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Multimodal Medical Volumetric Data Fusion Using 3d Discrete Shearlet Transform And Global To Local Rule

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***Abstract*-The fusion of three-dimensional (3-D) MRI slices must account for the information not only within the given slice but also the adjacent slices. In this paper, a fusion method is developed in 3-D shearlet space to overcome the drawback. On the other hand, the popularly used average–maximum fusion rule can capture only the local information but not any of the global information for it is implemented in a local window region. Thus, a global-to-local fusion rule is proposed. It show the 3-D shearlet coefficients of the high-pass sub bands are highly non-Gaussian. Then, we show this heavy-tailed phenomenon can be modeled by the generalized Gaussian density (GGD) and the global information between two sub bands can be described by the Kullback–Leibler distance (KLD) of two GGDs. Registration is necessary in order to be able to compare or integrate the data obtained from these different measurements provides more features and high accuracy than Fusion. Experiments on synthetic data and real data demonstrate that better fusion results can be obtained by the proposed method.**

Keywords-Three-dimensional (3-D) medical image fusion, 3-D Shearlet transform, generalized Gaussian density (GGD), Kullback–Leibler distance, Registration.

I. INTRODUCTION

MULTIMODAL medical image fusion technologies facilitate better applications of medical imaging for they provide an easy access for doctors to recognize the lesion structures and functional change by studying the data of anatomical and functional modalities. For example, the combination of the positron emission tomography (PET) and computed tomography (CT) imaging can be used to concurrently view the tumor activity by visualizing the anatomical and physiological characteristics in oncology[1]. 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 the hepatic metastasis Image fusion is a branch of data fusion where data appear in the form of arrays of numbers representing brightness, color, temperature, distance, and other scene properties. Such data can be two-dimensional (still images), three-dimensional (volumetric images or video sequences in the form of spatio-temporal volumes), or of higher dimensions. Use of the discrete wavelet transform (DWT) in image fusion was almost simultaneously proposed a steerable dyadic wavelet transform for image fusion[2].The need to combine visual and range data in robot navigation and to merge images captured at different locations and modalities for target localization and tracking in defense applications prompted further research in image fusion. Many other fusion techniques have been developed during the last decade. Today, image fusion algorithms are used as effective tools in medical, remote sensing, industrial, surveillance, and defense applications that require the use of multiple images of a scene. [3].

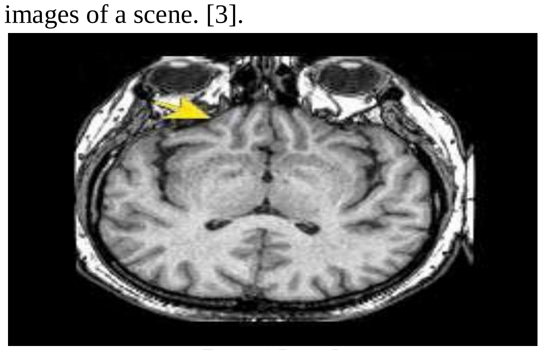

Figure 1.Brain Image

II.RELATED WORK

Evaluates the performance of all levels of multi focused image fusion of using Discrete Wavelet Transform, Stationary Wavelet Transform, Lifting Wavelet Transform, Multi Wavelet Transform, Dual Tree Discrete Wavelet Transform and Dual Tree Complex Wavelet transform in terms of various performance measures[4].

A curvelet based approach for the fusion of magnetic resonance (MR) and computed tomography (CT) images. The objective of the fusion of an MR image and a CT image of the same organ is to obtain a single image containing as much information as possible about that organ for diagnosis. Since medical images have several objects and curved shapes, it is expected that the curvelet transform would be better in their fusion. The simulation results show the superiority of the curvelet transform to the wavelet transform in the fusion of MR and CT images from both the visual quality and the peak signal to noise ratio (PSNR) points of view[5].

Focus on the fusion methods based on the discrete wavelet transform (DWT), the most popular tool for image processing. Due to the numerous multiscale transform, different fusion rules have been proposed for different purpose and applications. In this paper, experiment results of several applications and comparisons between different fusion schemes and rules are addressed[6].

III. ALGORITHM

The 3D shearlet transform helps in identifying the various morphological characteristics of the brain image. An efficient MSD tool is one of the foundations for the MSD based multimodal medical image fusion. shows an intuitive example of applying the shearlet transform and the wavelet transform on a circle. It is found that the circle can be decomposed into more high-pass subbands in each level than the only vertical, horizontal and diagonal subband of the wavelet transform. Therefore, more features information and directional sensitivity in different levels can be captured by the shearlet transform.

The 3-D shearlet transform mainly consists of two steps:
(a) 3-D Laplacian pyramid filter for the multiscale partition andwavelets;
(b) One 3-D shearlet.

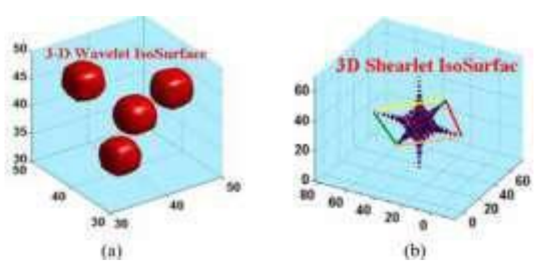

Figure 2. Shapes of the wavelet and the shearlet in 3-D space. (a) Four 3-D wavelets; (b) one 3-D shearlet Pseudo-spherical Fourier transform for the directional localization.In, the shapes of the 3-D wavelet and the 3-D shearlet are shown. Mapping into the 2-D plane, every four vertices of one wavelet form a square and it is an approximate trapezium for one shearlet. It is the different shapes that result in the shearlets are able to provide better image representations than the wavelets for the edges of the circle.

Marginal Statistics Of The 3-D Shearlet Coefficients:

The histograms of two high-pass subbands of the finest level, respectively for the MRI data of three modalities: T1, T2, and Pd. It shows that all the distributions 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). By testing 448 high-pass subbands from all the data, it is found that the histograms of the high-pass subbands in different levels all yield similar distributions.

IV. IMPLEMENTATION

The 3D discrete shearlet transform is implemented using MATLAB. Initially a input image of brain image is taken, which is an RGB image. To decompose the image into slices, the following steps are carried out.

Step 1:***Multiscale Decomposition***

In this framework, the source images are firstly decomposed into different levels and different directions in each level.multiscale decomposition (MSD) is applied, 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 the two corresponding high-pass subbands.. the MSD-based medical image methods outperform the other methods [7]–[9], for the source images can be decomposed into the low-pass subbands and the high-pass subbands in different levels to be more suitable to the mechanism of the human vision.

Step 2:***Heavy Tail Phenomenon***

The histograms of two high-pass subbands of the finest level, respectively for the MRI data of three modalities: T1, T2, and Pd. It shows that all the distributions 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 subbands in different levels all yield similar distributions. The marginal distributions of

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the 3-D high-pass subbands coefficients are highly non-Gaussian. Here propose to use the GGD to describe the heavy tailed phenomenon.The GGD is defined as

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

Where $\Gamma(\cdot)$ is the Gamma function

Step 3:***Measuring Global Relationship***

the PDF of the 3-D 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

$$\mathrm{KLD}(p(x;\theta_q)\|p(x;\theta_i))=\int p(x;\theta_q)\log\frac{p(x;\theta_q)}{p(x;\theta_i)}dx.$$

$$\mathrm{KLD}(p(.;\alpha_1,\beta_1)\|p(.;\alpha_2,\beta_2)) = \log\left(\frac{\beta_1\alpha_2\Gamma(1/\beta_2)}{\beta_2\alpha_1\Gamma(1/\beta_1)}\right)+\left(\frac{\alpha_1}{\alpha_2}\right)^{\beta_2}\frac{\Gamma(\beta_2+1/\beta_1)}{\Gamma(1/\beta_1)}-\frac{1}{\beta_1}.$$

According to the information theory, the KLD measures the difference between two probability distributions (supposing they are P and Q). Specifically, the KLD of Q from P is a measurement of the information lost when Q is used to approximate P. One of the mathematical properties for KLD is its asymmetry, i.e., it is nonsymmetric. The KLD of Q from P equals to the KLD of P from Q if and only if P = Q.

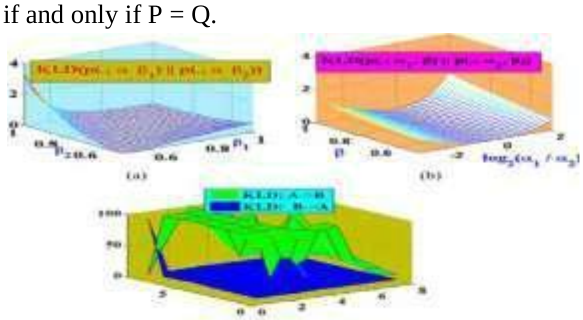

Figure 3 KLD between two GGD

Step 4**:*Image Registration*:**

Registering and summing multiple exposures of the same scene improve signal to noise ratio, allowing one to see things previously impossible to see. In this picture, the distant Alps are made visible, although they are tens of kilometers into the haze.Image registration is the process of transforming different sets of data into one coordinate system.

A. *Intensity-based vs feature-based*

Intensity-based methods compare intensity patterns in images via correlation metrics, while feature-based methods find correspondence between image features such as points, lines, and contours

B. *Transformation Models*

Image registration algorithms can also be classified according to the transformation models they use to relate the target image space to the reference image space. The first broad category of transformation models includes linear transformations, which include rotation, scaling, translation, and other affine transforms.

C. *Spatial Vs Frequency Domain Methods*

Spatial methods operate in the image domain, matching intensity patterns or features in images. Some of the feature matching algorithms are outgrowths of traditional techniques for performing manual image registration, in which an operator chooses corresponding control points (CP) in images. Frequency-domain methods find the transformation parameters for registration of the images while working in the transform domain.

D. ***Single- Vs Multi-Modality Methods***

Single-modality methods tend to register images in the same modality acquired by the same scanner/sensor type, while multi-modality registration methods tended to register images acquired by different scanner/sensor types.Multi-modality registration methods are often used in medical imaging as images of a subject are frequently obtained from different scanners.

E. *Similarity Measures For Image Registration*

Image similarities are broadly used in medical imaging. An image similarity measure quantifies the degree of similarity between intensity patterns in two imagesThe choice of an image similarity measure depends on the modality of the images to be registered.

Common examples of image similarity measures include cross-correlation, mutual information, sum of squared intensity differences, and ratio image uniformity.

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V. RESULT

Thus the disease on brain image from the input image is registration using 3D shearlet transform as shown in Fig(4)a(5),b and Fig(6)

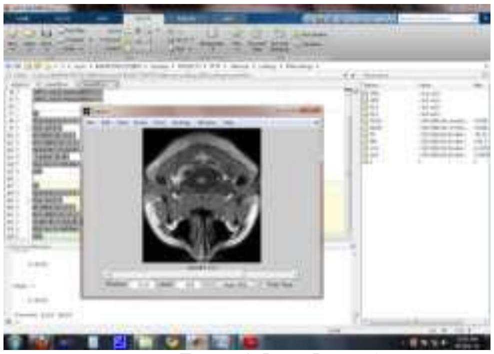

Figure 4. Input Image 1

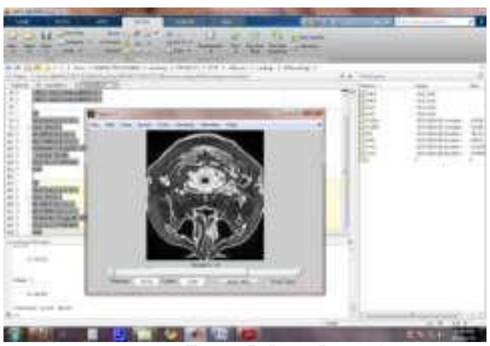

Figure 5. Input Image 2

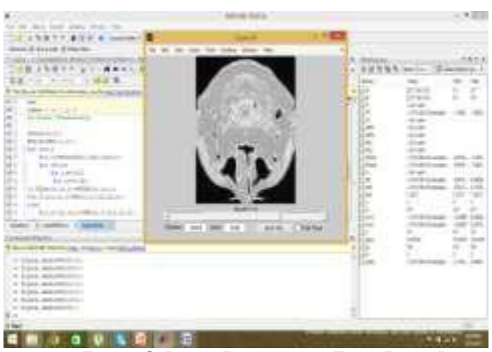

Figure 6. Image Registration From Brain Image

The average–maximum rule is used in the former three methods. Mutual information (MI) [27], Entropy [27], peak-signal-to-noise ratio (PSNR) [13], structural similarity index metric (SSIM) [28], and QAB/F [29] are selected as the quantitative metrics. can be identified compared with the standard parameter values in hand. The results are tabulated in table-1.

Table 1:Evaluation Results For The MRI images with

Noisy Data	Method	MI	Entropy	PSNR	SSIM
1%	LP	1.13	5.56	15.66	0.26
	Wavelet	1.22	5.16	16.34	0.27
	Shearlet	1.27	5.16	16.19	0.51
	3Ddiscreteshearlet	1.53	5.86	16.80	0.60
3%	LP	1.18	5.22	16.32	0.26
	Wavelet	1.20	5.18	17.00	0.27
	Shearlet	1.25	5.54	17.42	0.61
	3Ddiscreteshearlet	1.60	5.72	17.62	0.71
5%	LP	1.12	5.20	16.88	0.28
	Wavelet	1.16	5.21	17.30	0.24
	Shearlet	1.22	5.35	17.80	0.57
	3Ddiscreteshearlet	1.54	5.82	17.95	0.75
7%	LP	1.09	5.34	17.40	0.27
	Wavelet	1.12	5.26	17.69	0.23
	Shearlet	1.17	5.38	18.18	0.53
	3Ddiscreteshearlet	1.46	5.96	18.82	0.64
9%	LP	1.15	5.34	17.39	0.27
	Wavelet	1.13	5.25	18.69	0.22
	Shearlet	1.12	5.18	17.52	0.39
	3Ddiscreteshearlet	1.48	5.88	18.92	0.65

While considering a particular disease condition such as brain tumor, the success percentage can be calculated by performing the 3Ddiscrete shearlet transform on different images that are available in the database

VI. CONCLUSION

In this paper, The fusion of three-dimensional (3-D) MRI slices must account for the information not only with in the given slice but also the adjacent slices. Important features from the MRI image are to be isolated for the efficient detection of a particular disease. such average value for the evaluation for the MRI image with noise is done by 3D shearlet transform. this transform are used for more feature information and directional sensitivity in different level can be captured in a image. The proposed system finds image registration in an scan image.

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