Image Registration by Feature based Information Fusion

B.Narani
National Engineering College
Kovilpatti
naranibala@gmail.com

A.Shenbagavalli
National Engineering College
Kovilpatti
shenbanec@gmail.com

ABSTRACT
Image Registration plays an important role for fusion of information from multiple images. Applications of Image Registration can be found in medical images, robotics. Image registration is the process of finding the transformation which best matches, according to some similarity measure, two or more images that differ in certain aspects but essentially represent the same object. In the proposed algorithm, a novel non-rigid image registration algorithm has been used which combines information from different modalities to produce a unified joint registration. In this proposed method, Feature level information fusion is used which combines complementary information from different modalities which characterize different tissues using Gabor wavelet transform. Principal Component Analysis (PCA) is used for image fusion. By performing fusion to the registered images more accurate information can be obtained in the fused image. The proposed method has been tested on various medical images acquired using different modalities and evaluated based on its registration accuracy.

Keywords
Image Fusion, Gabor Wavelet Transform, Feature based image fusion.

1. INTRODUCTION
Medical imaging is the technique used to obtain images of the human body for clinical purposes. With the development in technology, many imaging modalities are available for clinical purpose. Some of the different imaging modalities are Magnetic Resonance Imaging (MRI), Computed Tomography (CT), and Positron Emission Tomography (PET). The different protocols of MRI are T1, T2, FLAIR, Diffusion Tensor Imaging (DTI) etc. These different protocols of MRI also called as different modalities. These different modalities characterize different tissues of brain. T1 image provides contrast between White Matter (WM), Gray Matter (GM) and Cerebrospinal Fluid (CSF). Diffusion Tensor Image (DTI) provides the directional information. Computed Tomography (CT) images provide the information about the bones. Computerized approaches offer potential benefits, particularly by accurately aligning the information in the different images, and providing tools for visualizing the combined images. A critical stage in this process is the alignment or registration of the images. The Image Registration can be done by using different Image Registration Methods. Some of the well Known Image Registration Methods is Land Mark Based Registration, Intensity Based Registration, Feature Based Registration and Non-Rigid image Registration. Land Mark Based registration requires prior knowledge to establish anatomical correspondences. Anatomical features are extracted by manually placing landmark points. Transformations are then estimated from those anatomical features. The landmark-based registration methods are usually computationally efficient but it requires additional work to manually place sufficient number of landmark points to give more accurate registration results. In Intensity based Registration method, the goal of Registration is optimizing the image intensity similarities between the source and the target images. This method tends to average out any errors caused by noise or random fluctuation due to intensity values. Feature-based registration methods use feature vectors as signatures to characterize each voxel in the image volume. Features may be points and lines. They should be distinct, spread over all images and efficiently detectable in both images. But it is typically confined to only small subset of voxels namely the feature points. Non-rigid image registration (NIR) is an essential tool for morphologic comparisons in the presence of intra- and inter-individual anatomic variations.

In medical imaging, nonrigid registration was initially used to standardize MR and CT brain images with respect to an atlas. Most nonrigid image registration methods are iterative and minimize a cost or an energy function, defined in terms of the geometric and intensity difference between images. The image fusion can be done at different levels like intensity based image fusion, pixel based image fusion and feature based image fusion. In intensity based image fusion and pixel based image fusion it is difficult to extract and difficult to differentiate the complementary and redundant information. The image registration is the process of computing the geometrical transformation between two images. The geometrical transformation is used to resample one image dataset to another. An excellent registration produces excellent image fusion. By using Feature based image fusion the complementary and redundant information can be discriminated much better than intensity and pixel based image fusion. The main advantage of integrating two images in to single image is that the redundant information provided by the two images reduces the overall uncertainty and increase the accuracy of the integrated image. The other important advantage is timelier information is obtained in the integrated image. For the fusion of the images multiresolution methods like Discrete Wavelet Transform (DWT), Dual Tree Complex Wavelet Transform (DT-CWT), Gabor Wavelet Transform can be used. Discrete Wavelet Transform (DWT) preserves different frequency information in stable form and allows good localization in both time and space frequency domain. The main drawback of Discrete Wavelet Transform (DWT) is it does not provide shift invariance. Even for a small shift in the input image causes completely different energy distribution in DWT coefficients at different scales [9]. In medical imaging it is important to know and preserve the exact location of this information but shift invariance causes inaccuracies. To overcome this shift invariance problem Dual Tree Complex Wavelet Transform (DT-CWT) was proposed (Kingsbury, 1999). This Dual Tree Complex Wavelet Transform (DT-CWT) satisfies the shift invariance property but it does not provide directional information [10]. The Fourier transform has been widely used for analyzing the frequency properties of a signal but after the transformation is taken the time information is lost and it is difficult to find where certain frequency occurs. To solve this problem a time frequency analysis technique was used. But this technique provides uncertainty in both space and frequency. As the Gabor wavelet transform minimizes the joint uncertainty in space and frequency and is widely used for feature detection [11], it is used in this paper. The magnitude of the coefficient of Gabor wavelet transform is more reliable to measure the characterization ability of images from different modalities. The Gabor wavelet transform is nothing but the Gaussian modulated complex sinusoid function. The features are extracted from input images using Gabor wavelet transform for different frequencies and orientations. The features obtained by using Gabor filter are fused by using the Principal Component Analysis (PCA) algorithm.

2. PROPOSED METHOD

The proposed method uses Gabor wavelet transform and Principal Component Analysis (PCA) to fuse the input images. Then various performance measures are used to evaluate the performance of the fused image.

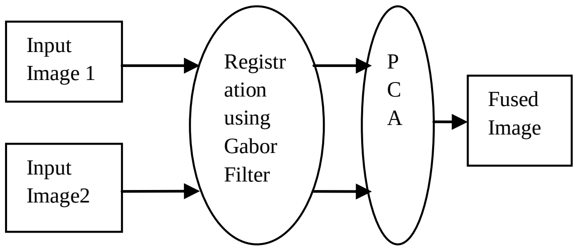

Fig 1: Block diagram of the proposed method

The Input image 1 and Input image 2 block in Figure.1. represents the two input images taken from the Magnetic Resonance Imaging (MRI) scanner and Computed Tomography (CT) scanner .The Computed Tomography(CT) images characterize the bones in the brain and the Magnetic Resonance Image (MRI) characterize the soft tissues of the brain. So the main advantage of performing fusion using the Magnetic Resonance Image (MRI) and Computed Tomography (CT) image is that both the bones and the soft tissues of the brain image can be viewed in a single image. These two input images are given as input to the Gabor filter block, where the features of the images are extracted and the two input images are registered by using Gabor wavelet transform. One Reference image is taken to register the two input images. The two input images are registered according to the Reference image. If Fusion is applied to the registered images then better result can be obtained that is the fused image contains all the fine information obtained from the two input images. Then Principal Component Analysis (PCA) is applied to these Gabor Registered images and then fusion is performed. Thus the Fused image is obtained. The performance of the fused image is evaluated by using Root Mean Square (RMSE), Correlation Coefficient (CC) and Standard Deviation (SD).

2.1 Gabor Filter

The Gabor filter, first proposed by Gabor is a useful tool for feature extraction and signal decomposition in image processing, computer vision, and medical image analysis. It has been applied to medical image registration. Gabor filters are a traditional choice for obtaining localized frequency information. They offer the best simultaneous localization of spatial and frequency information. However they have two main limitations The Registration method using Gabor adopts the filtered Gabor response of the Original image. The features of the input images are extracted using Gabor filter and then image registration is performed on the two input images. A Gabor filter is a Gaussian modulated complex Sinusoidal function. A Gabor filter is given by

$$G(x,y) = s(x, y)g(x,y) \qquad (1)$$

In Equation (1) s(x,y) is the complex sinusoidal function and g(x,y) is the Gaussian function and it is given by

$$S(x,y) = \exp\left[-j2\pi\,(u_o x+v_o y)\right] \qquad (2)$$

$$g(x,y) = \frac{1}{\sqrt{2\pi(\sigma x+\sigma y)}}\exp\left(-\frac{1}{2}\left(\frac{x^2}{{\sigma_x}^2}+\frac{y^2}{\sigma_y^2}\right)\right) \qquad (3)$$

σ_x and σ_y characterize the spatial extent and bandwidth of along the respective axes, and are the shifting frequency parameters in the frequency domain. Using G(x,y) as the mother wavelet, the Gabor wavelets, and a class of self-similar functions can be obtained by appropriate dilations and rotations of G(x,y) through

$$G_{m,n}(x,y) = a^{-m} G(x',y') \qquad (4)$$

Where

$$x' = a^{-m}(x \sin\theta + y \cos\theta) \qquad (5)$$

$$y' = (x \cos\theta + y \sin\theta) \qquad (6)$$

$a>1$, $\theta = {}^{n\pi}/_{O}$, m=1,……S n=1…….O.

O indicates the number of orientations, the number of scales in the multiresolution decomposition and is the scaling factor between different scales.

2.2 Principal Component Analysis (PCA)

Principal Component Analysis (PCA) is a classical technique in statistical data analysis, feature extraction and data reduction. Given a set of multivariate measurements, the purpose is to find a smaller set of variables with less redundancy that would give as good representation as possible. The redundancy is measured by correlations between data elements. PCA is the simplest of the true eigenvector-based multivariate analyses technique. If a multivariate dataset is visualized as a set of coordinates in a high-dimensional data space (1 axis per variable), PCA can supply the user with a lower-dimensional space. Principal

Component Analysis (PCA) is mainly used for Dimension Reduction. It is nothing but the process of representing the higher dimension to lower dimension space. This is done by taking only the first few principal components. To apply Principal Component Analysis (PCA), the covariance matrix and the Eigen values of the input image is calculated. Then by multiplying the Eigen values with the original image matrix values and then by adding all the matrix components, fusion is performed. Thus the fused image is obtained by using PCA and is shown in Fig 4.

The performance of the fused image is evaluated by calculating Root Mean Square Error (RMSE), Correlation Coefficient (CC) and Standard Deviation (SD).

2.3 Root Mean Square Error (RMSE)

RMSE is found between the fused image and the reference image. Here the reference image can be either one of those input images. The RMSE can be calculated using the following formula

$$RMSE = \sum \sqrt{\frac{\sum_{x=1}^{N}\sum_{y=1}^{M}\left(R(x,y)-F(x,y)\right)^2}{M \times N}}$$

Where, M x N denotes the size of the image.

R(x, y) denotes the reference image.

F(x, y) denotes the fused image.

2.4 Correlation Coefficient (CC)

Correlation Coefficient (CC) shows the small similarities between the fused image and the input images. This can be calculated using the following formula

$$CC(F,d) = \frac{\sum_{i=0}^{M-1}\sum_{j=0}^{N-1}(F(i,j)-\bar{F})(d(i,j)-\bar{d})}{\sqrt{\sum_{i=0}^{M-1}\sum_{j=0}^{N-1}(F(i,j)-\bar{F})^2\sum_{i=0}^{M-1}\sum_{j=0}^{N-1}(d(i,j)-\bar{d})^2}}$$

Here $\bar{d}$ and $\bar{F}$ denotes the mean values of reference image and fused image respectively.

3. RESULTS

Fusion can be performed only if the size of the input images is same. So first the size of the input image is checked. If the size of the image is equal then fusion is performed. If the size is not equal fusion cannot be performed. The size of the images can be resized and made equal and then fusion can be performed if image size is not equal. The two input images taken as input is shown in Fig 2 and Fig 3.

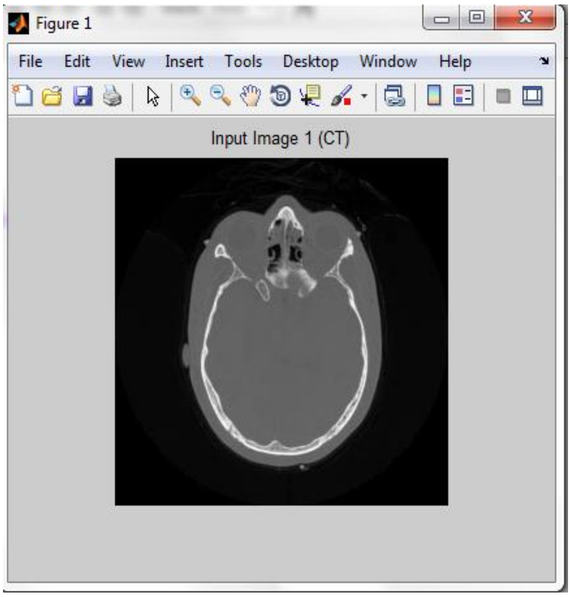

Fig 2: Input Image 1 (CT)

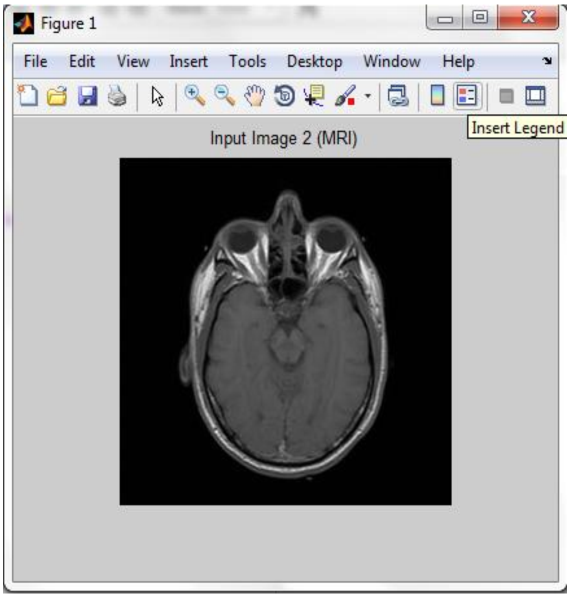

Fig 3: Input Image 2 (MRI)

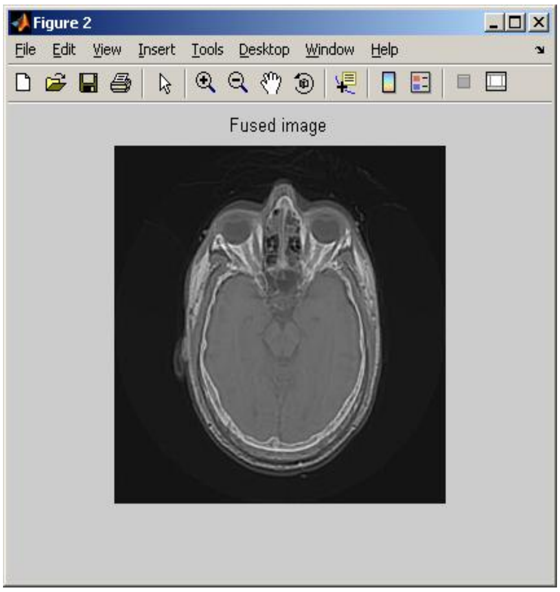

Fig 4: Fused Image

The Root Mean Square (RMSE) and Correlation Coefficient (CC) values are calculated for the fused images of different resolutions and the calculated values are shown in the Table 1.below

Table 1. Performance Measures

Resolutions	**Root Mean Square Error (RMSE)**	**Correlation Coefficient (CC)**
128 x 128	0.0052	0.9194
256 x 256	0.0026	0.9330
512 x 512	0.0013	0.9403

4. CONCLUSION

Thus the images are Registered and fused by using Gabor filter and Principal Component Analysis (PCA). The Root Mean square Error and Correlation coefficient are calculated for the fused image. The RMSE is found to be very small for the fused image. So the error value is low for the fused image. Correlation Coefficient values are also calculated for the fused image by using this method and it shows the higher similarity between the images. In future going to do the same using Independent Component Analysis (ICA), so that better result can be obtained.

5. REFERENCES

[1] Yang Li, Ragini Verma, "Multichannel Image registration by Feature-Based Information Fusion," IEEE Trans on medical imaging, VOL.30.3,March 2011.

[2] Young, L. Van Vliet, and M. Van Ginkel, "Recursive Gabor filtering," IEEE Trans. Signal Process., vol. 50, no. 11, pp. 2798–2805, Nov2002.

[3] J.Pluim, J.Maintz and M.Viergever, "Mutual Information Based Registration of Medical Images : A Survey," IEEE Trans. Med.Imag., vol 22, no.8, pp. 986-1004, Aug.2003.

[4] Joshi, D. Shattuck, P. Thompson, and R. Leahy, "Surface-constrained Volumetric brain registration using harmonic mappings," IEEE Trans. Med. Imag., vol. 26, no. 12, pp. 1657–1669, Dec. 2007.

[5] Dadgostar. M, Tabrizi .P.R, Fatemizadeh .E, Soltanian-Zadeh.H. 2009. Feature Extraction Using Gabor-Filter and Recursive Fisher Linear Discriminant with Application in Fingerprint Identification. Seventh International Conference on Advances in Pattern Recognition.

[6] J. Daugman, "Complete discrete 2D Gabor transforms by neural networks for image analysis and compression," IEEE Trans. Acoustics,vol. 36, no. 7, pp. 1169–1179, Jul. 1988.

[7] J. Friedman ,J. Tukey, "A projection pursuit algorithm for exploratory data analysis," IEEE Trans. Computers, vol. 23, no. 9, pp. 881–890, Sep.1974.

[8] A.Hyvarinen, "Fast and robust fixed point algorithms for independent component analysis," IEEE Trans. Neural Networks, vol. 10, no. 3, pp. 626–634, 1999.

[9] N. Kingsbury. The dual-tree complex wavelet transform: a new technique for shift invariance and directional filters. In IEEE Digital Signal ProcessingWorkshop, volume 86, 1998.

[10] Medical Image Fusion Schemes using Contourlet Transform and PCA Based Nemir Al-Azzawi and Wan Ahmed K. Wan Abdullah Biomedical Electronics group, Universiti Sains Malaysia.

[11] W. Ma and B. Manjunathi, "Texture features for browsing and retrieval of image data," IEEE Trans. Pattern Anal. Mach. Intell., vol. 18, no. 8, pp. 837–842, Aug. 1996.