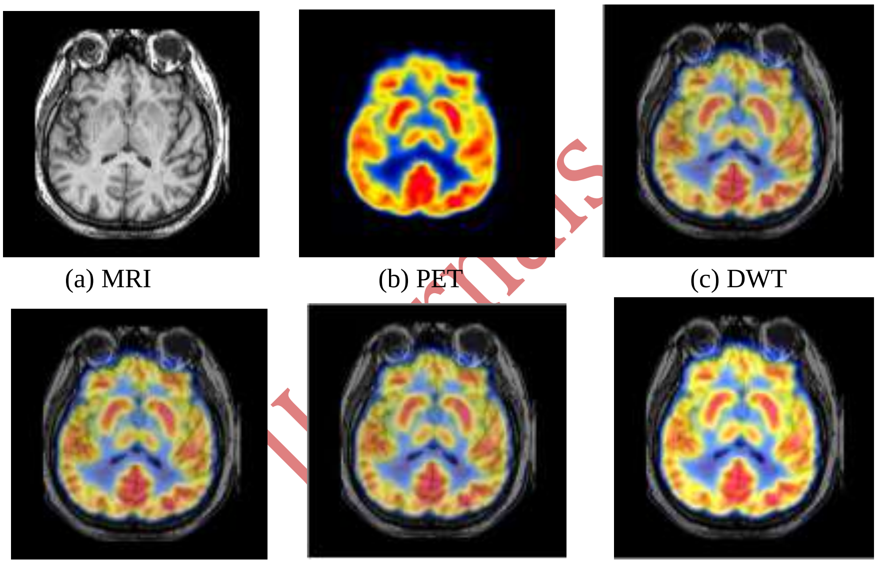
The MRI and PET images are shown in Figure 5(a) and Figure 5(b) respectively. Figure 5(f) is the output image of the proposed method. The existing methods DWT, NSCT and CVT outputs are shown in Figure 5(c), Figure 5(d) and Figure 5(e) respectively.



(a) MRI (b) PET (c) DWT

(d) NSCT (e) CVT (f) STSVD

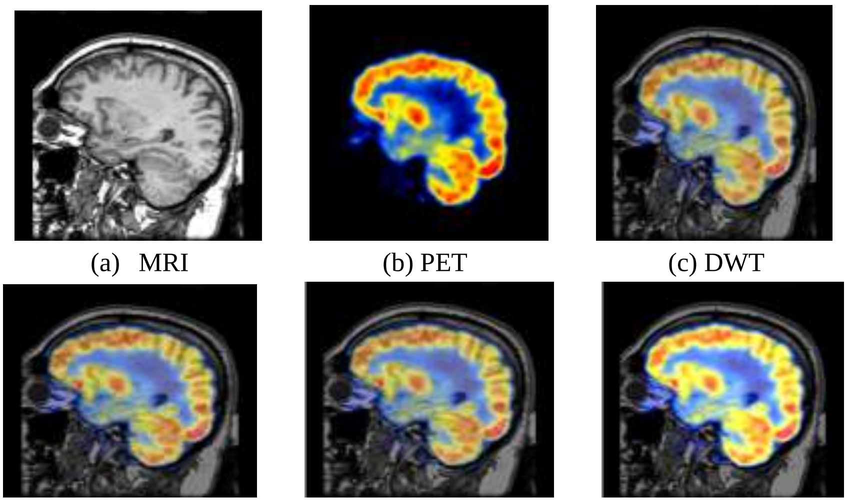
Fig 3: Results for Set I image.



(a) MRI (b) PET (c) DWT

(d) NSCT (e) CVT (f) STSVD

Fig4: Results for Set II image.



(a) MRI (b) PET (c) DWT

(d) NSCT (e) CVT (f) STSVD

Fig 5: Results for Set III image.

Three popular metrics are used for measuring the performance of proposed method; they are Mutual Information (MI), Cross Correlation (CC) and Edge Indexing (QI). The MI is used to measure the information which is reached to output image from the input image. The CC is used to measure the similarities between the input and the output images. The QI is used to measure the edge information transferred between the inputs to the output. The values of MI, CC and QI are noted in Table 1 for all the three set images and for all the existing and the proposed methods. In each row one value is bolded which is the highest value in that row.

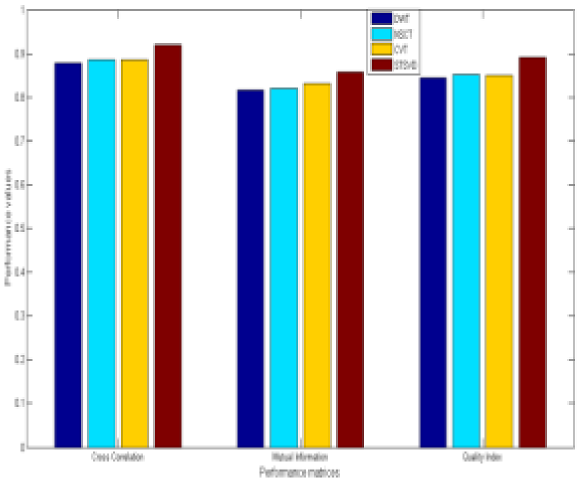
The results of estimated using MI and QI are shown in Table 1. Note that the highest value in each row of Table 1 are showed in bold. The graphs for all the three set images are shown in the Figures 6 (a), (b) and (c). From the Table 1 and Figure 6, it is clear that the proposed method exceeds the existing methods for all the performance matrices.

5. CONCLUSION

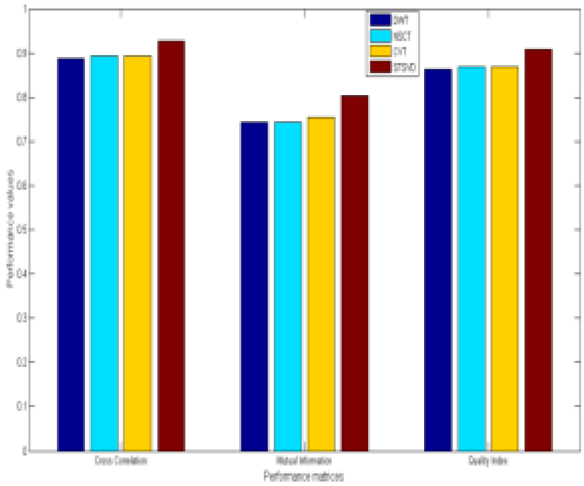
In this paper, initially the input image is divided into low and high frequency coefficients by using the ST. Then SVD is applied on low frequency coefficients to retrieve the effective features from the image. The main goal of STSVD is to maintain the significant information from the input images and also to keep the color components of the image as it is even the fusion is performed. This helps in finding the accuracy by bettering the smooth regions of the image. The experiments conducted on the three set of images show that the proposed method exceeds the existing methods.

Table 1. Comparative Results Analysis.

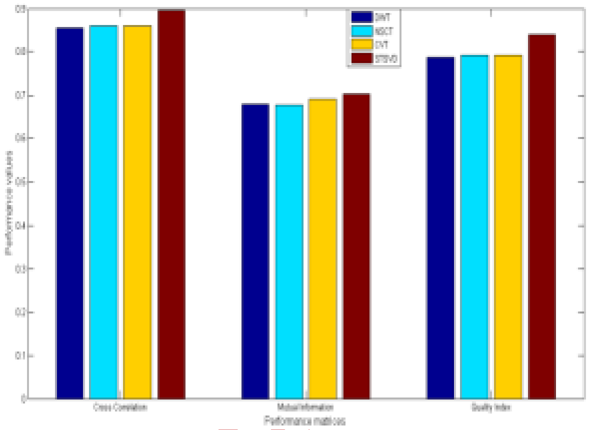
Method	Performance Metric	DWT	NSCT	CVT	STSVD
Image-1 (Set I)	CC	0.8787	0.8859	0.8852	**0.9193**
	MI	0.8161	0.8196	0.8321	**0.8576**
	QI	0.8450	0.8512	0.8505	**0.8925**
Image-2 (Set II)	CC	0.8883	0.8935	0.8930	**0.9266**
	MI	0.7432	0.7420	0.7549	**0.8032**
	QI	0.8643	0.8689	0.8688	**0.9084**
Image-3 (Set III)	CC	0.8545	0.8607	0.8600	**0.8955**
	MI	0.6794	0.6765	0.6913	**0.7025**
	QI	0.7877	0.7929	0.7921	**0.8397**



(a)



(b)



(c)

Fig 6: Comparative analysis for (a) Set-I, (b) Set-II and (c) Set-III.

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