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Multimodal Image Registration Using 3D Shearlet Transform and Global Rule

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Abstract*: Image Fusion is the process in which two or more images are combined into single composite image so that it could be more informative. Image Fusion is applied in variety of domains; particularly it has been used as an effective tool in medicine since it plays a major role in medical applications in order to improve diagnosis and for proper treatment planning. The main objective of this project is to extract relevant information by fusing medical images by various techniques and their comparative study together. Traditional Wavelets are not effective in dealing multidimensional signals containing discontinuities such as edges. To overcome this limitation, this project introduces a new discrete multiscale directional representation called the Discrete Shearlet Transform to provide a better image representation since the source images can be decomposed into more than three high pass sub-bands in each level. Therefore, more features information and directional sensitivity in different sub-bands can be captured. A global to local rule is also proposed in this project to combine the Shearlet coefficients in order to capture both the local and global information. The fused results are then compared with the Gabor Wavelet transformation and with the Spatial based technique to show that the proposed method increases the directional sensitivity and provided better image representation.*

1. INTRODUCTION

Image fusion is defined as the process of combining two or more different images into a single image retaining important features from each image with extended information content. In medical imaging, different medical imaging techniques may provide scans with complementary and occasionally conflicting information, such as magnetic resonance image (MRI), computed tomography (CT), positron emission tomography (PET), and single photon emission computed tomography (SPECT). Thus image fusion efficiently combines all these images and enhances information. Modalities like MRI provides details on soft tissue with more distortion and the brightness is related an amount of hydrogen atoms in tissue and bones cannot be seen whereas in CT, it provides the best information on denser tissue with less distortion and the brightness is related to tissue density therefore the brightness of bone is higher. This is considered to be complementary information with respect to the two images. There are two techniques in which we can perform image fusion: Spatial domain and Transform domain. In spatial approach, the process is directly applied to the individual pixels of the images and it also introduces spatial distortions in the fused image. The common technique in this domain is convolution mask. To overcome the distortions, we can go for Transform domain in which the fused image is obtained by the frequency spectrum of the image. The image fusion algorithms can be categorized into pixel, feature and symbolic level. In pixel level, the pixel values from both the images are blended to generate the fused image. In feature level, we can segment the images into regions and fuse those regions according to their various properties. In symbolic level, the combination of image descriptions (in the form of relational graphs) takes place.

This report is organized as follows: Section II presents brief description about the literature survey, Section III explains about the proposed algorithm, Section IV presents experimental results and discussion, section V gives the qualitative and quantitative analysis and finally, conclusion and future work is presented in Section VI

II. LITERATURE SURVEY

A. Cross scale fusion rule:

In this paper [6], the authors blended the pixel values in the monochrome source images to combine the information while preserving or enhancing image contrast. An efficient color fusion scheme is also proposed in this paper [6]. The belongingness or the membership of each fused coefficient to each source image is calculated and for each scale, an optimal set of coefficients are calculated and the coefficients are with similar characteristics are fused in a similar way thus the artifacts are avoided in the resultant image. Due to pixel level, this method introduces undesired side effects.

B. Performance comparison:

The authors evaluated the performance of all levels of multi-focused image fusion of using DWT, SWT, DTCWT, CVT and CT [5]. Stationary Wavelet provides details in 3 directions only for each scale. So they went for Dual Tree Complex Wavelet Transform. But this method and also DWT fails to detect the curves, edges and corner points of images well. So again they went for another method called Curvelet since it has a high accuracy of curve localization. And in this method also, reduced contrast and block artifacts plays a major limitation and results in wrong diagnosis.

C. Genetic algorithm:

Image fusion using Genetic algorithm is proposed in the reference [2] for the detection of brain tumor. Preprocessing is done on the input images to reduce or suppress noise and other small fluctuations in the image. Image Enhancement is also done in preprocessing to use to sharpen image features and in turn improves the quality of the input images. After the preprocessing operations, the input images are subjected to feature extraction. Feature Extraction is used to transform the image into a set of feature. Genetic algorithm is applied in extracted features of the image to fuse the images. The extracted features are considered as the population of chromosomes. The fitness function is calculated for all the chromosomes. Single; two point; uniform crossovers are used to generate offsprings. The offsprings are then mutated to generate the fused image but the resultant image produced is of reduced contrast and the information contained in this also less only.

III. PROPOSED ALGORITHM

A. Overview of the proposed framework:

In order to overcome all the limitations which are mentioned above, I would like to propose one method called 3-D Shearlet Transform and Global-to-Local rule based registration for increased directional sensitivity. The framework of this proposed image registration is shown in fig.1. Limitations exists in the above methods are:

a) The traditional methods are implemented in 2 Dimensional spaces. The results are not accurate when compared with the 3D results.
b) The source images can be decomposed into only three high pass sub bands in each level by the Wavelet transform losing the directional sensitivity.
c) MSD coefficients fails to capture the global relationship between the two corresponding high pass sub bands

The special characteristics of this proposed paper are:

a) The Shearlet transform provides better image representation since the source images can be decomposed into more than high-pass sub-bands in each level.
b) Global-to-local rule is proposed in this paper to capture both the local and global information. Kullback Leibler Distance is introduced to define the global relationship between any two high-pass sub-bands.

1) Multiscale decomposition (MSD)

For Multiscale decomposition, Shearlet Transform is used. Based on this; the pixel level fusion methods can be roughly classified into MSD-based or non-MSD-based methods. The MSD coefficients only know the local relationship in a small region but not any of the global relationship between any two corresponding high-pass sub-bands. In Shearlet Transform, the source images can be decomposed into the low-pass sub-bands and the high-pass sub-bands in different levels and it shears out into more slices giving out more information in each and every slice. The Shearlet transform consists of two steps: 3-D Laplacian pyramid filter for the multi-scale partition and for the pseudo-spherical Fourier transform for the directional localization.

2) Heavy Tailed phenomenon

The distributions of the high pass sub-bands are characterized by a very sharp peak at the zero amplitude and the extended tails in both sides of the peak (this is the so-called heavy-tailed phenomenon). It is found that the histograms of the high-pass sub-bands in different levels yields similar distributions. Thus, the marginal distributions of the 3-D high-pass coefficients are highly non-Gaussian. In this, GGD is used to describe the heavy-tailed phenomenon.

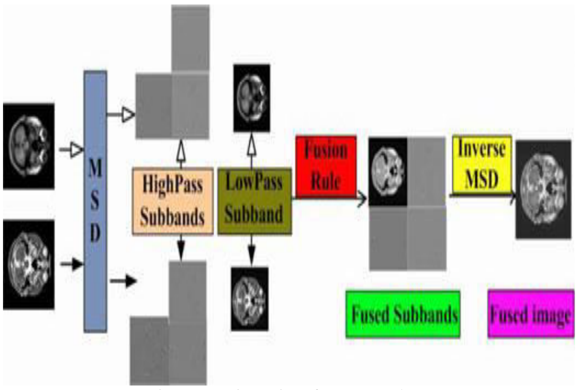

Fig.1. Registration frame work.

3) GGD for the Shearlet Coefficients

The heavy tailed phenomenon of the 3-D Shearlet coefficients are highly Non-Gaussian and it can be modelled by the Generalized Gaussian Density. The GGD is defined as

$$p(x;\alpha,\beta) = \frac{\beta}{2\alpha\Gamma\left(\frac{1}{\beta}\right)} e\left(-\left(\frac{|x|}{\alpha}\right)^{\beta}\right)$$

In this definition, the parameter α refers to the width of the probability density function of the Shearlet coefficient and the parameter β refers to the decreasing rate of the peak.The coefficient $C_{\lambda}^{l,k}(i,j)$refers to the high pass coefficient located at (i, j) in the l^{th} sub band at the k^{th}decomposition level. $\lambda =$ A andB are the source images.The PDF of Shearlet coefficient is called as GGD and in each sub band it can be completely defined via two parametersα *and* β.

4) KLD between two GGDs

Kullback Leibler Distance compares the entropy of two distributions over the same random variable. For two probability distributions f (x) and g(x) for a random variable X, the KLD or relative entropy is defined as

$$D(f \parallel g) = \sum_{x \in X} f(x) \log \frac{f(x)}{g(x)}$$

KLD is also known as relative entropy and it is a measure of how different two probabilities are. The properties of KLD are:

a) Non-Negative → $D(f \parallel g) \geq 0$
b) Divergence is zero if f=g → $D(f \parallel g) = 0$
c) Non symmetric $D(f \parallel g) \neq D(g \parallel f)$

Largest KLD between updated probability and current probability represents the largest gain. The distance measure between two GGDs is known as Kullback Leibler Distance.

5) Fusion rule

The fusion rule determines how to transfer the features information of the two sub bands into the fused sub bands. The low pass sub bands refers to approximation of the source images. Traditionally used method is averaging type to produce the fused results. The high-pass sub bands contains the important features information, such as the edges and the corners, in different directions. Let *A and B* denotes the source images to be fused, respectively, and let *F* denotes the fused image. Let $C_{\lambda}^{l,k}(i,j)$denotes the high-pass coefficient located at (*i, j*) in the l^{th} subband at the k^{th} decomposition level. The details of the proposed fusion rule are described as follows.

1) Compute the KLD between $C_A^{l,k}$ and $C_B^{l,k}$:

$$KLD_{AB}=\text{KLD}\left(C_A^{l,k},\ C_B^{l,k}\right)$$
$$KLD_{BA}=\text{KLD}(C_B^{l,k},\ C_A^{l,k})$$

2)Do the global fusion to compute: $C_G^{l,k}$

$$C_G^{l,k} = \begin{cases} C_A^{l,k} & KLD_{AB} < KLD_{BA} \\ C_B^{l,k} & KLD_{AB} > KLD_{BA} \end{cases}$$

3) Do the local fusion to compute $C_L^{l,k}$

$$C_L^{l,k} = \begin{cases} C_A^{l,k}(i,j), & R_A^{l,k}(i,j) > R_B^{l,k}(i,j) \\ C_B^{l,k}(i,j), & R_A^{l,k}(i,j) < R_B^{l,k}(i,j) \end{cases}$$

where $R_A^{l,k}(i,j)$ represents the locally computed energy.

4) Fused sub band: $C_F^{l,k}$

$$C_F^{l,k} = \frac{C_G^{l,k} + C_L^{l,k}}{2}$$

5) The fused results are obtained by applying the inversionof the Shearlet transform on $CF^{l,k}$

D. Image Registration Methodology:

Image re-sampling and transformation method is used. It is nothing but the alignment method to superimpose the structures contained in both the images. The aim is to gain larger a 2D view or a 3D representation of the scanned scene. For a given point p in a static image F, let f is the intensity of F and m the intensity in a moving image M. The estimated displacement (Velocity) u is required for point p to match the corresponding point in M and it is given in the equation (2). By this technique, we can go for maximizing the entropy value, minimize mean square to error, thus the similarity gets increased.

$$u = \frac{(m-f)\nabla f}{|\nabla f|^2 + \alpha^2(m-f)^2} + \frac{(m-f)\nabla m}{|\nabla m|^2 + \alpha^2(m-f)^2} \quad ..(3)$$

IV. EXPERIMENTAL RESULTS AND DISCUSSION

The input is chosen as MRI image and it is made into various slices. As the slice changes, the

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content and the structural properties gets changed and it is clearly shown in the fig.2 and fig.3

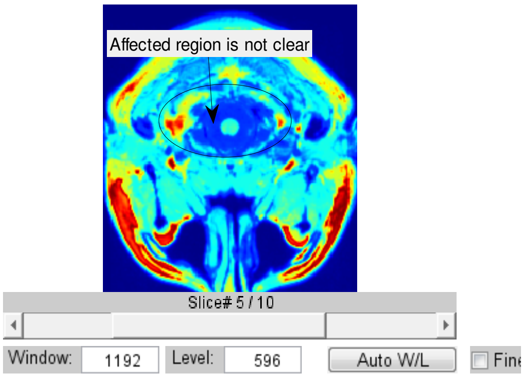

Fig.2. Input MRI image- showing slice 5

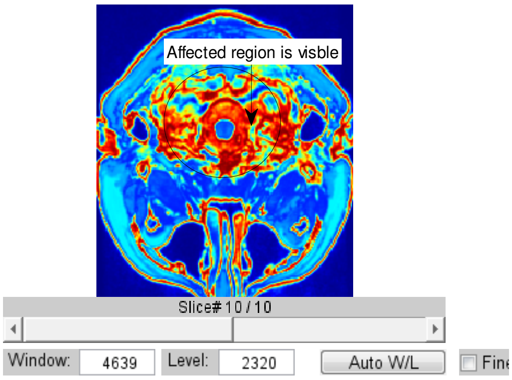

Fig.3. Input image MRI-showing slice 10

The Shearlet coefficients in each high pass sub-band are highly non-Gaussian and it is modelled by the Generalized Gaussian Density. GGD for the coefficients are shown in fig.4 and fig.5.

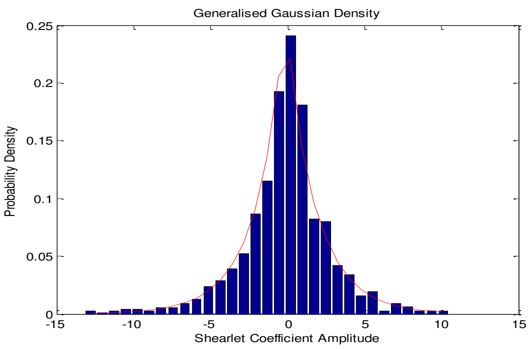

Fig.4. First high pass band- GGD

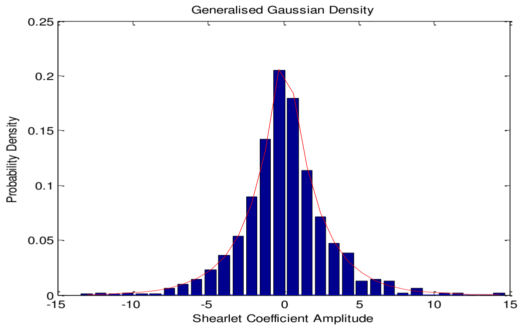

Fig.5. Second high pass band- GGD

The distance measure between any two GGDs is described by the KLD and it is shown in the fig.6 and fig.7. As the KLD gets increased, its content is enriched. That KLD has been selected for the next fusion and registration step.

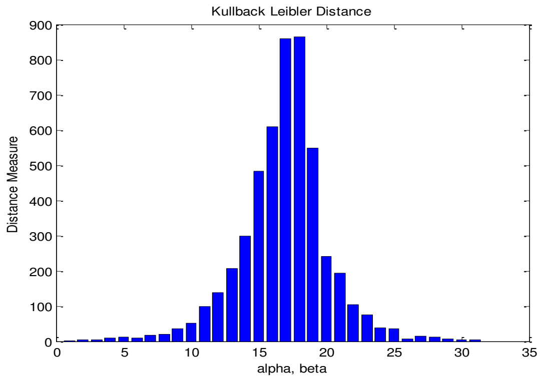

Fig.6. KLD between first high pass band and the input image

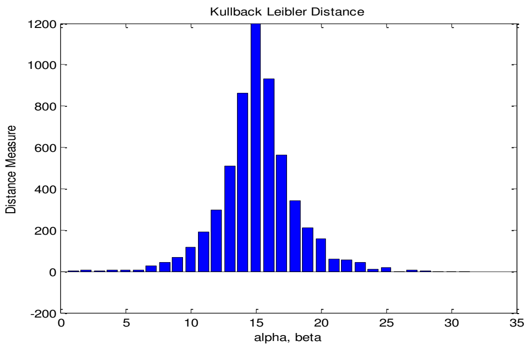

Fig.7. KLD between second high pass band and the input image

The chosen KLD has been fused under the Global to local rule. This rule combines both the global information and the local information and thus leads to great results when compared with the usually used averaging fusion method. Fuse image is shown in fig.8. To further increase the structural properties, the largest KLD has been registered under the rigid technique. The registered image is shown in fig.9.

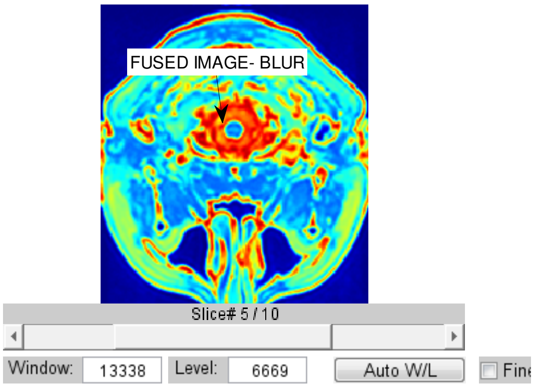

Fig.8. Fused image under global to local rule.

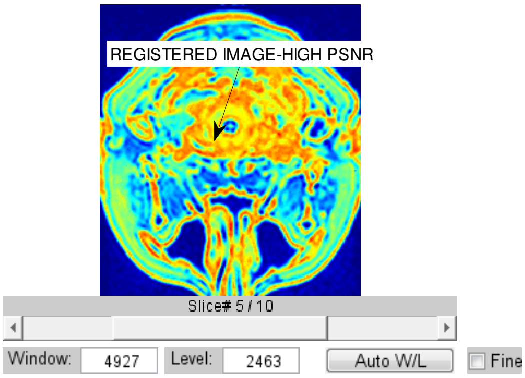

Fig.9. Registered image

V. QUALITATIVE AND QUANTITAIVE ANALYSIS

The quantitative and qualitative analysis such as entropy, Peak Signal to Noise Ratio(PSNR) and Mean Square Error (MSE) valuesare calculated for the fused and registered images.The input images were downloaded from the Whole Brain Atlas. First, the average value of the evaluation results for the MRI images without noise and then with 1%-7% has been considered and it is shown in Table 1-Table 5

Table 1 without Noise

Input Image	Method	Entropy	PSNR	MSE
MRI-1 and MRI-2	**Fusion**	**0.12**	**74.17**	**2.02**
	Registration	**0.14**	**92.85**	**0.68**
MRI-2 and MRI-3	Fusion	0.15	28.02	9.84
	Registration	0.31	49.93	3.94
MRI 3	Fusion	0.12	73.59	2.60
and MRI-1	Registration	0.17	78.97	1.81

From the Table 1, it is clear that the results of the Registration method based on the Shearlet Transform were much clearer when compared with the fusion scheme.

Table 2 with 1% Noise

Input Image	Method	Entropy	PSNR	MSE
MRI-1 and MRI-2	**Fusion**	**0.04**	**74.17**	**2.02**
	Registration	**0.05**	**92.84**	**0.68**
MRI-2 and MRI-3	Fusion	0.02	28.03	9.83
	Registration	0.05	49.96	3.94
MRI 3 and MRI-1	Fusion	0.04	47.08	9.48
	Registration	0.13	66.74	3.77

From the above Table 2, we can infer that the entropy value gets increased after registration process, thus the information contained is more when compared with the fusion technique.PSNR value also gets increased when we go for Shearlet transform based registration.

Table 3 with 3% Noise

Input Image	Method	Entropy	PSNR	MSE
MRI-1 and MRI-2	**Fusion**	**0.12**	**74.18**	**2.02**
	Registration	**0.02**	**92.85**	**0.69**
MRI-2 and MRI-3	Fusion	0.01	28.18	9.76
	Registration	0.02	49.96	3.94
MRI 3 and MRI-1	Fusion	0.02	28.18	2.61
	Registration	0.16	73.59	1.82

The mean square error is more in fusion approach when compared with the registration. Thus the registration based on Shearlet transform and global-to-local rule yields better reuslts and it is considered to be more effective. The results obtained by this proposed method could get the best values.

Table 4 with 5% Noise

Input Image	Method	Entropy	PSNR	MSE
MRI-1 and MRI-2	Fusion	0.01	74.21	2.02
	Registration	0.13	92.85	0.69
MRI-2 and MRI-3	Fusion	0.01	28.52	9.20
	Registration	0.12	50.04	3.96
MRI 3 and MRI-1	**Fusion**	**0.01**	**73.62**	**2.61**
	Registration	**0.18**	**80.84**	**0.93**

From the Table 4 and 5, it states that the proposed registration rule and Shearlet transform could capture more features information.

Table 5 with 7% Noise

Input Image	Method	Entropy	PSNR	MSE
MRI-1 and MRI-2	Fusion	**0.12**	74.25	2.02
	Registration	**0.02**	92.86	0.69
MRI-2 and MRI-3	Fusion	0.01	30.01	9.43
	Registration	0.02	50.15	3.95
MRI 3 and MRI-1	**Fusion**	**0.02**	**73.65**	**2.62**
	Registration	**0.16**	**80.67**	**0.18**

VI. CONCLUSION

In this paper, we have proposed image registration framework that combines information from different modalities based on the feature level information fusion. The 3D Shearlet transform provides better image representation since it decomposes the source images into more than 3 high pass sub-bands. This is about the fusion of 3dimensional images based on both the global and local rule that can capture not only the local information but also the global part.And also we compared the entropy values, PSNR and MSE of the fused image of Shearlet based image fusion and with that of the Registration method. Transform domain approach will have more information in the fused images. Traditional, 2D and 3D framework suffers from the loss of information about the fourth dimension. So, in future, we would like to propose 4D Shearlet transform and also extended global rule for fusing images which gives more enhancements in the fused and registered results.

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