EEG Based Neuropsychology of Advertising Video Using Fast Fourier Transform and Support Vector Machine

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***Abstract*—TV Ads are still considered as one of the most expensive cost in a particular promotional activity, hence it needs to be effective in accordance to its viewer neuro-psychological behavior. Electroencephalogram (EEG) can capture brain activity and inform a person's brain behavior while watching a particular video ad. This research proposed neuropsychological identification in real time every three second captured by an EEG wireless and then processed using Fast Fourier Transform (FFT) and Support Vector Machine (SVM) with three classes of: 1) interested, 2) less interested, and 3) not interested. The subjects were asked to fill out the interest questionnaire after recording to determine the class from the training data. Extraction using the FFT was performed by changing the frequency in 4-40 Hz, which contain alpha, beta, gamma and theta waves. FFT of all frames, was used as an input identification system using non-linear SVM by finding the best hyperplane that distinguished each class. The identification of three classes was done in storied. First, the researchers separated the interested and other classes. Then the second SVM was separated from the other classes into two: the less interested and the not interested. The research was conducted by identifying 9000 training data using 30 subjects for each 3 trials, 10 segments, watching 10 ads, video. The results showed 91.5% accuracy of training data, while testing against 4500 new data from 15 subjects received 71% accuracy with SVM gamma of 100. With 0.3 compute time, it was not significantly toward 10 seconds identification. Therefore, the system can be used in real time.**

***Index Terms*—EEG signal; Fast Fourier Transform; Neuropsychology of Advertising Video; Support Vector Machine**

I. Introduction

Neuropsychology is a field of science that studies the relationship between brain activity and a person's behavior. One of its implementations is the response of one person's interest to a particular video ad, as it can be used as a tool to test the effectiveness of that video.

In neuropsychology, we can use functional magnetic resonance image (fMRI), a near-infrared spectroscopy (NIRS), and an electroencephalogram (EEG). EEG measurement is more practical image to see the sequential changes of brain activity without time delay, which is important in grasping consumers' unconsciousness [1]. Wireless EEG development makes the development of research using EEG signals to be interesting, including neuromarketing in video advertising. EEG signal allows the use of brain activity identification to be performed in real time so that we can expand the testing video ads response every second. Neuromarketing can improve the response measurement of video ads by questionnaires and interviews in objectivity and real time.

Neuromarketing is an emerging interdisciplinary field, situated at the borderline between neuroscience, psychology and marketing [2]: It focuses on assessing consumers' cognitive and emotional responses to various marketing stimuli They require such information as neuromarketing tools to help increase the possibility of a particular sales. Neuromarketing has evolved in an attempt to understand better how customer's perceptions, emotions, memories, preferences, choices, and consumption are affected by sensory and unconscious processes, with the intention of appealing to them more effectively [3].

EEG is an instrument that represents electrical activity that is happening in the brain. EEG signals involve a great deal of information about the function of the brain. Attention information from the EEG can be obtained with real-time, so it can be monitored. Moreover, the use of wireless EEG provides comfort.

EEG signal transform becomes a model and it provides an effective way to classify the EEG signal [4]. The use of EEG signal in response to video ads can be related to the interests from the frequency region. There are alpha waves (8 – 13 Hz), which very often appears when people are in conscious and relaxed conditions; beta wave (14 – 30 Hz), often occurs when people are in thinking; theta wave (4 – 7 Hz), usually happens when people take a nap, feel sleepy, or suffer emotional stress; and delta wave (0.5 – 3 Hz), which very often appears when people are in deep sleep. As a consequence, a lot of researches concerning EEG signal analysis represent the signal into frequency domain. It can be used like Power Spectral Density [5] [6] [7], Wavelet [8], [9]. Besides, EEG model used Autoregressive [10]–[13], and Fractal Dimension [14] [15].

This research focuses on Neuropsychological or Neuromarketing of advertising video. EEG was extracted or analyzed in frequency region. Previous research using Power Spectral to discriminant of channel to like / dislike analysis with statistical analyzing [16]. Others using K Nearest Neighbor (KNN) and Probabilistic Neural Network (PNN) to investigate vehicle brand through video ads [17], investigate emotion neuropsychological consumers with offline advertising stimulation using spectral analysis [18], analyzing the relationship between emotions of EEG signals compare EMG and skin conductance toward using power spectral [19], and identification of one's brain activity based on EEG and MEG signals with video advertising [20]. This research is a continuation of the identification of two classes of video ads response (interesting or not interesting) using Autoregressive and Learning Vector Machine. However, this research utilizes offline system. Nevertheless, it gave 80% accuracy [21].

Meanwhile, to capture one person's interest response, it typically needs to be done in real-time as it can directly measure the effectiveness of a particular video advertisement.

This research performs the identification response system to a particular interest on a video advertisement taken from four channels of EEG signal using FFT and SVM in real-time three second interval. The system was built using FFT for feature extraction 4-40 Hz and identification using SVM, which integrates with wireless EEG in the form of software to identify video advertising response with three classes of interested, less interested, and not-interested.

Prior to the identification of video ad response in real time, a training with 30 subjects was conducted. Subsequently, respondents were requested to complete a questionnaire to determine whether the class is interested, less interested or not interested with the ads.

II. Material and Methods

A. Data Acquisition

The identification system contains two process that are learning or training process to the generalization of the training data in coefficient SVM. The learning process used in the training data of 30 subjects involved the following: For each three trials, respondetns watch 10 ads videos that resuls in 10 segments or 30 x 3 x 10 x 10 = 9000 training data. Each trial was accomplished to watch 10 video ads approximately 30-60 seconds. Data entered to the system which serve as training data is reduced to 30 seconds by eliminating the first quarter of seconds and the last quarter of a second.

Meanwhile the system was tested with training data and new data or testing data. Testing data was conducted on 15 subjects by the same procedure in the training data retrieval.

The profile of the subjects as respondents are as follows: They are at the age of 20 to 25 with perfect health and currently is not in a state of stress. Recording was done by using wireless EEG four channels AF3, AF4, T7, and T8 with 128 Hz sampling frequency. It was done in three conditions of time as trial, which are 08.00 am, 01:00 pm, and 05.00 pm. The surrounding of recording place is set in a quiet mode.

Table 1
McDonald's Commercial Video Advertisements

No	Advertising Video	Duration
1	McDonald's -Working Together- To Make Your Day Better	01.00
2	Baby - I'm Lovin' It	01.02
3	The Wind - McDonald's French Fries	01.00
4	He Loves Me	01.01
5	McDonald's Lonely Hearts	00.40
6	McDonald's 'Good Times'	00.30
7	My Dad - BBQ Chicken Legend Deluxe	00.32
8	McDonald's™ India - New Sharing Packs	00.29
9	Double - Bacon Clubhouse Double	00.30
10	McDonalds 30-Second Commercial	00.32

The retrieval of interest response data was done by providing visualization in the form of video ad. The video is a McDonald's commercial ad video consisting of 10 videos that can be found in YouTube (Table 1), in which all respondents are required to watch until completion. Recording was done in a quiet environment with sufficient lighting from the sun and from the monitor screen. Prior to being given visual stimulation in the form of video ads and installed EEG tools, all respondents were required to stretch for half a minute to achieve a relaxed state. Next, the respondents were allowed to sit in front of the monitor screen and begin the data recording process, which coincide with the start of the video ad. We also recorded the respondent's facial expression using a webcam upon viewing the video ads. After the recording process has been completed, a questionnaire was circulated to provide an assessment of the video ads seen.

Recorded data were labeled based on the results of questionnaires and respondent's facial expression. We used questionnaire questions from the previous research to describe their opinion on a particular advertisement: whether the ad is not monotonous, the products offered is as desired, the ads attract attention, advertisements offered can represent the quality of products, product promotion is widespread, completeness of products, products follow current market requests, effective advertisement, and reliable advertising and promotions [12]. The answer options provided are "yes", "not really", and "no", each representing the label of the training data. The calculation to determine the label of each ad was done by using the theory of "like it", calculating the answer value for each question. The highest value becomes the label for each ad in each questionnaire.

The recording data was obtained from each subjects by using EEG wireless 4 channel which has 128 Hz sampling frequency, which result in 128 data per second. The recording results were segmented into 3 seconds resulting in 384 data stored in the .txt file, the data consisting of signal values in amplitude and time units can be seen in Table 2.

Table 2
EEG Signal Recording

Index	Time(s)	Duration	AF3	AF4	T7	T8
1	0.00781	-28	-32	11	3	1
2	0.015625	-32	-12	3	-31	2
…	…	…	…	…	…	…
383	2.99218	9	31	-12	3	383
384	3. 0000	42	30	21	43	384
1	0.00781	-28	-32	11	3	1
2	0.015625	-32	-12	3	-31	2
…	…	…	…	…	…	…
383	2.99218	9	31	-12	3	383
384	3. 0000	42	30	21	43	384

B. Design of Neuropsychological of Advertising Video

Identification system of the EEG signal was built starting with the pre-process of segmentation recording the EEG signal every three seconds. EEG signals were recorded using a sampling frequency of 128 Hz for 30 seconds resulting in 10 segments. There are 128 x 3 seconds or 384 signal points for each segment. The number of points for each segment of an input signal extraction using FFT to obtain frequency characteristics in the area of Alpha, Beta, Gamma and Theta that is 4-40 Hz. The results of the extraction process using an FFT was then performed and the training phase identification using SVM. The identification system can be seen in Figure 1.

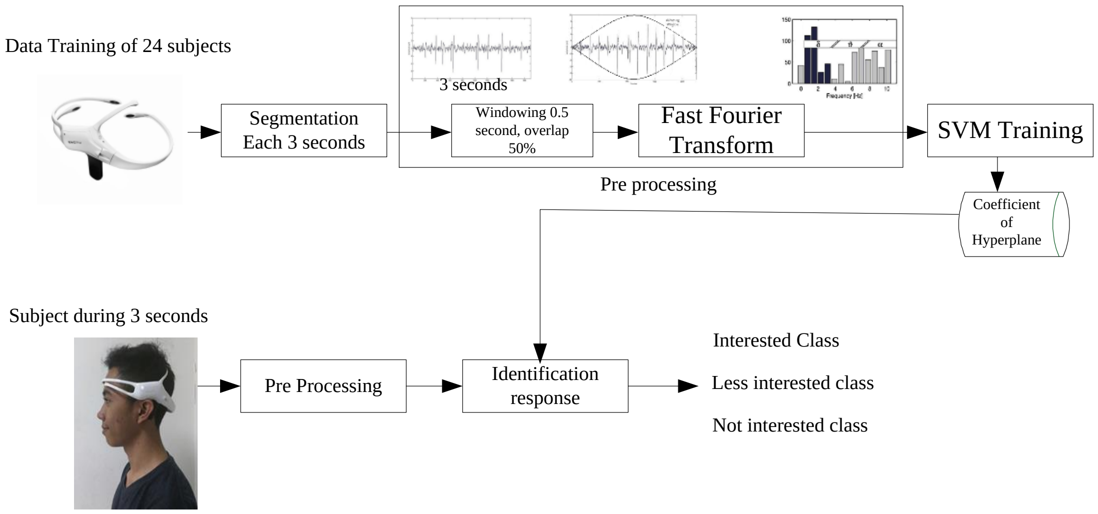

Figure 1: Identification of Neuropsychological against Advertising Video

EEG signals were recorded with a sampling frequency of 128 Hz during 30 seconds, which was then segmented into three seconds. It means that short time EEG signal is considered stationary. Then, the EEG signal extracted by the first FFT windowing passed with 50% overlap. The use of windowing method is intended to improve fluctuations in the lobes, which can interfere the estimated spectral resolution. FFT converts the EEG signal from the time domain into the frequency domain within the range of 4-40 Hz. Then, the results of the FFT were classified by SVM as a training data set.

1) Segmentation

The EEG signal recorded with a 128 Hz sampling frequency of 4 channels, was segmented every 3 seconds so that in 30 seconds of recording duration it produces 10 segments. Each segment contains 384 signal points. Segmented data is used as input to the next process.

2) Extraction Using Fast Fourier Transform

The signal was divided on the same frame and overlapped 50% of data length to reduce the discontinuity. Discrete Fourier transform give Equation (1)

$$X(k) = \frac{1}{N}\sum_{n=1}^{N-1} x(k)e^{-2\pi kn/N} \tag{1}$$

To improve the side lobe fluctuations, which can interfere with the spectral resolution, each frame is made windowing and then averaged as Equation (2):

$$x_w(k) = x(k)w(k) \tag{2}$$

Hamming window function is denoted by

$$\mathrm{w(k)} = 0.54 - 0.46\cos\left(\frac{2\pi \mathrm{k}}{\mathrm{N-1}}\right) \quad 0 \le \mathrm{k} \le \mathrm{N-1} \tag{3}$$

Suppose that point $t = NT_s$ give N data

$\{x(N): x(0), x(2), x(3), \ldots\ldots, x(N-1)\}$ with sampling T_s

Then N data of EEG signal $\{x(N)\}$ dived in K $\{x(i,L)\}$, $i = 1,2,3,\ldots,K$, each with length of $L < N$, where $\{x(i,L)\}$ is i^{th} of $\{x(N)\}$ data during L data. So, Discreet Fast Fourier Transform of

$\{x(i,L): x(i), x(i+1), x(i+2), \ldots, x(i+L-1)\}$ give:

$$S_{xi}(\Omega) = \left|\sum_{l=0}^{L-1} x(i+l-m)e^{-j\Omega l}\right|^2, \quad \Omega = \frac{2\pi}{N} \tag{4}$$

$m \ge 1$ that *overlap* factor. As windowing that gives:

$$S_x(\Omega) = \frac{1}{K}\sum_{i=1}^{K} S_{xi}(\Omega) \tag{5}$$

And spectral of all window give

$$S_{xw}(\Omega) = \frac{1}{2\pi N}\left|X(\Omega) * W(\Omega)\right|^2 \tag{6}$$

After FFT process (after frame based and windowing), we got 37 points data. If there was 11 frame, so there were 407 for each segment of data. After that, the extraction of each channel was combined into four channels that generate the data 407 = 1628 x 4 channels of data as inputs for identification SVM.

3) Identification of Neuropsychology using Support Vector Machine

In the identification system using SVM, the result of FFT is considered as the input data for training on SVM. The results of the classification using SVM in this study resulted in three classes that are interested, less interested, and not interested. Real time identification was used from the subjects who have not done the training. The result of feature extraction using FFT yielded 1628 data. Extraction data was then sought by the coefficient of separator function using kernel function that is Gaussian RBF.

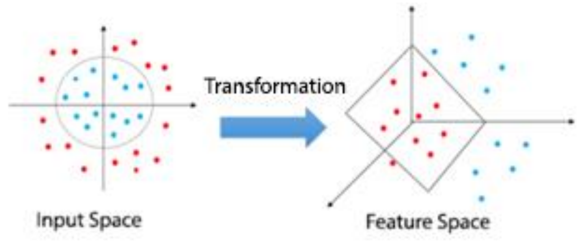

Figure 2: Transformation of input space vector to feature space

The SVM method can identify an object by finding the best hyperplane that serves as a separator of two classes. Hyperplane is essentially a linear separation function, but nonlinear hyperplane can be used for problems that could not be solved using linear hyperplane. For non-linear hyperplane, the data were transformed into a higher feature space, so the data can be separated linearly as shown Figure 2.

The process of finding a hyperplane in a new feature space requires a "kernel trick" to cope with large computing processes in search of transformation functions. There is a kernel used to search hyperplane in SVM, linear, polynomial, radial base function (RBF) and tangent hyperbolic (Sigmoid) with the equations, which can be seen in Table 3.

Table 3
Kernel Function

Kernel	Equation
Polynomial	$K(\vec{x_i}, \vec{x_j}) = (\vec{x_i}.\vec{x_j} + 1)^p$
Gaussian RBF	$K(\vec{x_i}, \vec{x_j}) = exp\left(-\gamma \lvert x_i - x_j \rvert^2\right)$
Sigmoid	$K(\vec{x_i}, \vec{x_j}) = tanh(\alpha\vec{x_i}.\vec{x_j} + \beta)$

In this study, the type of kernel used is Gaussian RBF. Each element of kernel $K(x_i, x_j)$ was used to replace *dot-product* $\boldsymbol{X}, .\boldsymbol{X_i}$ in Lagrange Multiplier Equation as Equation 5 and to obtain hyperplane coefficient w through Equation 6.

$$L = \sum_{i=1}^{N} \alpha_i - \frac{1}{2} \sum_{i}^{N} \sum_{j}^{N} \alpha_i \alpha_j y_i y_j (x_i . x_j) \tag{6}$$

$$w = \sum_{i=1}^{N} \alpha_i y_i (x_i \cdot x_j) \tag{7}$$

The equation of Lagrange duality was solved to get α. Where α>0 becomes the support vector to obtain coefficient w, which can be used in Equation 7.

$$w = \sum_{i=1}^{N} \alpha_i y_i \exp\left(-\gamma \left[x_i - x_j\right]^2\right) \tag{8}$$

$$f(x) = \sum_{i=1}^{N} \alpha_i y_i \exp\left(-\gamma \left[x_i - x_j\right]^2\right) + b \tag{9}$$

Thus, the non-linear Hyperplane function of identification system can be solved by Equation 8 with enclose $Sign(f(x))$ function.

III. Result and Discussion

EEG signal was x(n), where n = 128, followed by the frame-based windowing, and Fast Fourier Transfer of EEG signal in 4-40 Hz frequency range as shown Figure 3.

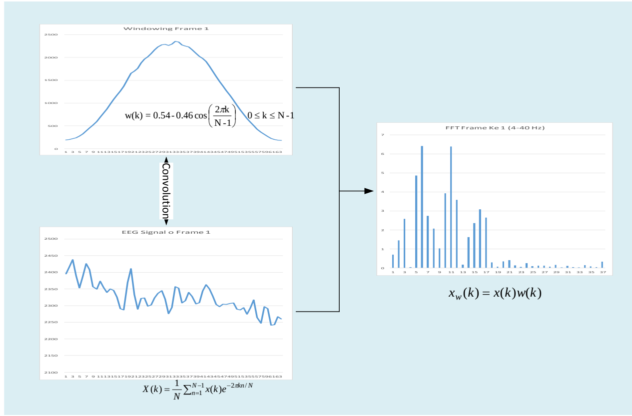

Figure 3: Frame based, windowing process

Furthermore, the identification of three classes was performed using SVM. Systems test were performed in three parts: the optimization of SVM parameter test, the influence of FFT pre-process in accuracy and the effect of amount of training data.

A. Optimize of SVM Parameter

The training data parameter testing process was performed to test the optimum parameters during the training process using SVM (gamma variable). The increase in gamma variables affects the accuracy level. The results of the SVM parameter test can be seen in Table 4. It used 9000 training data and 4500 testing data.

Table 4
Optimize of SVM Parameter

Gamma	Accuracy (%)	
	Training Data	New Data
10^2	89.5	69
10^3	88.7	60
10^4	88.0	69
10^5	88.0	70
10^6	87.2	67
10^7	87.0	69
10^2	91.5	71

Based on SVM parameter test, it is found that the increase on gamma parameter can decrease the accuracy level of training data. Gamma variable with the value 10^2 gets higher accuracy value from testing our training data compared to other gamma value, and therefore it was used on other tests.

B. Effect of Using FFT Extraction

Preprocess testing was performed to determine the effect of pre-processing stages into the system. The test results of data testing and training data through pre-processing were compared to those that did not go through pre-processing using different SVM parameter. The results of the pre-processing test can be seen in Table 5. It used 9000 training data and 4500 testing data.

Based on the series of test result, it is found that the identification using the preprocessor has a higher accuracy than the identification without using the pre-process. This shows that preprocess stage affects the accuracy of the system.

Table 5
Using FFT Extraction

γ	Accuracy with FFT (%)		Accuracy without FFT (%)	
	Training Data	New Data	Training Data	New Data
10^2	89.5	69	70	43
10^3	88.7	60	72	41
10^4	88.0	69	69	40
10^5	88.0	70	69	45
10^6	87.2	67	68	40
10^7	87.0	69	70	42
10^2	91.5	71	73	51

C. Effect of Amount of Training Data

This test is to determine the effect of the amount of training data that has been identified on the system. The amount used for the training data were 3000, 4500, 6000, and 9000 training data. The amount of each training data were obtained from the recording of 10-30 subjects. The result of testing of training data using Gamma parameter of 10^2 can be seen in Table 6.

Table 6
Effect of Number of Training Data

Number of Training Data	Time	Recognize Data	Accuracy Training Data (%)	Accuracy of New Data (%)
3000	00:35:00	70	87.5	60
4500	01:20:00	108	88,0	62
6000	02:50:00	134	89,0	65
9000	03:10:00	213	91,5	71

The result of this particular test shows that the increase of training data increases the level of accuracy. For the amount of training data sets or 4500 compared to 9000 doubled, increasing 9% and about 50%.

The off-line test showed that the 3 seconds identification gave 0.31 seconds response time, which is less significant than 3 seconds. Therefore, the system can be used in real time without significant time delays.

IV. CONCLUSION

This research has produced a neuropsychological identification system for video ads based on EEG signals with three classifications of result, which are “interested”, “less interested”, and “not interested”, using FFT as feature extraction and identification with SVM method. It yields 89% accuracy for training data and 71% accuracy for new or testing data. The results showed that feature extraction using FFT will increase the accuracy level compared to that without the extraction, with the result of 71% compared to 51%.

Training using SVM also contributed to the accuracy of 91.5% by using the most optimal parameter of 10^2 gamma value. Lastly, the amount of training data provides better accuracy level, but the addition of the amount of trainer data will give a longer training time of about 50% of its original calculation time. The off-line test shows the 3 seconds identification response time is obtained after 0.31 seconds, which is less significant than 3 seconds. Therefore, the system can be used in real time without significant time delays.

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