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3-D Discrete Shearlet Transform Based MRI, CT and PET Image Fusion: a Review

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ABSTRACT

Traditional two dimensional (2-D) fusion method suffers from the loss of the between slice information of the third dimension. The popularly used average- maximum fusion rule can capture only the local information but not any of the global information. In this paper, a 3D Discrete Shearlet Transform is proposed for 3D medical image fusion and to overcome the drawbacks of previous methods. A parallel study is done among wavelet, contourlet transform and 3D discrete shearlet transform. The experimental results demonstrate that better fusion results can be obtained by the proposed method.

Keywords:- Wavelet transform, contourlet transform, 3D discrete shearlet transform (3DDST)

I. INTRODUCTION

Image fusion has become a common term used within medical diagnostics and treatment. Here fusion occurs when multiple images of patient are registered and merged to provide additional information. Due to the great need in practical applications, different fusion technologies have been developed in recent years. The multimodal medical image fusion is a promising research in area of biomedical imaging system. Using medical images from multiple biomedical image sensors, increases robustness and enhances accuracy in medical research and clinical diagnosis. However medical image fusion can be broadly defined as the combination of visual information contained in any number of input medical images in a single fused image without introducing distortion and information loss [4]. For example, the combination of the positron emission tomography (PET) and computed tomography (CT) images can be used to concurrently view the tumor activity by visualizing the anatomical
and physiological characteristics in oncology. The
fusion of CT and magnetic resonance imaging (MRI) is helpful for the neuronevigation in skull base tumor surgery. The combination of PET and MRI is useful for the hepatic metastasis [1]. The different fusion methods can be generally classified into three levels: pixel level, feature level and decision level. Medical image fusion usually employs the techniques at the pixel level. According to whether multiscale decomposition (MSD) is applied, the pixel level fusion methods can be roughly classified into MSD based and non- MSD based methods.

As compared with source images, the fused images are more suitable for perception and comprehension. Frequently, the multiple sensor data are excess and complementary. The fusion of such data reduces the uncertainty and increases the exactness. Fourier transform is unsuccessful to analyze a non-stationary signal. The MRI and CT images can be processed by utilizing the wavelet transform. Wavelets in 2-D are good at eliminating noise for efficient analysis and isolating discontinuities at the edges, however won't get the smoothness along the contours and won't hold directionality and anisotropy. Contourlet transform mostly utilized for the reduction and denoising of images. But the contourlet transform has more computational complexity. A proper continuum theory is missing in this approach [2].

Most of the methods are implemented in two dimensional (2-D) space. Due to the loss of between slice information the results are not of the same quality as those of three dimensional (3-D) methods. The traditional 3D image fusion methods suffer from bad image representations. The edges and contours in the images cannot be well represented by these methods. The average maximum fusion rule can capture only the local information but not any of the global information [1].

II. LITERATURE SURVEY

Multimodal medical volumetric data fusion using 3-D discrete shearlet transform and global to local rule discussed by Lei Wang, Bin Li, Lianfang Tian. A 3D discrete shearlet transform is proposed to overcome the drawbacks of previous methods. A global to local fusion rule is proposed to get not only local but also global information [1].

G. Thamarai Selvi and R.K. Duraisamy discussed a novel 3D digital shearlet transform (3 D D S T) based image fusion technique using MR and CT Images for brain tumor detection. They have discussed a novel 3 D D S T for image sequence fusion and denoising. If MR and CT images contain noise, the noises may be transferred into the fusion image pixels [2].

Biswajit Biswas, Somoballi Ghoshal, Amlan Chakrabarti discussed a medical image fusion by combining SVD and shearlet transform where they first decomposed the source image at second level by shearlet transform and used SVD method on those individual decomposition levels to select higher singular value from the shearlet image to preserve the effective information [3].

Biswajit Biswas, Amlan Chakrabarti, and Kashi Nath Dey discussed in medical image fusion using regional statistics of shift-invariant shearlet domain a new scheme of medical image fusion based on shearlet transform. They have compared their technique with the other methods to prove that the shearlet transform has a good performance in regards to image fusion [4].

A medical image fusion scheme based on shearlet transform and human feature visibility discussed by Nemir Ahmed Al-Azzawi. The image fusion algorithm is an effective, efficient, and feasible. The visual and statistical comparisons demonstrate that the discussed method can preserve the important structure information. This quality makes the discussed method promising applications in medical diagnosis [5].

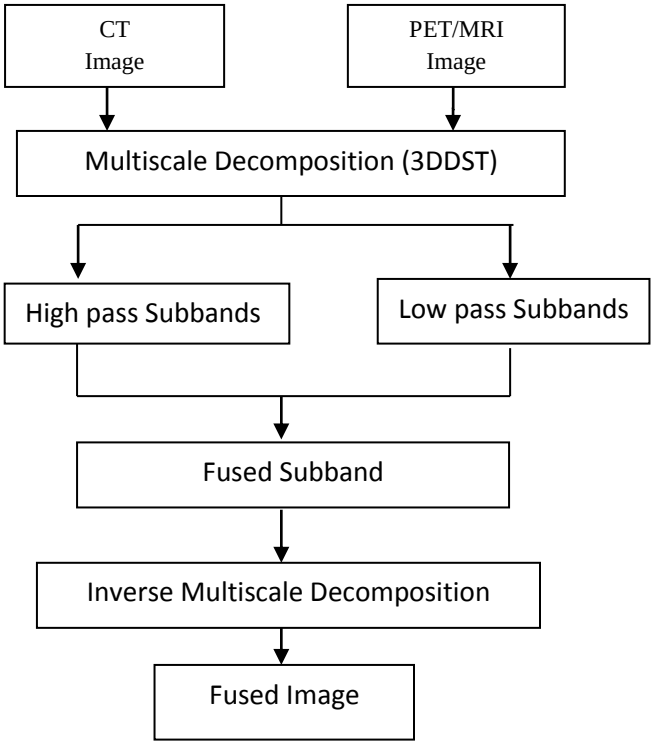
Shiji T.P, Rekha Lakshmanan, Vinu Thomas and Suma Mariam Jacob, Thara P discussed a despeckling of breast ultrasound images using level adaptive thresholding of discrete shearlet transform coefficients. The shearlet transform is very effective in removing speckle noise even with a simple thresholding scheme. The proposed method produces better quality ultrasound images for subsequent computer-assisted image analysis by medical experts [6].

III. METHODOLOGY

3-D Discrete Shearlet Transform (3DDST): Shearlets emerged in recent years among the most successful frameworks for the efficient representation of multidimensional data. Indeed, many other transforms were introduced to overcome the limitation of traditional multiscale transforms due to their poor ability of capturing edges and other anisotropic features. However, shearlet transform stands out since it has many advantages uniquely. It has a single or finite set of generating functions; it provides optimally sparse representations for multidimensional data, it allows a unified treatment of the continuum and digital realms. With these advantages, shearlet transform has been widely utilized in many image processing tasks such as denoising, edge detection , and enhancement.

In shearlet transform, shearlet function is parametreized by scaling, shear and translation parameter. With the help of these parameters discrete shearlet transform provides a multiresolution analysis useful for the development of fast algorithmic implemetations. Shearlets have properties such as they are well localized, in fact, they are compactly supported in the frequency domain and have fast decay in the spatial domain, Shearlets satisfy parabolic scaling, Shearlets exhibit highly directional sensitivity, they are spatially localized [6].

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 [1]. The major innovation of 3DDST is to be denoised the images by utilizing the direction filtering. The directional filtering design endeavors 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 [2].



In this framework, the source images are firstly decomposed into different levels and different directions in each level. That is they are decomposed into highpass subbands and lowpass subbands. Then,

the low-pass subbands and high-pass subbands are combined under the fusion rules to get the fused subband. 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 [1].

The contourlet transform, wavelet transform are two most of the popular MSD tools in image fusion. These methods, however, often produce undesirable side effects in the final fusion results, the reduced contrast, which may result in the wrong diagnosis. The reason is that wavelet-like tools decompose the source images into only three high-pass subbands, and the limited high-pass subbands result in that wavelets cannot well represent the sharp image features. As one of the state-of-the-art MSD tools, the shearlet transform has been reported to be the better MSD tool than the discrete wavelet transform in image fusion for it decomposes the source images into more than the wavelet-like vertical, horizontal and diagonal high-pass subbands. Therefore, more directional information can be captured. In addition, compared with the curvelet transform, contourlet transform, which have been successfully introduced into medical image fusion in the shearlet transform has better mathematical properties. For example, different from the contourlet transform, the number of directions for shearing the images is not restricted. Furthermore, compared with the inversion of the contourlet transform, the implementation of the inversion of the shearlet transform is more efficient computationally, more details can be found.

IV. EXPERIMENTAL RESULTS

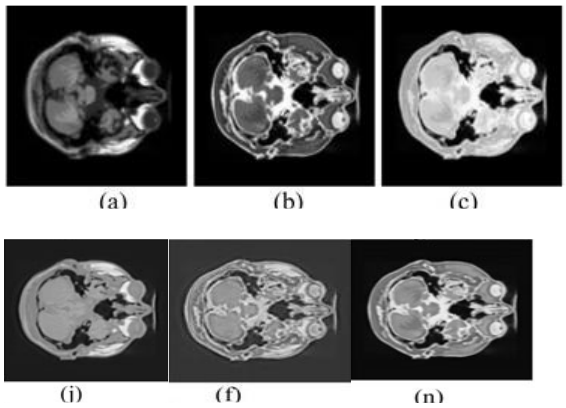


Fig.1 MRI brain images a) MRI T1 b) MRI T2 c) MRI Pd. Fig. j, f, n shows fusion results of T1 & T2, T1 & Pd, T2 & Pd respectively using 3D discrete shearlet transform.

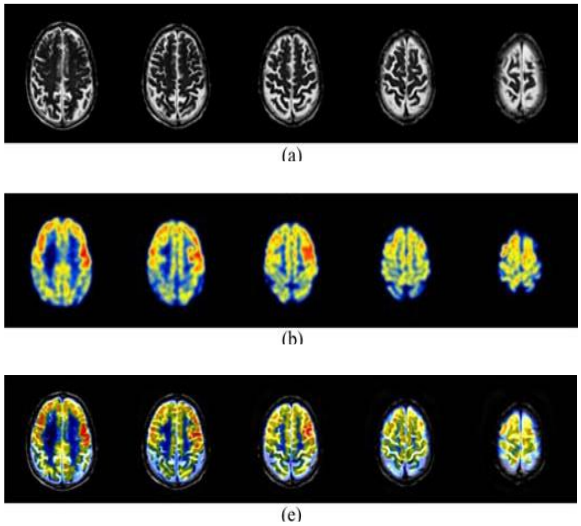


Fig 2: Fusion results of MRI and PET images using 3D discrete shearlet transform a) five slices of MRI b) five slices of PET c) Fusion result of MRI and PET

From fig. 1 and 2 we can observe a 3D discrete shearlet transform has better results than previous methods.

V. CONCLUSION

This paper proposes a novel 3D discrete shearlet transform for medical image fusion, denoising and to overcome the drawbacks of wavelet and contourlet transform. The proposed 3DDST can be more effective, efficient and feasible for the purpose of denoising MRI, CT and PET images. This method can preserve the important information from source image.

REFERENCES

[1] Lei Wang, Bin Li, Lianfang Tian " Multimodal Medical volumetric data fusion using 3-D discrete shearlet transform and global to local rule", IEEE Transactionson Biomedical Engineering. Vol. 61, NO, 1, January 2014.

[2] G. Thamarai Selvi and R.K. Duraisamy, " A novel 3-D digital shearlet transform based image fusion technique using MR and CT images for brain tumor detection" Middle-East Journal of Scientific Research 22 (2): 255-260, 2014, ISSN 1990-9233

[3] Biswajit Biswas, Somoballi Ghoshal, Amlan Chakrabarti,"Medical image fusion by combining SVD and shearlet transform", 2nd International Conference on Signal Processing and Integrated Networks (SPIN), 2015.

[4] Biswajit Biswas, Amlan Chakrabarti, and Kashi Nath Dey, "Medical image fusion using regional statistics of shift-invariant shearlet domain", IEEE Conference on Biomedical Engineering and Sciences, 8 - 10 December 2014.

[5] Nemir Ahmed Al-Azzawi," Medical image fusion based on shearlets and human feature visibility", International Journal of Computer Applications (975-8887) Volume 125 – No.12, September 2015.

[6] Shiji T.P, Rekha Lakshmanan, Vinu Thomas and Suma Mariam Jacob, Thara P " Despeckling of Breast Ultrasound Images Using Level Adaptive Thresholding of Discrete Shearlet Transform Coefficients" , The International Conference on Information Science 2014 (ICIS'14)