INDIAN INSTITUTE OF TECHNOLOGY, BOMBAY

EE338 APPLICATION ASSIGNMENT - **Group 27**

Alzheimer's disease detection by EEG Signal Processing and Supervised Learning

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Group 27

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Abstract

Background: Alzheimer's disease is a progressive disorder that causes brain cells to waste away (degenerate) and die. Alzheimer's disease is the most common cause of dementia — a continuous decline in thinking, behavioral and social skills that disrupts a person's ability to function independently. Current Alzheimer's disease medications may temporarily improve symptoms or slow the rate of decline. However there is a significant lag in being diagnosed for Alzheimer's disease in the villages and treatment for the same. An early detection of AD affected patients can be done through Digital Signal Processing techniques, in particular, perturbation of synchrony and slowing down of rhythms.

Methods: Using EEG signals, we make use of a procedure that applies feature extraction and classification techniques to distinguish between AD and other possible diseases like Mild Cognitive Impairment (MCI) and healthy control (HC). Specifically, we perform a time-frequency analysis by applying both the Fourier and Wavelet Transforms on 109 samples belonging to AD, MCI, and HC classes. The classification on a broad basis can be distinguished into three classes as discussed.

Atmanirbhar Bharat Initiative: We have chosen this problem statement because the current methods of diagnosis of Alzheimer's disease require heavy medical equipment for MRI and CT Scan, and Blood test which is time-consuming, costly and not feasible in remote locations. With this project, we aim to arrive at a solution which makes the diagnosis of Alzheimer's disease more accurate, less time consuming, less complicated and feasible for usage in remote locations of India.

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1 Background

Alzheimer's Disease with its ever increasing numbers and occurrences is one of the major problems faced by the modern society today. AD affects day to day life of the families besides affecting the social and cognitive functions of the patients. There is an inherent cognitive deficit associated with aging and dementia on the other hand is defined as Mild Cognitive Impairment (MCI). Several symptoms distinguish MCI, but the loss of memory is a major risk factor that can develop into AD. Timely diagnosis will possibly reduce the chance of progression. From biological point of view, conditions of brain physiology can be recorded from the EEG signals recorded, and thus abnormalities can be identified through detection of unusual frequency patterns. Different bands possible are : α, β, γ, δ, and θ.
Therefore, we can state that EEG signals related to healthy controls subjects can be distinguished from those ones of subjects affected by neuro degenerative diseases (e.g., AD) or other pathologies (e.g., epilepsy). However, despite advances in biological equipments, AD and MCI still suffer from huge variability and thus discriminating artifacts and patterns similarities to physiological brain activity still remain a crucial issue.
However, the above discussed being the best non-invasive and affordable method applicable for remote villagers with meagre sources of income. Using classification methods proposed, we can easily make a good estimation of the possible happenings of AD or MCI. Here, we use a procedure for EEG signal pre-processing and automatic classification with supervised learning methods. For the EEG pre-processing part, we are doing the spectrum analysis using wavelet transforms.

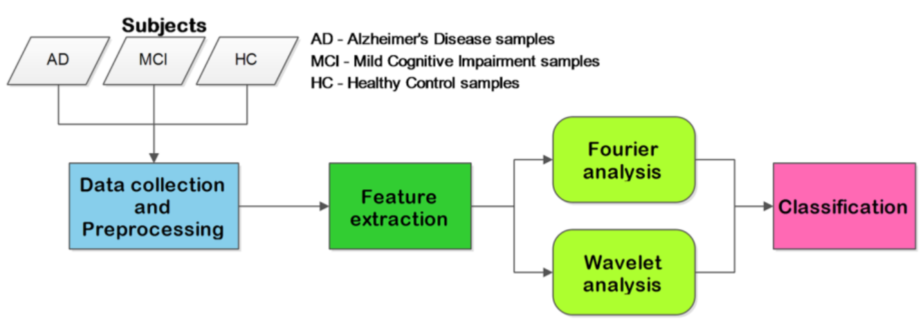

Figure 1: Flowchart of the EEG signal analysis procedure

2 Method

2.1 Dataset and Pre-processing

The dataset has been generated by the Open Access Series of Imaging Studies(Oasis) collected by testing 150 patients, multiple times to obtain 373 distinct samples of which 213 are Females(Not distinct, repeated samples exist) and 160 Males. Of the 373 samples, of them have been tested Dementia positive while of them as Not Demented.

The dataset we have obtained has been processed over in the following fashion. EEG values that are obtained are continuous time signals. These continuous time signals have been sampled.

2.2 Feature Extraction

Each sampled signal is analysed in the frequency domain by applying **Fast Fourier Transform (FFT)** and M (M=7) such coefficients are considered as features for Machine learning model.

Fast Fourier Transform (FFT) has been applied to obtain the spectrum of the EEG signals. The FFT relies on the **Discrete Fourier Transform (DFT)** computed as follows:

$$X[k] = \sum_{s=0}^{S-1} x[s]e_k[s]$$

with s representing the s $-\,th$ sample in the time domain; x corresponding to the signal time series $(s = 0, 1, 2, \cdots, S^{-1})$; X referring to the representation of the frequency domain for the time-series signal x; S representing the the whole number of samples of the signal x; k corresponding to k $-\,th$ frequency component $(k = 0, 1, \ldots, S^{-1})$; $e_k[s] = e^{-\frac{jt2x}{s}}$ referring to the k $-\,th$ basis function. $e_k[s]$ is calculated simultaneously during the sampling phase. Such a formula yields as output one complex number $X[k]$ for each k component.

Another method of generating features is through **Discrete Wavelet Transform (DWT)**. It is a slightly more effective way of decomposing time and frequency of EEG signal. DWT is a time-frequency representation of the signal, which is decomposed in different windows of variable size, i.e., sub-bands.

Conversely to the FFT, the DWT is able to catch the transient features of the analyzed signal, i.e., it enables to keep both the temporal (spatial duration) and frequency information of the signal. Indeed, WT allows to represent when transient events occur in the signal and with what intensity, as well as the time variations of the frequency contents. Given a signal, DWT decomposes it in simpler oscillating functions called wavelets. A family of wavelets ($\psi_{a,b}(t)$) are derived from a unique mother wavelet $\psi(t)$ by scaling (dilating and contracting) and by shifting it to different time positions.

$\psi_{a,b}(t) = \frac{1}{\sqrt{|a|}}\psi\left(\frac{t-b}{a}\right)$

In the above equation, t is the time variable, $a \in R0$ is the scaling parameter, and $b \in R$ is the shifting parameter. The wavelets are localized in both time and frequency with respect to the sinusoidal waves of Fourier, which are better localized in frequency, but infinitely extended in time. Additionally, the former are limited in band, i.e., they are composed of a defined range of frequencies.

When dealing with digital signals that are frequency band-limited, the continuous form of DWT can be discretized according to the sampling theorem. The Discrete Wavelet Transform (DWT) allows to process digital signals by keeping enough information in reasonable computational time. A relevant feature of the DWT is the combination with high and low pass filters, through which the signals can be processed to filter the high and low frequencies in order to compress and reduce the noise, e.g., hidden artifacts and background noise during the EEG signals recording. Indeed, the WT is a well-established signal representation and feature extraction technique for EEG processing.

For this work, DWT can be adopted in order to perform the spectral analysis on the previously described dataset. The choice of a simple DWT stems from the need of obtaining good performances over an arbitrary number of feature elements per channel and from the sampling frequency of the input signals (256 Hz). We adopt two types of discrete wavelet families: Daubechies (db) and Symlets (sym). Daubechies are compactly supported orthonormal wavelets, while Symlets are symmetrical wavelets proposed by Daubechies as modifications to the db family.

Given a single set of signals, each one is processed according to a feature extraction procedure composed of two main phases: noise reduction and feature extraction. Firstly, we perform a noise reduction phase, where each EEG signal is decomposed in n levels (i.e., sub-bands) by applying a DWT (Symlets order 3 wavelet type). For every sub-band x an upper and lower threshold value is calculated as:

$$\mathrm{Thr}_{\mathrm{up}}(x) = \mathrm{avg}(x) + 1.5 \cdot \mathrm{stdev}(x)$$
$$\mathrm{Thr}_{\mathrm{dwn}}(x) = \mathrm{avg}(x) - 1.5 \cdot \mathrm{stdev}(x)$$

The values of each sample s_i are then compared according to the defined thresholds above and if $s_i > Thr_{up}$ or $s_i <$ Thr $_{dwn}$ then s_i is reduced as follows: $s_i * (Thr_{up}(x) - Thr_{dwn}(x))\,/100$. This step is performed in order to obtain an effective artifact reduction and to avoid possible information loss. The artifact removal phase operates on two levels of signal decomposition: level 5 and level 8. We choose these decomposition levels, because their ranges take into account the alpha, theta, beta, and delta bandwidths, which are widely adopted for EEG analysis and have been proven to be effective when dealing with Alzheimer's diseased patients (see "Background" section for more details). The channel signal is then reconstructed with the obtained values, which are given as input to the feature extraction phase.

Secondly, for extracting the features, the Daubechies can be adopted of order 4 (db4) wavelet type with a sampling frequency of 256 Hz at decomposition level 5, which has been shown to guarantee a precise feature extraction in the brainwaves frequencies, and a large set of tests can be performed with different parameters obtaining lower performances. The feature extraction phase extracts the following statistical features: mean, standard deviation, and power spectral density of the wavelet coefficients. All the three feature types, representing the frequencies distribution of the EEG signals, are calculated over the n epochs of a channel-related signal. This phase makes use of the decomposition levels obtained by applying the DWT to the values produced during the noise reduction phase. Our method allows to apply an adaptive, threshold-based noise/artifact removal to the main bandwidths (i.e., alpha, theta, beta, delta).

Note: The EEG raw dataset is extremely difficult to acquire as it is the medical data of patients obtained with a lot of effort and resources going into it. Hence hospitals and other organisations do not make such data readily available. The dataset we obtained had already been processed by FFT and hence DWT could not have been done on the already processed data. However, the analysis would've still been very similar with the only distinction in the feature extraction process, which is mentioned above.

2.3 Classification

We perform supervised learning analysis to automatically classify the samples to their types (Demented or Not Demented) by processing their associated features. We make use of three machine learning algorithms namely Logistic Regression, Support Vector Machine,Decision Tree, Random Forest and AdaBoost to classify each sample into their categories (Demented or Not Demented) to check the performance of each algorithm and see which gives us the best results.

3 Results

The results of the supervised learning analysis by applying the five above mentioned algorithms are as follows.**Disclaimer**:Overfitting is possible considering the size of the dataset, hence the accuracy may not remain as large if the algorithms are applied on a large dataset.

Model	Accuracy	Recall	AUC
Logistic Regression	0.972222	0.941176	0.970588
SVM	0.972222	0.941176	0.970588
Decision Tree	0.972222	0.941176	0.970588
Random Forest	0.916667	0.941176	0.917957
AdaBoost	0.916667	0.941176	0.891641

Table 1: Result Comparison

Note: A 90:10 Train-Test dataset split was done for the above tasks

4 Conclusion

- Similar and very high Test accuracy is obtained through **LR, SVM** and **Decision Tree** algorithms, hence we can say that the dataset we have used has linear characteristics.
- Slightly lower but still impressive accuracies obtained through **Random Forest** and **AdaBoost** algorithms
- Such high accuracy imply that the classification of a patient having Dementia or not can very well be determined from the EEG data of the person using DSP techniques and simple machine learning algorithms
- Each FFT coefficient of the EEG signal is highly suggestive of whether a person has Dementia

5 Appedix

The relevent code used to generate the results can be found in the following git link:
https://github.com/harshpaal/EE338-Application-Assignment

A References

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