

Characterization of Alzheimer's disease using EEG as a potential early diagnostic tool

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Abstract—Alzheimer's disease (AD) is characterized by distinctive cytological, histological, and immunohistochemical changes that differentiate it from normal aging patterns. Although definitive diagnostic confirmation is anatomopathological, current diagnostic criteria combine clinical and biological evidence to formulate a probabilistic diagnosis. Given the high prevalence and socioeconomic impact of AD, there is an intensified search for early diagnostic tools. Electroencephalography (EEG) has emerged as a potential tool for early AD characterization and diagnosis, providing records of brain electrical activity that may reveal specific patterns of neuronal alteration associated with AD before clinical symptoms are evident. This study proposes using EEG to identify spectral power and complexity features to distinguish between healthy individuals and those with AD. The findings suggest that individuals with AD exhibit notable decreases in alpha (8-13 Hz) and beta (13-30 Hz) oscillations compared to healthy controls, which are associated with neuronal deterioration and loss of synaptic connectivity, hallmark characteristics of AD progression.

Keywords —EEG, Alzheimer disease (AD), relative power band (RPB), diagnostic tool, characterization.

I. INTRODUCTION

The Alzheimer's disease (AD) is characterized as a dementia with distinctive cytological, histological, and immunohistochemical changes that differentiate it from patterns of normal aging [1]. While definitive diagnostic certainty of AD is achieved through anatomopathological confirmation, current diagnostic criteria combine clinical and biological evidence to formulate a probabilistic diagnosis. This combination is based on the identification of intraneuronal neurofibrillary tangles, extracellular neuritic plaques, synaptic loss, and other characteristic neuronal changes [1].

Given the high prevalence of AD and its socioeconomic impact, the search for early diagnostic tools has intensified. Among these, the use of electroencephalography (EEG) has emerged as a potential tool for the characterization and early diagnosis of AD. EEG, by providing a record of brain electrical activity, can reveal specific patterns of neuronal alteration associated with AD before clinical symptoms

become evident. This early detection capability is crucial for more effective and timely interventions, which could significantly improve patients' quality of life and reduce the socioeconomic impact of the disease [1].

II. PROBLEM STATEMENT

Neurodegenerative diseases have increased in prevalence over recent years [2]. Currently, 50 million people are affected by these diseases, and this number is projected to exceed 100 million by 2050 [3]. Alzheimer's disease (AD) is a neurodegenerative condition that ranks as the leading cause of dementia worldwide, with early diagnosis posing a significant challenge [4].

Current diagnostic methods include clinical evaluations, neuropsychological tests, cerebrospinal fluid (CSF) biomarkers, and positron emission tomography (PET). These methods can be invasive, costly, and not always readily accessible. Moreover, they often fail to detect the disease until neurological damage is significant [5].

Electroencephalography (EEG) has emerged as a potential alternative tool for AD diagnosis. Several studies have identified specific brain activity patterns that distinguish individuals with Alzheimer's from healthy controls [6], with decreases in alpha and beta oscillations being characteristic features associated with Alzheimer's progression [6]. Furthermore, analysis of brain connectivity via EEG indicates that alterations in connectivity serve as an early marker of AD [7].

Early detection of Alzheimer's disease remains challenging due to its gradual and progressive nature; however, it also presents an opportunity, as current treatments are more effective when administered in the disease's early stages.

III. PROPOSED SOLUTION

The proposed solution involves using EEG for early Alzheimer's diagnosis by identifying power spectrum and complexity characteristics. Additionally, it aims to identify the most representative channels that exhibit significant differences in these characteristics between Alzheimer's patients and healthy individuals.

IV. METHODOLOGY

The methodology used in the study is explained in the diagram in Figure 1.

A. Acquisition of EEG Signals

Figure 2 illustrates the acquisition of signals. The control group comprised 4 male university students aged 20 to 23 from Universidad Peruana Cayetano Heredia. They underwent resting state tests with eyes closed (EC) and eyes open (EO), as well as arithmetic exercises with eyes closed (MAEC) and eyes open (MAEO), each lasting 5 minutes per sample [8]. For the Alzheimer's group, data from the Open Neuro database containing 36 signals from individuals diagnosed with AD was utilized [9].

The Ultracortex Mark IV system was used for signal acquisition, employing the international 10-20 system for electrode placement with 16 channels, following recommendations from the International Federation of Clinical Neurophysiology (IFCN). Electrodes were positioned with reference to the nasion (indentation between the forehead and the upper part of the nose) and inion (palpable prominence in the middle occipital region) [10].

To assess cognitive function in the control group, the Mini-Mental State Examination (MMSE) protocol was employed. This practical tool evaluates cognitive status with scores ranging from 0 to 30, where lower scores indicate severe cognitive impairment [11]. The protocol includes questions related to orientation, registration, attention and calculation, recall, language, and complex commands with eyes closed.

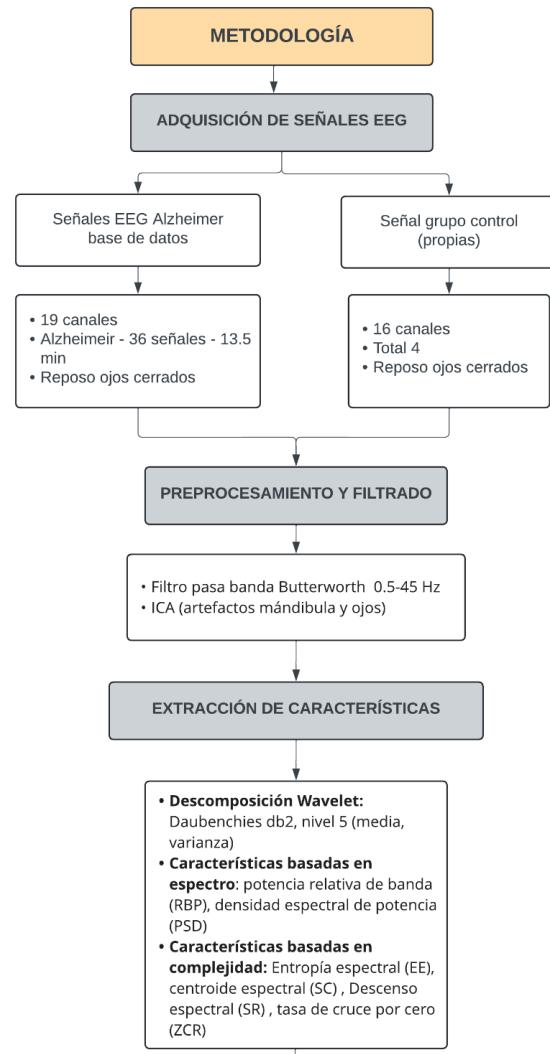


Figure 1. Methodology Flow Diagram



Figure 2. Experimental Setup for EEG Signal Acquisition

B. Preprocessing and Filtering

The signals from the control subjects underwent the same preprocessing and filtering as those from the AD group in the database. A Butterworth bandpass filter from 0.5 to 45 Hz was

applied. Additionally, Independent Component Analysis (ICA) was used for filtering to transform the 16 EEG signals into 16 ICA components and identify muscle artifacts.

C. Feature Extraction

The filtered signals underwent Daubechies wavelet type 2 decomposition with 5 decomposition levels to obtain the mean and variance of each coefficient. Frequency bands including delta (0.5 - 4 Hz), theta (4-8 Hz), alpha (8-13 Hz), and beta (13 - 30 Hz) were also extracted. Power spectrum-based features such as Power Spectral Density (PSD) and Relative Band Power (RBP) were extracted from the signals. Complexity-based features including Spectral Entropy (SE), Spectral Centroid (SC), Spectral Roll-off (SR), and Zero Crossing Rate (ZCR) were also obtained.

D. Statistical Analysis

Statistical analysis of EEG signals between AD patients and healthy controls involved mean, standard deviation, and independent samples t-test to analyze differences. Additionally, averages of relative power and complexity across all patient groups were calculated.

IV. RESULTS

The Independent Component Analysis (ICA) allowed for proper filtering by separating EEG signals into independent components and artifacts. For artifact identification, attention was paid to a positive spectral slope between 7 - 75 Hz, characteristic of muscle-origin ICA, and in the topographic map, peripheral foci away from the vertex and a single focal point that evidences low spatial smoothness, unlike neural components that distribute throughout the map. [12] According to the mentioned criteria, ICA1, ICA7, and ICA13 exhibit a single focal point coinciding with peaks of positive slope in the spectral power graph, along with high variance dispersion, thus identified as artifacts.

According to literature, EEG signals from AD patients may present specific patterns indicating the presence of the disease, such as a significant decrease in relative alpha power and an increase in theta power, reduced synchronization in frequency ranges of 0.5 to 25 Hz [13, 14], EEG signal slowing at rest due to observed neuronal loss in the cerebral cortex, reduced complexity [15], decreased neural network connectivity due to reduced synchrony [H], increased local power in low-frequency bands (delta and theta), and decreased local power in high-frequency bands (alpha and beta) [15].

For feature extraction, 16 common channels were considered between both electrode systems for better comparison of control group data acquired with database data, thus excluding data from Fz, Cz, and Pz channels present in control signals from the database.

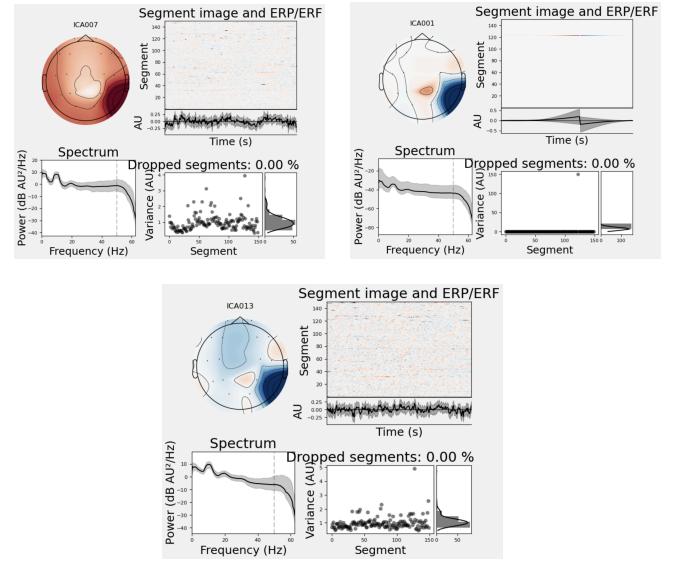


Figure 3. ICA Components 001, 007, and 013

In Figure 7, Relative Band Power (RBP) is presented for control group 1 (own), control group 2 (database), and AD group. The behavior of relative power bands at each frequency reveals a decrease in alpha and beta bands and an increase in delta band values, aligning with the mentioned literature, except for a decrease in theta values.

Additionally, Table I displays complexity-based features such as SE, SC, SR, and ZCR. The zero crossing rate tends to be less complex in individuals with AD, due to the signal not changing its sign from the slowing observed, showing a slight decrease in ZCR value compared to the control group.

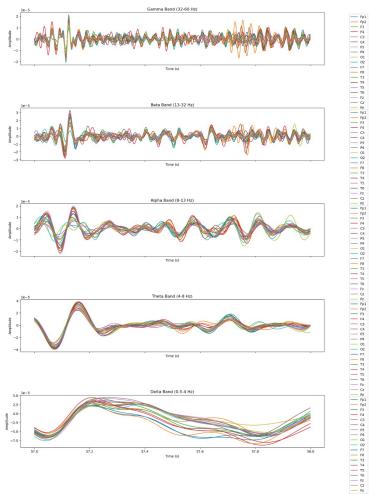


Figure 4. Wavelet Coefficients of Database Control Group

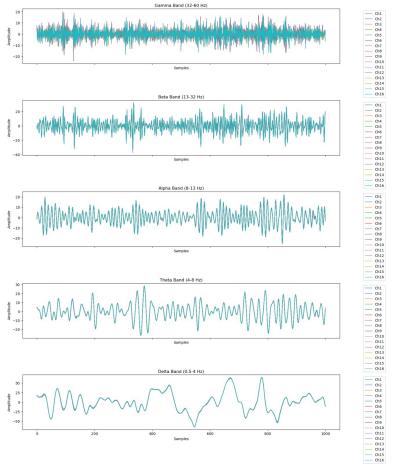


Figure 5. Wavelet Coefficients of Control Group using Ultracortex Mark IV

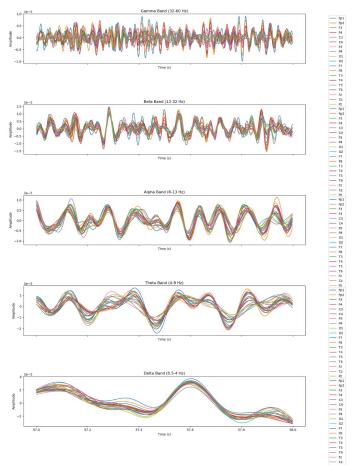


Figure 6. Wavelet Coefficients of Alzheimer's Database Group

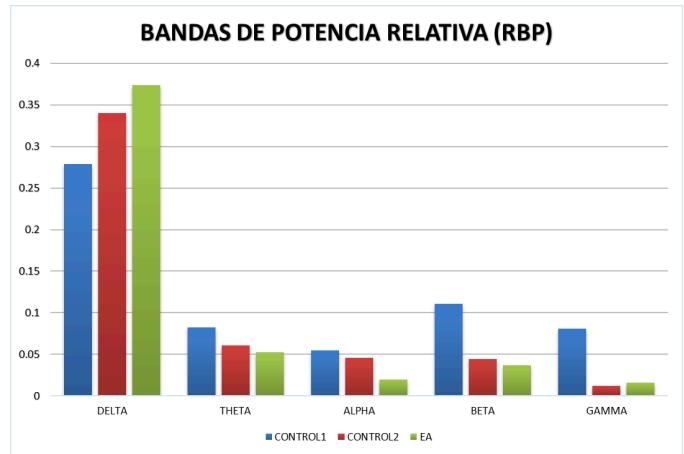


Figure 7. Relative Band Power (RBP) among Alzheimer's group, database control group, and Ultracortex Mark IV control group

Table I
t-test for Delta Band (RBP) in control group (1) and AD group

	Entropia espectral	Centroide espectral	Rolloff Espectral	Ratio de cruces por cero
CONTROL2	4.70E-09	4.7133	212.5	0.0165
AD	4.06E-09	4.2244	212.5	0.0153

The parametric t-test was used to determine if relative band power values differ significantly between the control group and Alzheimer's disease group. Table VI shows $p < 0.05$, indicating a significant difference in Beta band relative power between both groups.

Table II
Mean, standard deviation, and percentiles of RBP values in control group (1) and AD group (2)

group	Mean	SD	p25	p50	p75
1	.3429094 .0597316 .0440644 .0430594 .0112346	.0318876 .0131265 .0202678 .0032517 .0021262	.3205713 .0505529 .0299303 .0408213 .009892	.3514209 .0563371 .0390499 .043722 .0111492	.3652476 .0689104 .0581986 .0452975 .0125773
2	.3753237 .052457 .0196336 .0354957 .0144493	.0133479 .0089922 .0063115 .0040855 .0044825	.3660458 .0464106 .015244 .0326639 .0112809	.3784619 .0511377 .0181365 .0364168 .0129386	.3846016 .0585034 .0240233 .0383276 .0176178
Total	.3591166 .0560943 .031849 .0392775 .012842	.0285014 .0111184 .0190697 .0052944 .0036744	.3498387 .0489090 .0181365 .0364168 .0110989	.3652476 .0526998 .027119 .0389502 .0113313	.3784619 .0621407 .0390499 .043722 .0141846

Table III
t-test for Delta Band (RBP) in control group (1) and AD group (2)

. ttest DELTA, by(group) unequal						
Two-sample t test with unequal variances						
Group	Obs	Mean	Std. err.	Std. dev.	[95% conf. interval]	
1	4	.3429094	.0159438	.0318876	.2921692	.3936497
2	4	.3753237	.0066739	.0133479	.3540843	.3965632
Combined	8	.3591166	.0100768	.0285014	.3352888	.3829444
diff		-.0324143	.0172843		-.0803091	.0154805
		diff = mean(1) - mean(2)		t =	-1.8754	
H0:	diff = 0				Satterthwaite's degrees of freedom =	4.02
Ha:	diff < 0	Ha: diff != 0				
		Pr(T < t) = .00668			Pr(T > t) = .1336	
					Pr(T > t) = .9332	

Table VI
t-test for Theta Band (RBP) in control group (1) and AD group (2)

. ttest BETA, by(group) unequal						
Two-sample t test with unequal variances						
Group	Obs	Mean	Std. err.	Std. dev.	[95% conf. interval]	
1	4	.0430594	.0016259	.0032517	.0378852	.0482336
2	4	.0354957	.0020428	.0040855	.0289947	.0419967
Combined	8	.0392775	.0018718	.0052944	.0348513	.0437038
diff		.0075636	.0026108			.0010964 .0140389
		diff = mean(1) - mean(2)		t =	2.8970	
H0:	diff = 0				Satterthwaite's degrees of freedom =	5.71238
Ha:	diff < 0	Ha: diff != 0				
		Pr(T < t) = .9855			Pr(T > t) = .0290	
					Pr(T > t) = .0145	

Table VII
t-test for Alpha Band (RBP) in control group (1) and AD group (2)

. ttest THETA, by(group) unequal						
Two-sample t test with unequal variances						
Group	Obs	Mean	Std. err.	Std. dev.	[95% conf. interval]	
1	4	.0597316	.0065633	.0131265	.0388444	.0806188
2	4	.052457	.0044961	.0089922	.0381484	.0667656
Combined	8	.0560943	.003931	.0111184	.0467991	.0653896
diff		.0072747	.0079556		-.0128245	.0273738
		diff = mean(1) - mean(2)		t =	0.9144	
H0:	diff = 0				Satterthwaite's degrees of freedom =	5.30752
Ha:	diff < 0	Ha: diff != 0				
		Pr(T < t) = .7999		Pr(T > t) = .4001		Pr(T > t) = .2001

Table V
t-test for Alpha Band (RBP) in control group (1) and AD group (2)

. ttest GAMMA, by(group) unequal						
Two-sample t test with unequal variances						
Group	Obs	Mean	Std. err.	Std. dev.	[95% conf. interval]	
1	4	.0112346	.0010631	.0021262	.0078513	.014618
2	4	.0144493	.0022412	.0044825	.0073167	.0215819
Combined	8	.012842	.0012991	.0036744	.0097701	.0159139
diff		-.0032147	.0024806			-.009925 .0034956
		diff = mean(1) - mean(2)		t =	-1.2959	
H0:	diff = 0				Satterthwaite's degrees of freedom =	4.28498
Ha:	diff < 0	Ha: diff != 0				
		Pr(T < t) = .1302		Pr(T > t) = .2604		Pr(T > t) = .8698

V. CONCLUSION

The EEG signal of patients with Alzheimer's disease (AD) was characterized by a decrease in ZCR and a notable reduction in alpha (8-13 Hz) and beta (13-30 Hz) oscillations compared to healthy controls, with only beta oscillations showing a statistically significant difference between groups. These reductions are associated with neuronal deterioration and loss of synaptic connectivity, typical features of AD progression.

For future studies, it is recommended to validate the identified characteristics with a larger study involving patients within the same age range and applying the same protocol to both groups to obtain more comparable results. Ultimately, our long-term goal is to enhance analysis and feature extraction algorithms, as well as identify channels that exhibit significant differences in these characteristics for each group (AD/healthy). This approach aims to simplify electrode array placement for EEG signal acquisition and propose a compact and innovative design for timely and straightforward diagnosis.

. ttest ALPHA, by(group) unequal						
Two-sample t test with unequal variances						
Group	Obs	Mean	Std. err.	Std. dev.	[95% conf. interval]	
1	4	.0440644	.0101339	.0202678	.0118139	.076315
2	4	.0196336	.0031558	.0063115	.0095906	.0296767
Combined	8	.031849	.0067422	.0190697	.0159063	.0477917
diff		.0244308	.0106139		-.0064669	.0553285
		diff = mean(1) - mean(2)		t =	2.3018	
H0:	diff = 0				Satterthwaite's degrees of freedom =	3.57643
Ha:	diff < 0	Ha: diff != 0				
		Pr(T < t) = .9547		Pr(T > t) = .0906		Pr(T > t) = .0453

Table VI
t-test for Beta Band (RBP) in control group (1) and AD group (2)

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