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Differentiate Characteristic EEG Tobacco Smoking and Non-smoking

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Abstract- Electroencephalogram (EEG) signal is non-stationary signal that have low frequency component and amplitude compared to stationary signal. Therefore, present of unwanted substance (nicotine) in Tobacco smoking will alter the brain electrical activity. This paper is proposed to investigate the changes of EEG signal with the present of nicotine and identify the difference brain signal between smoker and non-smoker. There are 20 males (10 smokers, 10 non-smokers) are selected. The subjects are chosen based on inclusion criteria (abstained from smoking within 6 hours before experiment, and do not take any medication and caffeine). The recorded EEG signal contain a lot of noise such as head moving, muscle movement, power line, eyes blinks and interference with other device. Butterworth filter are implemented to remove the unwanted noise present in the original signal. Bandpass filter is used to decompose the EEG signal into alpha, theta, delta and beta frequency. Then, eight features (mean, median, maximum, minimum, variance, standard deviation, energy and power) have been extracted by using Fast Fourier Transform (FFT) and Power Spectral Density (PSD) method. Then, four different type of kernel function ('Linear', 'BoxConstraint', 'Polynomial' and 'RBF') of SVM classifier are used to identify the best accuracy. As a result, PSD (97.50%) have higher performance accuracy than FFT (97.33%) by using Radial Basis Function (RBF) of Support Vector Machine (SVM). Smoking activity caused slightly increase theta and delta frequency. Smoking is activated of five electrode channels (Fp1, Fp2, F8, F3 and C3) and caused additional emotion such as deep rest, stress releasing and losing attention. The attention of smokers can be measure by using stroop test. After smoking activity, smokers become more energetic and increase the time response (1.77 s) of stroop test compared to non-smokers (2.96 s). The result is calculated by using statistical analysis (t-test). The p-value is 0.037 which is less than 0.05. Thus, the null hypothesis is rejected and conclude there is significant different between smokers and non-smoker performance before and after smoking task.

1. Introduction

Brain is an important organ of human body that function as control centre that monitor and coordinate all activity. Cerebrum is the largest region in human brain, it is controls most of function such as speech, emotion, learning and control movement. Cerebrum divided into four lobe which is frontal lobe (F), occipital lobe (O), parietal lobe (P), and temporal lobe (T) [7]. Presenting the harmful substance such as nicotine, drug and alcohol will alter the brain signal activity. Smoking is bad habit that attributes to increase number of chronic diseases and death smokers due to the presence of nicotine. The statistical has

been approved 1017 per 100,000 death smokers in Malaysia due to smoking- related illness [1]. Generally, most of smokers aware about the effect of smoking but they cannot stop it. There are strong reasons why smoker addicted to smoke due to present of nicotine [2]. Nicotine is an addictive substance that will affect the EEG in transferring and processing the EEG brain signal [10]. The present of nicotine in human brain caused nicotine bind more effectively with receptor rather than neurotransmitter. Therefore, the cell become overstimulated compare to neurotransmitter. The cell no longer excited when there is no nicotine in body this caused smoker addicted to smoke to get the same effects [11]. In addition, smoking produce psychostimulant profile that effect the power reduction in theta and delta. Smoking one or two cigarettes causes a decrease in the delta in central-posterior head regions [12]. The objectives in this paper is to design the protocol to record EEG signal for smokers and non-smokers based on the previous research, to apply suitable EEG signal processing algorithm for extracting significant features and to compare the topographic EEG pattern before and after smoking task.

2. Literature Review:

In previous study, Edward F. Domino et. al study about tobacco smoking between smokers and non-smokers caused changes of dominant alpha electroencephalographic (EEG) frequency [12]. Subjects were asked to abstain 1 hour before the experiment. Two smoking task had been conducted which is sham smoke (non-smoker) and real smoke (smoker). The result of the experiment is sham smoking slightly increased dominant alpha frequency in Fp2, Fz, F4, F8 electrodes. The right hemisphere of non-smoker undergoes slightly change ($\pm$ 0.2 Hz) in alpha frequency after sham smoke due to brain response to smoking activity. Catherine P. Canamar et. al. studied about the effect of cigarette smoking toward attention bias by conducting smoking stroop test. There are 51 smoker's subject (age between 18 to 51 years old). The subjects need to perform two tests which are conduct a stroop test after 13-16 hours abstained and the second task conduct a stroop task after 1 hour abstained. Result of the experiment is increase time response speed of stroop test after smoking task [13]. The result is calculated by ANOVA to compare the performance of smokers before and after smoking task.

Bandpass filter is the most preferred filter used in previous study to remove unwanted noise present in raw signal [14][15][11]. Based on Edward F. Domino et. al, bandpass filter (5.0-6.0 Hz) is used to minimize the extraneous artefacts induced by body movement and eyes blinking [14]. Rass et. al study about EEG Signal and personality in daily and non-daily smokers. The author sampled the EEG signal at 1000 Hz sampling rate by using 0.1 until 200 Hz bandpass filter [15]. Murugesan and R.Sukanesh used PSD to extract the features in EEG signal by assuming short time stationary and energy content on EEG signal in conventional EEG frequency band such as alpha (8- 13 Hz), beta (13 - 40 Hz), delta (0-3.5 Hz) and theta (4 -7.5 Hz). The objective of using PSD to identify the power distributed. Spectral analysis in statistics is the process that decomposes a time series into a spectrum of cycles of varying lengths [16]. Goos et. al. applied FFT method to extract the EEG signal and classified the signal by using SVM with 100% accuracy. SVM is the best classifier to classified of two classes of EEG signals [16][17][18][19]. Murugesan and R. Sukanesh found that RBF is the best kernel function in classifying the two classes of EEG signal [16].

3. Methodology

Ten non-smokers and ten smokers were recruited from the local community surrounding University and paid for participation. Participants must satisfy of inclusion criteria of healthy and age range is 20 to 40 years old. Participants were excluded for a history of electroconvulsive therapy, neurological illness and chronic disease. Additional exclusion criteria included of abstain from take any caffeine and stop smoking within 6 hours before the experiment. Hardware EEG truscan and software EEG TruScan Explore was used to recorded brain signal. Thus, non-invasive electrode scalp 19 electrodes are used to obtain EEG signal. Total data of EEG signal is 18430 in one seconds. This data points were saved in ASCII file. After that, it was converted to text file to load into MATLAB software for filtering process. The sampling frequency of data is 1024 Hz. Then, smokers need to fill in the form of Fergerstrom Test Nicotine

Dependence (FTND) to identify the level of nicotine dependency of smoker. Based on FTND, there are 10% light, 20% heavy, 30% is low moderate and 40% is moderate smokers in this experiment.

3.1 Experiment Protocol

The experiment protocol is started with setup the electrode on subject scalp. Then subjects are asked to practice stroop test before start the EEG recording. The light is switch off within 3 minutes to ensure subject really relax and ready form EEG recording. Subjects are asked to close eyes within 3 minutes while EEG recording is started. All of the rest tasks are conducted with eyes closed. After complete rest task, subject required to perform the stroop test in the same time EEG is recorded. Next task is rest task (3minutes). After that is smoking task which is sham smoke (non-smoker task) and real smoke (smoker task). Then, subject asked to rest while EEG is recorded (3 minutes). Finally, second stroop test is conducted after smoking task**.**

3.2 Signal Processing

The pre-processing technique is used to remove the unwanted signal present during data collection. Head moving, muscle movement, power line, eyes blinks and interference with other device [2] [3] will be removed by using Butterworth Filter. 4th order Butterworth filter is used due to it has linear response. The cutoff frequency is 0.5 to 30 Hz. The delta frequency (below 0.5 Hz) is eliminated because it consider as noise. Second filter have been used in the research is bandpass filter. Bandpass filter is used to decompose the signal in form alpha (8-12Hz), beta (12-30Hz), delta (1-4Hz) and theta (4-8Hz). The signal is segmented from 60 to 120 seconds because during this state is optimum state [8] which subjects are really concentrate on task given thus this is an accurate time to measure EEG signal on given task.

Feature extraction method is the next step after pre-processing method. Feature extraction method is function to extract the signal value and to reduce the loss of important information of signal [20]. In this research, FFT and PSD are used to extract the waveform of EEG brain signal. There are total of eight features are extracted in FFT method which is the mean, median, variance, standard deviation, power, energy, minimum and maximum value. FFT is important to convert time domain to frequency domain to reduce the operation time and increasing the speed. The FFT is can compute the result 0 (N log N) operation [21]. N is mean by the length of the vector. The Equation (3.1) show the FFT functions and Equation (3.2) is function of Inverse Fast Fourier Transform (IFFT)

$$X(k) = \sum_{j=1}^{N} x(j)\omega_N^{(j-1)(k-1)}$$

(3.1)

$$x(j) = (1/N)\sum_{k=1}^{N} X(k)\omega_N^{-(j-1)(k-1)}$$

(3.2)

Another feature extraction method is by using PSD method is generally known as P-Welch method that implemented to transform the EEG signal form time domain to the frequency domain. In this research, hamming window technique is applied to extract eight significant features. Function of Hamming window is it acts as smoothing value known as an apodization of EEG signal ("removing the foot", i.e. smoothing discontinuities at the beginning and end of the EEG signal) [9].
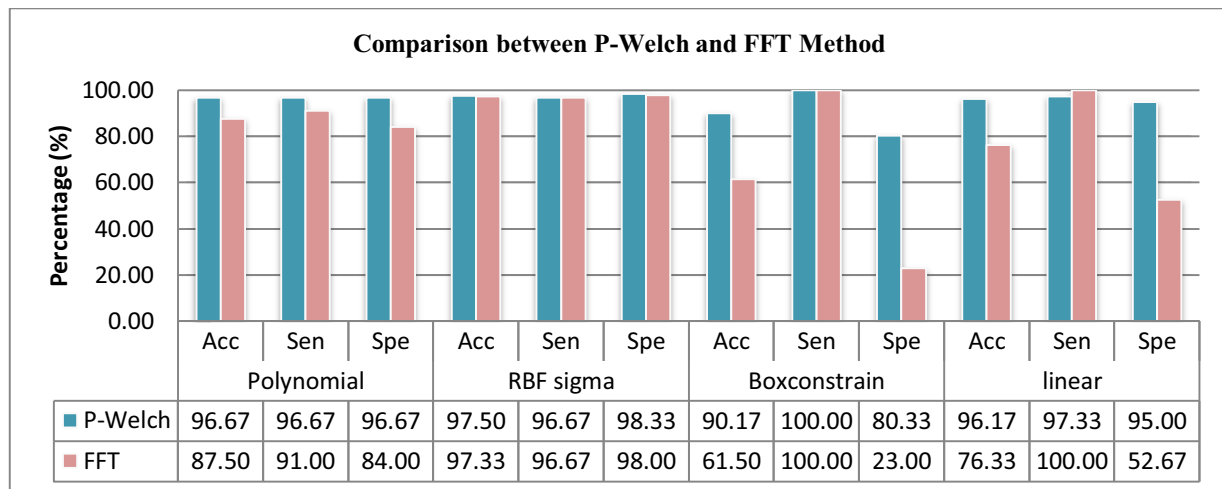
$$P_{xx}(\infty) = \frac{1}{2\pi} \sum_{m=-\infty}^{\infty} R_{xx}(m)e^{-jcom}$$

(3.3)

$$w(n) = 0.54 - 0.46 \cos(2\pi n/M-1) \qquad\qquad 0 \leqslant n \leqslant M-1 \qquad (3.4)$$

Support Vector Machine (SVM) is used to classify the EEG signal. Generally SVM can be implemented in two-classifiers due to large margin and mapping data into a higher dimensional space. SVM separate between smoking and non-smoking by using linear line (hyperplane) [20].
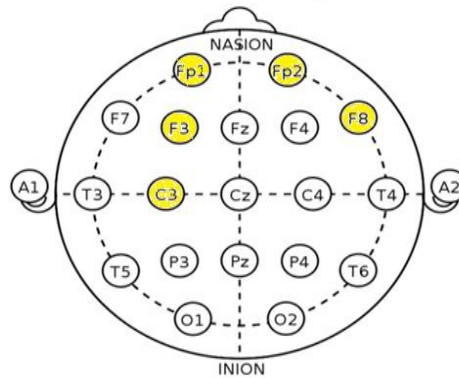
4. Result and Discussion

P-Welch is the best feature selection method due to the accuracy is 97.50% compare to FFT accuracy of 97.33% as in Figure 1. P-Welch method provides better performance than FFT method by using RBF kernel function which is 98.33% accuracy compare to FFT 61.50%. This is because P-welch method have high spectrum estimation signal to noise ratio and reduce frequency resolution [22]. P-Welch's method provides good resolution which is the ability to discriminate the feature. There are eight features had been extracted which is mean, medium, maximum, minimum, standard deviation, power and energy.

Comparison between P-Welch and FFT Method

	Polynomial			RBF sigma			Boxconstrain			linear		
	Acc	Sen	Spe	Acc	Sen	Spe	Acc	Sen	Spe	Acc	Sen	Spe
P-Welch	96.67	96.67	96.67	97.50	96.67	98.33	90.17	100.00	80.33	96.17	97.33	95.00
FFT	87.50	91.00	84.00	97.33	96.67	98.00	61.50	100.00	23.00	76.33	100.00	52.67

Figure 1. Comparison the performance of P-welch method and FFT method
(Note: Acc – Accuracy, Sen – Sensitivity, Spec – Specificity)
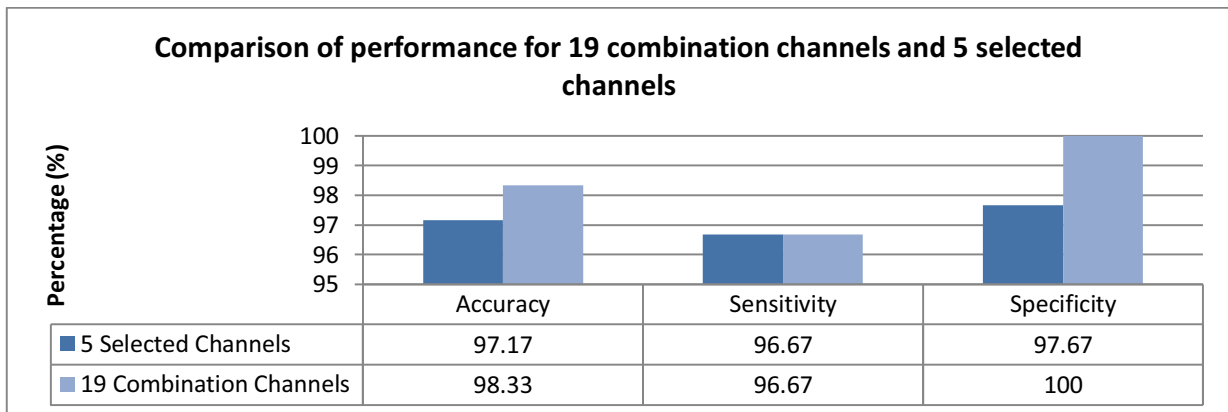
4.1 Feature Selection

There are 19 electrodes are used to record EEG signal. Each electrode provides 4 different types of decomposed signals which is alpha, beta, theta and delta frequency. Then, each four type of decomposed signal is extracted into eight features which is the value of mean, medium, maximum, minimum, standard deviation, power and energy. Thus, there are total 608 individual features is extracted from the EEG signal. Since there are too many features, the features selection needs to be done in order to select the best features for classification. All these 608 features will undergo individual classification using SVM and compare each other. The twenty-nine features have been selected as the best feature due to the accuracy is the highest among the others which is more than 57.45%. These twenty-nine features are contributed from five electrodes channels which are Fp1, Fp2, F8, F3 and C3 as show in Figure 2. All of these 29 features are activated during smoking activity and very important in identifying smoking behaviour. Smokers become more energetic after smoking task compare to non-smokers. Smoking behaviour resulted in increasing the theta and delta frequencies due to over stimulate of hormone such as neurotransmitter, melatonin and others [23]. This is have been proved by previous research smoking caused slightly increase the theta and delta frequency [4]. Moreover, smoking caused additional emotion benefits such as reduce stress and anxiety, less feeling of depression and deep rest [5] [6].

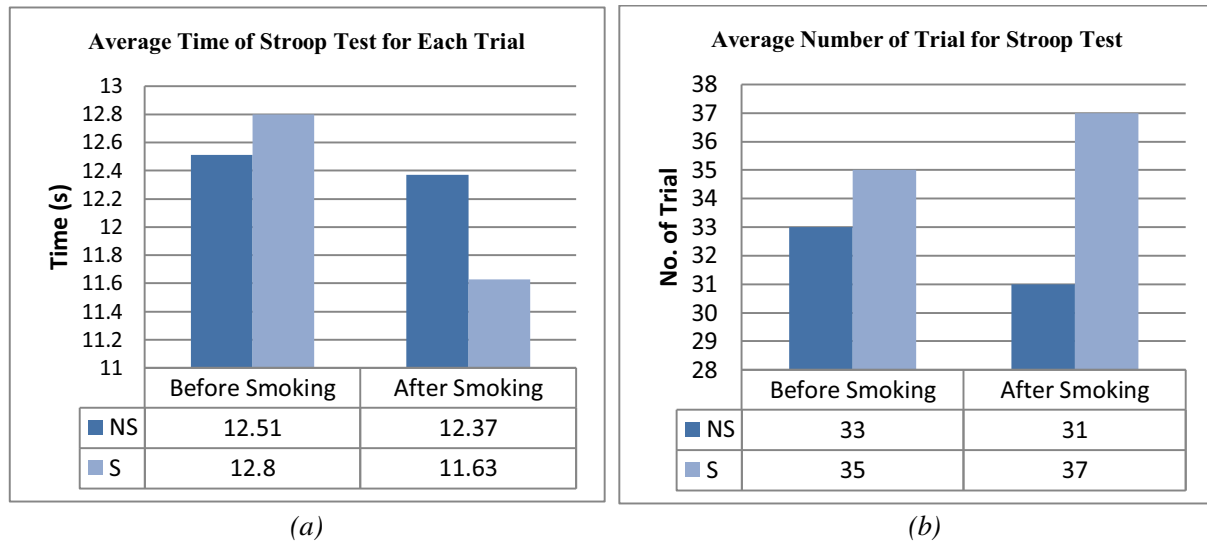**Figure 2.** Selected EEG Channels of Topographic

4.2 Classification

Classification between the smoker and non-smoker is done by using SVM classifier as shown in Figure 3. The input of the classifiers either is 19 combined channels or 5 selected channels. The combination channels are combined of 19 electrodes channels while selected channels are combined of five electrodes channel (Fp1, Fp2, F8, F3 and C3). The combination channels 98.33% have higher accuracy compare to selected channels 97.17%.

Comparison of performance for 19 combination channels and 5 selected channels

	Accuracy	Sensitivity	Specificity
5 Selected Channels	97.17	96.67	97.67
19 Combination Channels	98.33	96.67	100

Figure 3. Comparison of performance for 19 combination channels and 5 selected channels

During abstained stage (before smoking task) smokers have low time response of stroop test (12.8 s) compare to non-smokers (12.51 s). After smoking task smokers (11.63 s) have fast time response compare to non-smokers (12.37 s). Smokers perform more number of trials (trials = 37) after smoking and increase speed of response compared to non-smokers (trials = 31) as shown in Figure 4(b). The increasing of number of trial for smokers (trials = 37) lead to increase the time spending to complete the stroop test (430.26 s). The present of nicotine caused smokers become more energetic and reduce the attention level. Therefore, the tendency of smoker to do mistake is higher than non-smoker. The present of nicotine in human will increase the speed of response. The present of nicotine in human body caused over stimulated neurotransmitter in brain. In additional, the present of nicotine can reduce the attention biases of smokers. The over stimulated the Neurotransmitter caused smokers lost their attention to answer stroop test after smoking.

(a)   *(b)*

Figure 4. (a) Average response time of stroop test for each trial and (b) Average number of trials for stroop test

Statistical Analysis is calculated to identify the significant difference between smokers and non-smokers. From Table 1, the p-value is less than 0.05 which is 0.037. Thus can conclude there is significant different between smoker and non-smoker performance before and after smoking task.

Table 1. Statistical analysis of significant difference between smoker and non-smokers

		Paired Differences							
				Std. Error Mean	95% Confidence Interval of the Difference				
		Mean	Std. Deviation		Lower	Upper	t	df	Sig. (2-tailed)
Pair 1	non-smokers - smokers	-2.998350	8.778229	1.387960	-5.805764	-.190936	-2.160	39	.037

5. Conclusion

The EEG characteristic between tobacco smoking and non-smoking was successfully differentiated with the P-values is 0.037. The EEG signal is successfully recorded by using 10-20 electrodes placement system with 1024 Hz sampling frequency. The raw EEG signal is filtered by using bandpass and Butterworth filter. Moreover, the features of filtered signal are extracted by using FFT and PSD. Then, signal is classified by using four different type of kernel function of SVM classifier. For the feature extraction method, PSD has higher performances (97.50%) by using RBF kernel function method compare to other types of kernel function ('BoxConstraint', 'Linear' and 'Polynomial'). The present of nicotine can alter the human brain signal, which caused the response time is increased by 1.17 s and reduced in attention the trial number is averagely increased by twice.

To improve the result performance, the numbers of participants need to be increased to contribute large sample size of data. Then, the experiment is suggested to conduct in sound proof room in order to reduce the unwanted noise that will interrupt the recording of EEG signal. Some of the noise cannot be remove completely such as environmental noise, lighting of the room and noise due to muscle movement. Next, increase the abstaining duration which is more than 6 hours to examine the effect of abstain activity toward stroop test. There were will be large significant different between before and after abstain task. Additional of classifier such as Linear Discriminant Analysis (LDA), K-Nearest Neighbor (KNN) or Artificial Neural Network (ANN) to identify which classifiers is able to produce the higher accuracy.

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