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Discrete Wavelet Transform EEG Features of Alzheimer's Disease in Activated States

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Abstract— **In this study, electroencephalogram (EEG) signals obtained by a single-electrode device from 24 subjects - 10 with Alzheimer's disease (AD) and 14 age-matched Controls (CN) - were analyzed using Discrete Wavelet Transform (DWT). The focus of the study is to determine the discriminating EEG features of AD patients while subjected to cognitive and auditory tasks, since AD is characterized by progressive impairments in cognition and memory. At each recording block, DWT extracts EEG features corresponding to major brain frequency bands. T-test and Kruskal-Wallis methods were used to determine the statistically significant features of EEG signals from AD patients compared to Controls. A decision tree algorithm was then used to identify the dominant features for AD patients. It was determined that the mean value of the low-δ (1 - 2 Hz) frequency band during the Paced Auditory Serial Addition Test with 2.0 (s) interval and the mean value of the β frequency band (12 - 30 Hz) during 6 Hz auditory stimulation have higher mean values in AD patients than Controls. Due to artifacts, the less reliable low-δ features were removed and it was determined that the mean value of β frequency band during 6 Hz auditory stimulation followed by the standard deviation of θ (4 - 8 Hz) frequency band of one card learning cognitive task are higher for AD patients compared to Controls and thus the most dominant discriminating features of the disease.**

I. INTRODUCTION

Alzheimers disease (AD) is a "neuro-degenerative disease, the most common form of dementia, third most expensive disease and sixth leading cause of death in the United States." While no known cure exists, a number of medications are believed to delay the symptoms of the disease [1]. Because of its non-invasive and safe properties, electroencephalograph (EEG) signal is considered to be a potential tool that may complement current methods for early diagnosis of AD. However, diagnosis of AD with EEG signals remains a challenging problem as most of the existing methods are not validated and require significant improvement [2].

There are several approaches to EEG signal analysis, the most widely used being Fast Fourier Transform (FFT) power spectral approach. FFT methods have been applied to determine the discriminating features of AD in several studies [2–6]. Some of the results include finding optimal ranges of frequency bands, which have a better classification performance than the traditional δ, θ, α, and β bands [2], as well as an increase of δ and θ global field power (GFP) and a reduction of α GFP when compared to Control subjects [3]. Also, an increase in δ and θ power and a decrease in α and β power have been reported [5]. Because brain EEG signals appear non-stationary, FFT based methods have been shown to have an inherent disadvantage [7]. A second approach for analyzing EEG signal in AD patients is nonlinear dynamics approach, e.g. [5] [8]. However, this approach is computationally too complex and require extensive experience [9].

Another promising approach is the wavelet power spectral analysis [7]. The wavelet transform [10] is suitable for analyzing transient signals, since it contains both frequency and time information. For spectral analysis, wavelet transform can be more suitable than Fourier transform [11] depending on the properties of the mother wavelet [7]. There are two types of wavelet analysis: continuous wavelet transform (CWT) and discrete wavelet transform (DWT). DWT is generally more computationally efficient than CWT [12]. Both DWT and CWT have been used in EEG analysis and classification [13–15]. However, to our knowledge, very few studies have used DWT to extract AD features from AD derived EEG signals (e.g. [16], [17]) and evidence exists demonstrating that one can classify normal and abnormal EEG signals in major brain frequency bands [18–20]. In these studies, DWT was used to filter out noise at several decomposition levels. At each level, the statistical features such as minimum, maximum, mean, and standard deviation are computed. These quantities were then used for classification of normal and abnormal EEG signals, using classifiers such as neural network [19], fuzzy systems [20], support vector machine, and decision trees.

Alzheimer's disease is characterized by progressive impairments in cognition and memory [5]. Cognitive tasks have been extensively used to diagnose brain arrhythmias. The tasks of particular interest include attention [21], identification [22], and the Paced Auditory Serial Addition Test (PASAT) which represents a reliable method with persuasive clinical evidence [23]. Hence, EEG recorded during these activated states can help provide a complementary tool for more accurate assessment of brain abnormalities.

In this study we specifically focus on EEG recordings from AD and CN subjects under cognitive tasks, PASAT, and auditory stimulations. We use DWT for feature extraction from EEG signals in five decomposition levels, where at each level statistical features of the signal are calculated. The discriminating features of AD were determined using two statistical testing methods, t-test and Kruskal-Wallis, and a decision tree algorithm identified the most significant and dominant features of AD.

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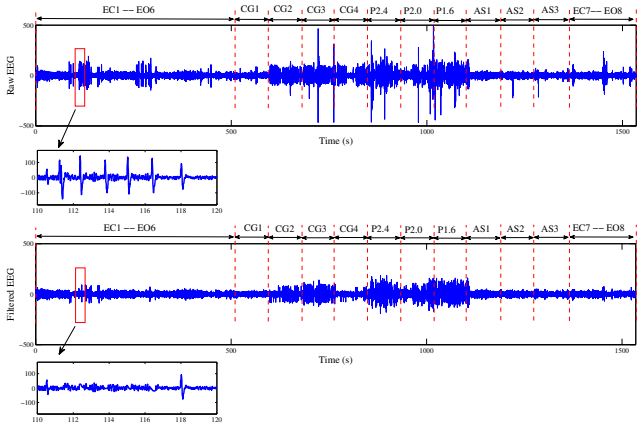

Fig. 1. Raw EEG signal of a CN patient before (top) and after (bottom) artifact detection . Y-axis is arb units from the onboard ADC

II. Clinical Study and Data Collection

EEG signals were recorded through a single-dry electrode device at position FP1 (based on a 10-20 electrode placement system) with a Bluetooth enabled telemetric headset. The headset sample rate is $f_s = 128$ Hz. However, the effective sample rate was $f_s = 125$ Hz in our experiments. Frequencies over 60 Hz and below 1 Hz are not reliable and filtered out [24]. Data from 24 subjects were considered, including 10 AD and 14 age-matched controls (CN). The EEG recording sessions in each case began with resting eyes-closed and eyes-open states and then proceeded to attention, identification, card flipping cognitive tasks, followed by PASAT and auditory stimulation tasks, and concluded with the resting eyes-closed and eyes-open states. Specifically, they were comprised of approximately seventeen 90-second intervals, for a total of about 25 minutes per subject. The duration and description of each task is presented in table I.

The electrically isolated telemetric EEG headset eliminated frequently observed artifacts including line noise. Furthermore, we subtracted the DC offset of EEG signals and implemented a relatively simple artifact detection to eliminate eye-blinks and other large amplitude artifacts which appear to have amplitudes greater than 4.5σ (standard deviation). An algorithm was developed to detect such signals, nullify, and then reconstruct the nulled signals using FFT interpolation of the trailing and subsequent recorded data [24]. For illustrative purposes, Fig. 1 shows all EEG recordings for a single subjects in arbitrary units from the ADC before and after artifact detection.

III. Discrete Wavelet Transform

DWT analyzes the signal at different resolutions through the decomposition of the signal into several successive frequency bands by utilizing a scaling and a wavelet function, associated with low-pass and high-pass filters. The original EEG signal forms the discrete time signal $x[n]$ and is first passed through a half-band high-pass filter $g[.]$, and a low-pass filter $h[.]$. Filtering followed by sub-sampling constitutes

TABLE I

Description and duration of each tasks for EEG recordings.

Task No.	Task Description	Task Duration (s)
1 – 6	Three consecutive resting eyes closed and eyes open (EC1 – EO6)	540
7	Cognitive task 1: Attention (CG1)	90
8	Cognitive task 2: Identification (CG2)	90
9	Cognitive task 3: One Card Learning (CG3)	90
10	Cognitive task 4: One Card Back (CG4)	90
11	PASAT: 2.4 (s) intervals (P-2.4)	90
12	PASAT: 2.0 (s) intervals (P-2.0)	90
12	PASAT: 1.6 (s) intervals (P-1.6)	90
14	Auditory Stimulation, Left = 397, Right = 403 with 6 Hz (AS1)	90
15	Auditory Stimulation, Left = 394, Right = 406 with 12Hz (AS2)	90
16	Auditory Stimulation, Left = 391, Right = 409 with 18 Hz (AS3)	90
17 – 18	One resting eyes closed and eyes open (EC7 and EO8)	180

one level of decomposition and can be expressed as follows:

$$d_1[k] = y_{high}[k] = \sum_n x[n].g[2k-n], \quad (1)$$

$$a_1[k] = y_{low}[k] = \sum_n x[n].h[2k-n], \quad (2)$$

where d_1 and a_1 are level 1 *detail* and *approximation* coefficients, respectively, $y_{high}[k]$ and $y_{low}[k]$ are the outputs of the high-pass and low-pass filters after the sub-sampling.

This procedure, called sub-band coding, is repeated until no more sub-sampling is possible. At each level, the procedure results in half the time resolution and double the frequency resolution. In this research, we used Daubechies2 (db2) mother wavelet which has been reported to have a better accuracy compared to most other wavelets [20]. Since the EEG signal in our study has the frequency range of 1–60 Hz, we went through five levels of decompositions. The frequency range of each of these levels and their corresponding major EEG frequency band are shown in table II. D_1 – D_5 along with the A_5 consist DWT representation of the EEG signal in our analysis. At each level, we compute the minimum, maximum, mean, and standard deviation values of the filtered data as the statistical features.

IV. Discriminating Features

A. Statistical Testing

We initially used a two-tailed t-test to compare the signals from 10 AD patients with 14 Controls. However, t-test requires normal distribution of data which is not a valid assumption for some of the data in our study. Hence, we used the Kruskal-Wallis test, a non-parametric method based on Chi-squared distribution to improve the statistical analysis.

TABLE II

DWT SUB-BAND FREQUENCIES AND THEIR CORRESPONDING EEG FREQUENCY BANDS.

Sub band	Frequency Range (Hz)	Corresponding EEG frequency band (Hz)
D_1	30 – 60	γ (> 30)
D_2	15 – 30	β (13 – 30)
D_3	7.5 – 15	α (8 – 13)
D_4	3.75 – 7.5	θ (4 – 8)
D_5	1.875 – 3.75	δ_u (2 – 4)
A_5	1 – 1.875	δ_l (0 – 2)

The results of these two statistical testing methods and their p-values are shown in Table III. These results represent all the statistically significant discriminating DWT features of AD patients in cognitive task, PASAT, and auditory stimulation states. It is clear that both tests yield similar results, but the Kruskal-Wallis method is more conservative. The reliable discriminative features from Kruskal-Wallis testing method are max$\{D_3\}$ (α) from attention cognitive task, mean$\{A_5\}$ (lower δ) from one card learning cognitive task, min$\{D_3\}$ (α) from one card back cognitive task, mean$\{D_2\}$ (β) from PASAT 2.4 (s) interval task, mean$\{A_5\}$ (lower δ) from PASAT 2.0 (s) interval task, and mean$\{D_2\}$ (β) from auditory stimulation at 6 Hz.

TABLE III

SIGNIFICANT DISCRIMINATING FEATURES BASED ON T-TEST AND KRUSKAL-WALLIS TEST.

Task	Feature-t-test	Feature-Kruskal
CG1	max$\{D_3\}$, p = 0.030	max$\{D_3\}$, p = 0.046
CG2	min$\{D_2\}$, p = 0.043	not significant
CG3	min$\{D_1\}$, p = 0.046	mean$\{A_5\}$, p = 0.046
CG4	min$\{D_3\}$, p = 0.007	min$\{D_3\}$, p = 0.016
P-2.4	mean$\{D_2\}$, p = 0.008	mean$\{D_2\}$, p = 0.023
P-2.0	mean$\{A_5\}$, p = 0.031	mean$\{A_5\}$, p = 0.024
AS-1	mean$\{D_2\}$, p = 0.044	mean$\{D_2\}$, p = 0.004

B. Decision Tree

Since many features were identified in our study, we applied the decision tree, a classification algorithm, to determine the most dominant discriminating feature of AD patients. The tree is made up of nodes and branches where the nodes are designated as either internal or a terminal. Internal nodes can split into two branches while the terminal nodes cannot [25]. Unlike the statistical testing methods, which use data distribution for comparison of different groups, decision tree attempts to segregate data using different splitting criteria. In this study, we used a well-known split criteria, which is Gini index. The Gini index is defined as [26]:

$$Gini(t) = \sum_i p_i(1 - p_i) \tag{3}$$

where p_i is the relative frequency of class i at node t, and node t represent any node at which a given split of the data is performed. p_i is determined by dividing the total number of observations of the class by the total number of observations.

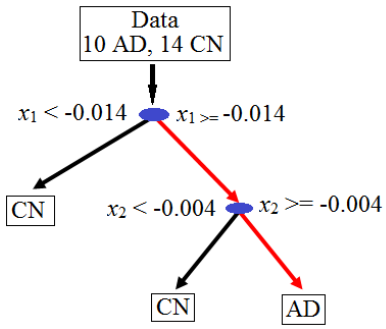

Fig. 2. Decision tree result for all sub-bands. x_1 is the mean value of lower δ band of PASAT 2.0 (s) interval task and x_2 is the mean value of the β band of auditory stimulation at 6 Hz.

The result of decision tree algorithm for comparing the AD and CN subjects in this study is shown in Figure 2. According to these results, mean$\{A_5\}$ of P-2.0 task was the first and most dominant discriminating feature of AD patients. The second discriminating feature was the mean$\{D_2\}$ of AS1 task. These results indicate that if the mean value of lower δ frequency band of PASAT with 2.0 (s) interval of a subject is greater than -0.014 and the mean value of β frequency band of auditory stimulation at 6 Hz of the subject is also greater than -0.004 (following the red line in decision tree), then the subject is identified as an AD patient. Both of these features were also determined to be statistically significant by t-test and Kruskal-Wallis testing methods, adding to the reliability of the decision tree classification.

However, the analog filters employed in the headset had a cutoff of approximately 1 to 2 Hz. Those filters have undisclosed properties making the signal in lower δ frequency band (1-2 Hz) unreliable. Furthermore, our simple artifact detection algorithm is amplitude-based and may not have removed all of low frequency artifacts. Hence, we removed the features corresponding to low-δ frequency band (A_5, 1-2 Hz) and re-applied the decision tree algorithm. The result is shown in Figure 3 where the mean$\{D_2\}$ of AS1 was determined to be the first and most dominant discriminating feature of AD patients. The second discriminating feature was changed to the standard deviation of D_4 of CG3. These results indicate that if the mean value of the β frequency band of auditory stimulation at 6 Hz of a subject is greater than -0.003 and the standard deviation of the θ frequency band of the one card learning cognitive task of the subject is also greater than 1.83, then the subject is identified as an AD patient.

V. CONCLUSIONS

We have used a discrete wavelet transform to determine the discriminating features of EEG signals from AD patients during several different cognitive task, the PASAT, and auditory stimulation states. Since AD is characterized by progressive impairments in cognition and memory, the underlying hypothesis is that EEG recorded during these activated states will have clearer discriminating features than resting states. To the best of our knowledge, this is the

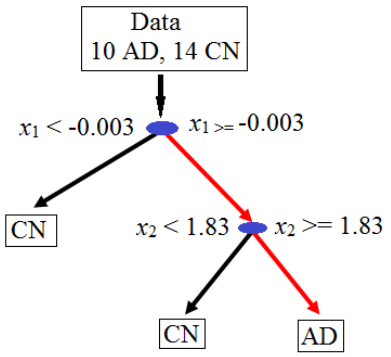

Fig. 3. Decision tree result after removal of A_5. x_1 is the mean value of β band of auditory stimulation at 6 Hz (AS1) and x_2 is the standard deviation value of the θ band of one card learning cognitive task (CG3).

first study with DWT to extract AD features from EEG signals in activated states. DWT statistical features from 5 level of decomposition were computed and compared during activated states. Many discriminating features were identified, from which a decision tree algorithm identified the most dominant ones required to classify AD patients. Based on these results, we have classified AD patients as those subjects with higher mean EEG low-δ band during PASAT 2.0 (s) interval and higher mean EEG β band during 6 Hz auditory stimulation. A second classification was achieved by removing the less reliable low-δ band features. In this case, we classified AD patients as those subjects with higher mean EEG β band during 6 Hz auditory stimulation and higher standard deviation of θ frequency band of one card learning cognitive task.

Based on this research, we suggest that further serial studies of AD patients and Controls might be useful in showing normal rates versus accelerated rates of change in the AD patients. Such studies may particularly be useful for patients with mild cognitive impairment (MCI) as a means of tracking their progression to AD. In addition, PASAT and auditory stimulation recordings may separate mildly impaired subjects from controls. Cognitive testing for minimally impaired subjects may also form a great baseline, that should be followed over time.

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