



AUTOMATIC DETECTION OF ALZHEIMER DISEASE USING EEG MODULATION ENERGY

Alok Pathak

Associate Professor, Dept. of Electrical Engg., IPS-CTM, Gwalior (M.P)

Email: alokpathak77@gmail.com

Abstract

In this paper, a new methodology Spectro-temporal EEG amplitude modulation energy along with an effective artifact removal algorithm, based on Independent Component Analysis (ICA) for diagnosis of Alzheimer disease using EEG signals is proposed; thereby increasing the diagnostic accuracy of the EEG signals & diagnosis. This paper presents it is concluded that EEG can play an important role in diagnosis of Dementia & Alzheimer Disease.

Keywords: Alzheimer, Disease, Dementia, EEG, Spectro-temporal EEG Amplitude Modulation Energy, Spectral Power Based Features

Introduction

Alzheimer Disease is one of the most common & tremendously growing neurological diseases in the world. Electroencephalogram signals (EEG) yields out powerful and relatively cheap tool of diagnosis of different neurological disease. EEG can be used the standardized tool for diagnosis of Alzheimer disease. The Electroencephalogram (EEG) is a tool for measuring the brain activity which reflects the condition of the brain. EEG is very effective tool for understanding the complex behavior of the brain. EEG provides the electrical action potentials produced by cerebral cortex neurons [1]. The EEG detecting machine is a video recording device and linked through wires to electrodes connected at specific points on the head of the patient Various abnormalities are found in the EEG signals of the patients suffering from Alzheimer disease. Hence, the need is to develop the detection of the disease in early stage called as Dementia, the first stage called Mild cognitive impairment (MCI). Role of EEG in diagnostic & clinical research of Alzheimer

disease has become more useful in present decades. In present, the most critical task includes the diagnosis of the AD & its early detection in the preclinical stage. The need is to improve the diagnosis accuracy of the EEG signal.

Literature Review

Although Cancer & Cardiovascular diseases are one of the most expensive diseases; Alzheimer Disease is now third most expensive disease & the sixth leading cause of death in United States. Basically, Alzheimer Disease (AD), the common form of dementia, is neurodegenerative disorder characterized by a progressive & several loss of memory with cognitive impairment [1] [2]. The prevalence of the disease in the world is assumed to double in next 20 yrs [3]. Alzheimer Disease is assumed to increase in future mainly due to aging phenomenon. There are no early symptoms which can be reliable & valid to diagnose the disease in early stage. In the mild stage of the Alzheimer Disease, loss & impairment of memory is noticed. As the disease progresses, several deficits are observed in cognitive abilities such as judgment, abstract or logical planning & organizing [5]. In the ultimate stage of disease, termed as Severe Alzheimer Disease (AD), almost all the cognitive functions are severely damaged along with motor functions such as chewing & swallowing [6]. According to the World health Organization report, it was estimated that there are 44.4 millions of people suffering from Dementia & Alzheimer Disease in the world. It is also expected that this number will increase till 75.6 million in 2030, and 135.5 million in 2050. It is observed that 61% of the people suffering from dementia are from developed countries. The fastest growth of the disease is taking place in

India, China, and South Asian & Western Pacific countries [7]. From the above survey done, we can conclude that it is essential to diagnose the Alzheimer Disease in early stage. The early diagnosis of disease is essential since medications can be given in early stage of disease. The early diagnosis of the disease also allows the patients family to take financial decisions related to the disease & plan for the future needs & care of the patients.

Numerous clinical methods are extensively used for the diagnosis of Alzheimer disease such as neuroimaging techniques, physiological markers, and genetic analyses. Neuroimaging is one of the well-accepted methods for definitive diagnosis of dementia. Various Neuro-imaging methods are used for the diagnosis of the Alzheimer disease. Several methods such as single-photon emission computerized tomography (SPECT), positron emission tomography (PET), and magnetic resonance imaging (MRI) have been successful for recognizing AD at an early stage. But the main problem of PET & SPECT is they impose the radiation risks. Other disadvantages are their costs; which are much expensive, time

consuming & inconvenient. So, apart from all these Neuro-imaging methods; EEG is one of the standard methods used for the diagnosis of the Alzheimer disease.

Electroencephalography is considered as one of the important and cheap tool for diagnosis of different neurological disorders such as Parkinson's, Epilepsy, Dementia & Alzheimer etc [9] [10]. Electroencephalography is Non-invasive, repeatable, & cheap tool for diagnosis of different neurological disorders. EEG directly correlates the brain function which is clinically for monitoring the brain activity. Different linear & non-linear analysis of sampled EEG signals gives us the unique features to reveal the diagnosis of neurological diseases.

Along with the above techniques, Electroencephalogram signals have high temporal resolution and several abnormalities are observed in EEG signal of the patients suffering from different neurological disorders. The table.1 shows the various methods & features used by the researchers for Electroencephalogram based diagnosis of Alzheimer disease.

Table 1
Comparative Study of various techniques developed By Researchers

Sr. No	Reference	Methods Used	Accuracy
1.	[17]	Independent Component Analysis (ICA)	60%
2.	[20]	Spectral Power Density	80%
3.	[13] [14]	Tsallis Entropy	82%

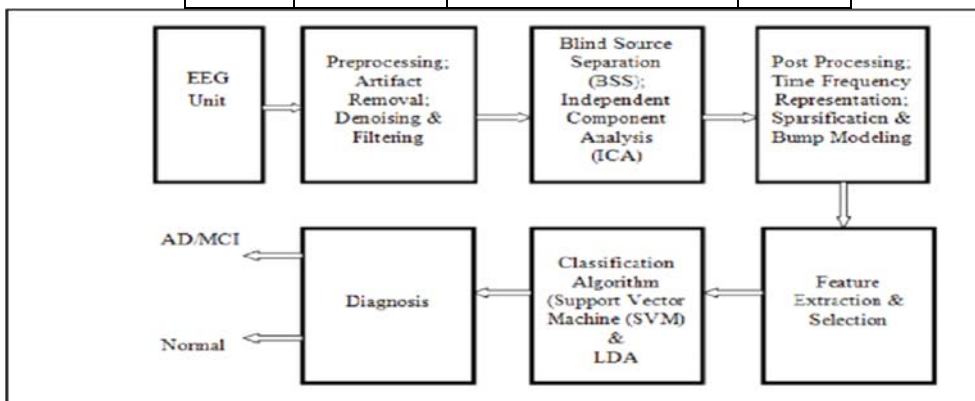


Fig. 1: Block diagram of Proposed System

PROPOSED METHODOLOGY

Let us discuss the proposed methodology in more detail.

(a) EEG Acquisition: The EEG signal will be acquired using EEG electrode cap placed on the patients head using International 10-20

system. The EEG acquisition kit will be used for displaying the EEG signal to computer in digital format [8].

(b) **Pre-processing:** It includes the noise removal from raw EEG signal. Basically, Pre-processing of EEG signal involves amplification, filtering of signal & artifact removal. To obtain more enhanced EEG signal, various techniques are used such as Blind Source separation (BSS) [17], Independent Component Analysis (ICA) [18] etc. Once the signal is cleaned, it is converted in frequency domain. This is called post preprocessing of EEG signals. Wavelet transform (DWT), Sparsification & Bump modeling are used for post preprocessing of EEG signals.

(c) **Feature Selection & Extraction:** In this process, some certain features of signal obtained are extracted from pre-processed EEG signal. The feature comprises of certain frequency bands of power spectrum. Various features of EEG signal can be extracted such as Spectral power, variations in EEG amplitude & frequency, measure of spatial synchronization etc. The above features can be calculated using various techniques such as Fast Fourier Transform (FFT), Discrete Wavelet Transform (DWT) etc.

(d) **Classification:** The features in the previous part are the input to the classifier. The classifier is a linear model or nonlinear model which will be trained to diagnose the disease. In our proposed research work, different algorithms will be used & tested such as Linear Discriminant Analysis (LDA), Support Vector machine (SVM), K-means Clustering, Artificial Neural Networks (ANN) etc, to compare the diagnostic accuracy of the signal & classifier used.

(e) **Diagnosis:** Depending on the output of the classifier, we will be in the situation to detect whether the patient is suffering from Alzheimer disease. Depending on the features used, we can also detect the stage of the disease. (EEG) is the recording of electrical activity along the scalp produced by the firing of neurons within the brain. These activities can be decoded by signal processing techniques, however, they are typically influenced by extraneous interference, like muscle movements, eye blinks, eye movements, background noise, etc. Therefore, a preprocessing step to remove artifacts is extremely important. This paper presents an effective artifact removal

algorithm, based on Independent Component Analysis (ICA)

Independent Component Analysis (ICA)

The first step in our proposed algorithm is the ICA transform. ICA is a computational method for separating a multi-channel signal into additive subcomponents supposing the mutual statistical independence of the non-Gaussian source signals. Assume that we observe an array of electrodes that provide a vector of N channel signals $\mathbf{v}(t)=[v_1(t), v_2(t), \dots, v_N(t)]^T$ that are linear combinations of N unknown and statistic independent sources $\mathbf{s}(t)=[s_1(t), s_2(t), \dots, s_N(t)]^T$.

When applying the ICA to the EEG signals, the resulting independent components represent the event-related potentials and non-event-related sources (including artifacts). This makes the ICA to be an effective method for removing the artifacts. The inverse matrix W^{-1} gives the relative projection strengths of the respective components to each of the scalp electrodes, which will be used as features for further clustering. These inverse weights define the scalp topography of each component, and provide the evidence for the components' physiological origin.

Several ICA algorithms have been implemented and are publicly available. In this paper, we use the Fast ICA algorithm in the EEGLAB [24] to transform the original multi-channel EEG signals into ICs.

EEGLAB & MATLAB toolbox will be used for processing of Electroencephalogram signal. EEGLAB is found to be an interactive MATLAB toolbox which will be used for processing the continuous & event related EEG data [19]. Using Independent component analysis (ICA), time/frequency analysis, EEGLAB also provides an interactive graphics user interface (GUI) allowing users to flexibly and interactively process their high density EEG data. Thus, MATLAB will be used as the software tool for evaluating the preprocessing, feature extraction & classification algorithms.

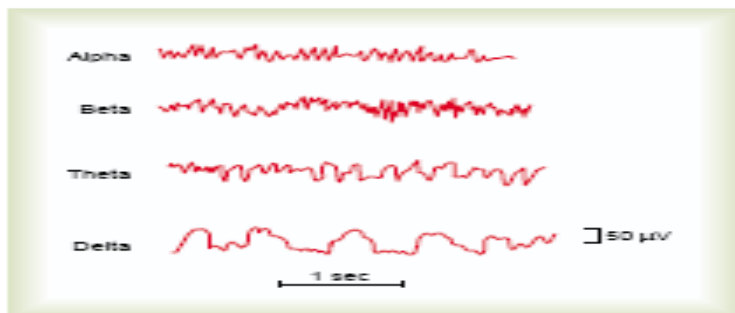
FEATURES USED FOR DIAGNOSIS OF ALZHEIMER DISEASE USING EEG SIGNALS.

There exist different features for diagnosis of Alzheimer disease in literature. Features play a significant role in automated diagnosis of Alzheimer Disease. Let us now discuss the

different features which can be used for diagnosis of Alzheimer Disease.

A. **Spectro-temporal EEG amplitude modulation energy** It is the novel feature for AD diagnosis which quantitatively monitors EEG amplitude modulation [22] [23]. The feature is termed as ‘EEG spectro-temporal modulation energy’. The following are the different steps involved in its computation. Firstly, the full-band EEG signal is decomposed into five well-known sub-bands: delta (0.1 - 4 Hz), theta (4 - 8 Hz), alpha (8-

12 Hz), beta (12 - 30 Hz) and gamma (30 - 100 Hz). The Temporal envelope of each sub-band signal is computed by means of a Hilbert transform. In order to quantify the rate of change of the sub-band temporal envelopes, further decomposition of the envelopes into the five modulation bands is done and then the energy computation is done present in each modulation band. In the resulting spectral modulation techniques, rate of change in the information for each sub-band amplitude envelope is observed.



Along with the same, the frequency range of modulation bands are empirically set to coincide with the frequency range of conventional bands. To distinguish between the two modulation bands are appended by a prefix ‘m’ (e.g. m-delta, 0.1 - 4 Hz; m - theta, 4 - 8 Hz) etc. The feature of this represents the percentage of overall modulation energy present in each of the five frequencies and five modulation frequencies [22] [23].

Methods for EEG Data collection/simulation

In the above study total 650 modulation energy features can be extracted per epoch per participant. So, total 25 features for total 19 channels & including 7 bipolar channels. So total we can compute the $25 * (19 + 7) = 25 * 26 = 650$ features per AD patient. The placement of the EEG electrodes consist of International 10-20 system for bipolar referential electrodes & it can be used for recording of the EEG signals of

19 channels namely Fp1, Fp2, F3, F4, F7, F8,

C3, C4, T3, T4, T5, T6, P3, P4, O1, O2, Cz, Fz, Pz. An EEG bipolar signal can be obtained by subtracting the two bi-auricular referenced signals involved. The commonly used bipolar signals include F3-F4, F7-F8, C3-C4, T3-T4, P3-P4, T5-T6, and O1-O2. The following figure shows EEG electrode placement according to the International 10 - 20 systems

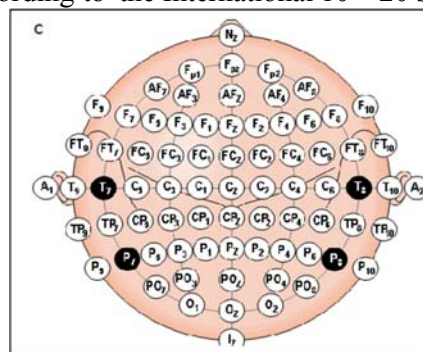


Fig. 3 International 10 - 20 EEG Electrode Placement System

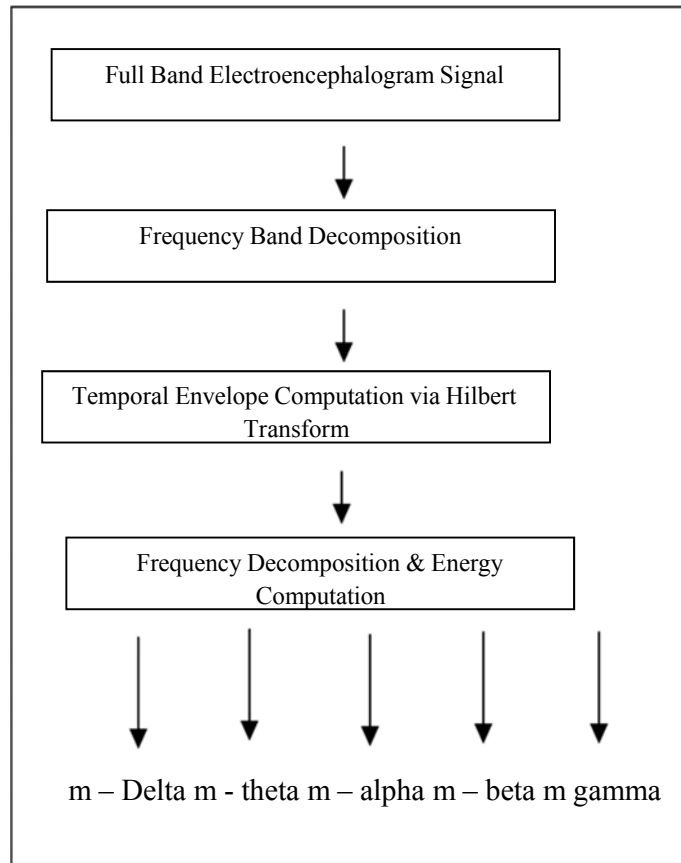


Fig.4 Spectro -temporal EEG amplitude modulation Energy

Thus, the Spectrum of the EEG signals can show a difference in power for AD patients, Dementia patients & normal patients. Thus, *Spectro-temporal EEG amplitude modulation energy* based features plays a significant role in diagnosing in Alzheimer Disease.

Conclusion

At the end, it is expected that we will obtain the high accuracy of EEG signal for diagnosis of Alzheimer Disease. By observing the *Spectro-temporal EEG amplitude modulation energy* based features of the EEG signal, classified according to the different frequency band & depending upon the output of the classifier and applying effective artifact removal algorithm, based on Independent Component Analysis (ICA) we will be in the position to detect the Alzheimer Disease with high accuracy up to 95% in early stage. The future work includes the more automatic tools for artifact removal of EEG signals and applying the algorithms on large datasets for increasing the accuracy of EEG signals. Several automatic artifact removal techniques such as principal component analysis (PCA), can be used to make the system completely automatic.

Thus, early diagnosis of disease can help us to take preventive measures to control the disease in early stage.

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