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FEATURE BASED INFORMATION FUSION BY GABOR WAVELET TRANSFORM

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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 and it is also more suitable for human visual perception as well as PC processing. Image Fusion is one of the major research fields in image Processing. This technique can be applied in variety of domains: Navigation, Remote Sensing, Object detection, Object recognition, etc. And 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 image fusion is to reduce redundancy and to extract relevant information. The purpose of this paper is to introduce Gabor Wavelet transform along with ICA technique which enables us to fuse images based on their mutual information. The fused results are registered and their entropy values are calculated based on transform domain and spatial domain approaches.

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 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 but 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 based algorithms, it segments the images into regions and fuses 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, and finally, conclusion and future work is Presented in Section V

II. LITERATURE SURVEY

A. Performance comparison: The authors evaluated the performance of all levels of multifocused 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.

B. 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.

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

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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 Featured based information fusion using Gabor wavelet transform. The Gabor filter finds its application in feature extraction, face recognition, object detection etc. The given input image is subjected to scale and orientation so that all the features are concentrated for the detailed analysis. The framework of this propped image fusion is shown in figure 1. Now am going to choose scale as 4 and orientation as 3, so totally I will be getting 12 Gabor features which are subjected into Independent Component Analysis for concentrating on particular tissue. By principal component analysis, the whitening matrix plays a major role. By this technique, the redundant data can be reduced by de correlating the input vectors. Then we have to calculate mutual information for all the independent components and then have to choose two components with the highest mutual information. The chosen components are subjected into fusion for much more detailed analysis and for optimal features. The fused image must be registered into the source image and the matching problem can be considered as a cost function based on the dissimilarity metric and that cost function must be low as possible and by optimizing the deformation field of the registration is obtained.

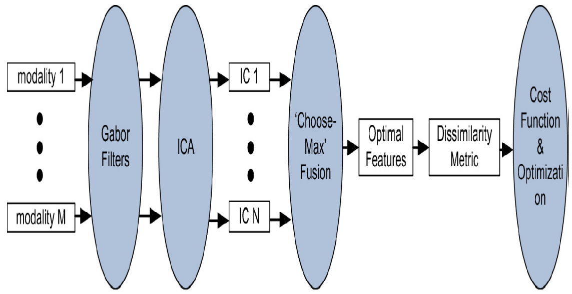

Figure1. Fusion scheme and its registration frame work.

1) Feature Extraction and the Measure of Tissue Characterization Ability: For the multiscale decomposition method, we use Gabor wavelets, as Gabor wavelet transformation has been shown to be optimal in the sense of minimizing the joint uncertainty in space and frequency, and has been widely used for feature extraction and hence, more appropriate for the purpose of matching/registration. Thus Gabor wavelets are a better choice for both feature extraction/matching and tissue characterization ability measurement, for our proposed information fusion-based multichannel image registration. A 2-D Gabor function is an oriented complex sinusoidal (1) grating modulated by a 2-D Gaussian function and it is given in equation (2). The parameters of the Gabor function are specified by the frequency, the orientation of the sinusoid (or represented by the center frequency), and the scale of the Gaussian function. The input image is generally filtered by a family of Gabor filters tuned to several resolutions and orientations.

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$$S(x, y) = [-j2\pi(\mu_0 x + \upsilon_0 y)] \ldots. (1)$$

$$g(x, y) = \frac{1}{\sqrt{2\pi}\sigma_x\sigma_y} \exp\left[-\frac{1}{2}\left(\frac{x^2}{\sigma_x^2} + \frac{y^2}{\sigma_y^2}\right)\right] \ldots (2)$$

2) Tissue-Pertinent Information Extraction Through Independent Component Analysis: For a particular tissue type, there is one or a combination of several modalities that gives relatively more information. For other modalities, most part of the information could be less reliable and hence redundant, although underlying tissue may still contain some useful information. Therefore, if the "Choose-Max" criteria are directly applied between different modalities, the residual useful information (usually a small amount) from the other "non-max" modality will be discarded. In some cases, the cost of this simple "Choose-Max" scheme would be high, if information about certain tissue type is quite evenly distributed among different modalities. To solve this problem and facilitate the subsequent information fusion, for each tissue type, it would be very beneficial to merge all the pertinent information of this tissue type from all modalities. By applying ICA to the Gabor features extracted from different modalities, each of the resultant independent components (ICs) combines all the information regarding a particular tissue type in the feature space. First step in ICA is to whiten the data that is we have to remove any co relations in the data. ICA decreases the amount of redundant data by de correlating the input vectors.

3) Information Fusion: Different independent components (IC) are needed to acquire the best characterization, because the underlying tissue type could be different for different voxels (pixels in 2D, voxels in 3D). Therefore, "Choose-Max" scheme is adopted to select the optimal IC according to the underlying tissue type and the complementary information is kept and enhanced while redundancy is reduced, via information fusion.

4) Dis-Similarity Metric: For each voxel, based on the optimal IC obtained through ICA and "Choose-Max" scheme, a dissimilarity metric is defined to find the correspondence between two multichannel images.

5) Cost Function and Optimization: Finally, based on the dissimilarity metric, the image matching problem is formulated as a cost function. By optimizing it, the deformation field of the
Registration is obtained based on image re sampling and transformation.

B. Wavelet Transform: The resultant images from the ICA are denoted as IC1, IC2…..ICN. Mutual information is calculated for all IC's and any IC's which has more useful information are chosen based on histogram calculation are fused by wavelet transform. If the images are unrelated, then the joint histogram of two images will be the sum of individual histogram of 2 images. If the images are similar, then the joint histogram will be less

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than the sum of individual histogram of 2 images.

C. Spatial Domain: The process is applied to the individual pixels of the image. Image re sampling and transformation method is used. 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 the equation (2)

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

IV. EXPERIMENTAL RESULTS AND DISCUSSION

The input is chosen as different MRI Protocols, MRI T1, MRI T2, MRI PD, DT1 and it is shown in fig2, fig 3, and fig 4.

RESIZED T1 IMAGE

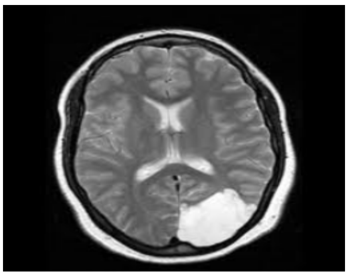

Fig.2. Resized MRI T1 image

The Gabor features for T1 image is shown in fig 5-8 for different scale and orientation

RESIZED PD IMAGE

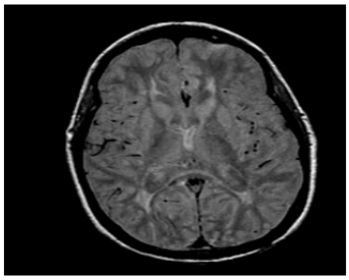

Fig.3. Resized MRI PD image

RESIZED T2 IMAGE

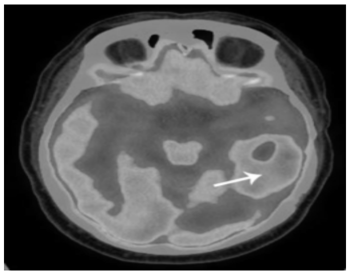

Fig.4. Resized MRI T2 image

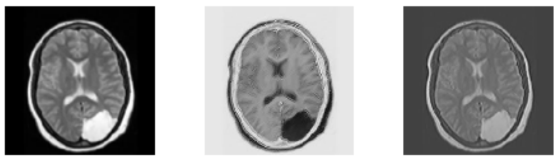

Fig.5. For scale =1, orientation=1-3

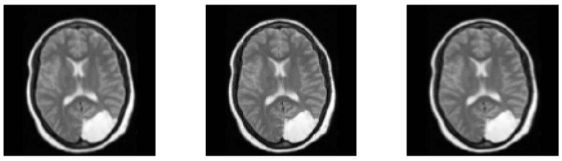

Fig.6. For scale =2, orientation=1-3

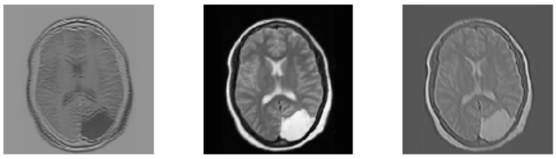

Fig.7. For scale =3, orientation=1-3

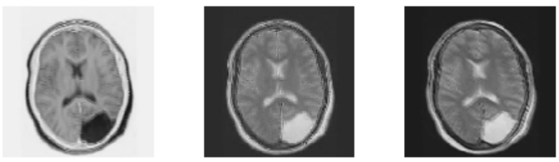

Fig.8. For scale =4, orientation=1-3

The Gabor features for PD image is shown in fig 9-12 for different scale and orientation

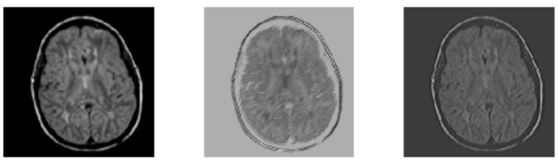

Fig.9. For scale =1, orientation=1-3

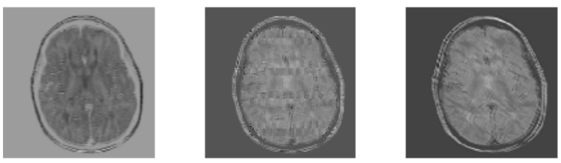

Fig.10. For scale =2, orientation=1-3

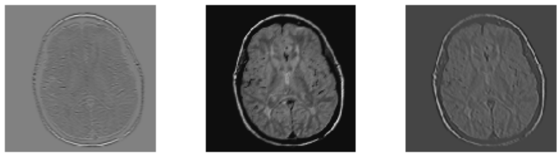

Fig.11. For scale =3, orientation=1-3

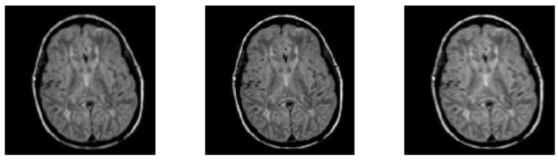

Fig.12. For scale =4, orientation=1-3

The Gabor features for PD image is shown in fig 13-16 for different scale and orientation

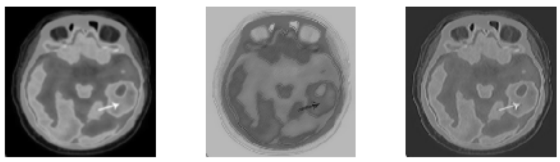

Fig.13. For scale =1, orientation=1-3

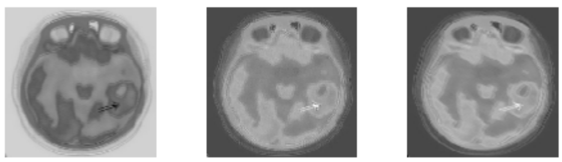

Fig.14. For scale =2, orientation=1-3

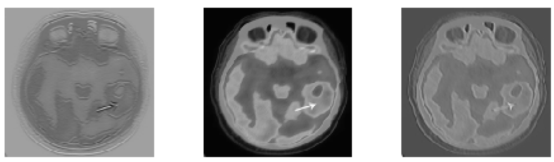

Fig.15. For scale =3, orientation=1-3

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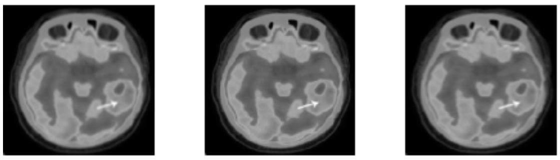

Fig.16. For scale =4, orientation=1-3

The independent components from the ICA are shown in fig 17-18.

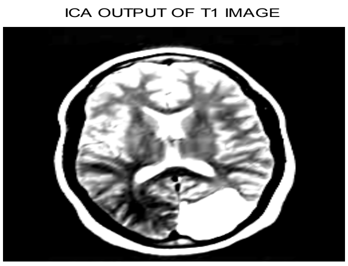

Fig.17. ICA output of T1 image

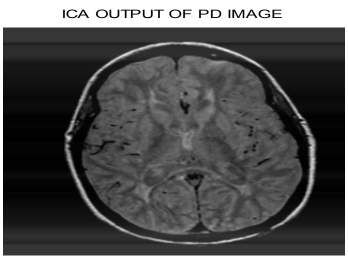

Fig.18. ICA output of PD image

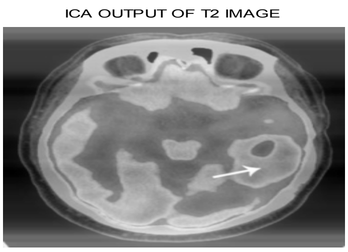

Fig.19. ICA output of T2 image

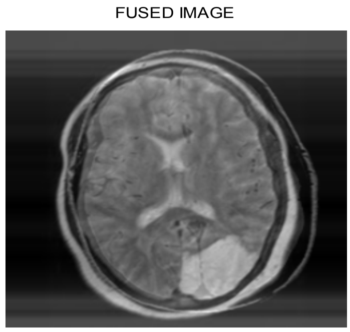

Fig.20. Wavelet based fused resultant image.

V. CONCLUSION

In this paper, we have proposed image registration framework that information from different modalities based on the feature level information fusion. This is about the fusion of 2 dimensional images based on the local rule that can capture only the local information but not any of the global information for it is implemented in a local window region. And also we compared the entropy values of the fused image of wavelet based image fusion and with that of spatial domain approach. Transform domain approach will have more information in the fused images. In future, we would like to propose 3D Shearlet transform and also global rule for fusing images which gives more enhance fused results.

References:

[1]. Susmitha Vekkot, and Pancham Shukla “A Novel Architecture for Wavelet based Image Fusion”. World Academy of Science, Engineering and Technology 57 2009

[2]. S.L.Jany Shabu, Dr.C.Jayakumar, T.Surya “Survey of Image Fusion Techniques for Brain Tumor Detection”.IJEAT-Vol.3, No.2, December 2013.

[3]. Smt.G. Mamatha (Phd), L.Gayatri, “An Image Fusion Using Wavelet and Curvelet Transform”Global Journal of Advanced Engineering Technologies, Vol1, Issue-2, 2012, ISSN: 2277-6370

[4]. M .Chandana,S. Amutha, and Naveen Kumar, ―A Hybrid Multi-focus Medical Image Fusion Based on Wavelet Transform‖. International Journal of Research and Reviews in Computer Science (IJRRCS) Vol. 2, No. 4, August 2011, ISSN: 2079-2557

[5]. Shutao Li, Bin Yang, Jianwen Hu, “Performance comparison of different multi-resolution transforms for image fusion”, Elsevier-Information Fusion, vol.12, no.2, 2011

[6]. R. Shen, I. Cheng, and A. Basu, “Cross-scale coefficient selection for volumetric medical image fusion,” *IEEE Trans. Biomed. Eng.*, vol. 60, no. 4, pp. 1069–1079, Apr. 2013.