MRI, CT and PET Image Fusion using 3-D Discrete Shearlet Transform and Global to Local Fusion Rule

Trupti B. Pawal¹, Dr. S. N. Patil²
Department of Electronics Engineering
PVPIT, Budhgaon, India

Abstract:
Two dimensional (2-D) fusion method suffers from the loss of the between slice information of the third dimension. In this paper a multimodal medical volumetric data fusion is developed using 3-D discrete shearlet transform to overcome the drawbacks of previous methods. On the other hand the popularly used average maximum fusion rule can capture only the local information but not any of the global information. Thus a global to local fusion rule is proposed. Firstly two images are decomposed by 3-D discrete shearlet transform and shearlet coefficients of high pass subbands are highly non-gaussian. Heavy tailed phenomenon present here can be modeled by generalized Gaussian density (GGD). The global information between two subbands can be described by the Kullback Leibler distance (KLD) of two GGDs. Finally the fused results can be selected according to the asymmetry of the KLD. The experimental results demonstrate better fusion results by using the proposed method.

Keywords: 3D discrete Shearlet transform (3DDST), generalized gaussian density (GGD), Kullback Leibler distance (KLD).

I. INTRODUCTION
Image fusion has become a common term used within medical diagnostics and treatment. The term is used when multiple patient images are registered and overlaid or merged to provide additional information. Fused images may be created from multiple images from the same modality or from multiple modalities [2]. The combination of the positron emission tomography (PET) and computed tomography (CT) imaging can be used to concurrently view the tumor activity. The fusion of CT and magnetic resonance imaging (MRI) is helpful for the neuronavigation in skull base tumor surgery and the combination of the PET and MRI is useful for the diagnosis of liver cancer. The popular fusion methods are based on multiresolution analysis, such as the discrete wavelet transform, stationary wavelet transform and contourlet transform. As these techniques have limitations the quality of fused medical images is sometimes unsatisfactory, which degrade the accuracy of human interpretation and further medical image analysis need to be improved[3]. Most of these methods are only implemented in two dimensional (2-D) space. The results are not of the same quality as those of the three-dimensional (3-D) methods due to the loss of between-slice information. For example, the fusion of MRI and PET slices must account for the information content not only within the given slice but also the cross and adjacent slices. The 2-D fusion framework, however, fails to do this. The traditional image fusion methods usually suffer from bad image representations. For example, the edges and the contours in the images cannot be well represented by the well-known 3-D wavelet transform. This is because the source images can be decomposed into only three high pass subbands in each level by the wavelet transform, losing the directional sensitivity. The popularly used average–maximum fusion rules are implemented in a local region of the current subband. Thus, the MSD coefficients only know the local relationship in a small region but not any of the global relationship between the two corresponding high-pass subbands. To deal with the earlier limitations, this paper presents a novel medical image fusion method.

II. METHODOLOGY
A) Block Diagram:

Figure 1. Framework of the proposed MSD-based fusion method.

In this framework, the source images are firstly decomposed into different levels and different directions in each level. Then, the low-pass subbands and high-pass subbands are combined under the fusion rule. Finally, the fused results are obtained by the inversion of the corresponding MSD tool. Thus, the fusion performance is highly determined by the MSD tools and the fusion rules.

B) 3-D Discrete shearlet transform
The 3D discrete shearlet transform can be depicted as the cascade of multi-scale decomposition, based on the Laplacian
pyramid filter, emulated by a phase of directional filtering. The major innovation of 3DDST is to be denoised the images by utilizing the direction filtering. The directional filtering design endeavours to reproduce the frequency decomposition provided by utilizing a process based on the pseudo-spherical Fourier transform. Hence, reduces the computation complexity of the 3DDST and improves the visual quality. The shearlet methodology function declares at different scales and locations and according to different orthogonal transformations controlled by shearing matrices. A shearlet system is acquired by suitably combining three systems of functions associated with the pyramidal regions in which the Fourier space is partitioned.

C) Non-gaussian Form

If the value of the noise have normal distribution then it is a Gaussian noise. If we plot the histograms of two high pass subbands of the finest level for the data of different modalities, it shows the heavy tailed phenomenon. We get the kurtosis of distribution larger than 3, which is the kurtosis of any univariate normal distribution. The kurtosis of each distribution shows the 3-D shearlet coefficients in each high-pass subband are highly non-Gaussian.

E) Heavy tailed phenomenon

In probability theory, heavy-tailed distributions are probability distributions whose tails are not exponentially bounded. That is they have heavier tails than the exponential distribution. As there is an existence of heavy tailed phenomenon in the histogram of high pass subbands therefore, how to model it is the key problem since it is obviously not shown as the typical Gaussian distribution. We here propose to use the GGD to describe the heavy-tailed phenomenon.

GGD (Generalized Gaussian distribution)

The GGD is defined as:

\[ p(x; \alpha, \beta) = \frac{\beta}{2\alpha \Gamma(1/\beta)} \exp\left(-\frac{|x|}{\alpha}\right)^{\beta} \]

where \( \Gamma(\cdot) \) is the Gamma function.

In this definition, the parameter \( \alpha \) determines the width of the probability density function (PDF) peak and the parameter \( \beta \) is related to the decreasing rate of the peak. Particularly, the Gaussian and the Laplacian PDF are special cases when \( \beta = 2 \) and \( \beta = 1 \), respectively. The heavy-tailed phenomenon in each high-pass subband can be well approximated by the GGD.

G) KLD (Kullback-Leibler distance)

The Kullback-Leibler distance is perhaps the most frequently used information-theoretic “distance” measure from a viewpoint of theory. If \( p_0 \) and \( p_1 \) are two probability densities, the Kullback-Leibler distance is defined to be

\[ D(p_1 \| p_0) = \int p_1(x) \log \frac{p_1(x)}{p_0(x)} \, dx. \]

The PDF of the shearlet coefficients in each high-pass subband can be completely defined via the GGD. Therefore, the global relationship of two subbands can be described by the relationship of two GGDs. According to information theory, two GGDs can be measured by the KLD, which is defined as

\[ \text{KLD}(p_1; \alpha_1, \beta_1, \alpha_2, \beta_2) = \log \left( \frac{\beta_2 \alpha_2 \Gamma(1/\beta_1)}{\beta_1 \alpha_1 \Gamma(1/\beta_2)} \right)^{1/\beta_1} \]

H) Fusion Rule

Image Fusion is a process of combining the relevant information from a set of images into a single image, where the resultant fused image will be more informative and complete than any of the input images. There are some important requirements for the image fusion process.

a. The fused image should preserve all relevant information from the input images.

b. The image fusion should not introduce artifacts which can lead to a wrong diagnosis.

The objective in image fusion is to reduce uncertainty and minimize redundancy in the output while maximizing relevant information particular to an application or task. The fusion rule determines how to transfer the features information of the two subbands into the fused subbands. The lowpass subbands are only the approximation of the source images. For convenience, we here use the typical averaging method to produce the fused low-pass subbands. The high-pass subbands usually contain the important features information, such as the edges and the corners, in different directions. Without loss of generality, let \( A, B \) denote the source images (or volumes) to be fused, respectively, and let \( F \) denote the fused results. Let \( L_{k}^{(i,j)}(i, j) \) denote the high-pass coefficient located at \((i, j)\) in the \(k\)th subband at the \(l\)th decomposition level \(\lambda = A, B\).

The procedure of calculating the fused coefficient \(L_{k}^{(i,j)}(i, j)\) by the maximum scheme is described as

\[ L_{k}^{(i,j)} = \begin{cases} L_{A}^{(i,j)} & \text{if } L_{A}^{(i,j)} > L_{B}^{(i,j)} \\ L_{B}^{(i,j)} & \text{otherwise} \end{cases} \]

where \(L_{A}^{(i,j)}\) and \(L_{B}^{(i,j)}\) are the local features that are computed in a window region centered by \((i, j)\), such as the local energy. Although such methods have been proved to be effective, they suffer from the loss of the global relationship between \(L_{A}^{(i,j)}\) and \(L_{B}^{(i,j)}\) because \(L_{A}\) and \(L_{B}\) are only locally calculated. To deal with this drawback, we propose a novel fusion rule, named global-to-local fusion rule. In this rule, the fused coefficient subband \(L_{k}^{(i,j)}\) contains two parts: the global part \(L_{k}^{A}\) and the local part \(L_{k}^{B}\). The details of the proposed fusion rule are described as follows.

1) Compute the KLD between \(L_{A}^{(i,j)}\) and \(L_{B}^{(i,j)}\)

\[ \text{KLD}_{A,B} = \text{KLD}(L_{A}^{(i,j)}, L_{B}^{(i,j)}) \]

\[ \text{KLD}_{H,A} = \text{KLD}(L_{H}^{(i,j)}, L_{A}^{(i,j)}) \]

Because the KLD is non symmetric and \(L_{A}^{(i,j)}\) and \(L_{B}^{(i,j)}\) come from different images, thus \(L_{A}^{(i,j)} \neq L_{B}^{(i,j)}\).

2) Do the global fusion to compute \(CL_{k}^{(i,j)}\)

\[ CL_{k}^{(i,j)} = \begin{cases} L_{A}^{(i,j)} & \text{if } \text{KLD}_{A} < \text{KLD}_{B} \\ L_{B}^{(i,j)} & \text{if } \text{KLD}_{A} > \text{KLD}_{B} \end{cases} \]

The reason being that the KLD measures the global difference between \(L_{A}^{(i,j)}\) and \(L_{B}^{(i,j)}\). \(\text{KLD}_{A} < \text{KLD}_{B}\) means...
contains more information of $\text{image}_A$ than the information that $\text{image}_B$ contains $\text{image}_B$. And vice versa since $\text{image}_A \neq \text{image}_B$.

3) Do the local fusion to compute $C_{L_{l,k}}$

$$C_{L_{l,k}}(i,j) = \begin{cases} C_A^{l,k}(i,j), & \text{if } R_A^{l,k}(i,j) \geq R_B^{l,k}(i,j) \\ C_B^{l,k}(i,j), & \text{if } R_A^{l,k}(i,j) < R_B^{l,k}(i,j) \end{cases}$$

where $\text{image}_A(i, j)$ represents the absolute value operation in our experiments.

4) The fused subband $C_{F_{l,k}}$ is calculated by

$$C_{F_{l,k}} = \frac{C_{L_{l,k}} + C_{L_{l,k}}}{2}.$$

5) The fused results can be obtained by applying the inversion of the shearlet transform on $C_{F_{l,k}}$

### III. EXPERIMENTAL RESULTS

![MRI and PET input](image1)

Figure 2. (a) and (b) shows 2-D MRI and PET input respectively. Fig. (c) shows fused result.

![CT and PET input](image2)

Figure 3. (d) and (e) shows 2-D CT and PET input respectively. Fig. (f) shows fused result.

![MRI and PET input](image3)

Figure 4. three views front, top and side of MRI input

![PET input](image4)

Figure 5. three views front, top and side of PET input

![MRI and PET input](image5)

Figure 6. fused output of three views front, top and side of MRI and PET input

![CT input](image6)

Figure 7. three views top, front and side of CT input

![PET input](image7)

Figure 8. three views top, front and side of PET input
IV. CONCLUSION

A medical image fusion method using 3-D discrete shearlet transform (3DDST), is more effective, efficient and feasible for the purpose of denoising MRI, CT and PET images and overcomes the drawbacks of traditional methods. The proposed global to local fusion rule represents better results than traditional average maximum fusion rule. This method can preserve the important information from source image.

V. REFERENCES


[4]. Richa Singh, Mayank Vatsa, Afzel Noore,” Multimodal medical image fusion using redundant discrete wavelet transform”.


