Multimodal Medical Image registration using Discrete Wavelet Transform

Hina Shakir
MS Computing
Shaheed Zulfiar Ali Bhutto Institute of Science and Technology
90 and 100 Clifton
Karachi -75600

Dr S.Talha Ahsan
Assistant Professor, Faculty of Computing
Shaheed Zulfiar Ali Bhutto Institute of Science and Technology
90 and 100 Clifton
Karachi -75600

***Abstract*—In image processing, image registration develops a relationship between two images using optimal transformation where the images could have been taken at various times, sources or devices, or from different perspectives. It aligns the reference and moving image using geometric transformations. This research study evaluates the performance of multimodal(images acquired from different sources)image registration technique using Discrete Wavelet Transform (DWT).The reference and the target images are decomposed into their respective DWT coefficients and then are processed for image registration. After registration, the resultant DWT coefficients are transformed back using Inverse DWT into their spatial coordinates in order to retrieve the registered image. The similarity of the two input images for image registration is calculated and investigated using a similarity metric known as Mutual Information (MI) which is maximized. The quality of registration is measured using cross-correlation coefficient (CCC) of the registered image with respect to the reference image. Finally the time taken for image registration in wavelet domain is analyzed and compared with the image registration taking place in spatial domain.**

KEYWORDS: Image registration, Discrete Wavelet Transform, multimodal

I. INTRODUCTION

Image registration is widely used technique for finding mutual dependence of two images on each other .Medical science has utilized this technique well for the correct diagnosis of fatal diseases, deformation of organs and changes in the anatomy .Registration techniques however face challenges like finding the correct metrics for calculating similarity between the registered and reference images. There is an ongoing research on how to optimize the registration process and also about selection of correct transformations with respect to the context of images captured. Another important issue to deal with is the time taken during registration process.

This research paper discusses and reviews the available image registration techniques for medical images and focuses on various modalities of images to achieve co-registration. In this work, discrete wavelet transforms have been used on the multimodal images and their performance for image registration is evaluated with the help of a simulation on Matlab.

The proposed algorithm will decompose the reference and the target medical images into their 2-D wavelets coefficients using db-2r wavelet. The registration process will use the two images' wavelets coefficients instead of the images data .After registration, the registered data will be inverse transformed to get the actual registered image. The quality of registration and the time taken for image registration will be evaluated using various standard parameters. In the last section of paper, conclusion of this study is given and possible future work for the proposed setup is suggested. The proposed algorithm is outlined in Figure 1.

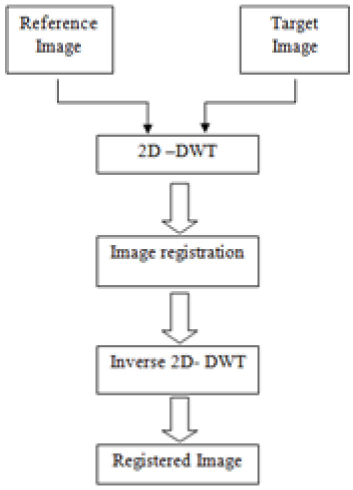

Figure 1: Proposed framework for multimodal image registration

II. LITERATURE VIEW

Since image registration can broadly be categorized into intensity based or feature based registration, the evaluation of the quality of registration is also different for both types of registration. Any measure that can represent mutual dependence between reference and the registered image is usually investigated by the researchers to assess the performance of registration techniques.

A new intensity-based similarity metric was proposed for the registration of multimodal images by Juan Du et al. [1] and was compared with the tradition Mutual Information and partitioned intensity uniformity technique. Derek et al. [2] outlined the challenges faced in intermodal and intra modal image registration including errors and degree of freedom required during registration. Barbara et al. [3] discussed feature based and area based image registration techniques. H. Costin and Cr. Rotariu [4] extensively discussed the multimodal image registration and the problems associated to it. A probabilistic reason was derived by Torsten et al. to use mutual information for multi modal image registration [5].

Alexis et al. [6] pointed out that images with large dissimilarities do not show good results with various proposed similarity metrics and correlation ratio can be used a similarity metric for multimodal image registration. Daewo et al [7] used the structural information of the neighboring pixels around the voxel of interest to propose a new similarity metric for multimodal image registration. Since this research work proposes wavelets coefficients for multimodal image registration, it is important to review the literature with similar work and research done which is presented ahead.Turcajova and Kautsky [8] experimented with LL coefficient of various orthogonal and biorthogonal wavelets using cross-correlation when the transformation was affine . Fonseca and Costa [9] worked on modulus maxima of LH and HL coefficients and found out the values of maxima of the correlation coefficients, computed from LL coefficients. Djamdji et al. [10] implemented registration using HH coefficients. Liu et al. [11] proposed Gabor wavelet transform for image registration and also Gaussian model of registration residua. The benefits of Daubechies and Haar wavelets for registration were investigated in [12].Jue and Chung [13] decomposed the multimodal images into the LL, LH, HL and HH coefficients and registered the LL coefficients to increase the efficiency of registration process.

Nagham et al. implemented a hybrid technique using hierarchical guassian pyramids with mutual information(MI for wavelet based multimodal image registration of dental panoramic X-ray images and magnetic resonance (MR) images of the brain[14] . Shajan et al[15] applied image registration on wavelet coefficients of LL band of the mono-modal images . P. Ramprasad et al. [16] performed wavelet decomposition of the dental x-ray images of poor quality and registered them. Ghantous et al. [17] adopted a Dual Tree-complex wavelet transform is employed to reduce the registration time.

Research survey also shows that wavelets have the potential to be used for successful and efficient image registration and in-depth investigation of its application in registration field may lead to for further development in this direction.

III. MEDICAL IMAGE REGISTRATION

Image registration is the process of establishing an association between two images of the same object or scene that are captured from similar or different sensors or devices at different time frames from different perspectives. It aligns two images known as reference and target images with the help of some transformation. The differences in the two images that need to be aligned occur to the conditions in which the imaging occurs. Image registration is very beneficial in image analysis processes like tumor growth, localizing lesions or deformation of an organ or tissue. Image registration is typically used to gain more information about a patient‘s disease when the information is not very clear in one image alone e.g. computed tomography (CT) image of patient's diseased organ can be mapped on the magnetic resonance (MR) image of the same body part to obtain complete information about the patient disease as shown in Figure 2

In medical field, there are two imaging modes that can be employed:

Anatomical imaging:This modality deals with the various morphological techniques like positron emission tomography (PET), CT, MRI, Ultra sound, X-rays etc.

Functional imaging: This imaging works on the primary functions within the organs .When two images are compared with each other and they have gone through different set of clinical events and before their integration alignment is needed in time domain .The integration process is called Registration.

It is important to know the dimensions of the registration because the registration of a 2D image can take place with a 2D or a 3D image and vice versa which will lead to different considerations and results that need to be taken care of .Moving from 2D to 3D which is a usual practice in tomographic imaging results in more complex calculations in comparison to 2D imaging .3D data is a projective data in contrast to the 2D data which is a spatial data. It is also to be remembered that most of the registration techniques work in time or spatial domain. However, slices of tomography images can be registered in 2D as well. The speed of the registration is also fast in 2D registration than in 3D.Keeping the registration complexities in mind the 2D to 3D registration is useful when of mapping and alignment of spatial data to projective data is desired. There are many occasions in clinical practices when more than two images of the patients are required to monitor growths or decay in the anatomy at various time intervals .In such cases too ,the imaging can be in completely 2D ,3D or in 2D as well as 3D which calls for the relevant registration technique accordingly.

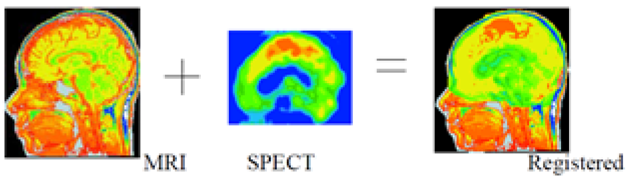

Figure 2: Multimodal medical image registration between MR and Single-photon emission computed tomography (SPECT) images

Transformations are of four types: Affine, rigid, projective and curved.

In rigid transformations, the image coordinates can only be translated and rotated. In Affine transformations, parallel lines in an image are mapped onto parallel lines.

Projective transformation maps lines on lines where as Curved transformation maps lines onto curves. Our choice of transformation is affine transformation. The classes of registration can be categorized on the basis of modalities of images or model that are being registered. Monomodal registration involves images from the same modality. The example of such registration is two SPECT images acquired under rest and stress conditions of the patient. Such registration is used for diagnosis.

In multimodal registration, the data that has to be registered belong to more than one modality. When a relation between dysfunction is to be established with the anatomy, a PET image is registered to an MR image of the patient.

IV. MULTIMODAL IMAGE REGISTRATION

Multimodal image registration is appropriate when disease diagnosis for a patient takes place with the help of multimodal imaging like CT, PET and MRI etc. The three processes that need to be performed for registration are transformation, using a similarity metric and optimization of the process. Rigid or non-rigid transformation may be used. If the images that need to be registered are coming from an imaging technique which producing rigid changes like change in size and rotation in the scale of the image then rotation and scaling defining affine motion can be an appropriate transformation model. For non-rigid transformations, one image is deformed in to order to find out the non linear variations between the images. To calculate the similarity between registered image and the reference image; many similarity metrics are used in medical image registration. Most prominent and most commonly used include normalized cross correlation, correlation ratio (CR), and mutual information. Normalized cross correlation (NRCC) and correlation ratio work for the image which show an association between the intensity values of the two images. For NRCC, the relationship is linear and for CR, any functional relationship is allowed.

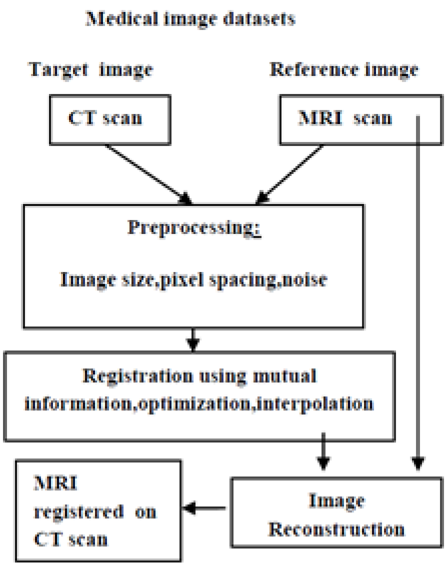

Figure 3: Block Diagram for multimodal medical registration

Another way to find similarity between two images is Mutual information. It is metric which works on information theory .It takes two random variables which in the case of image processing are two images and then it finds the mutual dependence of the two with each other. In general, mutual information of two discrete random variables I(X;Y) is given by:

$$I(X;Y) = \sum_{y \in Y} \sum_{x \in X} p(x,y) \log \left(\frac{p(x,y)}{p(x)\,p(y)} \right),$$

A good optimization technique should work in synchronization of the similarity metric and should align the images to the optimum for registration for a given parameter set and transformation

Consider fixed image F defined on image coordinates m and moving image M defined on coordinate's n. The registered moving image is called Mr. The registered image achieved after transformation is represented by the following equation:

Mr(m) =M(A(n)) , M(n) =Mr(A−1(m))

Where A is the affine transformation .We need to find the value of A which is responsible for mapping of r onto s or inverse of A which maps s on r. Mathematically, Affine transformation is a product of translation, scaling, rotation and skew. The relationship is given by

m=An where A is given by the following matrix

$$A_\alpha = \underbrace{\begin{bmatrix} 1 & 0 & t_x \\ 0 & 1 & t_y \\ 0 & 0 & 1 \end{bmatrix}}_{translation} \cdot \underbrace{\begin{bmatrix} \theta_c & -\theta_s & 0 \\ \theta_s & \theta_c & 0 \\ 0 & 0 & 1 \end{bmatrix}}_{rotation} \cdot \underbrace{\begin{bmatrix} 1 & k & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 1 \end{bmatrix}}_{skew} \cdot \underbrace{\begin{bmatrix} s_x & 0 & 0 \\ 0 & s_y & 0 \\ 0 & 0 & 1 \end{bmatrix}}_{scaling} = \begin{bmatrix} a_1 & a_2 & a_3 \\ a_4 & a_5 & a_6 \\ 0 & 0 & 1 \end{bmatrix}$$

The variable denotes:

t_x = positive value shifts image to the left
t_y = positive value shifts image up
θ = rotation angle, measured counterclockwise from the x-axis ($\theta_c = \cos(\theta)$ and $\theta_s = \sin(\theta)$)
k = shear factor along the x-axis = tan(skew angle) (the skew angle is measured from the y-axis)
s_x = change of scale in x direction
s_y = change of scale in y direction

V. DISCRETE WAVELET TRANSFORM

Discrete wavelet transforms work on the scale and frequency components of the image and can resolve the signal to many levels which shows their multiple resolution nature which make them suitable candidate for image registration.

The Wavelet Transform are different from other transforms because they work in both the domain for the signal .It was seen that earlier transforms were not able to analyze specific frequency details in isolation without affecting the rest of the image however Wavelets solved this problem by discretely decomposing the signal to many levels .On every level the signal is passed through a digital filter and sampled up by a factor of 2

We can express the scenario mathematically:

$$y[n] = \sum_{k=-\infty}^{\infty} h[k] \cdot x[2n-k]$$

For reconstructing the signal the coefficients achieved by the decomposition are passed through high pass and low pass synthesis filter and down sampled by 2.

VI. RESULTS AND DISCUSSION

We propose to combine Gaussian pyramid algorithm using mutual information with the discrete wavelet transform to achieve better registration performance for multimodal medical image registration. Our proposed algorithm is outlined in Figure 1.The reference and the target images are decomposed in their respective LL, HL, LH and HH frequency sub-bands using 2D –DWT and the chosen wavelet for this proposed algorithm is Daubechies-2 .Since the approximation information about the image lies in the LL band of the image data we choose to register the LL band of the images to speed up the registration as well as to increase the accuracy. Finally, the registered data in LL band is inverse transformed using IDWT into registered image. The proposed framework of image registration is outlined in figure 4.

To test our proposed algorithm, we have obtained CT, PET, MR-T2 image data which is volumes from Retrospective Image Registration Evaluation (RIRE) Project[18].The chosen dataset is a set of images from different patients made available on the website for researchers to test their algorithms. We have selected testing data of five patients from RIRE project to test our proposed algorithm. The physical voxel size of CT images is 0.65x0.65x4 mm3, for MR images it is 1.25 x1.25 x 4 mm3 , and 2.59 x 2.59x 8 mm3 for PET images. The registration takes place between PET-MR and CT-MR images for the available datasets of the patients. Dimensions of the images are given in Table 1.

VII. Experiment Setup

Affine transformation is used for image registration which performs transformation of rotation, scaling and translation. Larger image is scaled down to the smaller image if the sizes of the two images to be registered are not same. Size information of all the images is given in Table 7.1.

The system configuration used for the experiment is 4GB RAM with Itanium 5 processor. The proposed image registration technique has been implemented using Matlab 2012.The variables of optimizer and metric has been set with the following values:

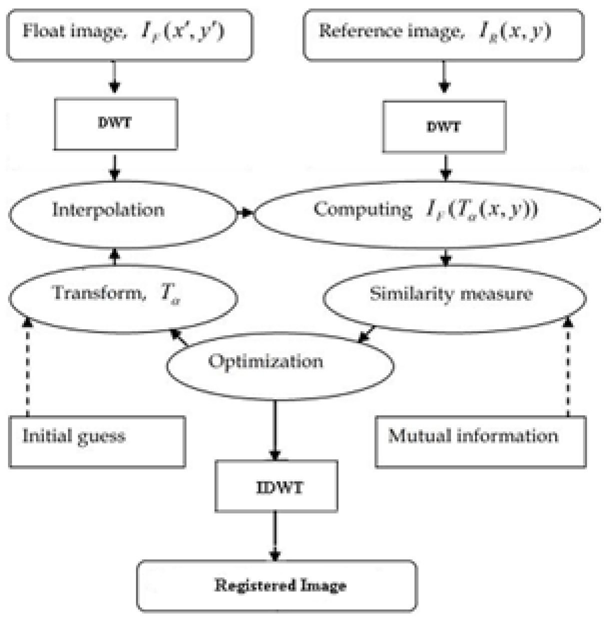

Figure 4: Proposed framework for image registration

Variable	**Data type**	**Fields**	**Value**
Optimizer	OnePlusOneEvolutionary	GrowthFactor	1.01
		Epsilon	1.5e – 6
		InitialRadius	0.002
		MaximumIterations	200
Metric	MattesMutual Information	NumberOf SpatialSamples	500
		NumberOf HistogramBins	50
		UseAllPixels	1

VIII. Performance of the Algorithm

The performance of registration is evaluated using Cross correlation coefficient (CCC) and the time elapsed during registration with wavelets and without wavelets. Average value of MI is also mentioned for both processes.

Cross correlation between the reference and the registered image is measured using the following equation:

$$CC = \frac{\sum_{x,y}\left[I_R(x,y) - E(I_R(x,y))\right]\sum_{x,y}\left[I_F(T(x,y)) - E(I_F(T(x,y)))\right]}{\sqrt{\sum_{x,y}\left[I_R(x,y) - E(I_R(x,y))\right]^2}\sqrt{\sum_{x,y}\left[I_F(T(x,y)) - E(I_F(T(x,y)))\right]^2}}$$

Where IR is the registered image and IF is the fixed image

	Image	Dimensions
Patient 01	MR-T2	256x256x26
	PET	128x128x15
	CT	512x512x28
Patient 02	MR-T2	256x256x26
	PET	128x128x15
	CT	512x512x29
Patient 03	MR-T1	256x256x26
	PET	128x128x15
	CT	512x512x33
Patient 04	MR-T1	256x256x26
	PET	128x128x15
	CT	512x512x28
Patient 05	MR-T1	256x256x26
	PET	128x128x15
	CT	512x512x28

Table 1: Dimensions of the patients medical images

IX. Results

PET, CT and MR-T2 images are registered for all five patients and the performance parameters are recorded in Table 2 and Table 3 for spatial domain registration and wavelet based registration respectively. Registration process using wavelets of MR-T2 and CT images of patient 01 is outlined in figure 5.Common area between the reference and the registered image is shown in figure 5(d) using grey color whereas the difference is shown using violet and green color.

The statistical performance parameters recorded reveals that our algorithm outperforms traditional time domain image registration with maximum time elapsed during wavelet registration is 1.4616 seconds. On the other hand the time taken during spatial domain registration is 4.3591 seconds. The cross-correlation coefficient of the two registrations is almost same except the case of patient 01 where the CCC for MR-T2/PET spatial domain registration is 0.9421 and that for wavelet based registration is 0.8887.

The proposed wavelet based registration has come out superior over spatial registration based on its performance of CC and time elapsed. Looking at the experimental results, wavelet based registration with Gaussian pyramid proposed by the authors offer good prospects for multimodal medical image registration.

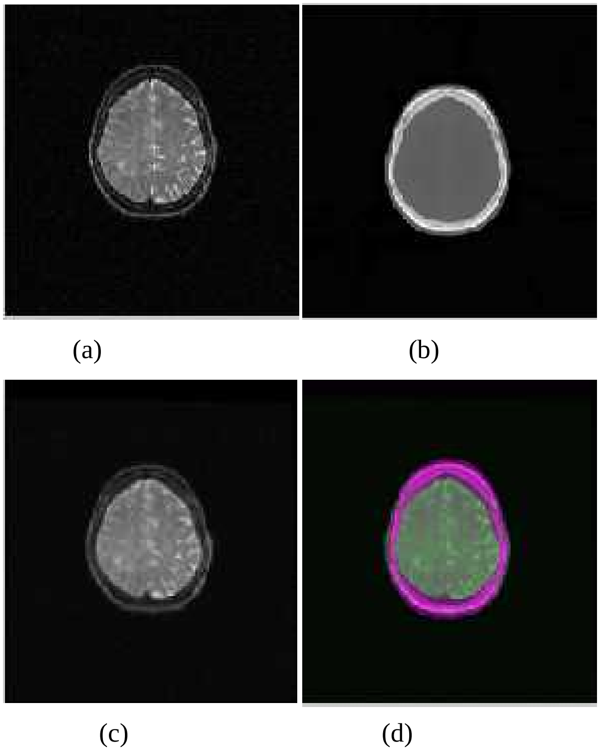

Figure 5: 2-D view of brain images of patient 01
(a)MR-T2 (reference) (b) CT image (target) (c) Registered image (d)Pair of registered and reference image shown together

The data in the table have been plotted in different charts to make a clear comparison between the two registration types. Chart 1 is a comparison of average MI of the two registration techniques. It is evident from the graph values that both the techniques deliver almost same MI and perform on the same level.

Chart 2 outlines the values of CCC for the two registration techniques. It can be observed that there is no significant difference between the average MI values of the algorithms which can make one registration technique superior to the other technique. In-fact wavelets based technique performs slightly better than the spatial domain registration.

Chart 3 involves comparison between the time elapsed during registration based on wavelets and spatial domain. It is observed that spatial based registration is computationally quite expensive than the wavelet based technique.

Based on the findings of average NMI, CCC and time elapsed for the two registration techniques we can establish that our wavelet based multimodal image registration can be adopted for medical diagnosis as its performs is better than the traditional image registration technique

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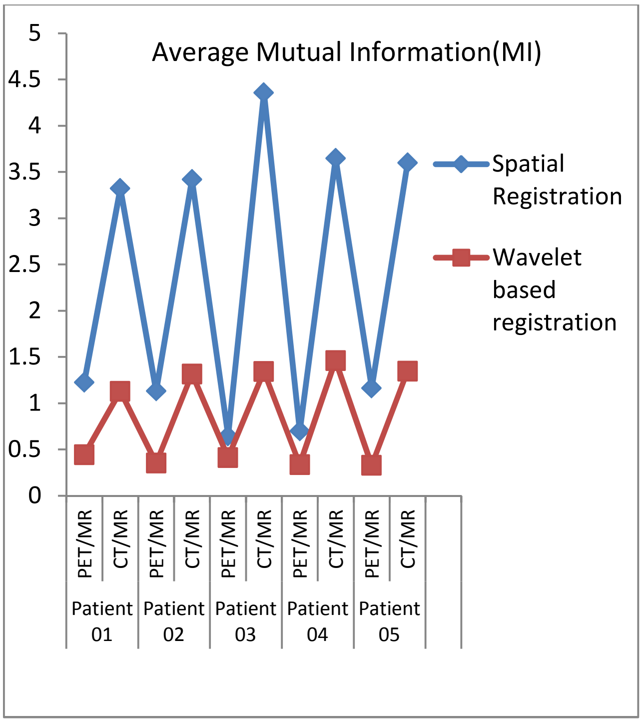

Chart 1: Average Mutual Information for the registration techniques

X. CONCLUSION

This research paper proposes a new algorithm where wavelet decomposition of images has been combined with Gaussian pyramid using Mutual information for registration of medical images .The performance of the registration has has been assessed using statistical parameter including cross correlation coefficients and average values of mutual information during registration of each patient data. The wavelet used in this study is db-2.

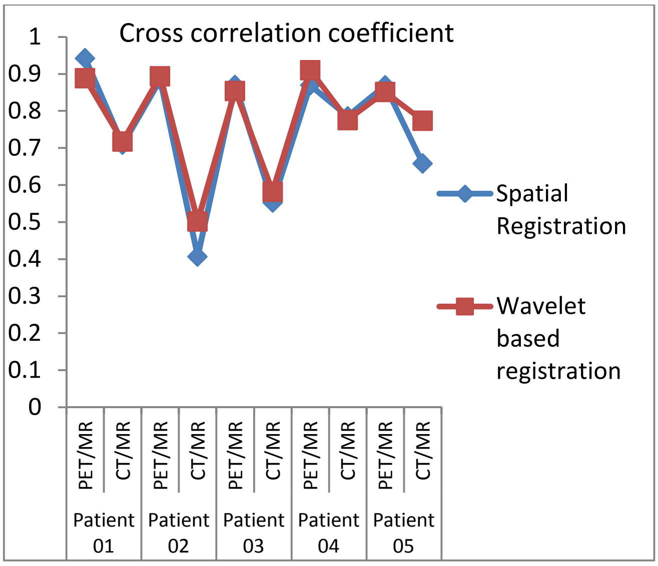

Chart 2: Average cross-correlation coefficient for the registration techniques

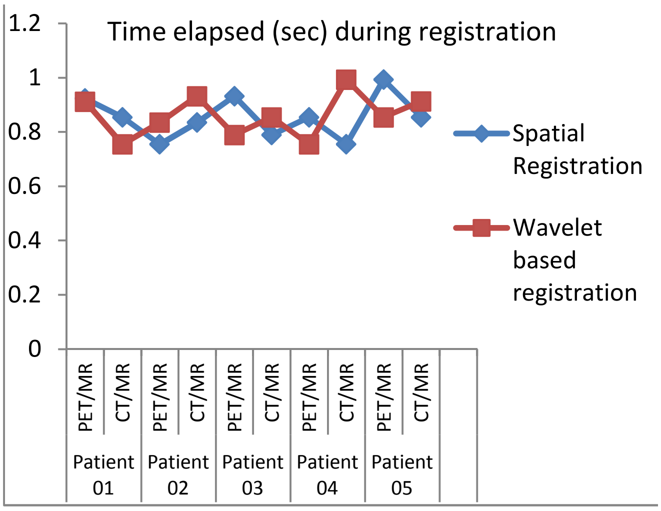

Chart 3: Time elapsed during registration techniques

In future work, other wavelets will be tested on the proposed technique to further our findings in the field of medical image registration.

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