Published by :
http://www.ijert.org

International Journal of Engineering Research & Technology (IJERT)
ISSN: 2278-0181
Vol. 6 Issue 05, May - 2017

# An Application of Shearlet Transform for Medical Image Fusion

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***Abstract*— Recent advances in modern technology have developed the theory for multidimensional data to provide the higher directional sensitivity in medical imaging. Shearlets are a multidirectional and multiscale framework which allows to efficiently encoding anisotropic features in multivariate problem classes. In this paper, we have presented medical image fusion which is the technique of registering and combining complementary information from two or more multimodality images into a single image to improve the imaging quality and reduce randomness and redundancy. Shearlets are the most widely used today due to their optimal sparse approximation properties in medical image analysis improvement to efficiently handle such diverse types and huge amounts of data. Here the medical images can be particular organ focused by the different types of modalities which include X-ray, magnetic resonance imaging (MRI), computed tomography (CT), positron emission tomography (PET) and magnetic resonance angiography (MRA) images. Recently, the improvement of medical treatment procedure, medical images fusion being used further in the diagnosing diseases, tumor tissues analysis and treatment plain strategies.**

***Keywords*— Shearlet Transform, Medical Images, Image Fusion, Multimodality image, Image registration, CT/MRI images.***

## I. INTRODUCATION

In recent years, the medical images are increasingly being used within healthcare for diagnosis of various diseases, planning treatment, guiding treatment and monitoring disease progression. In many of medical research studies, multiple images are acquired from subjects at different times, and often with different imaging modalities. In the medical research studies, it is sometimes desirable to compare the various medical images obtained from patient cohorts rather than just single subjects imaged multiple times. Image fusion has become a common term used within medical diagnostics and treatment. The term Medical Fusion is used when multiple images of a patient are registered and overlaid or merged to provide additional information. Within medical research, especially neuroscience research, image fusion are used to investigate diseases, processes and understand normal development and ageing.

Medical image fusion is the technique to obtain a single image by combining complementary information or data from two or more medical images. Thus to reduce randomness and redundancy and to improve the image quality. The resulting image after fusion will be thus more informative than any of the input images. The medical images can be particular organ of human body or body part which is focused by the different types of modalities. General medical images include X-ray, magnetic resonance imaging (MRI), computed tomography (CT), magnetic resonance angiography (MRA), and positron emission tomography (PET) images. The general concept of medical image fusion is as shown in the below figure.

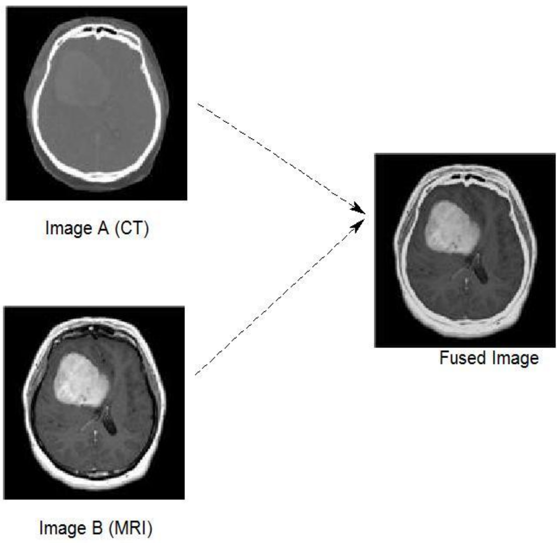


Fig -1: Medical image fusion

The medical images fusion are required in the diagnosing diseases, tumor tissues analysis and treatment plain strategies etc. For example, the resultant image after fusing MR and CT images is beneficial for the operational results in computer assisted navigated neurosurgery of temporal bone tumors, image fusion of MRI/PET useful in brain tumors, PET/CT useful in lung cancer, SPECT/CT useful in abdominal studies and ultrasound images/MRI fusion useful for vascular blood flow. In recent years, medical image fusion techniques have shown remarkable achievements in improving the accuracy of decisions based on medical images. This shows improvement in diagnosing and analysing diseases and its treatment. The various fusion methods are based on multiresolution analysis, such as the wavelet transform, stationary wavelet transform, discrete wavelet transform, and contourlet transform.

With advances in new technology, the theory for multidimensional data has been developed to provide higher directional sensitivity than wavelets which is using in medical image analysis improvement.

Medical image fusion techniques generally involve the pixel level fusion techniques which has the advantage that pixel fusion images use to contain the original information. Shearlets are a multiscale and multidirectional framework which allows to efficiently encoding anisotropic features in multivariate problem classes. The shearlet transform possess the ability to detect directionality and is thus unlike the traditional wavelet transform. Shearlet has one of the most significant property as the information that they provide optimally sparse approximations. Shearlet and Contourlet transform are mostly similar to each other. But the shearlet transform has an important advantage over the contourlet transform that there are no restrictions on the numbers of directions.

## II. FROM WAVELET TO SHEARLET TRANSFORM

It is well-known that wavelet transform do not perform well in dimensions larger than one. This situation is illustrated as, for example, by the problem of approximating a function of two variables containing a discontinuity along a curve. As the discontinuity is spatially distributed, thus it interacts extensively with the elements of the wavelet basis. And, as a consequence, the wavelet representation is not sparse, that is, many wavelet coefficients are needed to accurately represent the discontinuous function. This limitation has stimulated an active research both in the mathematical and the engineering literature.

Shearlets are very similar to curvelets in the sense that both perform a multiscale and multidirectional analysis. Still, there are a number of differences between shearlets and curvelets

- Shearlets transform are generated by applying a family of operators to a single function, while curvelet basis elements are not in the form of equation.
- Shearlets are normally associated to a fixed translation lattice, while curvelets are not. This is of importance for applications such as when combining information from multiple scales and orientations, for example, to model inter- or intrascale dependencies. While curvelet techniques need to take into account that the translation lattice is not fixed.
- In the construction of the shearlet tight frame, the number of orientations doubles at every scale, while in the construction of curvelet frame, this number doubles at every other scale.
- Shearlets are associated to a multiresolution analysis, while curvelets are not.

## III. SHEARLET TRANSFORM

Shearlets are a multidirectional and multiscale framework which allows to efficiently encode anisotropic features in multivariate problem classes. Originally, shearlets were introduced in 2006 for the analysis as well as sparse approximation of functions. Shearlets transform are a natural extension of wavelets. Shearlets accommodate the fact that multivariate functions are typically governed by anisotropic features such as edges in images. However, wavelets as isotropic objects are not capable of capturing such phenomena.

Shearlets are generated by parabolic scaling, shearing and translation applied to a few generating functions. In the construction of the shearlet tight frame, the number of orientations doubles at every scale. At the fine scales, shearlets are essentially supported within skinny and directional ridges following the parabolic scaling law, which reads as length² ≈ width. Shearlets arise from the affine group and allow a unified treatment of the continuum and digital situation leading to faithful implementations. They for a frame allowing stable expansions of arbitrary functions $f \in L^2(R^2)$.

The construction of continuous shearlet systems is based on parabolic scaling matrices $A_a = \begin{bmatrix} a & 0 \\ 0 & a^{\frac{1}{2}} \end{bmatrix}$ as a mean to change the resolution, on shear matrix $Ss = \begin{bmatrix} 1 & s \\ 0 & 1 \end{bmatrix}$.

Let $\psi 1 \in L^2(\mathbb{R})$ be a function satisfying the discrete Calderón condition, i.e., with

$$\sum_{j \epsilon Z} |\psi_1(2 - j\xi)|^2 = 1, \ \xi \epsilon \mathbb{R}$$

where$\psi_1$ denoted the Fourier transform of $\psi_1$.

With $\psi_1 \in C^\infty(\mathbb{R})$, supp$\psi_1 \subseteq [-1/2, -1/16] \cup [1/16, 1/2]$.

Furthermore, let $\psi_2 \epsilon L^2(\mathbb{R})$ be such that $\psi_2 \in C^\infty(\mathbb{R})$, supp $\psi_2 \subseteq [-1, 1]$ and

$$\sum_{k \epsilon \mathbb{Z}} \psi_2(\xi + k)^2 = 1, \ \xi \epsilon \mathbb{R}$$

One typically choose $\psi_2$ to be smooth function then

$$\psi(\xi) = \psi_1(\xi_1)2(\xi_2/\xi_1)$$

where $\xi = \xi_1, \ \xi_2 \in \mathbb{R}^2$

The SH($\psi$) is called a classical shearlet . This classical shearlet constitutes a Parseval frame for $L^2(\mathbb{R})$ consisting of band-limited functions. It can be shown that the corresponding discrete shearlet system ( ,$\psi$, $\psi$ ; $c$) , the frequency domain is divided into a low-frequency part and two conic regions

$$R = F^L = \{(\xi_1, \xi_2) \in \mathbb{R}^2 \mid |\xi_1|, |\xi_2| \leq 1\},$$

$$C^H = \{(\xi_1, \xi_2) \in \mathbb{R}^2 \mid \xi_2/\xi_1| > 1, |\xi_1| > 1\}$$

$$C^V = \{(\xi_1, \xi_2) \in \mathbb{R}^2 \mid \xi_1/\xi_2| > 1, |\xi_2| > 1\}$$

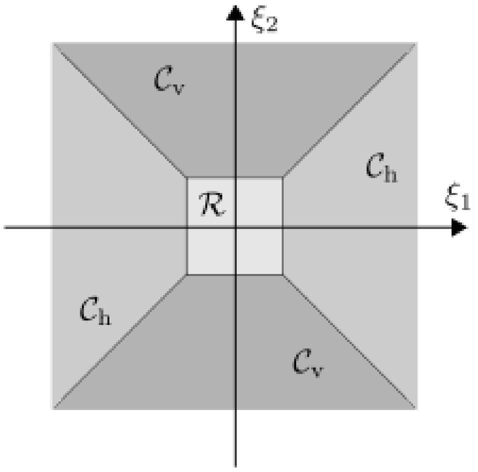


Fig -2: Decomposition of the frequency domain into cones.

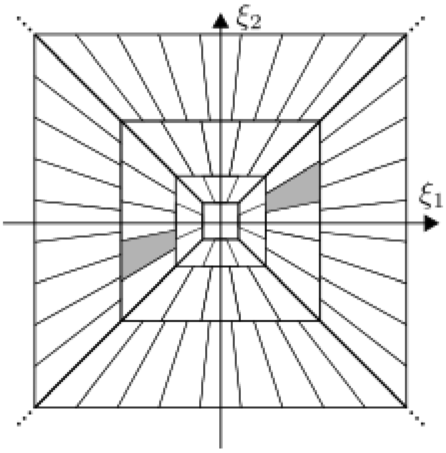


Fig -3: Frequency tiling of the cone-adapted shearlet system generated by the classical shearlet.

## IV. ALGORITHM OF PROPOSED TECHNIQUE

The medical image fusion carried out using the shearlet transform can be divided into four steps. These are image preprocessing, decomposition, fusion rules and reconstruction of the registered images

### A. *Medical Image Preprocessing*

The image preprocessing is carried out by suppressing the unwanted distortions or enhancing the image features which will require for further processing. Thereafter, applying image registration which is the process of aligning two or more images of the same scene. This process involves designating one image as the reference, also called the reference image or the fixed image. And applying geometric transformations to the other images called as movable image, so that all images align with the reference image. It is useful to overcome issues such as image rotation, scale, and skew that are common when overlaying images. Image registration process allows to compare common features in different images.

### B. *Decomposition*

In this, the registered image A (CT) and registered image B (MRI), respectively are decomposed with shearlet transform, and obtain the their corresponding shearlet coefficients. In this method, both horizontal and vertical cones are adopted. The decomposition of each image is composed by two parts as, decomposition of multi-direction ($K^{th}$ directions) and J-level multi-scale wavelet packets.

### C. *Fusion Rule*

To perform the selection of shearlet low frequency coefficients, the human feature visibility fusion scheme is used. The concept of human feature visibility is introduced as a method to evaluate the quality of an image. The human visual feature is useful to provide better details and conform to the human observer. Local mean intensity value of the image can be expressed as:

$$^{(AorB)}(m, n) = \sum_{k,l \in W} W.\mathrm{Coff}_{sh}^{L,(AorB)}(m, n)$$

Where, W is the template of size k × l and satisfies the normalization rule.

After that the normalized weight $D^{L,A}$ and $D^{L,B}$ are calculated.

The fused image has the same energy distribution as the original input images. The coefficients of low frequency components for fused image F is shown below:

$$\mathrm{Coff}_{sh}^{L,F} = \mathrm{Coff}_{sh}^{L,A}.\ D^{L,A} + \mathrm{Coff}_{sh}^{L,B}.\ D^{L,B}$$

Where, $\mathrm{Coff}_{sh}^{L,A}$ and $\mathrm{Coff}_{sh}^{L,B}$ represent low frequency coefficients of image A and B respectively.

Similarly, for the coefficients of the high-frequency, we calculate larger value of coefficients in shearlet domain. It means there is more high frequency information. The weights $D^{H,A}$ and $D^{H,B}$ are calculated. Thus the coefficients of high frequency components in shearlet domain for fused image F is,

$$\mathrm{Coff}_{sh}^{H,F} = \mathrm{Coff}_{sh}^{H,A}.\ D^{H,A} + \mathrm{Coff}_{sh}^{H,B}.\ D^{H,B}$$

### D. *Reconstruction*

The modified fused coefficients are reconstructed by inverse shearlet transform to obtain fused image.

### E. *Block Diagram*

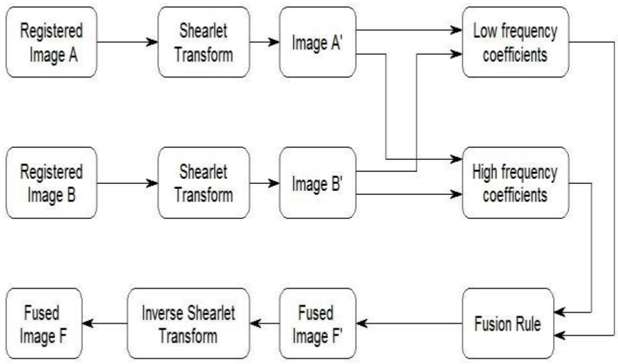


Fig -4: Block diagram for Image Fusion based on Shearlet Transform

International Journal of Engineering Research & Technology (IJERT)
ISSN: 2278-0181
Vol. 6 Issue 05, May - 2017

The fusion of two source images as Image A (CT) and Image B (MRI) is as shown below.


Fig -5: Image A – CT Scan image (Fixed Image)

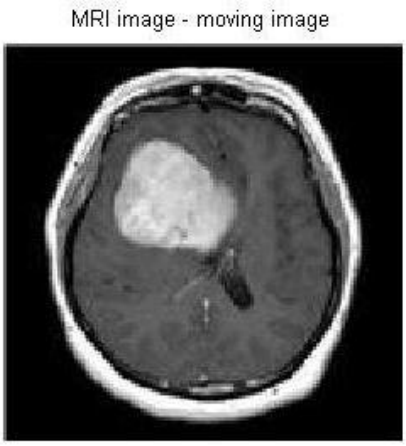


Fig -6: Image B – MRI image (Moving Image)

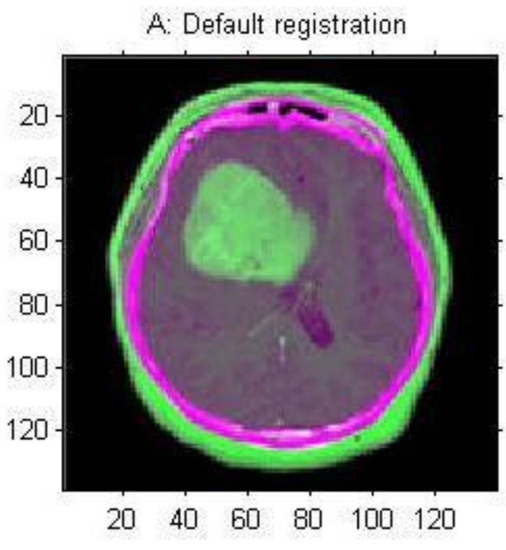


Fig -7: Registered MRI- CT image pair.

## V. APPLICATIONS

The image fusion using the shearlet transform has wide variety of applications in medical field. The fusing MR and CT images is a useful for the operational results in computer assisted navigated neurosurgery of temporal bone tumors. The fusion of PET/CT is useful in lung cancer, SPECT/CT in abdominal studies, MRI/PET in brain tumors and ultrasound images/MRI for vascular blood flow. In addition to this image fusion based on shearlet transform has applications in remote sensing and in astronomy.

The shearlet transform has wide applications like

- Edge and Ridge Detection and Analysis : The shearlet based representations are specifically designed to capture anisotropic structures makes them perfect candidates for the extraction and analysis of edges and ridges.
- Inpainting : Inpainting is the task of filling in missing parts of an image with the goal of restoring the original as close as possible. It is a widespread problem in image processing and there are different approaches to its solution. One promising approach is to promote sparsity in the resulting image by thresholding or minimizing the norm of its representation in a fitting dictionary. Due to their optimally sparse approximation of cartoon-like images shearlets are well-suited for the use in such dictionaries.
- Image Separation : Images often contain two classes of components that differ distinclty in their morphological structure such as point-like and curve-like features. In many applications it is necessary to seperate these features, e.g. in medical imaging when analyzing neurons, which are composed of splines and dendrites.
- Image Denoising : Denoising is a classical and highly relevant task in image processing. The approach from applied harmonic analysis utilizes the fact that the coefficients of noise in representation systems such as wavelet, curvelet or shearlet systems are quite evenly distributed whereas the features of the actual picture are preserved in few significant coefficients. By simply thresholding the coeffiecients of the signal in the transformed realm and then applying the inverse transform the signal can thus be denoised. However, this method tends to produce artifacts around sharp discontinuities. To overcome this problem, shearlets are used in more sophisticated algorithms that e.g. involve total variation or diffusion methods.
- Image Interpolating : Digital images are often viewed on devices with varying display sizes and therefore have to be rescaled for proper viewing. The process of creating a high-resolution image from a low-resolution image is referred to as image interpolation, upscaling or upsampling. A major challenge of this problem is to avoid blurring of sharp edges. An approach from applied harmonic analysis aims to overcome this by utilizing the sparse representation of such curve-like singularities in shearlet systems.
- Generalized Sampling : In some medical imaging applications, e.g. MRI, signals have to be recovered from a finite set of measurements. The method of taking those measurements, and thus the representation system used to

International Journal of Engineering Research & Technology (IJERT)
ISSN: 2278-0181
Vol. 6 Issue 05, May - 2017

model this process, is usually mostly fixed. However, the reconstruction system can be chosen freely. By using extra information about the signal to chose the system carfeully the reconstruction can be optimized. If the sizes of the sampling and reconstructing systems are allowed to vary independently of each other the setting is called Generalized Sampling.

- Inverse Scattering : When waves are transmitted through a medium and reach inhomogeneities they are scattered. The inverse scattering problem aims to determine characteristics of these inhomogeneities, e.g. density and shape, from information about the scattered waves. This is used in applications such as echolocation or ultrasound tomography.
- Digital Watermarking : Digital images can be reproduced and distributed very easily. This makes it hard to determine their authenticity or the ownership of their copyright. One method to solve this problem is to mark the image with a so called digital watermark before distribution. In order to preserve the value of the image, the watermark should not change the visual appearance of the image notably. However, there also must be a reverse algorithm to extract the watermark again. Additionally, the marking should be robust against modifications, also called attacks, of the watermarked image. Such attacks include lossy compression, cropping, adding noise or histogram equalization.

## VI. CONCLUSION

Shearlet transform is an effective, efficient, and feasible algorithm for the medical image fusion. Shearlet transform is multiscale and multidirectional framework. It has anisotropic features. Hence possess the ability to detect directionality which is advantage over the traditional wavelet transform. The image fusion based on the shearlet transform has wide variety of applications in medical imaging. Shearlets provide optimally sparse approximations. An important advantage of the shearlet transform over the contourlet transform is that there are no restrictions on the direction numbers.

The medical image fusion is needed for diagnosis of various diseases, planning treatment, guiding treatment and monitoring disease progression. Shearlet is useful to efficiently handle such diverse types and huge amounts of data. Hence image fusion scheme based on shearlet transform will have wide applications in future like for the capabilities of modern computers and high-precision measuring devices which need 2D, 3D, and even higher dimensional data sets of sizes..

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