Comparative study of DWT and DTCWT for 3D Medical Image Registration

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Abstract:

Image Registration is one of the most important step in medical diagnosis and treatment planning, an accurate and efficient alignment of images is needed to improvise the planning process. Medical image registration is the area of active research. Many algorithms have already been proposed and implemented in various domain, wavelet transform is found as one of them that has been proved very simple and effective, which is a multiresolution analysis of an image using a set of analyzing functions that are dilations and translations functions. Discrete Wavelet Transform (DWT) and Dual Tree Complex Wavelet Transform (DTCWT) are most popular techniques for medical image registration. DTCWT has been found better than DWT due to its properties like shift invariance, less aliasing and better directionality than DWT. These properties play an important role in medical image registration. To gain some improvements in image registration process, DWT is replaced by Dual tree complex wavelet transform. Experimental results are presented to illustrate the comparison of DWT and DTCWT to a set of medical images.

Keywords—***Medical* image Registration, DWT, DTCWT, MI**

I. INTRODUCTION

The goal of medical image registration is to find transformation that maps to input image to reference image by optimizing certain criteria. It is a vital step in medical image processing or computer based diagnosis. For medical diagnosis, Computed Tomography (CT) provides the best information on denser tissue with less distortion. Magnetic Resonance Image (MRI) provides better information on soft tissue with more distortion. In this case, only one kind of image may not be sufficient to provide accurate clinical requirements for the physicians. Therefore, the registering the multimodal medical images result in accurate treatment or diagnosis.

In feature based image registration, features such as regions, edges and points are sensed from the input image and compared with the features in reference image[1]. A transformation is carried out so as to minimize the distance between these features. Maximally Stable External Regions (MSER)[2], Features from Accelerated Segment (FAST)[3], SURF[4]has been estimated considering correspondence between image pairs. In area based registration, cross-correlation (CC) [9] and mutual information (MI)[5] methods are used for registration without extracting features. Similarities are measured by computing displacement vectors, sum of absolute differences and normalized cross correlation. Techniques such as Parzenwindows[13], joint probability histogram and Marquardt-Levenberg[12] optimizer are used in MI based image registration. Huizhong Chen [11] and Nick Kingsbury [6] have used Dual Tree Complex Wavelet Transform (DTCWT) coefficients to align images by considering phase information of coefficients. The DTCWT front-end filter is shift invariance and directional selective and hence the registration algorithm is robust to local mean and contrast changes in images to be registered.

Main challenge for the researchers was to preserve details of image for accurate registration as there are some problems with Discrete wavelet transform like it produces artifacts and lack of directional sensitivity due to which image registration is done at the cost of complications in preservation of features of image like edges, ridges and boundaries. Complex wavelet transform was thought of as a

solution of such problems but CWT uses complex filtering approach to decompose a signal into real and imaginary parts in wavelet domain. Hence CWT could not find much useful in image processing domain. In wavelet domain approach, Dual tree complex wavelet [6] transform has been devised and observed to provide shift invariance and still produces perfect reconstructed signal.

Experimental results of medical image registration have proved that DTCWT has better performance, details preservation and low computation complexity than DWT. The rest of paper is organized as follows: Section 2 gives the basic concepts of Wavelet transform and its types. In Section 3, methodology adopted for medical image registration using DWT and DTCWT is explained in detail. Section 4 presents the results registration of brain images MRI and CT images and finally, Section 5 draws the conclusion.

II. WAVELET TRANSFORM

Wavelet transform is a technique by which a signal can be decomposed into set of basis functions called wavelets[7]. Prior to wavelet transform, Fourier transform were used. But Fourier transform can onlyretrieve the frequency content of a signal and consequently time information of the same gets lost. Wavelet transform retrieves both time domain and frequency domain information of the signal. The wavelet transform can be represented mathematically as follows:

$W_k^j = \int f(x)\Psi\left(\frac{x}{2^j} - k\right) dx$(1) where ψis called the mother wavelet which is a transforming function and the signal which is to be transformed is given by f(x), j is scale of decomposition and k is the translation parameter. Wavelet transform can be broadly classified as:

a) Continuous wavelet transform (CWT)
b) Discrete Wavelet Transform (DWT)
c) Complex Wavelet Transform (CWT)

Continuous wavelet transform (CWT): It is similar to Fourier transform, in which convolution between signals and analyzing function is done to find the similarity between them. The difference between both lies in different analyzing function for them. In Fourier transform the analyzing function are complex exponential,whereas in CWT the analyzing function is wavelet Ψ.

Discrete Wavelet Transform (DWT): Discrete wavelet transform is multiresolution in nature which has made it popular in image compression application etc., where scalability and tolerable degradation are important. DWT transforms a discrete time signal to a discrete wavelet representation by using filter banks. To calculate DWT of the signal, the signal is passed through a chain of two complementary filters known as quadrature mirror filter as they are essential to be related with each other. First the signal s(n) is passed through low pass filter with impulse response g(n) leading to emergence of approximation coefficients The convolution can be expressed mathematically as:

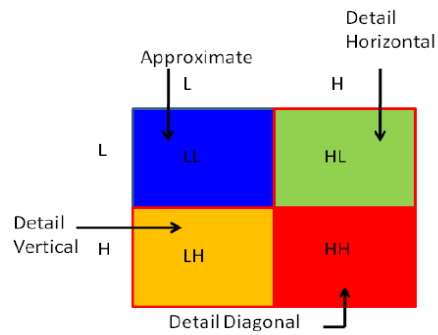


Figure 1: Decomposition Levels

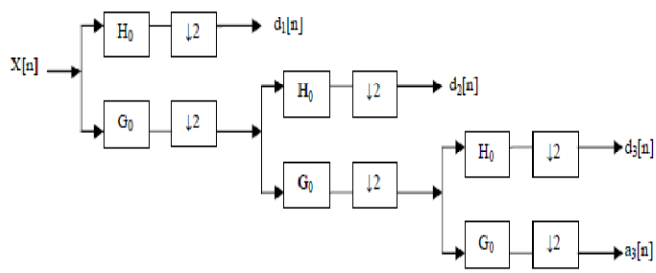


Figure 2: Levels of Decomposition.

d(n) = (s∗ g)[n] = $\sum_{k=-\infty}^{\infty} s[k]g[n-k]$(2)

Wheredn) is the output signal after the application of g(n) filter coefficients on the input signal x(n). The above mentioned mechanism has been shown in fig. 2 where the same signal x[n] is simultaneously fed to low pass filter g(n) and high pass filter h(n) whose output are approximation coefficients d detail coefficients and y respectively.

$d_{low} = \sum_{k=-\infty}^{\infty} x[k]g[2n-k]$

$d_{high} = \sum_{k=-\infty}^{\infty} x[k]h[2n+1-k]$(3)

After the decomposition and down sampling approximation and detail coefficients are obtained, All the components are assembled back to reconstruct original signal such that no loss of information must take place. DWT for an Image: Image is a two dimensional signal the high frequency and low frequency sub images form an image can be obtained

by therefore DWT by applying 1D DWT along the rows of an image signal first followed by applying on the columns of the image, the high frequency sub images comprise image's edge features information and detail information which can be further decomposed into N levels to get 3N+1 different frequency bands i.e. LL,LH,HL and HH bands, which is shown in fig. 1. 1- Decomposition levels, H- High frequency bands, L- Low frequency bands. All subbands contain different features of an image such as LL Band provides approximation coefficients, LH contains horizontal details, HL band provides vertical details and HH band contains the diagonal details of an image at a specific level of decomposition.

3D –DWT : A 3-D wavelet decomposes a 3-D image set into a number of slices based on the X, Y and Z direction. Each slice contains the various frequency bands. A separable 3-D wavelet transform can be computed by extending the 1-D pyramidal algorithm[14]-[17]. The decomposed or disintegrated image slice provides an excellent representation for further quantization and coding. The scaled and translated basis elements of the 3-D wavelet transform are given by Eq (4)Themultiresolution representation of scaling and wavelet functions for the 3-D given below:

$\phi^{j}_{,,l}(x, y, z) = 2^{j/2}\phi(2^{j}x - m, 2^{j}y - n, 2^{j}z\text{-}l)$

$\psi^{i}_{j,,,l}(x, y, z) = 2^{j/2}\psi(2^{j}x - m, 2^{j}y - n, 2^{j}z\text{-}l)$(4)

wherei = { H,V,D} where the super scripts H, V, and D refer to the decomposition direction of the wavelet.

$LLL = \phi\ (x, y, z) = \phi(x)\ \phi(y)\ \phi(z)$

$LLH = \psi\ 1\ x, y, z = (\ )\phi(y)\ \psi(z)$

$LHL = \psi\ 2\ x, y, z = (x)\ (y)\ \phi(z)$

$LHH = \psi\ 3\ x, y, z = (x)\ (y)\ \psi(z)$

$HLL = \psi\ 4\ x, y, z = (x)\ (y)\ \phi(z)$

$HLH = \psi\ 5\ x, y, z = (x)\ (y)\ \psi(z)$

$HHL = \psi\ 6\ x, y, z = (x)\ (y)\ \phi(z)$

$HHH = \psi\ 7\ x, y, z = (x)\ (y)\ \psi(z)$

The discrete wavelet transform function f(x, y,z) of size M x N x L is given below in the Eq. (6) and (7):

1. Scaling function of the wavelet representation is shown as

$$W_{\phi}(m, n, l\ \ ) = \frac{1}{\sqrt{MNL}}\sum_{x=0}^{M-1}\sum_{y=0}^{N-1}\sum_{z=0}^{L-1} f(x, y, z)\phi_{j0,m,n,l}\ \ (x, y, z) \quad (6)$$

The corresponding wavelet function of the horizontal, vertical and diagonal representation of the images are as follows:

$$W^{i}_{\psi}(j, m, n, l\ \ ) = \frac{1}{\sqrt{MNL}}\sum_{x=0}^{M-1}\sum_{y=0}^{N-1}\sum_{z=0}^{L-1} f(x, y, z)\ \psi^{i}_{j,m,n,l}\ (x, y, z) \quad (7)$$

where i = H,V,D From the above mentioned scaling and wavelet functions, namely, W_{ϕ} and W_{ψ} , one can easily acquire through the inverse discrete wavelet transform as in Eq (8)

$$f(x, y, z) = \frac{1}{\sqrt{MNL}}\sum_{m}\sum_{n}\sum_{l} W_{\phi}\ (j_0, m, n, l)\phi_{j0,m,n,l}(x, y, z) f(x, y, z) = \frac{1}{\sqrt{MNL}}\sum_{i=H,V,D}\sum_{j=j0}^{\infty}\sum_{m}\sum_{n}\sum_{l} W^{i}{}_{\psi}\ (j, m, n, l)\psi^{i}_{j,m,n,l}(x, y, z) \quad (8)$$

Complex Wavelet Transform: There are some disadvantages of ordinary wavelet transform like

1) Down sampling operation at each level in wavelet transform leads to Lack of shift invariance due to which a high variation in amplitude of wavelet coefficients occurs because of a slight change in input signal.

2) Lack of directional selectivity, which occurs due to incapability of DWT to distinguish between the opposing diagonal directions.

3) Absence of phase information, which is the incapability of DWT to provide the local phase information when there is complex valued signal whose phase can be found from its real and imaginary projections and DWT uses separable filtering with real coefficient filters that gives real valued detail and approximation coefficients.

If complex wavelet filters are used then good directionality approximate up to six directions and improved shift variance can be achieved. Such improved form of DWT is called Complex wavelet transform (CWT) which is used to generate complex wavelet coefficients but complex wavelet transform has not been used much in image processing because complex filters were not easy to design.

Kingsbury [6] put forward a new implementation of complex wavelets known as Dual tree complex wavelet transform (DTCWT) which has been proved more efficient than DWT and also overcome the difficulty of designing complex filters. DTCWT is found to produce all the effects of complex coefficients without the use of complex filters. Two separate DWT decompositions are used in DTCWT using two filter banks to calculate the complex transform of a signal. If care is taken while designing the filters such that the filters used in one decomposition stage are related with those in other one then it is possible to produce both real and complex coefficients. For an N point signal this transform produces 2N DWT coefficients which make it two times expansive. DTCWT has proven better than DWT in preserving details of an image and giving phase information which plays important role in clinical diagnosis applications.

DTCWT are based complex wavelet coefficients that supports near shift-invariance and directional selectivity property in multi-dimensions which use Hilbert pair of real DWT filters to compute real and imaginary coefficients. 3D DTCWT is performed by three separable filters of rows, columns and slices on 3D data sets. The bandwidths of complex wavelets are one octave wide and detection of edges and surfaces

becomes simpler due to localization in space and trade-off between linear phase and displacement characteristics. In 3D DTCWT two trees of filtering in each dimension produces octal-tree system, with each sub band in the octal-tree system comprising of 8 real coefficients. The 8 sub bands (LLL, LLH, LHL, LHH, HLL, HLH, HHL and HHH) yield 4 directional sub bands of complex coefficients by performing arithmetic sum and difference operations. The LLL sub band is considered for next level of decomposition and hence at each level of DTCWT 28 directional sub bands are produced along with LLL sub band. The 3D DTCWT sub band can be mathematically represented as in Eq. (4),

$$\begin{aligned}\psi_1(x,y,z) &= [\psi_a(x)+j\psi_b(x)][\psi_a(y)+j\psi_b(y)][\psi_a(z)\\ &\quad + j\psi_b(z)]\\ &= [\psi_a(x)\psi_a(y)\psi_a(z) - \psi_b(x)\psi_b(y)\psi_a(z)\\ &\quad - \psi_a(x)\psi_b(y)\psi_b(z) - \psi_b(x)\psi_a(y)\psi_b(z)]\\ &\quad + j[\psi_a(x)\psi_a(y)\psi_b(z) - \psi_b(x)\psi_b(y)\psi_b(z)\\ &\quad + \psi_a(x)\psi_b(y)\psi_a(z) + \psi_b(x)\psi_a(y)\psi_a(z)]\end{aligned} \tag{4}$$

$$\psi_2(x,y,z) = [\psi_a(x)-j\psi_b(x)][\psi_a(y)+j\psi_b(y)][\psi_a(z) + j\psi_b(z)]$$

$$\psi_3(x,y,z) = [\psi_a(x)+j\psi_b(x)][\psi_a(y)-j\psi_b(y)][\psi_a(z) + j\psi_b(z)]$$

$$\psi_4(x,y,z) = [\psi_a(x)-j\psi_b(x)][\psi_a(y)-j\psi_b(y)][\psi_a(z) + j\psi_b(z)] \quad 5)$$

$\psi_a(i)$ and $\psi_b(i)$, I = (x,y,z) represents wavelet filters, subscripts a and b represents real and imaginary filters that are applied in all three directions of row, column and slices. The filters in all other three quadrants are represented as in Eq. (5).

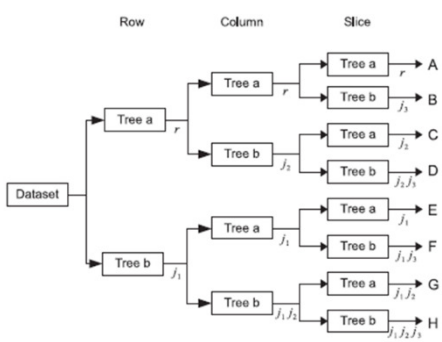


Figure 3: 3D DTCWT tree structure

Fig. 3 illustrates the octal tree structure for computing 3D DTCWT of one band. The row, column and slice filter comprises of low pass and high pass filtering with real and imaginary filter coefficients

III. PROPOSED ALGORITHM

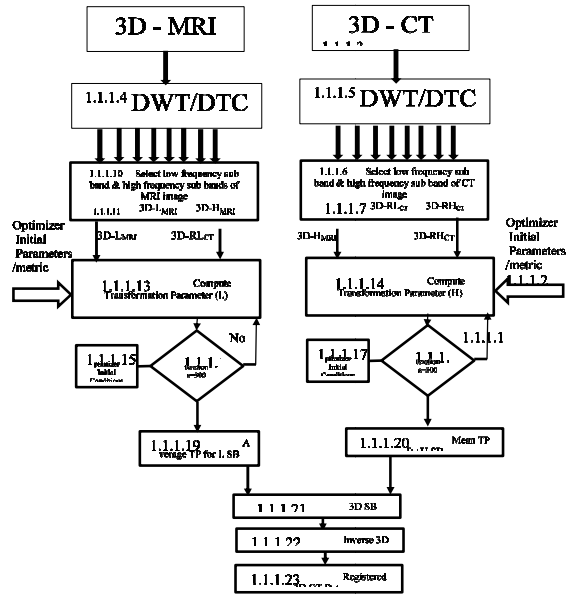


Figure 5: Proposed algorithm

In the proposed image registration algorithm, the two unregistered images MRI and CT are first decomposed into wavelet sub bands by considering discrete wavelet transform/ dual tree complex wavelet filter of 10-tap coefficients. The eight octave bands are processed to carry out image registration. Figure 5 illustrates the proposed image registration process for one octave DTCWT sub bands. DTCWT decomposition comprises of 64 sub bands of which one low pass band (3DLMRI) and 7 high pass bands (3DHCT) are considered for registration. The Low Sub Band (L SB) and High Sub Band (HSB) denoted by {RL_{MRI}, RH_{MRI}, RL_{CT}, RH_{CT}}. The function "imregtform" is invoked in MATLAB with input parameters {$3DL_{MRI}$, RL_{MRI}, $3DL_{CT}$, RL_{CT} and transformation type} to compute the optimum transformation {TPL or TPH}. MMI metric and optimizer are set with optimizer parameters {initial radius, epsilon, growth factor and maximum iterations}. The function processes the 3D DTCWT sub band and estimates the optimum transformation parameters. For each octave comprising of eight sub bands one TPL for low pass band and seven TPH for high pass bands are obtained. As there are eight octaves in DTCWT decomposition, the average of all eight TPL is computed and the mean value of all 56 TPH is computed. The eight sub bands {$3DL_{CT1}$,

$3DL_{CT2}$, $3DL_{CT3}$, $3DL_{CT4}$, $3DL_{CT5}$, $3DL_{CT6}$, $3DL_{CT7}$, $3DL_{CT8}$} and 56 sub bands {$3DH_{CT1}$, $3DH_{CT2}$, ……., $3DH_{CT56}$} are transformed by considering TPL_{AVG} and TPH_{MEAN} by invoking "imwarp" MATLAB function to obtain the 64 sub bands that are transformed by considering MRI data as reference. The 64 sub bands are organized and inverse DTCWT is computed to obtain the registered CT 3D image. The registered 3D CT image and the reference MRI 3D image are compared to evaluate the performance of the proposed algorithm.

IV. Results & Discussion

The proposed algorithm is modeled in MATLAB by considering the inbuilt functions for performing optimization and transformation. For validation of proposed algorithm 3D data sets of 20 patients are considered from more than 100 test images. All data sets consists of both CT and MRI images with each image of size 512 x 512 and with maximum of 52 frames. The pixel size of each frame is 0.45 units for CT image and 0.86 units for MRI image on both x and y directions, with 16-bit signed number representation. Visual presentation of registered images both in wavelet domain and time domain are presented for analysis. Figure 6 presents the registration results of CT and MRI data of frame 1 in wavelet domain by considering the low pass bands. The objects in CT and MRI are aligned after registration and are clearly observed with color changes in the images.

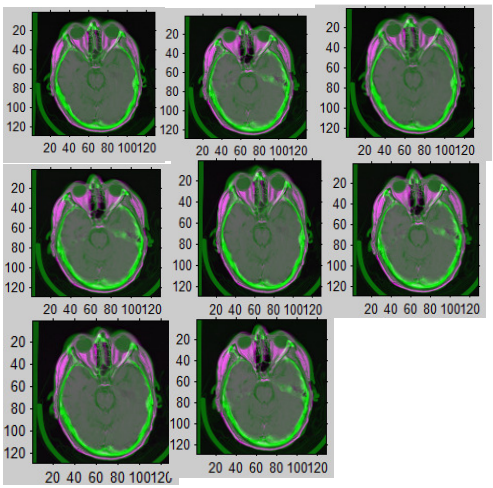
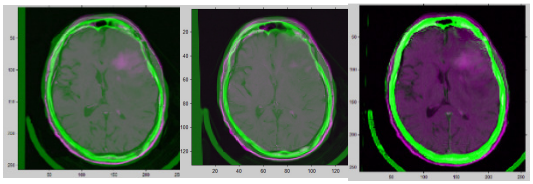


Figure 6. Low pass bands registration results

Figure 7 presents the results of image registration in time domain. The input images are registered using intensity based technique, DWT and DTCWT based registration algorithm. Figure 7(c) presents the results of DTCWT based registration technique, the intensity perception is of very good clarity as compared with the results of intensity and DWT based techniques.



(a) (b)(c)

Figure 7. Registration Results (a) Intensity(b) With DWT (c) With DTCWT

Frame	Data Sets	Mutual Information (Intensity)	Mutual Information (DWT)	Mutual Information (DTCWT)
Frame 1	CT-MRI	-0.5426	-0.5428	-0.5052
Frame 4	CT-MRI	-0.5990	-0.5990	-0.5909
Frame 20	CT-MRI	0.328	0.328	0.4128
Frame 32	CT-MRI	-0.6158	-0.6157	-0.6057

Table 1. Comparison of DWT and DTCWT based on MI

From the results presented in the Table 1, the registered images mutual information using DWT and DTCWT found improvement thus indicating that the registered image contains information from both the input images after registration. In order to further improve registration results, the low sub bands can be decomposed into higher levels by computing level 2 and level 3 decomposition and selecting features from pyramids of DTCWT sub bands.

V. Conclusion

Improved MI are found with the use of DTCWT when compared to that of ordinary DWT. This improvement is due to nearshift invariance and good directionality of wavelet coefficient using DTCWT which can be thought as an efficient method and will be very useful in medical image registration.

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