

Rotational Wavelet Filters for Analysis of Brain MRI in Detection of Alzheimer's Disease

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Abstract: In this paper, a method is suggested for multi directional analysis of Magnetic Resonance Image (MRI) scans for detection of Alzheimer's disease (AD). This is a novel technique which utilizes, two-dimensional (2-D) rotated complex wavelet filters (RCWF) for feature identification. DTCWT identifies the features in 6 directions ($\pm 15^\circ \pm 45^\circ, \pm 75^\circ$) while RCWT identifies the features in different 6 directions ($-30^\circ, 0, +30^\circ, +60^\circ, +90^\circ, +120^\circ$), which enhances the directional selectivity of the transform coefficients and results in well description of corresponding textures. Dual-tree rotated complex wavelet transform (DT- RCWF) and dual-tree complex wavelet transform (DT- CWT) are applied to the sample images at a time thus the transform coefficients in twelve different directions is obtained simultaneously. The obtained transform coefficients are used for calculation of various texture features such as energy, entropy and standard deviation. The obtained parameters form the feature vectors which are given as input to the classifiers to get the input classified as Normal control or AD sufferer. This proposed algorithm produces results which are superior in terms of accuracy, feature extraction rate, sensitivity, specificity, precision and recall necessary to realize the efficiency of diagnosis of Alzheimer's Disease as compared to other existing methods.

Keywords: MR images, DTCWT, RCWT, Alzheimer's Disease

1. Introduction

Alzheimer's disease (AD) is the disease which was very rarely known in 1990s but now a days, it is very common form of brain disease. It is becoming a major challenge for healthcare in the twenty-first century. In Alzheimer's disease, there is atrophy of brain, which results in progressive memory loss. Since there is deformation in structure of brain, this disease affects the overall behavior of human being. Progression of disease is very fast. Within few days of progression of this disease, sufferer becomes totally dependent on care takers. Atrophy of brain increases to the level where all the body functions get disturbed which eventually cause the death of sufferer. The structure of brain suffered with AD is as shown in figure 1. As of now, a five million folks aged above sixty-five and even older are suffering from AD overall the globe. AD is one of the major causes of the death now a days. The wrong medication for Alzheimer's disease proven fatal for patient's health. So, it is a necessity of hour to work on AD detection technique to improve the accuracy of AD detection and reduce the confusion in detection of AD [1]. Various approaches are suggested for detection Alzheimer's using pathological testing such as blood test, urine test and by using physiological testing that is by testing the senses and mini mental state examinations (MMSE) etc. Similarly, AD can be detected by using neuroimaging techniques as well. Advancements in neuroimaging techniques shows the improvement in diagnosis. Here in this paper, the approach is suggested which uses MRI scans for the same.

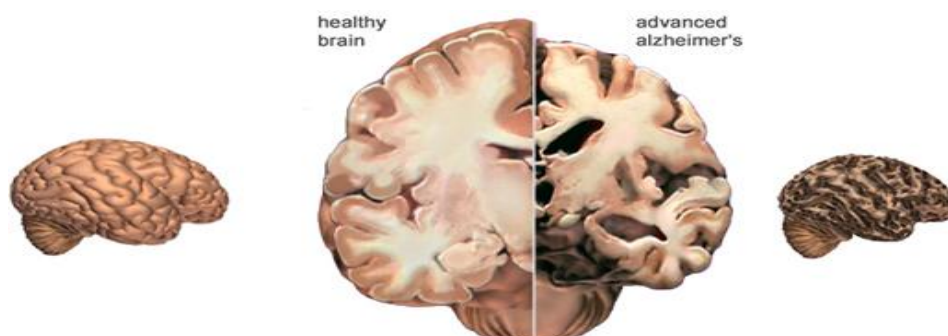


Figure 1. Atrophy of Alzheimer's Disease Brain compared to Healthy brain [14]

In recent years, there is quite advancement in the computer aided artificial intelligence and machine learning fields. Many advance algorithms are designed developed and tested for classification of subjects as AD or Normal control (NC). Neural network specifically fast forward neural network (FNN) is also one of them which is suggested in this paper. FNN requires the feature vector as input. Many methods are there for feature vector formation like voxel-based morphometry (VBM), Curvelet transform, wavelet transform etc. Wavelet transform with advancement as dual tree complex wavelet transform (DTCWT) and dual tree rotated complex wavelet transform (DTRCWT) are used in this paper for feature extraction.

The contribution of this experimentation can be claimed as, 1) Magnetic resonance imaging (MRI) data classification is presented using 2 D rotated complex wavelet transforms and dual tree complex wavelet transform, which produces the wavelet coefficients in various twelve directions. 2) Spatial features such as energy, entropy and standard deviations are calculated to obtain compact but optimal feature vector. For classification purpose, Forward Neural Network classifier is proposed. 3) The results obtained from the suggested method are compared with recent modern approaches. The rest of paper is organized as follows. In section 2, feature extraction of MRI dataset and classification of extracted features as Alzheimer and Non-Control is discussed. In section 3, the experimental results and their comparison with previous method is presented and last section 4 describe the conclusion of the suggested work.

2. Dual -Tree Rotated Complex Wavelet Transform (DT-RCWT)

The wavelet analysis is a proven technique and significant tool for feature extraction. It is successfully applied to obtain the wavelet coefficients from MRI scans as per the previous studies. Wavelet transform is the transform which analyses the signals in the time domain and frequency domain at certain point. The primary significance of application of wavelet transform method is that for low frequency components, it provides the enhanced frequency resolution and for high frequency components, better temporal resolutions

Discrete wavelet transform (DWT) is characterized by lack of orientation discrimination and shift invariance. Along with this, DWT coefficients suffers from aliasing effect. All these problems can be overcome up to certain extent by using complex wavelet transform (CWT) instead of real DWT only. But by using CWT, the generated coefficients are complex in nature since the filters used are complex one. This makes the system complex and difficult to analyze. The problem with CWT and DWT can be resolved up to certain extent is suggested by Nick Kingsbury [6] in 1998 by making certain modifications in CWT called as DT-CWT.

Nick Kingsbury suggested that DTCWT can be implemented by using two discrete wavelet transforms for each tree that is tree 1 and tree 2 as shown in figure 2.

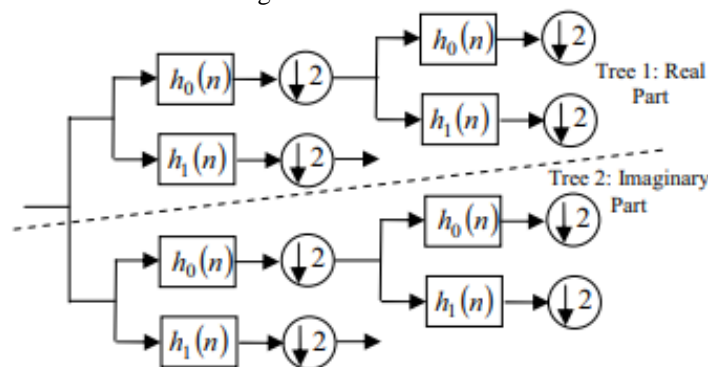


Figure 2. 1-D dual-tree complex wavelets transform. [7]

Filters used for implementation of DTCWT are linear-phase sustaining perfect reconstruction filters to make the output nearly analytic. Here the input signal is applied to high pass and lowpass filters as shown in figure 2. The outputs are decimated by two and then again applied to the next level. This way, the same procedure is repeated for further levels.

A function which represents the DTCWT is given as

$$\psi(x) = \psi_h(x) + j\psi_g(x) \tag{1}$$

Where, $\psi_h(x)$ is represented real wavelets and $\psi_g(x)$ is represented as complex wavelets generated by the two DWTs. Additionally low-pass filters for tree1 and tree2 are considered such that the corresponding wavelets form an approximate Hilbert transform pair as below

$$\psi_g(x) = H\{\psi_h(x)\} \quad (2)$$

Where, $\psi_h(x) = \sqrt{2} \sum_k h_1(k) \phi_h(x)$ (3)

$$\phi_h(x) = \sqrt{2} \sum_k h_0(k) \phi_h(x) \quad (4)$$

To achieve this, low pass filters should be half sample shift with each other

Thus

$$g_0(k) \approx h_0(k-0.5) \Rightarrow \psi_g(x) = H\{\psi_h(x)\} \quad (5)$$

Half sample delay in DTCWT makes it nearly shift invariant wavelet transform [9]

Along with the analysis of 1D signal, DTCWT is having multiple applications for 2D datasets as well. 2D signal analysis by using DTCWT produces coefficients which are proximately analytic and oriented. It gives the excellent results for applications which requires edge detection, surface detection, object segmentation etc. DTCWT has proven successful results for various applications such as object recognition, video processing, texture-based analysis, feature identification etc.

The output coefficients of DWT are oriented vertically and horizontally. Whereas the for DTCWT, the coefficients are oriented in six directions ($\pm 15^\circ, \pm 45^\circ, \pm 75^\circ$) as shown in figure. But the wavelet coefficients in more six directions ($-30^\circ, 0, 30^\circ, 60^\circ, 90^\circ, 120^\circ$) can be obtained by rotating filters used in 2D DT-CWT by 45° called as directional analysis using 2D Rotational Complex Wavelet Filters. Thus, the obtained coefficients are also rotated by 45° . The 2D DT-CWT and DT-RCWT combinedly offer better directional selectivity in various mentioned twelve directions ($15^\circ, 30^\circ, 45^\circ, 60^\circ, 75^\circ, 90^\circ, 120^\circ, -15^\circ, -30^\circ, -45^\circ, -75^\circ$) than the DWT and DTCWT alone.

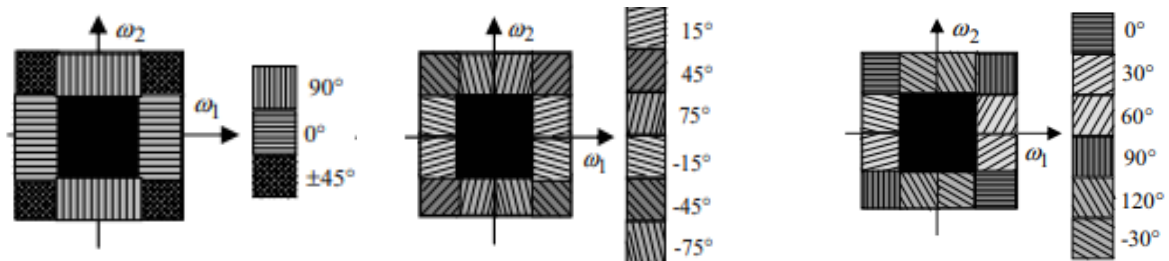


Figure 3. Directional analysis for frequency domain [7]
 (a) for DWT (b)for DT-CWT (c) For DT-RCWT

3. Design of CAD system using DT-CWT and DT-RCWT.

Design of CAD system for AD detection is implemented using DT-CWT and DT-RCWT as explained in section 2. The generalized block diagram of the system is given in the figure below.

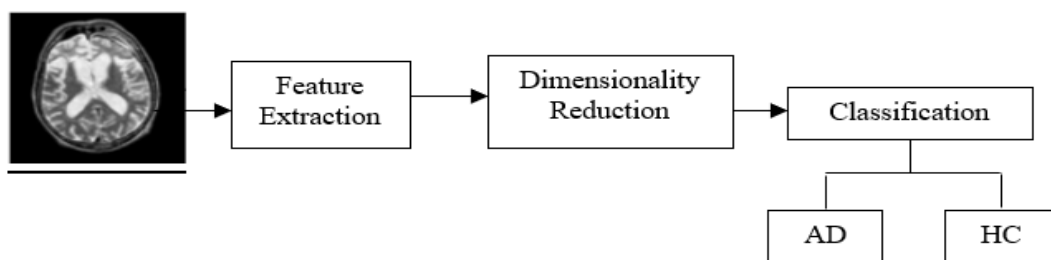


Figure 4. Block Diagram of CAD system for AD detection

Database used for experimentation here is MRI database since with the progression of AD, there are significant changes in the parameters related to white matter and gray matter. MR images gives more details about the white matter and gray matter as compared to other imaging modalities such as CT scan, PET scan, SPECT scan etc.

Standard databases available to researchers for diagnosis of brain related disease are Open Access Series of Imaging Studies (OASIS), Alzheimer's Disease Neuroimaging Initiative (ADNI), Open-Access Medical Image Repositories (OAMIR) etc. Here for experimentation of proposed method some of data samples from OASIS and ADNI databases are considered. The details of the experimentation databases and their statistics is mentioned in the table below.

Table 1. Statistical Summary of OASIS Database [13]

Factors	Healthy Control	Alzheimer's Disease
Number of patients	20	20
Gender(M/F)	10/10	10/10
Age	75+	77+
Clinical Dementia Rating (CDR)	0	1

Table 2. Statistical Summary of ADNI Database [15]

Factors	Healthy Control	Alzheimer's Disease
Number of patients	20	20
Gender(M/F)	10/10	10/10
Age	75+	77+
Clinical Dementia Rating (CDR)	0	1

Databases given on the websites needs to viewed and saved as 2D MRI scans. Number of software tools are available online for the same. In this demonstration the MRICro software is used to view the 2D MRI data scans. The sample of extraction of scan is as shown in figure 5. By using MRICro software tool, the data acquisition and pre-processing is done. For this experimentation, we have acquired total 80 data samples.

In the next step, feature extraction using wavelets that is DTCWT and DTRCWT is performed for the complete dataset upto 5 levels. In this, the feature vectors are formed by computing the parameters energy, entropy and standard deviation for every subband separately. The parameters energy, entropy and standard deviation are calculated using the equations (6) and (7) respectively.[11]

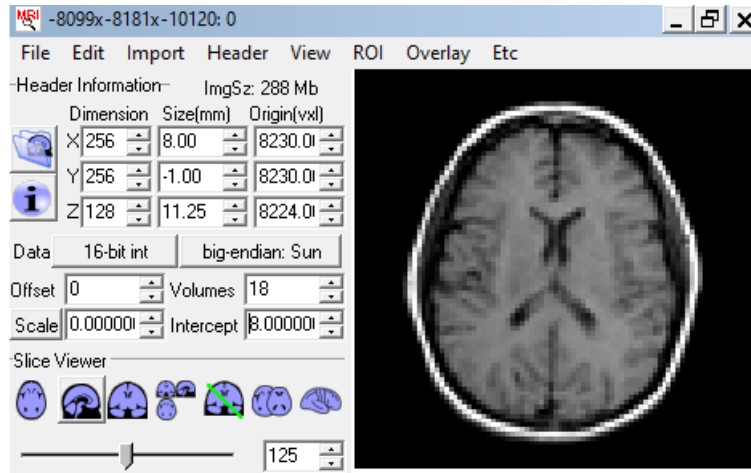


Figure 5. Image viewing using MRICro software tool

$$E_k = \frac{1}{M \times N} \sum_{i=1}^M \sum_{j=1}^N |W_k(i, j)| \quad (6)$$

$$\delta_k = \left[\frac{1}{M \times N} \sum_{i=1}^M \sum_{j=1}^N (W_k(i, j) - \mu_k)^2 \right]^{\frac{1}{2}} \quad (7)$$

$$Ent_k = \frac{1}{M \times N} \sum_{i=1}^M \sum_{j=1}^N W_k(i, j) (-\ln W_k(i, j)) \quad (8)$$

Where, $M \times N$ represent the dimensions of corresponding sub band

$W_k(i, j)$ represent the k^{th} sub band

μ_k represent the mean (average) of k^{th} sub band.

The feature vector obtained after computing and combining the parameters energy and standard deviation from wavelet coefficients of DTCWT and DTRCWT can be represented as

$$\vec{f}_{\delta E} = [\delta_1, \delta_2, \dots, \delta_n, E_1, E_2, \dots, E_n, Ent_1, Ent_2, \dots, Ent_n] \quad (9)$$

The algorithm given below explain the step-by-step process in experimentation

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- Step 1: Acquisition of MRI data from standard database OASIS and ADNI using MRICro tool which are normal scans or Alzheimer’s Disease sufferer scans.
 - Step 2: Resize the database images to size 256 by 256.
 - Step 3: Obtain the DTCWT and DTRCWT on the acquired MRI scans upto 5th level of decomposition.
 - Step 4: Calculate the parameters Energy E_k , Entropy Ent_k and standard deviation δ_k for all subbands obtained from wavelet decomposition.
 - Step 5: Obtain the feature vector by combining parameters

$$\vec{f}_{\delta E} = [\delta \ U \ E \ U \ Ent]$$
 - Step 6: Consider the set of input feature vectors for training the feed-forward neural network by their corresponding labels.
 - Step 7: Perform the step 2 to step 5 for test images.
 - Step 8: Classify the test images as normal control or AD brain.
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Step 9: Obtain the performance indicators and construct the confusion matrix.

Step 10: Divide the input data into 5 folds and apply 5-fold cross validation method to get the parameters accuracy, sensitivity, specificity, precision and recall.

Step 11: Compare with modern approaches.

4. Result and Discussion

The proposed CAD system is executed using MATLAB 2013 on Pentium V computer with 64bit operating system. The experiment is conducted 3times for different datasets, once for OASIS dataset, secondly for ADNI dataset and thirdly for combined dataset OASIS and ADNI to obtain the efficiency of the system. As per the available literature, number of methods are available to evaluate the efficiency of system specifically the classifiers used in the system. The widely used method to find the efficiency of the system is confusion matrix. Confusion matrix include the true and false results of experimentation in terms of performance indicators true positive (TP), true negative (TN), false positive (FP), and false negative (FN). Using the performance indicators, the evaluation parameters accuracy, sensitivity and selectivity are calculated using following equations.

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \quad (10)$$

$$Sensitivity = \frac{TP}{TP + FN} \quad (11)$$

$$Specificity = \frac{TN}{TN + FP} \quad (12)$$

$$Precision = \frac{TP}{TP + FP} \quad (13)$$

$$Recall = \frac{TP}{TP + FN} \quad (14)$$

The accuracies, sensitivities, specificities and precision are obtained for OASIS database and ADNI database are given in Table 3 and 4 respectively. We have applied 5-fold Cross validation method to overall dataset of 80 MRI scans for result authentication. In 5-fold Cross validation method, the dataset is divided into 5 parts. Out of that, 4 parts are used for training 1 and part is used for testing. The same procedure is carried out for various times called as runs. The accuracies obtained with 10 runs of 5-fold cross validation method is shown in Table 5.

Table 3. Performance Assessment over OASIS Dataset

Methods	Accuracy	Sensitivity	Specificity	Precision
DTCWT+DTRCWT (proposed)	91.72	92.01	88.00	88.79
DTCWT [3]	90.06	92.00	87.78	89.6
DWT	86.32	88.35	82.98	87.51

Table 4. Performance Assessment over ADNI Dataset

Methods	Accuracy	Sensitivity	Specificity	Precision
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DTCWT+DTRCWT (proposed)	90.46	89.12	87.55	87.65
DTCWT [3]	88.53	86.10	88.54	88.06
DWT	86.58	85.23	86.69	89.37

Table 5.Performance Assessment with 5 folds and10 Runs for overall dataset

Folds	Run1	Run2	Run3	Run4	Run5	Run6	Run7	Run8	Run9	Run10
1	92.11	100	82.35	100	94.44	88.88	82.35	87.5	91.81	98.55
2	100	91.81	82.35	89.23	82.35	94.11	81.25	91.81	91.81	88.88
3	92.11	87.5	94.11	88.88	100	82.35	100	100	88.88	88.23
4	87.5	88.23	77.77	91.81	88.23	77.77	87.5	93.75	93.75	93.75
5	87.5	77.77	88.88	91.81	88.23	100	77.77	94.11	83.33	87.5
AVG	91.844	89.062	85.092	92.346	90.65	88.622	85.774	93.434	89.916	91.382
Average Accuracy: 89.812										

The accuracy, sensitivity, specificity, precision and recall for combined dataset is as given in table number 6.

Table 6.Performance Assessment for overall dataset

Algorithms	Accuracy	Sensitivity	Specificity	Precision	Recall
DTCWT+DTRCWT (proposed)	89.812	88.01	90.00	89.79	87.75
DTCWT [3]	87.08	89.00	87.78	89.6	88.05
DWT	85.32	88.06	87.53	87.36	86.77

The suggested approach is compared with other modern approaches which uses different methods for feature extraction and classification such as voxel-based morphometry, Gabor transform etc. for AD detection. The bar graph shown in figure 6 indicate the comparison with other algorithms.

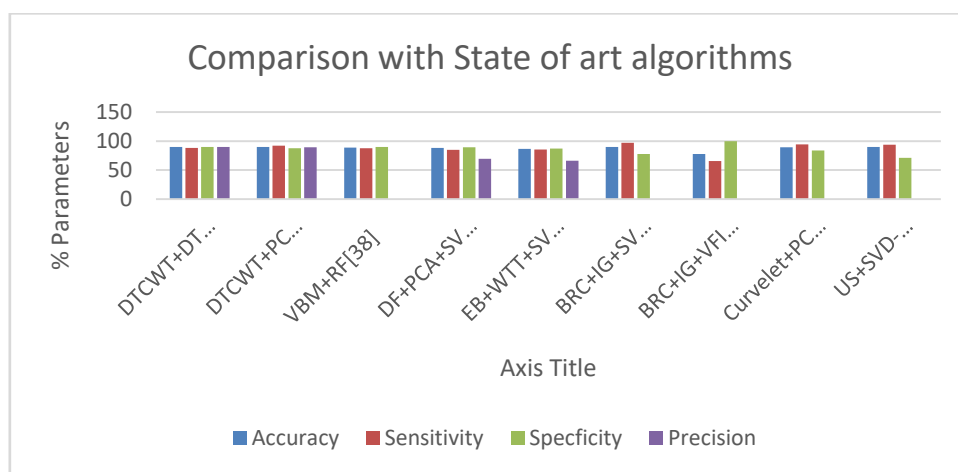


Figure 6. Bar Plot of parameters of comparison for various algorithms

5. Conclusion

Highly efficient CAD system for detection of AD using DTCWT and DTRCWT is designed and implemented in this paper. Implementation of this algorithm is done using software MATLAB. The performance parameters like accuracy, sensitivity, specificity along with precision and recall are analyzed for OASIS and ADNI database. The result depicts that the suggested algorithm yields an accuracy of 89.812%, a sensitivity of 88.01%, a specificity of 90.00%, a precision of 89.79% and recall value of 87.75%.

It can be claimed that, the designed CAD system yields the optimal results as compared to the other modern approaches which uses wavelets for feature extraction methods in terms of accuracy with high values of other parameters as well. Similarly, it can be concluded that, the use of DTCWT makes the coefficients shift invariant and combination of DTCWT and DTRCWT improves the directional selectivity of the proposed algorithm. Significant performance values of the wavelet coefficients yield the substantial values of the parameters like entropy, energy and standard deviation which are further applied to the FNN classifier for classification of samples as Normal control or AD.

Moreover, this proposed experiment for OASIS data obtained the promising results as compared to other approaches. Thus, the cognizance of detection of Alzheimer's disease can be effectively increased if this proposed algorithm is considered in medical research and education.

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