An Efficient MRI Brain Image Registration and Wavelet Based Fusion

Vidhya K, Mala C Patil, Siddanagouda S Patil

Abstract: Over last few decades, 3D reconstruction of medical images becomes advance technique in medical image processing. Reconstruction of 2D images of such data sets into 3D volumes, via registration of 2D sections had become a most interesting topic. In current years, MRI has been used for many medical analysis applications. The proposed system considered MRI images are taken from the same view, different times or acquired by different imaging modalities to increase the information. T1, T2 and PD MRI are taken as an input; T2 image is registered with a reference of T1 image using affine transformation, the registered T2 image is fused with T1 using DWT. The Fused T1T2 image is taken as reference image to register PD image using B-Spline transformation. DT-CWT technique is used to fuse the T1T2 image with registered PD image. The performance of the system shows that the proposed system gives more information by fusing T1T2PD images.

Keywords : Affine Transformation, B-Spline Transformation, DWT (Discrete Wavelet Transformation), DT-CWT (Dual Tree-Continuous Wavelet Transformation), MRI (Magnetic Resonance Image), T1, T2 And Proton Density (PD) Image, MI (Mutual Information).

I. INTRODUCTION

Three dimensional [3D] image or model is generally used to describe about the shape of the object. The 3D modelling of an image plays a vital role in number of application area like entertainment, education, cultural heritage, medical industry, manufacturing and robotics. The image acquired from a single view cannot give the complete data about the object; therefore it is significant to construct the 3D image from the acquired 2D images [19]. The construction of 3D object required to register and integrate the set of 2D images which are taken in different viewpoints. However, the traditional MRI only give 2D images and cannot been used to create an explicit 3D model. Therefore 3D reconstruction of medical image using 2D MRI becomes an active research topic. It is a difficult task to reconstruction 3D MRI using 2D MRI with high accuracy from the MR images.

MRI is broadly used imaging modality but its main limitation remains the need for choosing, at the acquisition stage, a compromise between signal/contrast to noise ratio, resolution and scan time. There are different medical imaging system is used in medical field such as CT scanners, MRI, ultrasound etc, are widely used.

However, for detailed imaging of the MRI is a method used commonly. In an MRI scan, detailed information about the complex 3D anatomic structures is given as a 2D section of images. Illustration of 20 volumetric images in the form of 20 slices may result in loss of information and cause into erroneous interpolation of result.

Image registration is broadly used in medical filed for providing connection between images and efficient registration is also a one of the difficulty in this field. Registration computes spatial transformation that aligns two or more source to target image. Registration techniques is also defined as a matching the related features in the images. The images are taken from the identical view, different times to increase the information.

- T1 Image: T1 is time constant which calculates the rate at which excited protons return to equilibrium. T1 time is measured between the times taken for spinning protons to realign with applied external magnetic field. T1-weighted images are produced by using short TE and TR times.
- T2 Image**:** T2 is the time constant which measure the rate at which excited protons reach equilibrium. It is time taken for spinning protons to lose phase coherence among the nuclei spinning perpendicular to main field. T1-weighted images are produced by using short TE and TR times
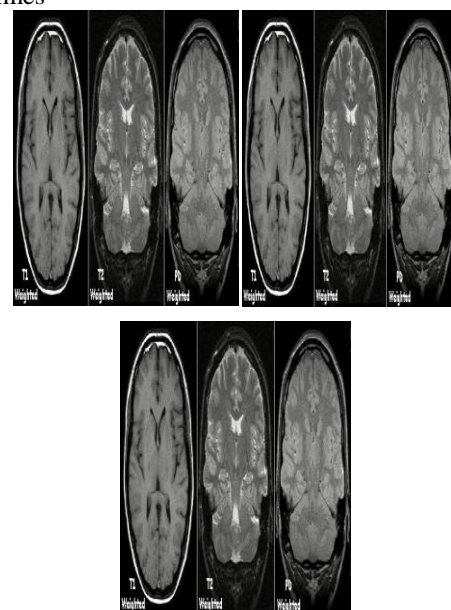

Figure 1: MR Brain Images

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● PD Image: When TR is very long and TE (time to echo) is very short, the MR signal is directly proportional to the un-weighted number of spinning protons present in the scanned volume. Images acquired with such a technique are minimally weighted by the relaxation times and are, therefore, termed PD weighted.

Typically registration methods are classified based on intensity, region and feature based. In intensity based system, determining the likeness between the images plays a vital role, which quantifies the connection of transformation among images. Intensity differences, CC and information theory are frequently used similarity measure. MI has owned better interest in registration field [20].

The complexity of the transformation depends on the application. The complexity of transformation is considered by parameters that present the degrees of freedom of the transformation. When the geometric connection among the two points is constant then the transformation can be rigid. Global gross overall distortion, scaling correction is done using affine transformation.

Techniques for registration: The images which are taken from the identical modality but obtained using altered parameters are considered for registration, such as registration of T1-MRI image with T2-MRI or PD MR Images. The classification of registration method is generally based on feature space image information. Some techniques use frequency domain or fourier transform for better registration. Amount of information is also one of the parameter considered to registration of an image. The complete voxel there in the Region of Interest (ROI) is used then it is classified as global. If only part of voxel is used in the ROI is used then it is classified as local. Feature based registration are local and intensity based methods are global.

Geometric Transformations (GT): GT is used when it is essential to the success of a registration and it is based on the information to be registered. Typically, the GT are divided two types, rigid and non-rigid. The rigid transformation includes of 6 parameters, 3 translational and 3 rational parameters are defined in 3D space. The non-rigid transformation consists of similarity transformation, affine, projective and curved.

Optimization: The resemblance calculation can be understood as an n-dimensional function; where n are the degrees of freedom. The aim of the optimization technique is to search for the maximum or minimum values of the similarity measured.

Typically, the similarity measure as a function is not smooth, it includes of many local extremes. In those local extremes some of these gives best solutions, but others are consequences of implantation, such as interpolation imperfections and decrease of robustness. The repeated optimization techniques are frequently used with a multi-resolution.

Interpolation: Generally in the registration of an image, when a point is mapped from one space into another space using a transformation, it is generally assigned a non-rigid location. Thus, it is required to evaluate the intensity value in the new mapped location. The aim of the interpolation is to guesstimate the intensity at the allocated new location. It affects the accuracy parameter and speed of registration. During optimization simple interpolation is used to amplify the speed, or linear interpolations is used [18]

Fusion image

Basically in medical image, multi-modality fusion is to combine the advantages of two or more images taken from different imaging devices for obtaining more rich and valuable information. The fusion of the image is done using efficient algorithm. In the medical field image taken from computed tomography (CT) image gives more information about bone tissue, but for the soft tissues it does not gives boundaries. To get data about the soft tissues MRI are used but tissues with dense bones or lungs includes gases; MRI is very poor in imaging. In MRI, radiological features various. In the T1-weighted MRI anatomic structures information is observed easily. Whereas T2 –weighted images are related to water. Fusion of medical image becomes hot topic in research of medical field for diagnosis and planning.

II.   LITERATURE SURVEY

Lianghao Han et.al [01] has proposed a hybrid image registration module to integrate non rigid, intensity and biomechanical techniques to coordinates both prone and supine breast MR images. Breast tissues material parameters and direction of the gravitational forces are estimated by using biomechanical model. Remaining deformation details are finding out by using non-rigid intensity based image registration. The performance of the designed module is estimated by using five breasts; in which overall system meet approximately $8.44 \pm \pm 5$mm registration rate for 45 fiducial markers.

Dongdong Yu et.al [02] has proposed a novel image registration technique, in which registration is done by using A-NSIFT and GMM algorithm to meet effective output on fast rotated images. Introduced A-NSIFT algorithm enhances the interest key point extraction procedure. Compare to conventional NSIFT, A –NSIFT is 200 time faster in interest point extraction. Further key point matching a probability density estimation Gaussian mixture model is used for alignment. From the experimental result it is concluded that the given module presents the faster 3D alignment even though there is poor initialization.

Hassan Rivaz et.al [03] has proposed unique medical registration module, in scanned MRI and Ultrasound images considered for the registration.   Integration of various medical images gives more biological information which can be used in diagnostics. But the most challenging thing is to integrate or fuse two different medical images. The referred paper propose an efficient algorithm to integrated both MR and ultrasound images. Robust PaTch-based cOrrelation Ratio (RaPTOR) used to register the 3D volumetric data of both ultrasound and MR data. The referred system proposed a decent approach towards the image registration module which speeds up the performance.

Zhang Li et.al [04] proposed an autocorrelation based image registration techniques, in which local structure of given input images are analysed in terms of local similarity structure.   Autocorrelation of LOcal STructure (ALOST) algorithm is planned to calculate the local structure in terms of standard deviation. The referred algorithm is less sensitive to the intensity distortions.

Due to the silent features of designed algorithm, the referred algorithm meets highest correlation.

Ghaffari A et.al [05] finding similarity between fixed image and moved image is tough in image registration. Varying in spatially intensity was always important and most challenging in image registration.

A similarity based image registration module in which correlation among the pixel is computed by Sum-of-Squared-Difference (SSD) is presented. Along with SSD the aid of the low rank matrix theory is applied. Application of the theory will compensate the intensity distortion which leads to the rank regularised SSD (RRSSD). The proposed architectures effectively perform intensity distortion correction and image registration at a time. Experimental result concluded that designed algorithm effectively meets the clinically acceptable image registration output.

Kasiri K et.al [06] has presented a multimodal registration by measuring a similarity of two images, by measuring the statistical similarity based on statistical dependency of the intensity values between images. When complex and spatially dependent intensity relation between images to be registered it is difficult to apply MI based registration. A new similarity measure on self-similarity using a patch based paradigm is proposed. Unlike other registration techniques, self-similarity registration make use of statistical dependency, the innovative measure is able to take the internal structural relationship into account. The system gives better alignment accuracy.

Su M et.al [07] has proposed a multimodal medical brain image registration using optical flow and Speeded-up Robust Features (SURF). Before applying the registration, histogram specification is used for transformation. Using SURF features points are extracted and preliminary registered image is obtained. Optical flow algorithm is applied to registered image to get the accurate result. The system is evaluated using multimodal brain image.

Shakir H et.al [08] has proposed an image registration using DWT followed by Gaussian pyramids. The dwt is applied to target and reference image, LL, LH, HL and HH sub-bands are used for the registration and also Gaussian pyramids also used for registration. The quality of the registered image is calculated using the maximum MI and CC values.

Lakshmanan A.G et.al [09] has proposed an intensity based image registration of medical image. AT used for registration, the proposed algorithm AT is tested over MR brain image and brain images with lesion and also test with the brain image with the brain images with various noise levels. The registered image helps in reduces the time for decision making in diagnosis and treatment.

The paper organization is as follows: section II explains Literature Survey, section III explains Methodology, section IV explains Experimental Results and section V explains Conclusion.

III. METHODOLOGY

Image registration is widely used in medical imaging to align between two images, and it is difficult to register two images. Registration computes a spatial transformation that aligns a source to a target image. Figure 2 shows the proposed system block diagram, T1; T2 and PD images are

taken as an input image. Affine transformation is used to register the T2 image by considering T1 as a source image. The registered T2 image is fused with T1 image to enhance the information. The PD image is registered using B-Spline transformation by considering fused image as source image. DT-CWT transformation is used to fuse the registered with T1T2 image.
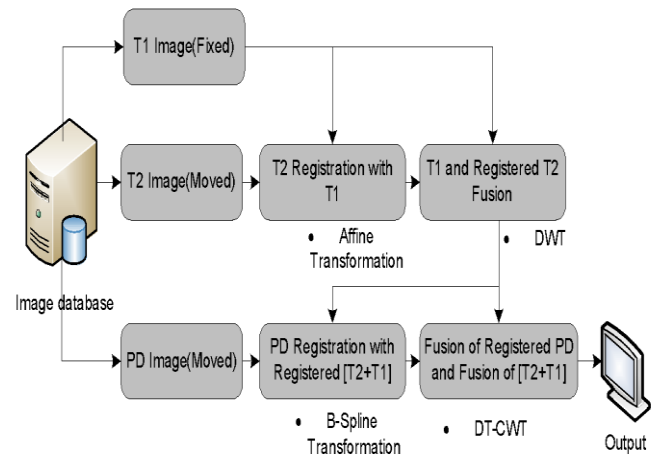

Figure 2: Proposed System Block Diagram

3.1 Input Image

MRI Input Brain Image: In medical field there are number of medical imaging types are used such as PET, MRI, Ultra sound and CT etc. MRI is frequently used medical image type in neurology and neurosurgery. MRI gives complete details about brain, spinal cord and vascular anatomy and it able to picture anatomy in all three planes axial, sigittal and coronal.

Over CT imaging, MRI has a benefit to find flowing blood and cryptic vascular malformations. MRI is also able to find demyelinating disease and beam hardening artefact can be seen in CT but not in MRI. Compare to CT, in MRI posterior fossa can be more clearly visualized. The input considered here is T1, T2 and PD images.

3.2 Image Registration

Registration of images is broadly used in medical field. Most of the image registration is done on MRI features to give more information to medical assessment. To register the T2 image by considering the T1 as a reference image

3.2.1 AT: AT is used for registration. T1 brain image is taken as a target to register the T2 image. To register the T2 image with T1 AT is applied. The parameters considered for registration are

- Similarity Metric: When T2 register with T1, the similarity between the images is considered.
- Transformations: The idea of transformation is to align the both the images and after aligned the images, the anatomical structures should match.
- Global Transformation (Affine): In the global method, all the pixels in the image undergo transformation, which results in fast and simple computation because of usage of less parameter. Rigid and AT is considered as global transformations.

An AT it is a group of number of several special mappings, such as the identity, a translation, a scaling, a rotation, a reflection and a shear. Figure 3 shows parameters considered in image registration.
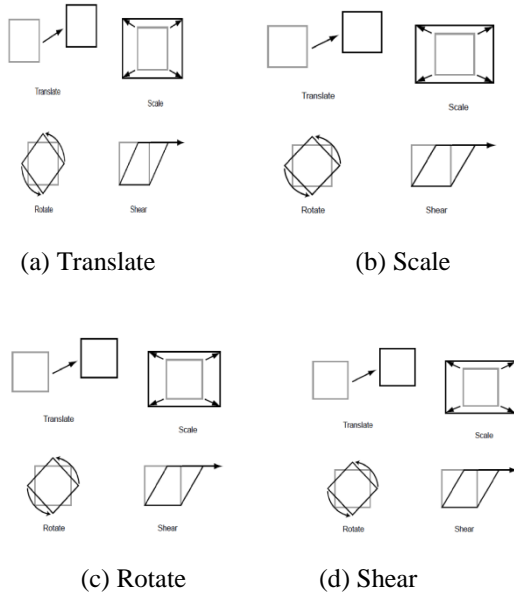

(a) Translate   (b) Scale

(c) Rotate   (d) Shear

Figure 3: Parameters Considered in Image Registration
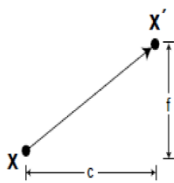
Consider a point $x = (x; y)$. AT of x are all transforms that can be written as given in Eq. (1)

$$x` = \begin{bmatrix} ax + by + c \\ dx + ey + f \end{bmatrix} \tag{1}$$

Where aa through ff are scalars. For example, if $a, e=1,$ and $b, d=0$, then we have a pure translation as given in Eq. (2)
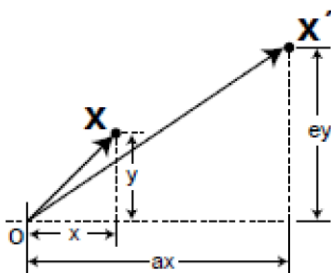
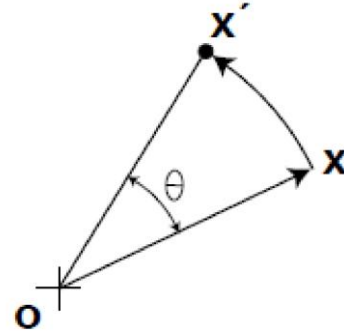$$x` = \begin{bmatrix} x + c \\ y + f \end{bmatrix} \tag{2}$$

If $bb, d = 0$ and $c, f = 0$ then we have a pure scale as given in Eq. (3)

$$x` = \begin{bmatrix} ax \\ ey \end{bmatrix} \tag{3}$$

If $aa,$ $e = \cos\theta$, $d = \sin\theta$, and c, f=0, then we have a pure rotation about the origin, given in Eq. (4)

$$x` = \begin{bmatrix} x\cos\theta - y\sin\theta \\ x\cos\theta + y\sin\theta \end{bmatrix} \tag{4}$$

Finally if $a, e=1`$ and $c, f=0$ we have the shear transforms given in Eq. (5)

$$x` = \begin{bmatrix} x + bx \\ y + dx \end{bmatrix} \tag{5}$$

Matrix Representation of linear transformation: The AT used to register the image can be represented in matrix and scale, rotate and shear are actually linear transforms, given in Eq. (6)

$$\begin{bmatrix} x` \\ y` \end{bmatrix} = \begin{bmatrix} ax + by \\ dx + ey \end{bmatrix} = \begin{bmatrix} a & b \\ d & e \end{bmatrix}\begin{bmatrix} x \\ y \end{bmatrix} \tag{6}$$

Or $x` = Mx,$ where MM is the matrix.

The benefit of using matrix representation is complex transformation into a set of easy and simple transforms. One example, when on object to scale to a new size, shear the object to new shape, and finally rotate the object. Where SS is the scale matrix, HH is the shear matrix, and RR is the rotation matrix in Eq. (7)

$$x` = R\big(H(Sx)\big) \tag{7}$$

Defines a sequence of three transforms, 1st step is scale, 2nd step is shear and 3rd

rotate. MM is a new matrix after, matrix multiplication with associative property given in Eq. (8).

$$x\hat{} = R(H(Sx)) \quad = Mx$$

(8)

Matrices are the best way to encapsulate a complex transform and to store it in a compact and convenient form. The Eq. (9) gives the linear transforms

$$Scale: \begin{bmatrix} s_x & 0 \\ 0 & s_y \end{bmatrix} Scale: \begin{bmatrix} s_x & 0 \\ 0 & s_y \end{bmatrix},$$

$$Rotate: \begin{bmatrix} \cos\theta & -\sin\theta \\ \sin\theta & \cos\theta \end{bmatrix}$$

$$Rotate: \begin{bmatrix} \cos\theta & -\sin\theta \\ \sin\theta & \cos\theta \end{bmatrix},$$

$$Shear: \begin{bmatrix} 1 & h_x \\ h_y & 1 \end{bmatrix} \tag{9}$$

$$Shear: \begin{bmatrix} 1 & h_x \\ h_y & 1 \end{bmatrix} \tag{9}$$

Where s_x s_x and s_y s_y scale coordinates xx and yy of point, $\theta\theta$ is an angle of counter clockwise rotation around origin, $h_x h_x$ is a horizontal shear factor and $h_y h_y$ is a vertical shear factor.

3.3 Fusion of registered T2 image with T1 image

The registered T2 is fused with the T1 image. The fused image conserve all the important data and that can be helpful for providing clinical diagnosis and surgical design. DWT is applied to both registered T2 image and input T1 image.

3.3.1 DWT

Wavelet transformation can gives a frame in which a signal is decomposed to different bands. Figure 4 represents the elements of a 1D, 2 channel perfect reconstruction filter bank. The input discrete sequence xx is convolved with high-pass and low-pass filters $aHaH$ and $aL,aL,$ and output is down sampled by two, yielding the transformed signals $xHxH$ and $xLxL$. The signal is reconstructed through up-sampling and convolution with high and low synethsis filters $sHsH$ and $sL.sL.$
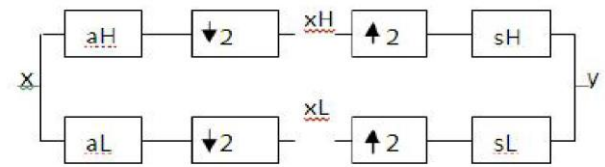

Fig 1. A two-channel perfect-reconstruction filter bank.
Figure 4: Reconstruction Filter Bank

Here we are using 1D dwt, when the dwt is used to perform on rows and columns of the data by filtering and down sampling. This results in one set of estimate coefficients and three sets of detail coefficients, which represent the horizontal, vertical and diagonal directions of image. The output is four sub-bands based on the frequency of the image, LL, LH, HL and HH. Figure 5 shows 1 level decomposition of an image $f(x,y)f(x,y)$ in to four sub-bands
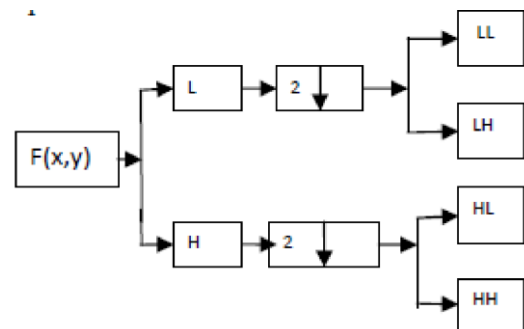

Figure 5: Image Decomposition

After the image decomposition, maximum fusion rule is applied to each bands of both T1 and T2 registered image. The maximum values from each sub-bands (LL, LH, HL and HH) of both image is considered and IDWT is applied to reconstruct the decomposed image.

Algorithm 1: DWT Fusion
Input: T1 and T2 registered images
Step 1. T2 image is registered with reference of T1 image to align corresponding pixels.
Step 2. The DWT is applied to both image, these images are decomposed. The transformed images consists of one low frequency and three high frequency components (LL, LH, HL and HH)
Step 3. The transform coefficients of two images are fused based on max rule fusion, both images max values of each band is considered.
Step 4. The fused image is constructed by performing an inverse wavelet transform
Output: fused image

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3.4 Registration of PD image with Fused T1T2 image

To register PD image, fused image of T1T2 image is considered as a reference image. B-Spline transformation technique is used to register PD image. Flow chart of registration of PD image with T1T2 image is as shown in Figure 6.

3.4.1 B-Spline Transformation: The fused T1 and T2 image is used as a reference to register PD image. B-spline transformation technique is adopted to register PD image. The registration is first starts by rigidly registering PD MRI to the fused T1 and T2 to get a good initial alignment.

3.4.2 After aligning the image, next is deformable image registration using similarity measures. The B-spline transformation it is based on using a grid of control points and the deformation vectors are computed using B-Spline interpolation from the deformation values of points located in the grid

- Similarity measures: MI, Mean Squared Differences (MSD) and Normalized Cross Correlation (NCC) are the parameters considered. For similarity measures definition, we use the following notations: μ is the transform parameters vector, a is the fixed image and b is the moving image
- Mutual information MI:

$$MI(\mu; a, b) = \sum_{m \in La} \sum_{f \in La} p(f, m; \mu) \, log_2 \left(\frac{p(f, m; \mu)}{p_a(f) p_b(m; \mu)} \right) \quad (10)$$

In Eq. (10), L_a and L_b are sets of regularly spaced intensity bin centres, P is the discrete joint probability. p_a and p_b are the marginal discrete probabilities of the fixed and moving image, got by adding m over f, respectively. The joint probabilities are estimated using B-spline Parzen windows.

- MSD

$$MSD(\mu; a, b) = \frac{a}{|\cap_a|} \sum_{x_i \in \cap_a} (a(x_i) - b(T_\mu(x_i)))^2 \quad (11)$$

In Eq. (11) $\cap_a$ the domain of the fixed image a, $|\cap_a|$ the number of voxels and T is a transformation.

- NCC:

$$NCC(\mu; a, b) = \frac{\sum_{x_i \in \cap_a} (a(x_i) - \bar{a})(b(T_\mu(x_i)) - \bar{b})}{\sqrt{\sum_{x_i \in \cap_a} (a(x_i) - \bar{a})^2 \sum_{x_i \in \cap_a} (b(T_\mu(x_i)) - \bar{b})^2}} \quad (12)$$

In Eq. (12), where $\bar{a}$ and $\bar{b}$ given in Eq. (13) and (14)

$$\bar{a} = \frac{1}{|\cap_a|} \sum x_i \in \cap_a \, a(x_i) \quad (13)$$

$$\bar{b} = \frac{1}{|\cap_a|} \sum x_i \in \cap_a \, b(T_\mu(x_i)) \quad (14)$$

3.5 Fusion of Registered PD image with fused T1T2 image

Using B-Spline transformation PD image is registered, the registered PD image is fused with T1T2 image using DT-CWT technique.

3.5.1 DT-CWT Fusion: DT-CWT considered for image fusion it contains higher directionality and shift invariance property. In the DT-CWT the given image is decomposed into sub-bands in such a way that two fully decimated trees, i,e tree-a and tree-b is formed. a tree-a and tree-b consist of real and imaginary part coefficients. The DT-CWT is used mainly to increase the directionality through the use of the complex extension of the DWT After decomposing the images, the fusion rule is applied to combine the corresponding wavelet coefficients which is defined in Eq. (15) and (16)

$$G_{HF}(a, b) = \max\left(G_1(a, b), G_2(a, b)\right) \quad (15)$$

$$G_{LF} = 0.5\left(G_1(a, b), G_2(a, b)\right) \quad (16)$$

Average selection Rule given in Eq. (17) and (18)

$$G_{HF}(a, b) = 0.5\left(G_1(a, b), G_2(a, b)\right) \quad (17)$$

$$G_{LF} = 0.5\left(G_1(a, b), G_2(a, b)\right) \quad (18)$$

Where $G_1(a, b)$ and $G_2(a, b)$ are the corresponding DTCWT coefficients. Finally DTCWT is applied for obtaining the final image [21].

DT-CWT can be represented by the rectangular matrix in Eq. (19)

$$F = \begin{bmatrix} F_h \\ F_g \end{bmatrix} \quad (19)$$

F_h and F_g represents real DWTs. Where the square matrices F_h and F_g represent real DWTs. The vectors $W_h = F_h X$ and $W_g = F_g X$ represent the real and imaginary parts of the DT-CWT, and the vector x represents a real signal. The complex coefficients are given by $W_h + jW_g$, The inverse of F is given by Eq. (20)

$$F^{-1} = \frac{1}{2}\left[F_h^{-1} F_g^{-1}\right] \quad (20)$$

IV. EXPERIMENTAL RESULT

The results and evolution of the proposed system is described in this section. MATLAB R2012a tool is used to evaluate the proposed system. Image registration is described as a aligning two or more images of the same view which are taken at different and/or acquired by different time. The main advantage of image registration and fusion, the registered and fused images gives more and valuable information.
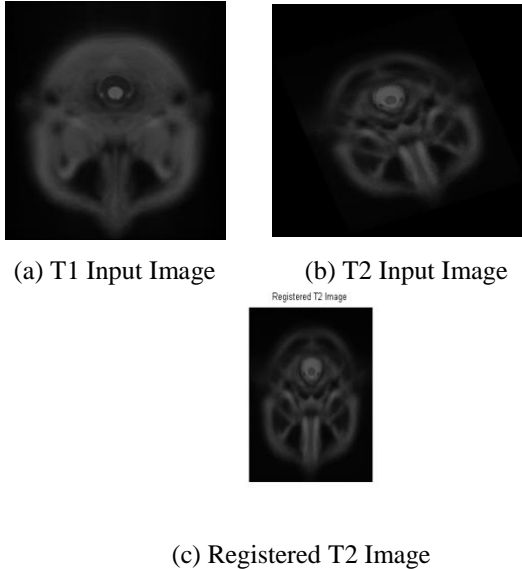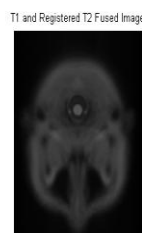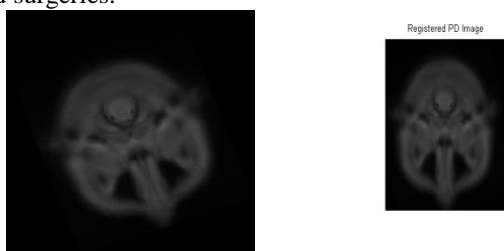

(a) T1 Input Image   (b) T2 Input Image

(c) Registered T2 Image

Figure 7: T1 and T2 Input Image and Registered T2 Image

Figure 7 shows the three different brain images as input image. The images considered here as a input are the same anatomical region of brain but the images are acquired with different time. T1 and T2 image show in the Figure 7(a) and (b) respectively. Figure 7 (c) shows the registered T2 image. To get the registered T2 image, T1 image is considered as reference image.

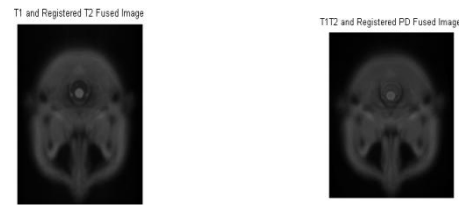(d) Registered T2 Image Fused with T1 Image

Figure 7 (d) shows the fused image, the registered T2 image is fused with the T1 input image. The fused image gives much information which is required for computer aided surgeries.

(e) PD Input Image   (f) Registered PD Image

Figure 7 (e) shows the input PD image. To register the PD image, the fused T1T2 image is considered as a reference image, the registered PD image is as shown in the Figure 7 (f).

(g) Registered T2   (h) Fused T1T2 Image
Image Fused with T1   Fused with Registered PD
Image   Image

Figure 7 (g) and (h) shows the fused T1T2 image and fused T1T2PD image. Registered T2 image is fused with T1 input image, the fused T1T2 image is fused with registered PD image. DWT technique is applied to fuse registered T2 image with T1 image. DT-CWT technique is used to fuse registered PD image with T1T2 image.

The DT-CWT technique is applied to registered PD image and also fused T1T2 image for fusion.

Entropy: Entropy defines the degree of useful data content in the fused image. It is the mediocre number of bits needed to quantize the pixel strength in the image and is given in Eq. (21)

$$Entropy = \sum_{g=0}^{N-1} X_g \log_2 X_g \qquad (21)$$

Where $X_g X_g$ is the ratio between the no number of pixels with gray values and total number of pixels, higher the entropy value gives high information in the fused image [21]. Table 1, 3 and 5 shows the entropy calculated values for set 1 image, set 2 image and comparison. Figure 11 shows the comparison of proposed entropy with other method

Table 1: Entropy Calculation for Set 1 Images

Images	Entropy
MRI T1 Image (3T1S.png)	5.755255
MRI T2 Image (3T2_20.png)	4.315452
MRI PD Image (3PD_20.png)	4.224435
Fused T1T2PD	5.168265

MI: MI represents the measures of dependency of the two input images. The input images are MA and MB. MI defined as given in Eq. (22) and (23). Table 2, 4 and 6 shows the MI calculated values for set 1, set 2 images and comparison of MI values. Figure (9) and (10) shows the MI of before and after registration value. Figure (12) shows the comparison of MI with other methods.

$$MI = N(M_A; M_F) + N(M_B; M_F) \qquad (22)$$

$$N(M_R; M_F) = \sum_{X=1}^{L} \sum_{Y=1}^{L} \frac{g_{R,F}(X,Y) \log}{g_R(X)}$$

Where g_R g_R, $g_F g_F$ are the normalized gray level histograms of $M_R M_R$ and $M_F M_F$ respectively. $g_{R,F} g_{R,F}$ is the joint gray level histogram of M_R M_R and M_F M_F and LL is the number of bins. M_R M_R and M_F M_F correspond to the reference and fused images respectively. $N(M_R; M_F)$ $N(M_R; M_F)$ Signifies how much information the fused image $M_F M_F$ conveys about the reference $M_R M_R$ [21]

Table 2: MI Calculation for set 1 Images

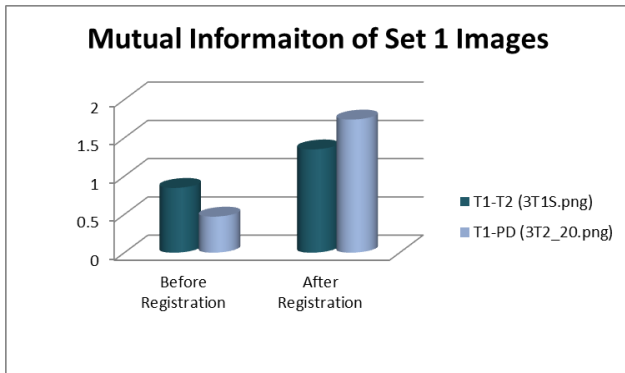| Images	MI (Before Registration)	MI (After Registration)
T1-T2 (3T1S.png)	0.8460	1.3488
T1-PD (3T2_20.png)	0.4707	1.7389

Figure 9: Mutual Information of Set 1 Images

Normalized Correlation Coefficient (NCC): The normalized correlation for two time series is given in Eq. (24) . Table 7 shows NCC calculated value compare with other methods and figure (13) shows the graph of comparison of NCC value.

$$\bar{\varphi}_{xy}(t) = \frac{\varphi_{xy}(t)}{\sqrt{\varphi_{xx}(0)\varphi_{yy}(0)}} \quad (24)$$

$$\bar{\varphi}_{xy}(t) = \frac{\varphi_{xy}(t)}{\sqrt{\varphi_{xx}(0)\varphi_{yy}(0)}} \quad (24)$$

The normalized quantity $\bar{\varphi}_{xy}(t)$ $\bar{\varphi}_{xy}(t)$ will vary between -1 and 1. A value of $\bar{\varphi}_{xy}(t) = 1 \bar{\varphi}_{xy}(t) = 1$ indicates that at the alignment tt, the two time series have the exact same shape while a value $\bar{\varphi}_{xy}(t) = -1$ $\bar{\varphi}_{xy}(t) = -1$ indicates that they have the same shape except that they have the opposite signs. A value of $\bar{\varphi}_{xy}(t) = 0 \bar{\varphi}_{xy}(t) = 0$ shows that they are completely uncorrelated

Table 5: Entropy comparison

Sl.No	Author	Methods	Entropy
1	B.Deepa et.al [13]	DWT (T1-T2)	1.09
2	Hongbing Ji et.al [14]	PCA(T1-T2)	1.00
3	Proposed System	DT-CWT(T1-T2-PD)	5.16
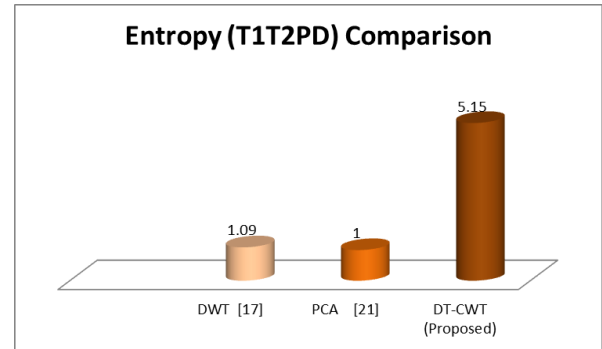
Figure 11: Entropy Comparison of Fused T1T2PD Image

Table 6: MI Comparison of Fused T1T2PD Image

Sl.No	Author	Methods	MI
1	Gaurav Bhatnagar et.al [15]	Wavelet(T1-T2)	1.02
2	B.Deepa et.al [14]	DWT(T1-T2)	1.54
3	Gaurav Bhatnagar et.al [16]	Contourlet(T1-T2)	1.32
4	Proposed System	DT-CWT(T1-T2-PD)	2.24
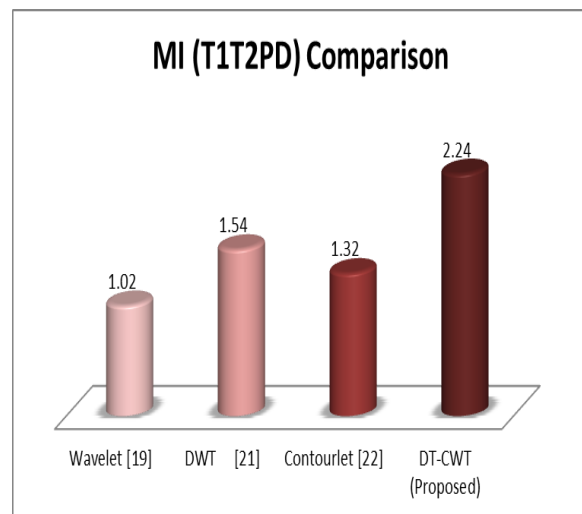
Figure 12: MI Comparison of Fused T1T2PD Image.

Table 7: NCC Comparison of Fused T1T2PD Image

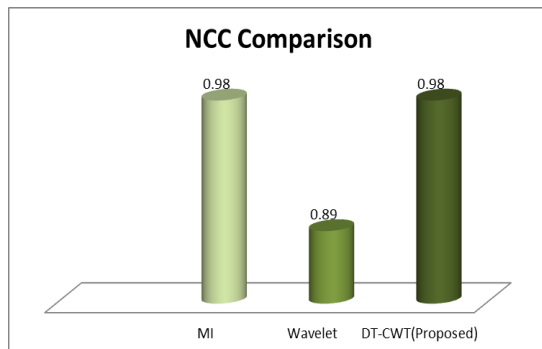| Sl.No	Author	Methods	NCC
1	Mengchao Su et.al [17]	MI	0.98
2	Hina Shakir et.al [18]	Wavelet	0.89
3	Proposed System	DT-CWT	0.98

Figure 13: NCC Comparison of Fused T1T2PD Image.

V. CONCLUSION

Over the last years registration and fusion MRI brain image become a vital topic in medical image processing, it helps in computer assisted diagnosis and computer aided surgery. The proposed system considered the MRI brain images for Registration. T2 images are registered with reference of T1 image using affine transformation and the registered T2 image is fused with T1 using DWT. Fused T1T2 used as a reference image for PD registration using B-Spline transformation and fused with T1T2 using DT-CWT. The performance of the system is evaluated using Entropy, NCC and MI. The proposed system gives the better information than the traditional system.

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