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Role of EEG for Diagnosis of Alzheimer Disease

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Abstract: ***In the recent years, costliest Alzheimer disease (AD) is now primary reason for the cause of death. An early finding is essential as there is no cure for severe AD. Despite recent advances, early finding of Alzheimer disease from electroencephalography (EEG) remains a difficult job. In this paper, we focus a spectral and signal complexity measures through which such early findings can possibly be improved. Power spectral and nonlinear features, which have been utilized for classification of Alzheimer disease subjects (ADS) from the normal healthy subject (NHS). So far, the power in the various EEG bands has been intensely analyzed. The main aim of this research article is to study the power and nonlinear analysis for the finding of AD to consider as a probable biomarker to recognize AD subject and normal healthy subject. Relative power (RP) was independently calculated from various EEG bands which indicate the slowing of EEG signals acknowledge the Alzheimer disease subjects. In this study, EEGs signal had been acquired at the rest condition from 20 normal healthy subject whose age around 60 years along with same number of Alzheimer disease subjects. The result shows that relative power is increased towards lower frequencies while decreased towards higher frequencies in AD. Such analysis of power may additionally explore to differentiate Alzheimer disease's stages.***

Keywords: Alzheimer diseases (AD), Electroencephalography (EEG), Relative power (RP), Bump modeling, nonlinear analysis

I. INTRODUCTION

As per the survey of world health organization (WHO), after the cancer and cardiovascular disease, Alzheimer disease (AD) is now at third position in the list of expensive disease worldwide. In the United States, Alzheimer disease is sixth primary reason for the death issue. Alzheimer disease, neurodegenerative disease, is general type of dementia. Continuous and numerous memory losses along with cognitive declinations are some of the characteristic of AD [1] [2]. In the world, the occurrence of the Alzheimer disease is twice in the next 25 years [3]. Commonly, aging is the major reason of Alzheimer disease which reflects the loss of neuron connectivity in the brain and makes tangles and senile plaques, responsible for AD, in the different part of brain [4]. There are no initial indications which can be solid and significant to analyze the AD in the early stages called mild cognitive impairment (MCI). Early sign of the AD is memory loss, mood changes suddenly and problem with attention. As the severity increase of the disease, the symptoms such as depression, anxiety, irritability, not recognize the familiar faces and more unresponsive has been observed. The development of AD arranged into remarkable stages, for example, mild cognitive impairment (MCI), moderate AD and severe AD. A positive diagnostic of the disease offers times to the patients and their family members to get conscious about the disease, to settle on life and budgetary choices identified with the AD and to get ready for the future plan and patients health. An early finding of AD increases the possibility of giving medical care to patients at promising phase prior to the patients suffers from permanent brain damage [5]. As per the dementia statistics report of WHO, 47.5 million peoples are suffering from dementia in 2018 worldwide. In India, 4.2 million people are suffering from the dementia. In every 3 seconds, someone develops dementia in the world. Figure 1 shows an evaluation of growth rate of individuals suffering from dementia in the nations like low income, middle income and high income. Beside this, death rates due to heart disease have decreased in previous year, but death rates due to AD have increased by 68% in between 2000 to 2015. Furthermore, it does not exist a solution for AD and completely diagnose after the post mortem analysis [6] [7]. There is some conventional clinical assessment test to measure the severity of AD based on psychometric scales, for example, global deteriorating score (GDS), clinical dementia rating (CDR), mini mental state examination (MMSE) and ADAS-cog. These criteria are totally based on the previous history for diagnosis of AD. From the above discussion, detection of initial stage of AD is important.

II. METHODS

Different diagnosis techniques such as neuroimaging and non-neuroimaging methods are utilized for the detection of AD. Neuroimaging technique is one of the notable and all around acknowledged methods for determination of dementia like AD compared to non-neuroimaging method such as genetic analysis, physiological markers etc. Distinctive neuroimaging methods, for example, positron emission tomography (PET), magnetic resonance imaging (MRI) and single photon emission computed tomography (SPECT) are regularly utilized for detection of AD. Even though various neuroimaging methods are mostly utilized, still they experience some drawbacks. The basic drawbacks of these neuroimaging methods are, it is very costly, it takes more time and it has radiation risk. With the exception of these methods, electroencephalography (EEG) is also considered as classic tools for detection of AD [8].

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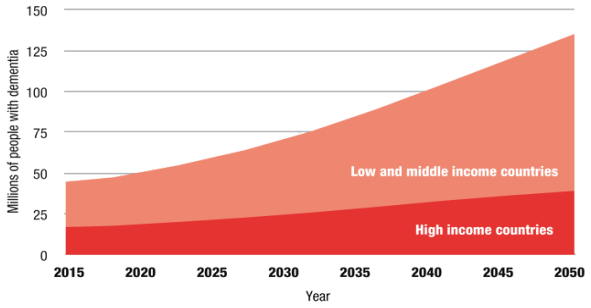

Fig. 1 Dementia people in low, middle- and high-income countries

Electroencephalography is also considered for finding of various neurological issues other than AD, for example, Parkinson's, epilepsy and so forth as significant tool. EEG is non-repeatable pattern, non-invasive techniques and inexpensive tool for finding of various neurological issues [9]. EEG straightforwardly relates the brain activity which is used for observing the various function of brain. Different neurological disease is diagnosed based on the significant features computed from the various non-linear and linear analyses of sampled EEG Signals [10]. Different methods for diagnosing the AD are compared in the table I and literature summary for the detection of AD based on EEG signals summarized in the table II.

III. EEG ANALYSIS IN ALZHEIMER DISEASE

Table II has revealed that AD has been recognized based on EEG analysis in view of its vital peculiarities. The obtained accuracy was remarkable after applying the different method along with various important features. In the event that the subject experiencing AD, a portion of the significant impacts happened in the EEG signals, for example, EEG slows down, complexity of EEG reduced and disturbance occurs in EEG synchronization [11].

1. Slowing of EEG

It was observed from the literature survey, slowing of EEG signal is occurred in the AD subjects. AD is directly related to the spectral power variation in different frequency bands of multidimensional EEG. In AD subjects, decrease of power in higher frequencies like alpha (8-13 Hz), beta (13-30 Hz) frequency bands with power increase in lower frequencies

Table- I: Various neuroimaging methods comparison

Parameter	MRI	PET	SPECT	EE
Radiation	Yes	Yes	Yes	No
Time Resolution	High	High	High	Less
Temporal Resolution	Reasonable	No	No	Hig h
Cost	High	High	High	Less
Portability	No	No	No	Yes
Biomarker	Indirect	Indirect	Indirect	Dire

Table-II: Literature summary for diagnosis of AD based on EEG signals

Sr. No.	Ref.	Method used	Accuracy
1	[11]	Relative power and complexity measure	83 %
2	[12]	Tsallis entropy	82 %
3	[13]	M3 model	89.4 %
4	[14]	Spectral modulation	89 %
5	[15]	Nonlinear features	70.5 %
6	[16]	Integrative EEG biomarker	60 %
7	[17]	ICA enhanced EEG measurement techniques	88 %
8	[18]	Analysis of spectral and nonlinear dynamical methods	80 %
9	[19]	Quantitative method for measuring the EEG variability	88 %

like delta (0.5-4 Hz) and theta (4-8 Hz) frequency band. One has applied the different transform and bump modeling called as time frequency map on the EEG signal to compute the changes in the spectral based features. Slowing of EEG signifies the changes in the power of different band in the signal.

2. Complexity of EEG reduced

In Alzheimer disease, due to loss of neuron, the EEG complexity reduced. Different techniques are utilized for measuring vital feature present in the EEG signals for differentiation of normal healthy subject and Alzheimer disease subjects. Various strategies, for example, Tsallis entropy, multi-scale entropy, information theory, approximate entropy, mutual information and sample entropy are used to quantify EEG complexity.

3. Disturbance occurs in EEG synchronization

A large number of parameters based on synchrony have been utilized for the AD analysis. In the digital signal processing sciences, these synchrony parameters are estimated. From the previous study of the same topic, it is noticed that synchronization of EEG decreases in the AD subjects. Different synchrony parameters like stage synchrony, granger causality, magnitude phase coherence and pearson correlation coefficient computed from the EEG signal. These features are influenced by brain signals. So, synchrony parameters performed most important role for the determination of the AD.

IV. METHODOLOGY

In this study, used EEG database was received from SKN General Hospital and Research Centre, Pune including equally AD subjects (ADS) and normal healthy subjects (NHS). Subjects have been considered for the different age group between 52-75 years from various locations with a document of decline the cognitive and behavioral functioning certified from well-known neurologists.

Neurologist diagnoses these subjects totally based on psychometric scales. Recorders and Medicare Systems (RMS) is used for acquiring the EEG signal with specification of sampling rate is of 1024 Hz and 12 bits resolution. The impedance of the device always kept below 10 MΩ and the arrangement of the electrodes as per international 10-20 systems. In this device, additionally biauricular referential electrodes have connected as certified through American EEG Society. Low pass filter is used to eliminate the power grid interference. Table III shows the details of the acquired EEG database. Subjects were alert and relaxed with eye closed during EEG examination and acquiring. The artifacts present in EEG signals like eye blinking and muscle activity were manually removed. The acquired EEG is given to the preprocessing unit such as band pass filter which is used for eliminating the artifact from the signals. After filtering process, wavelet function is applied to the EEG and classified into the various frequency bands. Implemented methodology shown in the figure 2. On the other side, one often computes the relative power via time-frequency graph; such graphs are mainly beneficial if anyone is keen in the power spectrum at a particular occurrence of time and consequently, time frequency graph had been utilized in this study. Fascinatingly, time-frequency maps called bump model of EEG signal are often thin; in this map most of the energy is contained in explicit area called bumps equivalent to transient oscillations. Newly, one should propose a procedure to take out such transient oscillation from the bump model. It was demonstrated that starting phase of AD and severe AD patients, transient oscillation in the EEG signal frequently occur at delta and theta bands compared to normal healthy subjects.

1. Spectral Analysis

Recent research survey has reported that the neurodegenerative disease like AD directly affects on the EEG spectrum which reflects the brain activity. The main characteristic of AD is slowing of EEG which signifies the alteration in the power spectra of EEG. In Alzheimer subjects, effect of slowing EEG is observed by calculating the relative power of various frequency bands. This method, in various

Table- III: Details of EEG database

Variable	Alzheimer Disease	Normal Healthy
Number of Samples	20	20
Age Group	52-75	50-65
Average Age	63.5	57.5
Gender	13 Male/7 Female	15 Male/5 Female
Diagnosed by	MMSE and CDR	MMSE and CDR

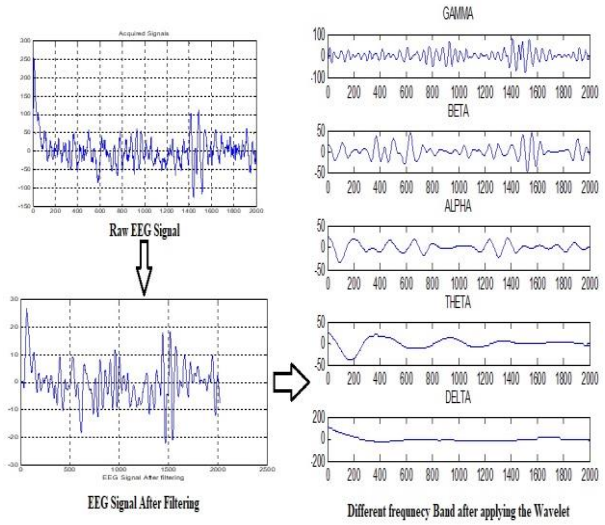

Fig. 2 Implemented methodology flow

points of views, has been applied to classify AD and normal healthy subjects. As a result of, the significance of EEG spectral analysis and the performance of each frequency band in the power spectrum with respect to detection of awareness are assessed [20]. Relative power (RP) is calculated by adding the involvement of the preferred spectral elements and is given by (1)

$$RP(f1, f2) = \sum_{f1}^{f2} PSDn(f) \quad (1)$$

Where f1 and f2 are the lower and the higher cut off frequency of every band and PSD is power spectral density.

2. Complexity Based/ Nonlinear Analysis

In the current study, distinctive complexity/non-linear based features are determined, for example, spectral centroid (SC), zero crossing rate (ZCR), spectral roll off (SR) and spectral entropy (SE). These nonlinear features are associated with plaques and tangles which is formed after the death of neurons in the brain which itself sign the AD. Hence, in this paper, various non-linear based features were calculated and analyzed. Spectral centroid is a degree of the power spectrum. High value of spectral centroid related to more energy is concentrated at high frequencies. Unpredictability measure and uncertainty in the range of power spectrum called as spectral entropy. Spectral entropy is high in the Alzheimer disease subjects. Spectral Roll – off shows concentration of the spectral magnitude distribution at which frequencies. Zero crossing rates are the rate at which signal cross the zero line which indicates the EEG signal complexity [21].

V. RESULT

In Alzheimer, most affected part of brain is central, temporal, frontal and parietal lobe. Relative power which is spectral feature is calculated for each frequency band on EEG data for a different region of the brain.

The experimental value of relative power is placed for frontal and temporal region in table IV. For AD subjects, the result shows that relative power of delta and theta bands which is slow frequencies band is increased whereas relative power of fast frequencies like alpha and beta is decreased. However, maximum relative power of gamma band observed in mild cognitive impairment (MCI). In case of NHS, the relative power observation is exactly opposite to AD subjects, power of slow frequencies is low and power in fast frequencies is high. After performing the experimentation, obtained results in table IV matched with the result in the literature using the above EEG dataset. The graphical representation of RP analysis is shown in the figure 3. Database utilized in this research; the bump showed which time frequency representation of the EEG signal. Bump is far found that transient oscillation inside the EEG of Alzheimer disease subject arises more regularly at lower frequencies in comparison with normal subjects as shown in the figure 4. It is found that bump model gives the arithmetical contrasts in the theta band among normal and AD subjects in EEG. Present study included the utilization of various nonlinear features which were calculated for frontal and temporal region mentioned in the table V. In this paper, spectral centroid (SC), spectral roll off (SR), zero crossing rate (ZCR) and spectral entropy (SE) are computed for EEG signals. The value of these complexity-based features in AD decreases as compared to normal healthy subjects as shown in figure 5 and 6.

Table-IV: Relative power of distinct frequency band of frontal and temporal region of various subjects

	RP-- Delta		RP-- Theta		RP-- Alpha		RP-- Beta		RP-- Gamma	
	Frontal	Temporal	Frontal	Temporal	Frontal	Temporal	Frontal	Temporal	Frontal	Temporal
Alzheimer Subjects										
Case 1	17.84	8.28	7.25	6.12	12.19	8.29	9.51	3.17	12.36	7.82
Case 2	18.42	9.29	14.72	5.21	10.92	3.49	6.14	3.79	13.17	6.13
Case 3	14.21	5.23	12.43	4.87	10.54	6.23	9.23	4.21	10.89	6.46
Case 4	16.93	6.21	10.11	5.12	16.05	9.21	15.21	7.57	11.38	21.68
Case 5	10.69	4.18	8.83	5.373	3.56	1.21	8.85	3.39	8.16	4.16
Case 6	8.31	3.54	10.12	3.21	6.12	3.19	11.93	2.41	7.14	5.18
Case 7	6.93	3	10.11	4.16	17.05	15.56	11.01	17.57	21.38	23.64
Case 8	12.93	6.31	09.51	6.12	12.19	8.29	9.51	3.17	12.36	7.82
Case 9	10.69	5.18	8.16	5.21	10.92	3.49	6.14	3.79	13.17	6.13
Case 10	9.31	4.58	7.14	4.87	10.54	6.23	9.23	4.21	10.89	6.46
Case 11	9.93	5	21.38	5.12	16.05	3.19	11.93	2.41	7.14	5.18
Case 12	15.93	7.31	15.31	5.373	3.56	15.56	11.01	17.57	21.38	23.64
Normal Subjects										
Case 1	5.64	7.23	7.23	11.82	21.32	6.16	10.32	5.13	8.12	10.36
Case 2	6.45	8.2	8.15	13.63	14.39	3.61	8.38	9.3	9.25	31.69
Case 3	24.51	14.52	35.26	14.27	38.24	16.38	13.61	25.84	14.58	24.85
Case 4	7.86	6.48	3.96	10.25	3.84	15.13	12.14	6.81	14.68	10.18
Case 5	34.8	18.5	44.56	13.71	44.98	13.51	20.94	21.13	13.12	27.12
Case 6	34.8	18.5	44.56	13.71	44.98	5.64	7.23	7.23	11.82	31.69
Case 7	14.8	14.7	13.71	13.71	44.98	6.45	8.2	8.15	13.63	24.85
Case 8	12.14	6.81	14.68	10.18	21.32	6.16	10.32	5.13	8.12	10.36
Case 9	20.94	21.13	13.12	27.12	14.39	3.61	8.38	9.3	9.25	31.69
Case 10	12.14	6.81	14.68	10.18	38.24	16.38	13.61	25.84	14.58	24.85
Case 11	38.24	16.38	13.61	25.84	14.58	15.13	12.14	6.81	14.68	10.18
Case 12	21.47	31.5	16.38	13.61	25.84	14.58	13.26	7.34	13.54	12.36

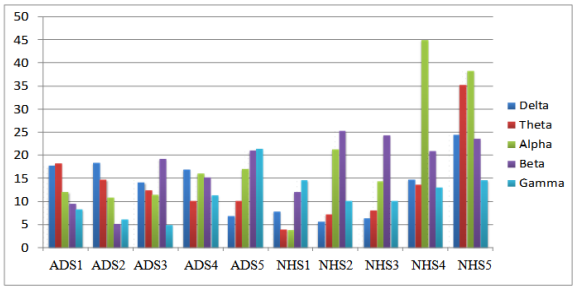

Fig. 3 Relative power of frequency bands

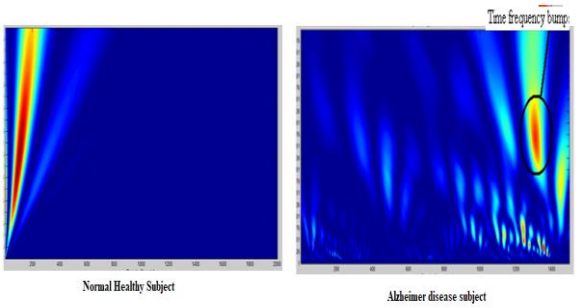

Fig.4 Time-frequency representation of EEG signal for NHS and ADS

Table-V: Complexity based features

	Alzheimer Disease Subjects							
	Frontal				Temporal			
	ZCR	SC	SR	SE	ZCR	SC	SR	SE
Sample 1	0.0018	0.0952	1.5423	2.8722	0.0143	0.055	0.9876	2.98
Sample 2	0.0709	0.0802	1.9987	5.5409	0.0756	0.1104	0.801	3.9801
Sample 3	0.0033	0.0437	0.9921	3.7955	0.0032	0.032	0.8878	3.089
Sample 4	0.033	0.0443	1.0932	3.9773	0.143	0.564	2.323	5.5567
Sample 5	0.0034	0.087	0.878	3.0545	0.034	0.0023	0.879	3.9704
Sample 6	0.0167	0.0175	0.998	2.879	0.0233	0.0824	1.3432	4.9456
Sample 7	0.043	0.1321	0.889	4.1765	0.0033	0.0943	0.9565	4.4555
	Normal Subjects							
	Frontal				Temporal			
	ZCR	SC	SR	SE	ZCR	SC	SR	SE
Sample 1	0.033	0.0297	1.9121	3.4978	0.03	0.0637	1.3221	4.6784
Sample 2	0.0833	0.1185	1.0921	5.6421	0.0567	0.1219	1.9324	5.4312
Sample 3	0.0578	0.1167	1.9712	5.6117	0.0967	0.1313	0.5654	5.6529
Sample 4	0.177	0.1392	1.992	5.895	0.13	0.1893	1.9922	6.1844
Sample 5	0.0367	0.0759	1.8923	4.9045	0.099	0.1892	0.9321	3.0932
Sample 6	0.0233	0.9832	1.7821	5.276	0.0233	0.0243	1.9343	5.5654
Sample 7	0.0567	0.1102	1.9922	5.5852	0.544	0.0834	1.922	5.095

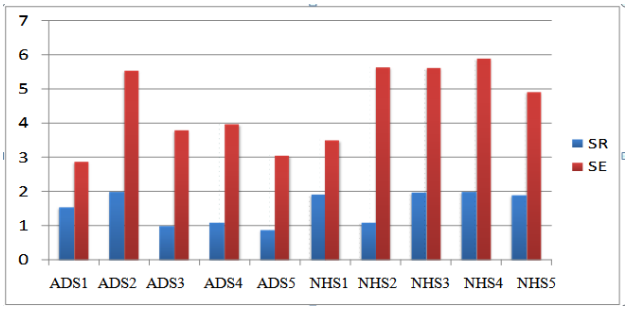

Fig. 5 Representation of SR and SE for ADS and NHS

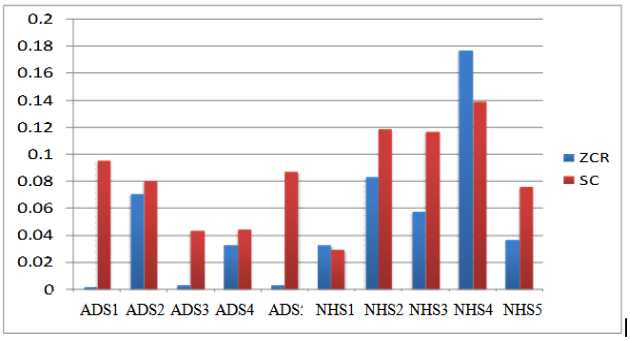

Fig. 6 Representation of ZCR and SC for ADS and NHS

VI. CONCLUSION

Spectral based features like relative power of EEG signals, well known diagnostic tool, is used to classify the AD from the normal healthy subject. It is observed that the power spectrum over the frequency distribution of EEG signal changes which pointing out the brain abnormalities in the AD subject. The consequences emphasize the usefulness of study with a view to help neurophysician to differentiate AD and normal subject based on EEG data. At the same time, result computed for non-linear features in the table V give the vital information to differentiate the normal and AD. The value of these complexity-based features is decreased in the Alzheimer disease subjects. So, we tried to classify the AD from the normal subject based on the spectral and complexity feature successfully.

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