

NON-SEPARABLE COMPLEX WAVELET TRANSFORM BASED IMAGE SEGMENTATION FOR CLASSIFICATION OF MR IMAGES IN ALZHEIMER'S DISEASE

Chiranjit Das

cdas@bridgeport.edu

Zeinab Al obaidi

zalobaid@bridgeport.edu

Prof. Navarun Gupta (Advisor)

navarung@bridgeport.edu

University of Bridgeport-School of Engineering

221 University Ave, Bridgeport-CT-06604

Abstract: Image based analysis methods play important role in biomedical images. One of the biomedical imaging applications is Alzheimer's disease classification. The proposed paper talks about the feature extraction of the MR Images in Alzheimer's disease. Here we introduce the concept of Non-Separable Wavelet Transform which can be used as an image segmentation technique. We use the Q-shift 10 length filter bank combination which reveals more information in the low frequency signals, thus segmenting the image to highlight the portion of concern. Then we use the area technique to classify the image. Finally, a GUI is used to show the results based on the proposed method.

Keywords: - MR Images, DWT, 2DT-CWT, Alzheimer's disease, Segmented Image.

Introduction:

Diagnosing patients affected by Alzheimer's disease at an early stage plays a crucial role in treating the condition at a faster rate. Definitive diagnosis is possible only after the condition is severe. Many different methods have been suggested using supervised and unsupervised classification techniques [1]. Our method moves away from those techniques and introduces an innovative new idea of utilizing the information present in the image signal itself. Here we introduce the concept of wavelet transform to reveal the information present at low frequency. This way we can segment the image which in turn helps us to classify the image.

We take the help of Complex Wavelet Transform to reveal the information in the low frequency and also in turn help us to maintain the analytic conditions of the Fourier Transform.

Non-Separable Complex Wavelet Transform (DT CWT)

The idea is to use two Real DWTs and pair them up in a way that they function as analytically satisfying complex wavelet transform[2][5]. The DT CWT uses two different sets of filters for the two trees as shown in the diagram (fig.1) so as to satisfy the condition of ‘Perfect Reconstruction’[5]. They are jointly designed to be approximately analytic. There is no data flow between the two trees in general. In the two Real DWT’s the Parseval’s Relationship is satisfied where the energy of the input signal is equal to the energy in the wavelet domain.

The following idea requires the design of new filters satisfying the Hilbert transform pair.

Here the filters are themselves real and satisfy the following Hilbert condition as –

$$\psi_h(t) := \psi_h(t) + j\psi_g(t)$$

The filters are related in the analytic condition as $\psi_g(t) \approx H[(\psi_h(t))]$ [3].

The Filter Relationship condition –

As per as the well-developed relationship between the low pass filter and the high pass filter the low pass filter transfer function is of the form –

$$H_0(z) = (1+z)^k Q(z) : \text{For some } Q(z)$$

Here both the real wavelets in question are orthonormal to each other and on its’ own form an orthonormal set[4][5].

Since the Hilbert Pair transform is dependent fully on the scaling function and the wavelet function and the two functions are fully dependent on the filters to be designed in question then it is important to relate the filters in such a way for the analytic condition to be satisfied. The perfect reconstruction condition satisfies the requirement of analyticity.

We hereby go with the half sample delay condition. The simplest of the statement where one the filters in the lower branch is the half sample shift of the other filter in the other branch.

Hence the following relationship is –

$$g_0(n) \approx h_0(n - 0.5)$$

The Fourier Transform of the above stated equation is –

$$G_0(e^{j\omega}) = e^{-j0.5\omega} H_0(e^{j\omega})$$

Using the Fourier Transform of the above equation in question we try to prove the necessary and sufficient conditions. The half sample condition is considered because it leads to aliasing cancellation and results in nearly shift invariant wavelets. The half sample condition oversamples the low pass signal at each scale by 2:1 thus avoids the aliasing due to low pass down samplers.

The magnitude and the phase relationship are as follows –

$$|G_0(e^{j\omega})| = |H_0(e^{j\omega})| : \text{Magnitude Relationship}$$

$$\angle G_0(e^{j\omega}) = \angle H_0(e^{j\omega}) - 0.5\omega : \text{Phase Relationship..... (1)}$$

In reality, if the filters are to be of exact relationship then this will result in infinitely long filter $h_0(n)$. So we approximate the delay condition leading to $\psi_c(t)$ be approximately analytic.

Design of the Dual Tree Complex Wavelet Filters –

q – shift solution –

$$g_0(n) = h_0(N - 1 - n)$$

Here N is even length filter and hence the time reversal condition is satisfied. Here magnitude part is satisfied and we have to design filters such that it satisfies the phase relationship.

$$|G_0(e^{j\omega})| = |H_0(e^{j\omega})|,$$

$$\angle G_0(e^{j\omega}) \neq \angle H_0(e^{j\omega}) - 0.5$$

After the representation as above we get:

$$\angle G_0(e^{j\omega}) = -\angle H_0(e^{j\omega}) - (N - 1)\omega$$

Using equation (1) we get the following relationship –

$$\angle H_0(e^{j\omega}) \approx -0.5(N - 1)\omega + 0.25\omega$$

True orthonormal solutions are possible and the filters exhibit approximate analytic condition[6].

The q – shift condition satisfies the PR condition and as well as the linear phase condition.

2-D Dual Tree Complex Wavelet Transform

In 2-D signals we know that the DWT does not effectively reveal the singularities (curves and lines). The separable 2-D DWT is used to be implemented in an effective way and is characterized by three wavelets[2].

Since the wavelet function is a real function hence not able to distinguish between the +45 degrees and -45 degrees and leads to confusion in spatial domain as shown in (figure.2).

Moving towards 2D-Dual Tree CWT

Here we derive the oriented wavelets as using the check-board pattern as explained earlier. This method implements the row-column technique and derives the real part and the imaginary part non-separately and hence we have it set up only on one side of the check-board box. We can obtain the summed version of two real parts and imaginary parts separately.

$$\psi_1(x, y) = \phi(x)\phi(y) = [\phi_h(x) + j\phi_g(x)][\psi_h(y) + j\psi_g(y)]$$

$$\psi_2(x, y) = \psi(x)\phi(y) = [\psi_h(x) + j\psi_g(x)][\phi_h(y) + j\phi_g(y)]$$

$$\psi_3(x, y) = \psi(x)\psi(y) = [\psi_h(x) + j\psi_g(x)][\psi_h(y) + \psi_g(y)]$$

The summed real part has values in the two quadrants and is expectedly symmetric.

Translation invariance can be achieved by using the parallel filter bank as in effect using the dual-tree complex wavelet transform where the addition of a filter bank with shifted analysis filters $z^{-1}G_{0a}(z)$, $z^{-1}G_{1a}(z)$ and synthesis filters $zG_{0b}(z)$, $zG_{1b}(z)$ results in the term $X(-z)$ to be taken care of.

The computation of the images using DT-CWT is done by applying the transform to the columns first and then to the rows. The resulting image is a pyramid of sub-images and hence we obtain the directional sub-images which are horizontal, vertical and diagonal as shown in (figure.3).

Method or Steps for GUI

We implemented the technique using Matlab GUI to have a better organization and to show the steps that has been done to obtain the final results as graphical user interface, also creating the program using the GUI enables the analyzer to have a quick detection for the brain image

So the algorithm for the program is as follows:-

Step1- Select an image from a set of brain images stored in a file. Then store the selected image in a handler variable after displaying it on the axes. The handler variable is passed to the next step.

Step 2- Process the selected image using Non-Separable Complex Wavelet Transform, which includes focusing on the part of interest in the image and process that to get the segmented image from the brain Image. Then display the segmented image on other axes in the GUI.

Step 3-Enhance the segmented image obtained from the previous step. This is done by applying a thresholding and mask to have a smoothened image. In this step also we have calculated the total number of black pixels in the segmented image for classification purposes.

The GUI shows us the following results -

The final segmented image.

Histogram for the final image to show the contrast of black and white pixels.

A text showing the image that has Alzheimer's falls into which stage (early or advanced).

Results

GUI Results after applying the technique (figure 4a) MR Image with advanced stage Alzheimer's disease, (figure 4b) MR Image with early stage Alzheimer's disease

There is a graph that has been obtained by automating our technique and applying it to 100 MR Images shown in (figure .5).

Discussion of Results

From the figure (4) and figure (5), we can see that Dual Tree CWT works much better than DWTs in analyzing 45 and -45 degree lines. This is very useful in image segmentation and we have exploited this feature to our advantage in analyzing brain scans of Alzheimer's patients. The figure (4) shows that we can use this technique to successfully categorize the different stages of Alzheimer's disease.

Conclusion

Dual Tree CWTs provide superior results when used for image segmentation. This technique has been successfully used in this paper to categorize the stage of Alzheimer's disease based on brain scans of patients.

References

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Tables and Figures:

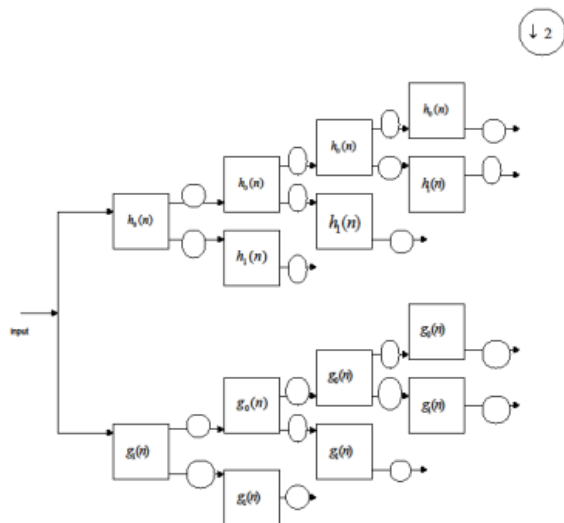


Figure - 1

Dual Tree Filter Concept

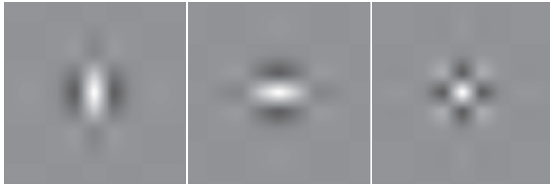


Figure – 2

DWT Wavelet Functions (check board pattern)

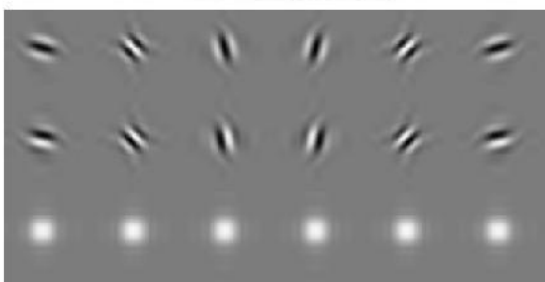


Figure – 3

2D Dual-Tree Complex Wavelets

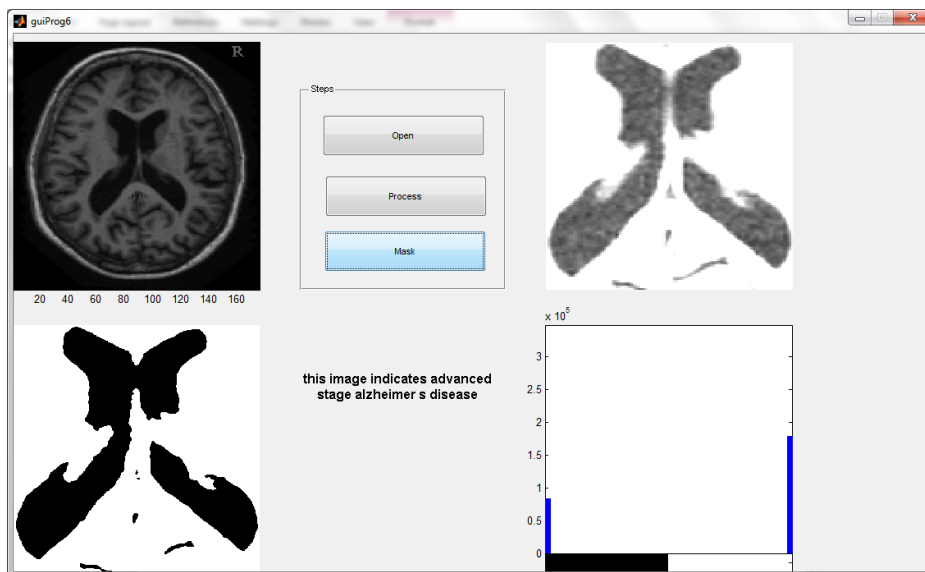


Figure-4(a)

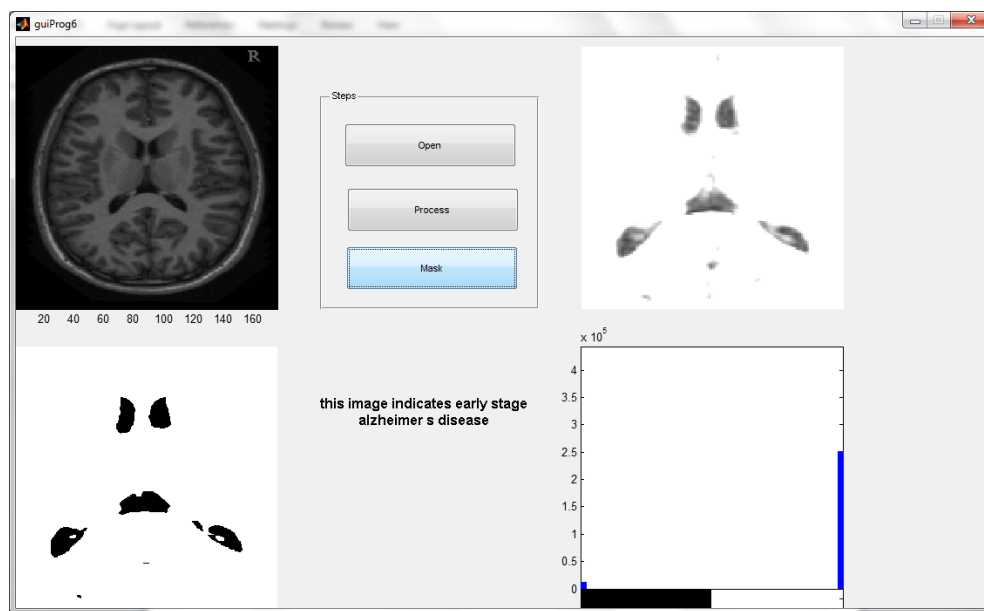


Figure -4(b)

GUI Results after applying the technique (a) MR Image with advanced stage Alzheimer's disease, (b)MR Image with early stage Alzheimer's disease

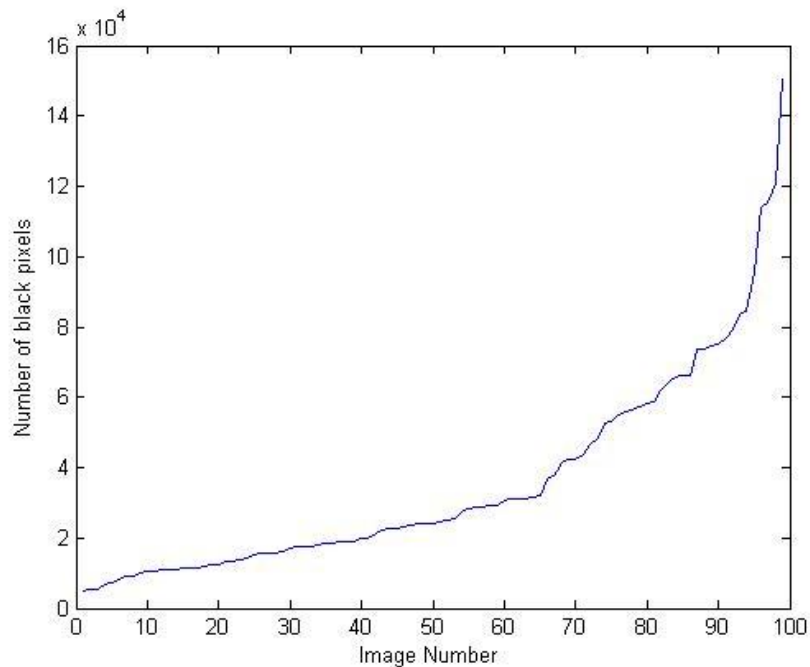


Figure -5

This graph has been obtained by automating our technique and applying it to 100 MR Images