Detection of Mind Wandering using EEG Signals

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A thesis submitted to the Department of Computer Science and Engineering
in partial fulfillment of the requirements for the degree of
B.Sc. in Computer Science

Department of Computer Science and Engineering
Brac University
January 2020

Declaration

It is hereby declared that

1. The thesis submitted is our own original work while completing degree at Brac University.

2. The thesis does not contain material previously published or written by a third party, except where this is appropriately cited through full and accurate referencing.

3. The thesis does not contain material which has been accepted, or submitted, for any other degree or diploma at a university or other institution.

4. We have acknowledged all main sources of help.

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Ethics Statement

We are ensuring quality and integrity of our research. We respect the confidentiality and anonymity of our research respondents. Our research is independent and impartial.

Abstract

Mind Wandering (MW) is the recurrent occurrence in which our mind gets disengaged from the immediate task and focused on internal trains of thought. In terms of intelligent interfaces MW can both have good as well as detrimental effects; hence it is crucial to measure MW. This interesting phenomenon and part of our daily life can be effectively measured using electroencephalogram (EEG) Signals. There are several techniques that have been used to predict MW however; literature review shows that there are still chances of further improvement in this field. Therefore, in this paper we proposed a framework based on data mining and machine learning to detect MW using EEG signals. In our framework, we extracted a number of features from 64 internal EEG channels. We evaluate the performance of our proposed framework using 2 subjects with total of 19 sessions. The prediction accuracy of the proposed framework is higher than the other researches under this field that indicates the superiority of our proposed framework and efficiency of the data.

Keywords: Electroencephalogram (EEG), Mind Wandering (MW), Machine Learning, J48, Support Vector Machine (SVM).

Dedication

Dedicated to all our beloved ones for their Inspiration and support.

Acknowledgement

Firstly, all praise to the Great Allah for whom our thesis have been completed without any major interruption.
Secondly, to our supervisor Dr. Mohammad Zavid Parvez sir for his kind support and advice in our work. He helped us whenever we needed help.
And finally to our parents without their throughout support it may not be possible. With their kind support and prayer we are now on the verge of our graduation.

Table of Contents

List of Figures

List of Tables

Chapter 1

Introduction

Mind Wandering (MW) is the self-generated thoughts drifting our mind away from the current task. It is a psychological phenomenon that is diverting our attention from a task. MW usually happens while driving [1], reading [5] and other activities where there is less attention. It is a temporary state and is a common trait that people share where they do not remember what was going on in their surroundings since their minds were decoupled. MW can both be intentional and unintentional [2]. While MW is a common phenomenon, it relates to various psychological problems too [3].

MW covers about 30-50% of the waking time which is known to be initiated from the transitions between outwardly steered and self-generated thoughts [4]. Electroencephalogram (EEG) is a well-accepted tool in detection of MW to identify artifacts from multi-channel EEG data [3],[8-10]. It has a few limitations in measuring circumstance, and a passable amount of information is expected. In uninvestigated conditions the EEG indicator can divulge the nature of MW.

As MW tends to occupy half of our waking time it plays a crucial role in our everyday life. Indeed there are benefits to MW [11]. MW is an essential measure of our self-identity and has also been knotted to creative problem-solving [7]. It results in helping us make plans about the future. MW enhanced human's creativity above and beyond the positive effects of their reading ability or fluid intelligence, the general ability to solve problems or puzzles [11]. Admittedly, it was found that happiness of a person who is in MW decreases suggesting that a negative mood might be a consequence [4] of a wandering mind. Besides, it is a menace to transportation safety, resulting in substantial number of crashes and fatalities [1]. Taken together whether MW is good or bad depends on when we mind wander and what we wander about [9].

Furthermore, reviewing the prior research under this field, a good sum of work has been dedicated in detection of MW. There are numerous existing research works employed to extract various features such as EEG variables and non-linear regression [3], oculometric features [6], incubation paradigm to assess performance [7], oscillatory activity of the entire brain [10], spontaneously adopted problem solving approaches using self-reports [11], kernel size and stride [12], EEG markers used as features for the classifier [13] spatial patterns to discover scalp topologies [14].

Grandchamp et al. [6] used oculometric data such as pupil size, blink rate, gaze position and the experimental result shows Subject 1 detected a overall 264 MW episodes, whereas subject 2 noticed merely 160 such episodes. The average MW rate was of one MW occurrence every 45 8 s (mean SD) for subject 1 and 73 14 s for subject 2. One limitation in this paper is that only two sub-networks were taken into consideration and it would have been better to explore the interactions between more sub-networks into the general network. Ibáñez- Ibáñez-Molina et al. [10] projected a large-scale neural network model to simulate the complexity of brain signals generated during EA and MW. Kawashima et al. [3] fitted a number of regression models, that predicts the MW intensity obtained from probe-caught thought sampling with several EEG variables and Support Vector machine (SVM) Regression. However, in this paper they did not consider all the nodes of EEG.

Jin et al. [8] EEG markers that considerably predicted MW and found that greater levels of attentiveness was predicted by smaller alpha power. Nevertheless, they classified two different mental states within a single task, which made the two states highly similar. Hence, this caused lower prediction accuracy. Dhindsa et al. [9] there were 15 thought probes were administered across the two lectures (eight during the first and seven during the second), all 23 participants resported on this. On average, in the first lecture participants reported MW during 32% of the probes and 38% of the probes in the second lecture, resulting in an average of 35% across both lectures. However, machine learning approach was based upon data-driven feature learning with common spatial patterns which led to a lower prediction accuracy.

1.1 Aims and Objectives

In this paper we present a framework that uses data mining and machine learning approaches to predict MW using EEG signals. The main idea to avoid very similar results was by finding the starting and ending time of each MW episodes in every session of each Subject. In order to achieve a higher accuracy, classification of different combinations of features were done. SVM gave a higher accuracy than Decision tree so applying two classification methods aided our precision level. The main factor in our paper is that we have worked with EEG signals solely to detect MW and has also achieved a promising result which thus elevated our method over other research method under this field.

Chapter 2

Literature review

Human mind is not static; it fluctuates over time especially in an attention demanding task. When our brain fluctuates, our mind works in both task-relevant and irrelevant processes but in a less detailed manner.[6],[15-18] We have worked on detecting wandering of our mind using EEG signal which is an electro physiological method to record electrical activity of the brain. It works with both noninvasive and invasive electrodes placed along the scalp. Our data has record of brain's spontaneous electrical activity over a period of time, recorded from multiple electrodes placed on the scalp. We have also observed the brain waves in EEG signal in the frequency domain. Among various classifiers we have used J48 algorithm to generate a decision tree from our featured data. For classification we have used SVM classifier. By giving a set of trained data example SVM built a model that assigned our data's in positive or negative MW categories.

Many researchers have worked on this field. Julia W. Y. Kam Julia et al. [15] have used two experiments, in one experiment they have used traditional performance measures and found that both volitional and automatic forms of visual–spatial attention orienting were significantly attenuated when MW episodes occurred. In the second experiment they have used event-related potentials (ERPs) to examine whether cortical hypersensitivities in migraines extend to MW , or periods of time wherein we transiently attenuate the processing of external stimulus inputs as our thoughts drift away from the on-going task at hand [16-18]. Their goal was to examine if volitional attentional functions change as we drift in and out of MW states. Another group Romain Grandchamp et al. [6] worked on oculometric variations during MW. They have worked on gaze position, blink frequency and pupil size to check if they were correlated with the occurrence and time course of self-reported MW episodes [19-23]. Another group Jaechoon et al. [24] have worked on online education limitations by performing a verification research to see if high frequency words can detect mind wandering to resolve existing limitations. They developed a Minimum Learning Judgment System (MLJS) that can automatically detect MW in a video-based online lecture. One more group Benjamin W. Mooneyhamet al.[25] have worked on states of Mind by characterizing the Neural Bases of Focus and MW through dynamic Functional Connectivity. They have used Electrophysiological recordings, EEG data processing, event-related potential and phase locking factor[26-27]. Yuyu Zhang et al.[28] in their research Automatic detection of MW in a simulated driving task with behavioral measures have measured accuracy of 72% by driving behavior measurements to automatically detect MW state in the driving task. Another group Benjamin Baird et al. [29] and others have worked on decoupled mind by processing EEG data and have found MW disrupts cortical phase-locking to perceptual events. Todd C. Handy[30] and others have worked on MW and selective attention to the external world. The main focus of their work is visual attention, executive function and mental simulation [31-34]. Another group Jonathan Smallwood et al [35] has examined whether the periods of mind wandering are associated with reduced cortical analysis of the external environment.

Julia W.Y. Kam et al.[34] researched about how the Brain allows us to mentally wander off to another time and place. Kiret Dhindsa et al. [9] have worked on Individualized pattern recognition for detecting MW from EEG during live lectures. They have recorded EEG simultaneously from 15 participants during live lectures and used a data-driven method known as common spatial patterns to discover scalp topologies for each individual that reflects their differences in brain activity when MW versus attending to lectures and achieved an average accuracy of 80-83%. Jin CY et. Al. [43] have worked on Predicting task-general MW with EEG. They have classified the participants current state by two different paradigm, one is sustained attention to response task (SART) and a visual search task to detect either MW or on task. Qin et al. [44] haveworked on Dissociation of subjectively reported and behaviorally indexed MW by EEG rhythmic activity. By implementing time frequency analysis and means of beamformer source imaging they have found that found subjectively reported MW within the gamma band to be characterized by increased activation in bilateral frontal cortices, supplemental motor area, paracentral cortex and right inferior temporal cortex in comparison to behaviorally indexed MW. Compton RJ ET AL. [45] have worked on the wandering mind oscillates: EEG alpha power is enhanced during moments of MW. During a demanding cognitive task, to find whether episodes of MW increases in EEG alpha power they have used a within-subjects experience-sampling design.

In the research of Kiret et al.[9] the drawbacks of their work was with only 16 EEG signals they lack the spatial pattern needed for accurate source localization. MW has been mainly detected through two thought-report methods: discrete thought-probes [49-51] and spontaneous self- reports [49].

A method that have been used is spontaneous self-reports. In this method participants are requested to specify the moment when they become conscious of MW. From the participant's side, this method continuously track of MW. This method limits the ability of researchers to maintain consistent evaluation among different participants. We have overcome this problems through our work and analysis.

Chapter 3

Work Procedure

The principle goal of this paper is to detect MW precisely with high accuracy and low false alarm. A line of actions have been followed to complete the procedure. A diagram has been given to illustrate in Figure 3.1 with a comprehensive description given in section. Data pre-processing, feature extraction, and classification are the plausible scheme to detect MW.

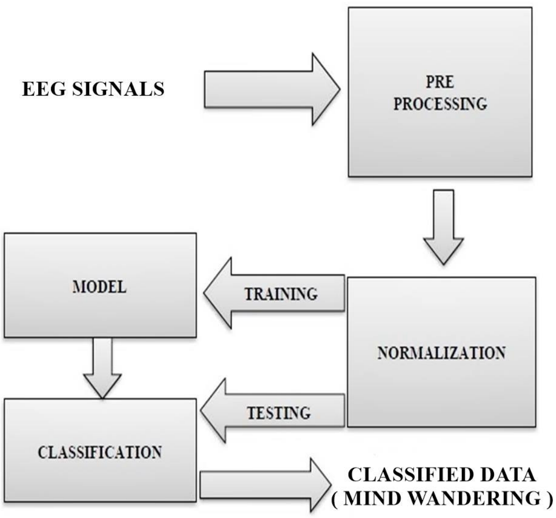

Figure 3.1: Work Procedure

3.1 Dataset Description

The dataset utilized in this paper was tailored from a French research groups work on oculometric changes in MW episodes, Braboszcz and Delorme [6] and was open to all for EEG analysis under "CeCILL v2.0" license. The subjects (1 male , 1 female) performed their given task in a lowly lighted and soundproof space ahead of a visual display unit . The subjects had to perform a breath counting task like they had to count their breath in backward cycles (inhale/exhale) from 10 to 1 and had to report whenever they lost track of their breath count by pressing a button. A number of questions were presented on the screen immediately after they press the button. It took less than 60 seconds to complete the form and then the method resumed once more. By repeating the process a total of 19 sessions are recorded from both the subjects. Using a BioSemi EEG system, EEG signals are recorded from 64 scalp channels from BCI device (an elastic cap) and different biometric channels are concerned in remainder of the channel information recordings. Initial sampling rate of data recording was 1024Hz. Skin Conductance (SC), Electrocardiogram (ECG), further as eye movements and pupil size were additionally recorded. By performing these procedures 19 sessions were recorded of 2 subjects. In this 80 channeled dataset first 64 channels are EEG channels and remainder of the channels are other biometric channels like Pupil size , Gaze position , Skin conductance (SC), Electrocardiogram (ECG) etc. In our paper we only present the findings on EEG information basis .

3.2 Pre-Processing

To record the data from 64 scalp channels and other biometric electrodes Cz referencing method was initially used . Then the data is high-pass filtered using an IIR digital filter with a cut-off frequency of 2 Hz (order 6, 0.7-Hz transition bandwidth) executed in the EEGLAB software. Then all the questionnaire sessions were removed from the data and were down-sampled to 256 Hz. Channel signals containing high frequency noise or electrical artifacts (as assessed by visual inspection) were removed and clean dataset reformed. Then the signal was converted to average reference level . 80-channel Biosemi EEG dataset was converted to "CSV" format for easy data analysis. Lastly , dataset was normalized for data mining.

3.3 Feature Extraction

Feature extraction is related to dimensional reduction. In the process of feature extraction it is expected to contain relevant information from the input data, so that the desired task can be performed by using this reduced representation instead of the complete information. Our data-set consist of 19 sessions containing specific task related to our investigation. This sessions was acquired from two subjects. Then we used built in methods of MATlab and various Python libraries to extract 7 features, which are mentioned below:
1. Skewness
2. Kurtosis
3. Standard Deviation
4. Maximum
5. Minimum
6. Mean
7. Energy

Skewness:
In a statistical distribution, skewness is asymmetry, in which the curve is distorted or bent either to the left or right. Skewness can be quantified in order to define to what extent a distribution differs from a normal distribution. The graph appears as

a classical, symmetrical "bell-shaped curve" in a normal distribution The mean, or average, and the mode, or maximum point on the curve, is equal. When a distribution is biased to the left (red dotted curve) the tail on the left side of the curve is longer than the tail on the right side, and the median is smaller than the norm. We sometimes point to this condition as detrimental skews or negative skews. When a distribution is distorted to the right (blue dotted curve) the tail on the right side of the curve is longer than the tail on the left side, and the mean is greater than the normal. We have shown the Skewness result of our subject 1 task 1 in Figure 3.2.

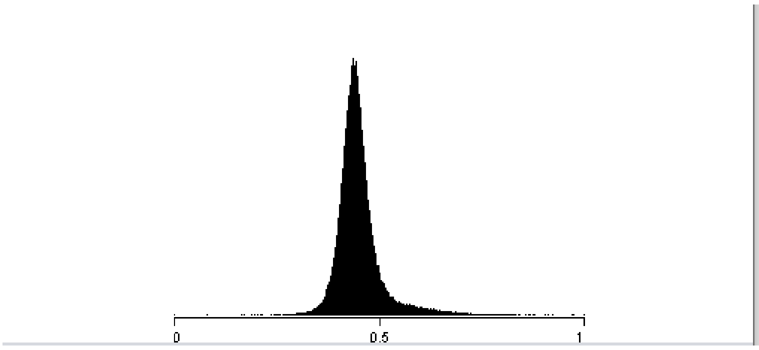

Figure 3.2: Skewness Result for subject 1 Task 1

Kurtosis:
Kurtosis is a measure of the "Tailedness" of the probability distribution of a real-evaluated random variable in probability theory and statistics. Similar to the concept of skewness, kurtosis is a descriptor of the shape of a probability distribution and there are different ways to quantify it for a theoretical distribution as well as corresponding ways to estimate it from a population sample. There are different interpretations of kurtosis, depending on the specific measure of kurtosis used, and how specific measures should be interpreted.In the Figure 3.3 we have showed the Kurtosis result of our subject 1 task 1.

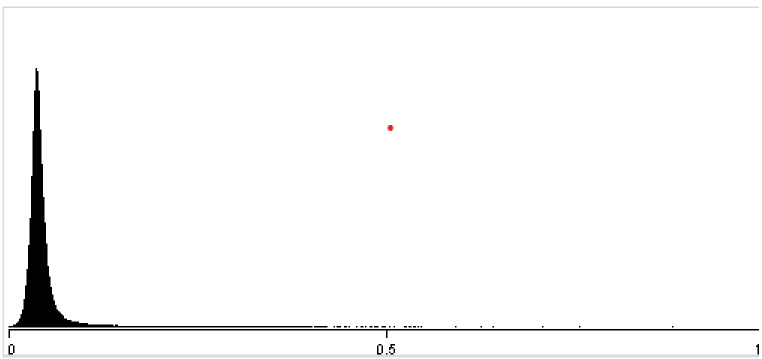

Figure 3.3: Kurtosis Result for subject 1 task1

Standard Deviation:
Standard deviation, also represented by the lower case Greek letter sigma or the Latin letter in statistics is a measure used to quantify the amount of variation or dispersion of a set of data values. A low standard deviation indicates that the data

points tend to be close to the set mean (also known as the expected value), whereas a high standard deviation indicates that the data points are spread across a wider range of values. In the Figure 3.4 we have showed the Standard Deviation result of our subject 1 task 1.

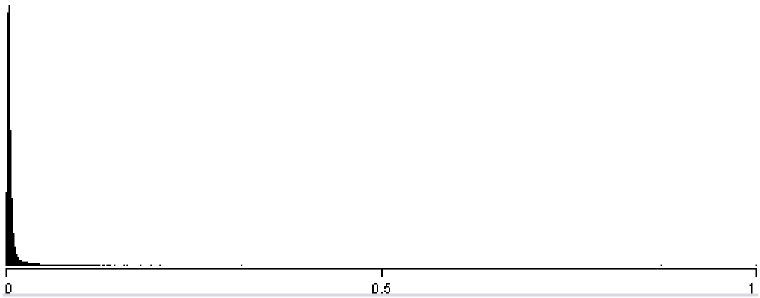

Figure 3.4: Standard deviation Result for subject 1 task1

Maximum and Minimum frequency: To be able to get the higher and the lower limit of frequency we have used maximum and minimum frequency. We have used MATlab built in method max (a) and min (a) to get these two features.In the Figure 3.5 we have showed the Min and Max result of our subject 1 task 1.

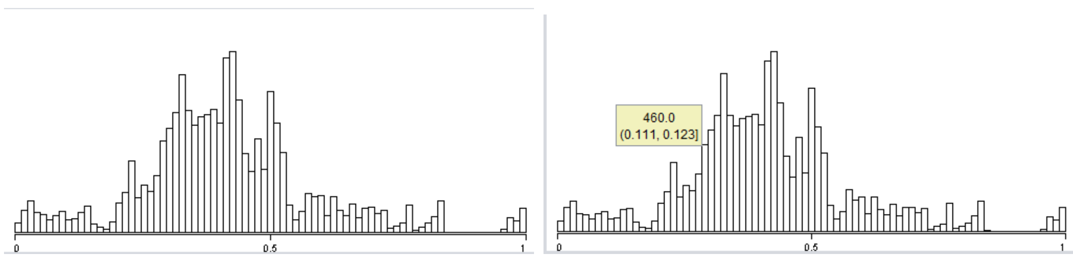

Figure 3.5: Max (left) and Min (right) result for subject 1 task1

Mean:

In this paper we extracted seven features form our dataset to make the classification and result output. Mean is one of our main feature among those seven feature we extracted.In the Figure 3.6 we have showed the Mean result of our subject 1 task 1.

Generally, mean is a value which can be found by adding sampled values divided by number of items. There are three kinds of mean we can see in mathematics and statistics. Here, mean is the average or arithmetic mean of the data. Here, we calculated mean value for every subject several times based on the time interval of mind wandering. Then for every session of a subject we also calculated mean values. And from that mean value later we got all starting and ending points of mind wandering. This mean value helped us to corelate other two important features, min and max in our research. The below graph represents the mean values we got during the research.

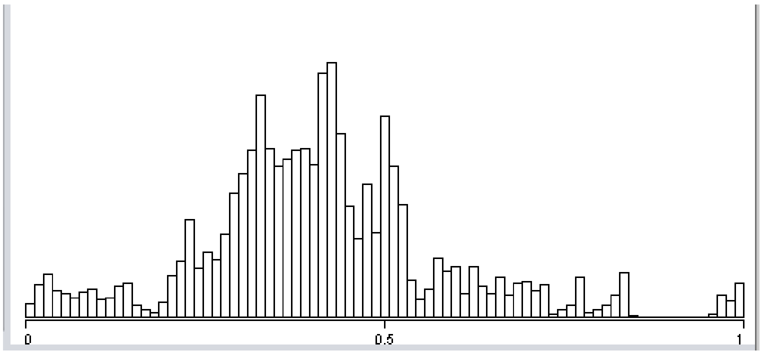

Figure 3.6: Mean result for subject 1 task1

Energy:
An electric signal is nothing but electrons moving in an electric field. Causing these electrons to move takes energy. Energy of an abstract signal is not associated with physical voltage or current. It is just and abstract measure of the signal. As for discrete signals, Energy is what any signal will have when converted to continuous time. In other word, we can say, Energy is a continuous-time signal area under the squared magnitude of the considered signal. Here we took the energy of every signal and considered it as one of our main entropy. Along with mean attribute considering Energy attribute we got the highest level accuracy of MW in every session.In the Figure 3.7 we have showed the Energy result of our subject 1 task 1.

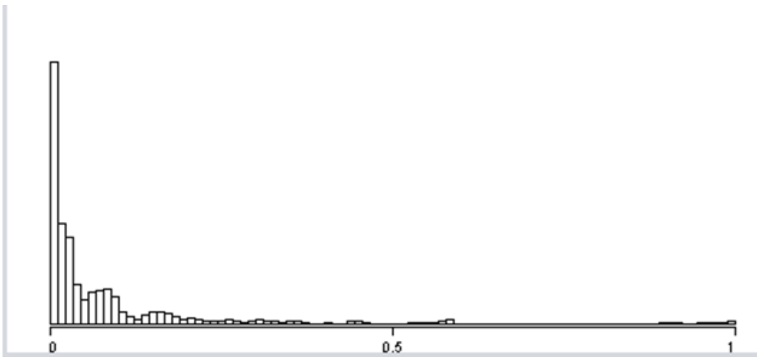

Figure 3.7: Energy result for subject 1 task1

3.4 Class Labeling

Referring to few papers and our study on this field [6] the table provided with the dataset [Table 3.1] it is seen that there are total about 264 Mind Wandering for subject 1 in all 10 sessions and 160 for subject 2. There are five columns, duration of the session in minutes, number of MW per session, mean duration before MW in seconds, mean questionnaires duration in seconds and total questionnaires duration over session in minutes respectively.
Number of Questionnaires= β

Total Questionnaires duration over session= θ
Mean Questionnaires =σ
$\beta = \theta \div \sigma$ ....(1)
Total time before Mind Wandering= η
Mean Duration before Mind Wandering= ϵ
Number of Mind Wandering=μ
$\eta = \epsilon \times \mu$ ....(2)
Total duration of Mind Wandering= τ
Duration of session=δ
$\tau = \delta - \eta$ ....(3)
Mean duration of MW=α
$\alpha = \tau \div \mu$ ....(4)

Table 3.1: Initial Assumption from Dataset

Subject	**Session**	**Duration (mn)**	**nb. MW**	**Mean Duration Before MW(s)**	**Mean Questionnaire Duration (s)**	**Total Questionnaire Duration over session (s)**	**Total nb. MW**
1	1	29.65	19	60.30	30.75	9.74	264
	2	31.38	25	49.14	27.65	11.52	
	3	29.11	23	45.63	24.19	.27	
	4	29.90	26	45.63	23.26	10.12	
	5	33.77	34	33.69	24.71	14.00	
	6	29.38	25	47.39	22.96	9.57	
	7	29.27	21	55.48	26.68	9.37	
	8	28.95	26	44.06	20.93	9.10	
	9	28.77	29	40.95	18.48	8.93	
	10	30.89	36	32.43	18.60	11.19	
	Mean	30.01	26.36	45.47	23.59	10.18	
	Std	1.49	5.07	8.18	3.78	1.45	
2	1	29.61	11	103.96	52.65	9.65	160
	2	30.79	14	81.12	46.56	10.86	
	3	28.57	13	82.12	39.93	8.65	
	4	30.69	16	72.45	40.50	10.80	
	5	33.16	20	59.11	39.97	13.32	
	6	30.56	19	61.05	33.80	10.70	
	7	27.81	17	67.36	27.89	7.90	
	8	25.31	14	82.34	23.14	5.40	
	9	25.88	14	77.60	25.31	5.99	
	10	29.78	22	50.70	27.05	9.29	
	Mean	29.33	16.09	73.46	35.83	9.44	
	Std	2.30	3.30	14.48	9.34	2.31	
	Mean	29.67	21.23	53.71	27.44	9.81	
	Std	1.92	6.71	38.21	12.57	1.95	

Firstly, we have found the number of questionnaires(1) asked by dividing the total questionnaires duration over session by mean questionnaires and found that there are 19 questions asked which means the number the MW is equal to the number of questionnaires asked. We were also provided with mean duration before MW, so it was assumed there same number of MW and pauses before MW. Total time before MW(2) was found by multiplying mean duration before MW with number of MW. According to our assumption, we found the total time spent in MW(3) by subtracting the total time before MW from total duration of the session, which gives us the total time of MW. The mean duration of MW(4) is then found by dividing the total MW time by number of MW. All these steps are followed in order to find the starting time and ending time of each MW in each session.

First Starting point= 60.30
First ending point= First Starting point + 33.33
Ending point= Starting point + 33.33
Starting point= Ending point + 60.30

At the beginning of each session there was no MW whose duration was 60.30s then MW starts which means the starting point is 60.60 s and lasts for 33.33s and ends at 93.63s. So the ending time for first MW of first session is 93.63s. Likewise all the starting points and ending points of each MW of each session is found.

3.5 Classification

MW detection has no standard method to interpret the result. That is why machine learning approach is suitable to examine the dataset and apply an algorithm. In order to detect the mind wandering we classified the data using both J48 for all the features and SVM (Support Vector Machine) based classifier for mean

and energy. Using both classifiers gave us the opportunity to measure the highest accuracy label. Classification accuracy not only depends on the classifier but also the input EEG signal. We have scrutinized our data using 1024 hz frequency rate. We differentiate the result using binary value where 1 defines MW and 0 considers focusing time. The change in MW with the features are given in Figure 2. Here in y axis we can see the value of the features are changing with the time illustrated in x axis. The value of MW also fluctuates between 1 and 0 with the change in the value of the features.

SVM restrict optimization programming in its higher computational burden so we mostly rely on this classifier than the data that J48 provided [37]. SVM uses kernel trick to separate the data based on the defined label or output.Radial basis Function kernel is used to linearly divide the data in two section, mind wandering (MW) and not mind wandering(NMW). The Linear Support Vector Machine (LSVM) is particularly suited for use with wide datasets, that is, those with a large number of predictor fields. The LSVM node is equivalent to the SVM node however it is linear

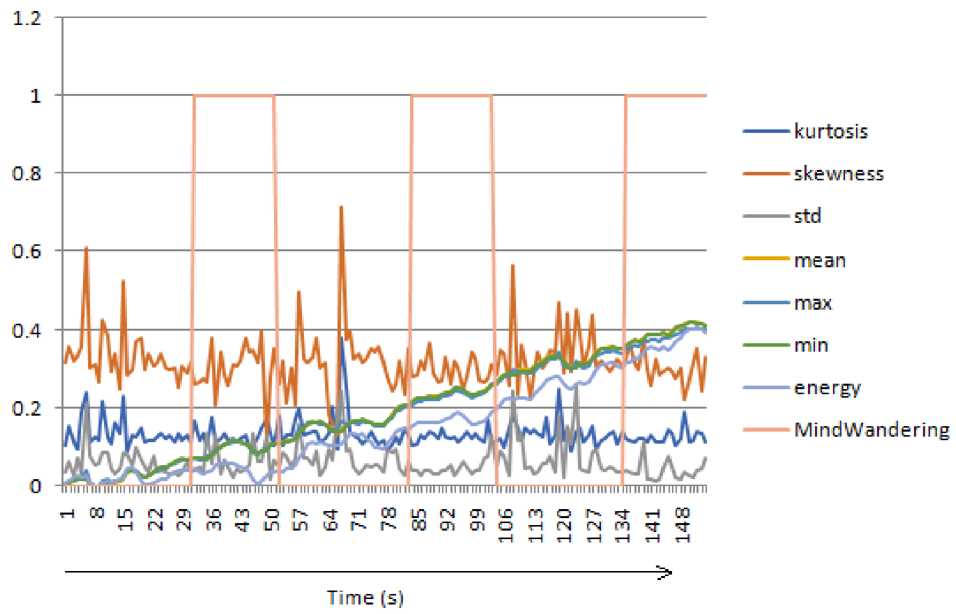

Figure 3.8: Relation of mind wandering and the extracted features

and better at handling a large number of records. The equation of LSVM illustrate as,[38]

$$f(x) = sign\left[\sum_{m-1}^{N} a_m y_m \lambda + b\right]$$

To demonstrate, a_m is the Langrage multiplier followed by y_m which is a training output pair. λ is the Radial-basis kernel function. This kernel finds the support vector classifier in infinite

$$\lambda = e^{\partial\,|\,a-b\,|^2}$$

dimension and it capable of dealing with overlapping data. Here (a-b) is the difference between the measurement data and ∂ is the cross validation scale. Lastly e is the exponential function. This equation calculates the inner products of new input vector with all support vectors in training data. The coefficients ∂ must be greater than zero(0) and estimated from the training data by the learning algorithm.

As for the parameter tuning of the EEG data K-fold cross validation technique applied. K- is the learning experiments and the set of k is our training set. The classifier L-SVM learns nonlinear mapping from the training set .The value of K = 5, which demonstrates that our training set is divided into 5 classes. Finally, every classes contains 90% training data and 10% testing data to check the validity.

Our dataset is consist of independent variable and a list of dependent variable.This is the scenario where J48 allow us to detect the target variable[54]. In this case the target variable is Mean and Energy which allows us to re-classify the data using

SVM.

The objective of the classifier is to classify the disorganized EEG signals to organized and labelled data using machine learning approach. The drawback of our dataset is that it was not mapped and the real challenge is to labeling it precisely to get the best outcome from the classifier. The classifier is a non-linear SVM where it uses a function that transforms our data in high dimensional space. It is hard to obtain a result accurately where the data in not linearly separated in high dimensional space. Achieving an unbiased classification result, the data is divided in training and testing set with the help of K-fold cross validation technique. Lastly, we have achieved accuracy for both classifier which is explained in the result and discussion part.

Chapter 4

Result And Discussion

4.1 Result

Analysis of the features extracted from the acquired EEG signals of both subjects led to the identification of multiple mind wandering episodes on each session . Two different classifier, SVM and J48 is used for classifying the data . Previous study on data analysis indicates that J48 decision tree gives better accuracy in prediction making tasks based on data mining [39-40] But a recent study indicates that SVM classifier is more appropriate on EEG Data analysis [41-42]. After applying both classifiers on our extracted features we also found better accuracy from SVM classifier. In addition, we got better accuracy from the features - Mean and Energy among 7 extracted features . Table 4.1 indicates that accuracy of SVM classifier is significantly higher on the feature - Mean and Energy .

$$\textbf{Accuracy} = \frac{\textbf{TP+TN}}{\textbf{TP+TN+FP+FN}} \quad \text{..............(7)}$$

Here,
TP= True positive value
TN= True Negative value
FP= False Positive value
FN= False Neagative value

Table 4.1: Accuracy rate in Percentage

Dataset	**Session**	**Accuracy**(%)		
		J48	**SVM**	
		All features	**All features**	**Mean and Energy**
Subject 1	1	64.70	66.97	78.65
	2	59.73	58.56	75.69
	3	66.87	70.98	86.61
	5	54.88	56.51	63.87
	6	76.35	65.86	86.34
	7	71.18	70.37	82.85
	8	71.30	67.26	79.15
	9	69.51	68.21	82.85
	10	61.40	59.09	77.27
Subject 2	1	76.98	69.40	89.80
	2	91.94	66.76	95.78
	3	92.96	79.03	94.07
	4	67.32	67.16	92.75
	5	87.66	66.81	95.02
	6	65.75	64.61	84.70
	7	74.15	71.98	88.36
	8	92.96	79.44	94.81
	9	76.07	74.57	81.20
	10	65.86	60.71	80.71

4.2 Discussion

For the both subject, in every session after counting both the number of MW and NMW we found out in average 30% to 40% or in some cases more than that percent of total duration of each session MW happened. Along with that we have also observed that when MW duration is larger, then number of times MW also increases. But, looking closely to the Table 4.2, we can see that for the same duration of MW time, number of MW times are also close to each other.

Table 4.2: Recording of Mind Wandering

Dataset	**Session**	**Duration of MW(Min)**	**MW**	**NMW**	**Total**	**% of MW**	**%of NMW**
	1	10.554998	652	1131	1783	36.57	63.43
	2	12.16333967	755	1138	1893	39.89	60.11
	3	10.27299033	641	1153	1794	35.74	64.26
	5	14.67901783	860	1047	1907	45.10	54.90
Subject 1	6	9.6341585	606	1213	1819	33.32	66.68
	7	9.851996	614	1441	2055	29.88	70.12
	8	9.857329333	619	1166	1785	34.68	65.32
	9	8.977494833	569	1246	1815	45.67	54.33
	10	11.43199573	682	1078	1760	38.75	61.25
	1	10.55800367	581	1027	1608	36.13	63.87
	2	11.86200233	678	1122	1800	37.67	62.33
	3	10.653833	652	1236	1888	34.53	65.47
	4	11.3699905	696	1180	1876	37.10	62.90
Subject 2	5	12.78383027	785	1144	1929	40.69	59.31
	6	11.22749	657	1095	1752	37.50	62.50
	7	8.724670833	539	1318	1857	29.02	70.98
	8	6.097335833	379	1624	2003	18.92	81.08
	9	7.773333667	480	1392	1872	25.64	74.36
	10	11.19000258	657	1045	1702	38.60	61.40

4.3 Pattern Analysis

In our research, from the very beginning we focused on finding out a pattern of MW, following which MW happens for both subjects every session. To get the pattern firstly, we selected the best features depending on which's MW happen. And, we got that Mean and Energy values are highly liable for MW. To be more specific we considered the both algorithms result accuracy margins. There, we saw, accuracy margin is higher during using SVM algorithm considering only Mean and Energy. And with J48 algorithm, there MW is getting detect based on some specific Mean and Energy values. Which we are considering as out pattern. And using that pattern we have drawn tree in Figure 2, where we used specific Mean and Energy values as our leaf for the graph.

The pattern with a graph make it easier for anybody to understand the basic happening here. We have considered the session 10 of subject 1, where every time when mean is less or equal 0.069094, no MW happened 30 times. But mean greater than 0.069094 along with max being less than or equal 0.11605 and 0.11159 NMW happened 3 times where MW happened 20 times, and max greater than .011159 NMW happened for 2 occasions.

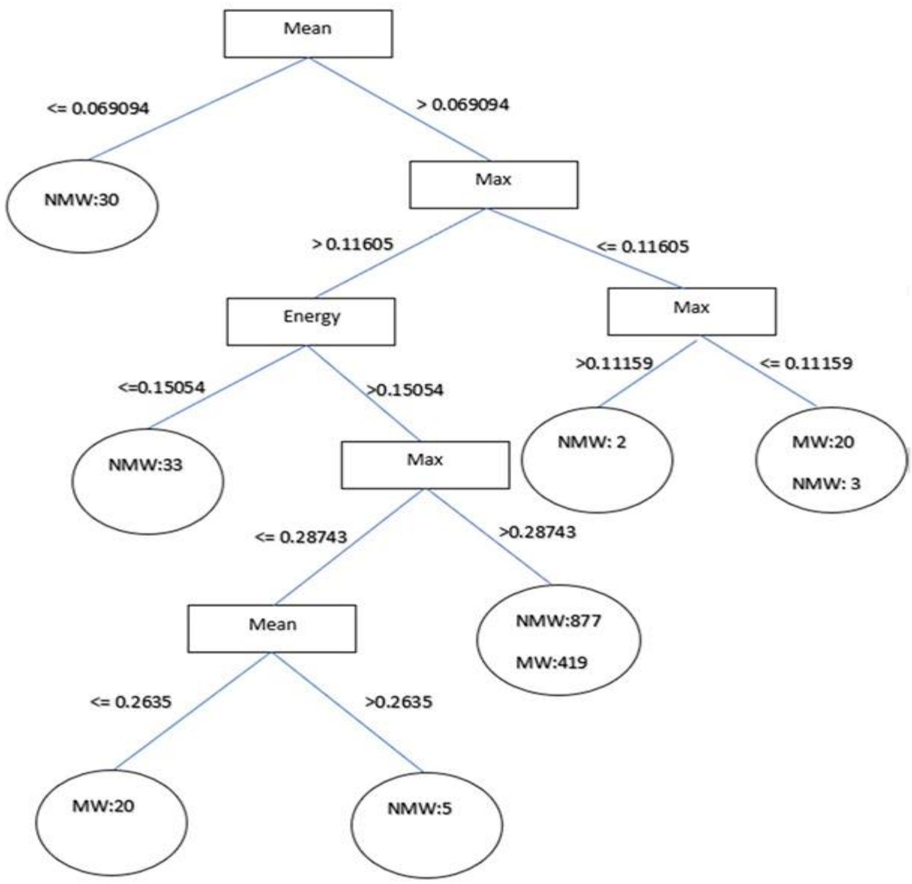

Figure 4.1: Decision Tree for Subject 1 session 10

But max being less than 0.11605 along with energy less than or equal 0.15054 NMW counted for 33 times. But energy being greater than 0.15054 when max is also greater than 0.28743 NMW counted 877 times and MW counted 419 times. And max less than or equal .028743 when mean is also less than 0.2635 MW recorded 20 times. But mean being greater than 0.2635 NMW recorded for 5 times.

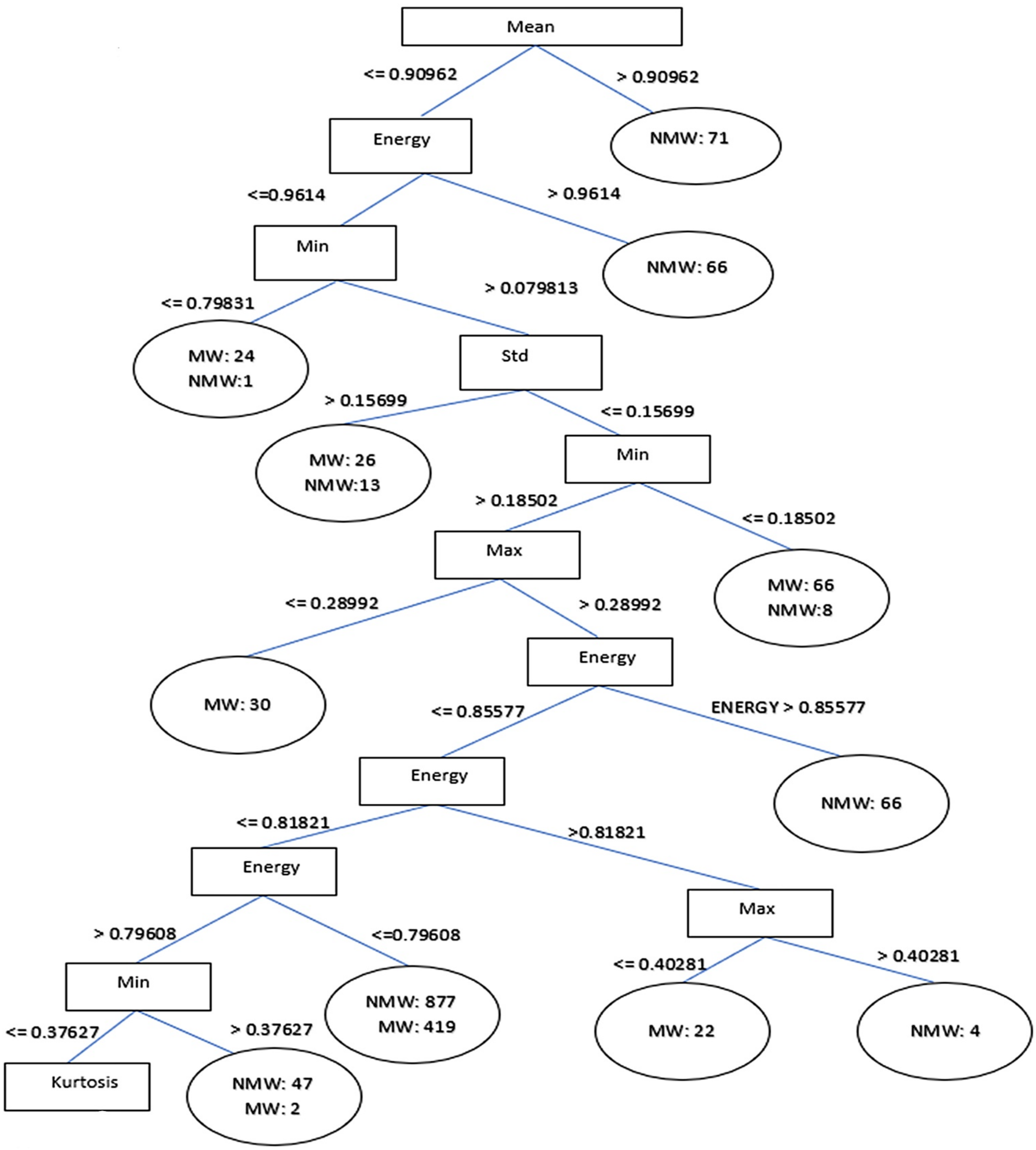

Figure 4.2: Decision Tree for Subject 1 session 7

Table 4.3: Pattern for Subject1 session 8

No.	Pattern
1	energy <=0.95718 and energy <= 0.91778 and min <= 0.17465: 0 (43.0)
2	energy <= 0.95718 and energy <= 0.91778 and min > 0.17465 and energy <= 0.8079 and min > 0.29885 and energy <= 0.71732 and energy <= 0.58042 and energy <= 0.52375 and energy <= 0.36814 and energy <= 0.32075 and energy > 0.29984 and skewness <= 0.26902 and skewness <= 0.26184 and mean <= 0.81347: 1 (7.0)
3	energy <= 0.95718 and energy <= 0.91778 and min > 0.17465 and energy <= 0.8079 and min > 0.29885 and energy <= 0.71732 and energy <= 0.58042 and energy <= 0.52375 and energy <= 0.36814 and energy <= 0.32075 and energy > 0.29984 and skewness <= 0.26902 and skewness <= 0.26184 and mean > 0.81347 and max <= 0.79496 and kurtosis > 0.077187 0 (4.0)
4	energy <= 0.95718 and energy <= 0.91778 and min > 0.17465 and energy <= 0.8079 and min > 0.29885 and energy<= 0.71732 and energy <= 0.58042 and energy <= 0.52375 and energy <= 0.36814 and energy <= 0.32075 and energy > 0.29984 and skewness <= 0.26902 and skewness <= 0.26184 and mean > 0.81347 and max > 0.79496: 1 (5.0)
5	energy <= 0.95718 and energy <= 0.91778 and min > 0.17465 and energy <=0.8079 and min > 0.29885 and energy <= 0.71732 and energy <= 0.58042 and energy <= 0.52375 and energy <= 0.36814 and energy <= 0.32075 and energy > 0.29984 and skewness > 0.26902 and std <= 0.2832 1 (27.0)
6	energy <=0.95718 and energy <= 0.91778 and min > 0.17465 and energy <= 0.8079 and min > 0.29885 and energy <= 0.71732 and energy <= 0.58042 and energy <= 0.52375 and energy > 0.36814 and max > 0.70281: 1 (23.0)
7	energy <= 0.95718 and energy <= 0.91778 and min > 0.17465 and energy <= 0.8079 and min > 0.29885 and energy > 0.71732 and kurtosis <= 0.16399 1 (22.0)
8	energy <= 0.95718 and energy > 0.91778 and kurtosis <= 0.096653: 1 (22.0)

Detecting a MW is a tough task but not impossible. Generally, when MW happens to anybody he, himself can't recognize it, but identify it later. Our aim is to identify it in current times, whenever it happens based on the EEG signal. And here we found out some specific data fluctuating pattern of our attributes which we can call our pattern, during the happening of MW. Though, due to lack of 100% accuracy level, very small change in terms of any attribute value of a specific pattern might give us reverse value. Which means, due to small change of mean, energy, kurtosis, std value in pattern table NMW could also happen. Here, in our pattern table we have only considered the 100% accurate and high volume of result pattern when MW happened on that specific session. In Table 4.4, subject 1 session on pattern table for MW, we got our very first pattern, mean > 0.037385 and mean <= 0.078298 and min < 0.077012, which resulted with happening of MW. Similarly, in every session for each subject, MW happened for very specific and individual pattern.

Table 4.4: Pattern fot Subject 1 session 10

No.	Pattern
1	mean > 0.037385 and mean <= 0.078298 and min <= 0.077012: 1 (20.0)
2	mean > 0.037385 and mean > 0.078298 and mean > 0.1251 and mean <= 0.17271 and max <= 0.1591: 1 (19.0)
3	mean > 0.037385 and mean > 0.078298 and mean > 0.1251 and mean > 0.17271 and mean > 0.19915 and min <= 0.23732 and mean <= 0.22901: 1 (18.0) (22.0)
4	mean > 0.037385 and mean > 0.078298 and mean > 0.1251 and mean > 0.17271 and mean > 0.19915 and min > 0.23732 and mean > 0.26463 and mean <= 0.30033 and mean <= 0.29029: 1 (18.0)
5	mean > 0.037385 and mean > 0.078298 and mean > 0.1251 and mean > 0.17271 and mean > 0.19915 and min > 0.23732 and mean > 0.26463 and mean > 0.30033 and mean > 0.33 and energy > 0.62125 and mean <= 0.34861: 1 (19.0)

Chapter 5

Conclusion

In an era where people are constantly looking out for new technologies for a little comfort, they are predicting mind wandering (MW), its effects on emotion, the consequence it brings will be playing a fundamental role in the near future. Based on our approach we predicted MW with 85% accuracy in average on both subjects. Utilizing EEG signals which is found to be a characterized technique for detecting MW Different classification techniques were used to predict MW episodes and Focusing periods by putting the values on different algorithms for a better accuracy. SVM classifier seems very handy here on extracted features as it is accurate on processing EEG data. It can also be observed that the features such as mean and energy have provided better classification accuracy. In the future, we would like to measure physical activities in real-time using our proposed approach and utilize this concept in various places as per need. There are few researches on this and more coming up with more interesting aspects of MW and soon it is predicted to be one of the largely growing topics to work on.

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