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SINGLE CHANNEL ELECTROENCEPHALOGRAM FEATURE EXTRACTION BASED ON PROBABILITY DENSITY FUNCTION FOR SYNCHRONOUS BRAIN COMPUTER INTERFACE

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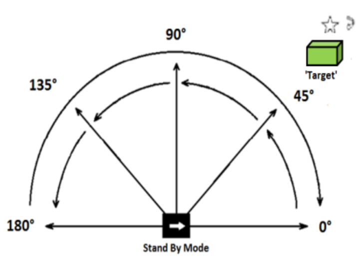
Graphical abstract



Abstract

Over recent years, there has been an explosive growth of interest in Electroencephalogram (EEG) based-Brain Computer Interface (BCI). Technically any architecture of a BCI is designed to have the ability of extracting out a set of features from brain signal. This paper demonstrated the extraction process based on Probability Density Function (PDF).A shared control scheme was developed between a mobile robot and subject. In general, subjects were required to synchronously imagine a star rotating and mind relaxation at specific time and direction. The imagination of a star would trigger a mobile robot suggesting that there is an object at certain direction. The mobile robot was then looking for a target based on probability value assigned to it. The result shows that 95% of theta activity was concentrated at target's direction (during star imagination) and reduced when there is no target (during mind relaxation).

Keywords: Brain computer interface, single channel, electroencephalogram

Abstrak

Beberapa tahun kebelakangan ini, telah berlaku pertumbuhan pesat pada Perantara Komputer Otak (PKO) berasaskan Electroencephalogram (EEG). Dari segi teknikal setiap PKO yang direka mempunyai keupayaan mengestrak satu set informasi dari isyarat otak. Kertas kerja ini menunjukkan proses pengekstrakan berdasarkan Fungsi Ketumpatan Kebarangkalian (FKK). Satu model perkongsian kawalan telah dibangunkan antara robot mudah alih dan subjek. Secara amnya, subjek adalah dikehendaki untuk membayangkan serentak dengan gerakan robot, bintang berputar dan menenangkan minda pada masa tertentu dan hala tuju. Imaginasi bintang akan menyebabkan robot mudah alih memahami bahawa terdapat objek pada arah tertentu. Robot mudah alih kemudian mencari sasaran berdasarkan nilai kebarangkalian yang diberikan kepadanya. Kajian menunjukkan bahawa 95% daripada aktiviti theta tertumpu pada arah sasaran (semasa bintang imaginasi) dan berkurangan apabila tiada sasaran (semasa menenangkan minda).

Kata Kunci: Perantara komputer otak, satu channel, electroencephalogram

1.0 INTRODUCTION

Over recent years, there has been an explosive growth of interest in Electroencephalogram (EEG) based-Brain Computer Interface (BCI). This is due to the fact that the EEG based BCI allows a practical acquisition of brain signal to be applied in real life environment. Previous studies have successfully demonstrated the feasibility of various applications of EEG based BCI with wide range of system complexity. Regardless of what the applications are, the BCI was and still meant for the people affected by Amyotrophic Lateral Sclerosis (ALS), spinal cord injury, cerebral palsy and other diseases often lose normal muscular control[1, 2].

Technically any architecture of a BCI is designed to have the ability of extracting out a set of features from various combinations of physiology and non-physiological signals, translate them to digital codes and issue commands to external devices.

In most studies, those features are often quantitatively computed by applying power spectral density (PSD) estimation for specific mental tasks. To be more precise, quantitative EEG analyses are concern with the power spectral changes (increase, decrease and constant) in sub-band frequency (delta, theta, alpha, beta, gamma and high gamma). For instance, it was found that frontal scalp region exhibited an increasing trend of theta and alpha power during a given period of relaxation time [3].Other study statistically claims that the frontal region shows significant reduction in normalized alpha power during relaxation period [4]. A study by Gott *et al*. (1984), reported that one of their subject have the capability to voluntarily suppress alpha waves in the left or right brain's hemisphere. Notice that, the aforementioned literatures [3-5] (but not limited to) reported inconsistent finding concerning specific sub-band's power/activity during a given relaxation time period. However, it is out of our scope to prove or disprove those argumentative inconsistencies. This is expected due to the non-stationary nature of EEG signal.

Thus, statistical technique has been proposed in various BCI studies [6-11] for it can estimate the probability of each task and assigns new instances into the class with the highest probability. This paper applied histogram based extraction for it often uses as a graphical representation to estimate probability distribution for discrete random variable. A random process can be characterized by its PDF which representing the probabilities of occurrence for all possible value of variable under investigation.

The main objective of this paper was to extract the highest probability features and to observe their behavior quantitatively.It is important to initially identify the scalp's locations which correspond to specific discriminative mental tasks. Nevertheless our previous studies has succeeded in recognizing and statistically verified a scalp position (F_8) (Figure 1) which corresponds to a unique mental task [4, 12]. Frontal lobe (include F_8) is a structure which inhibits response to the environment, planning future action and control the movements [13-17].

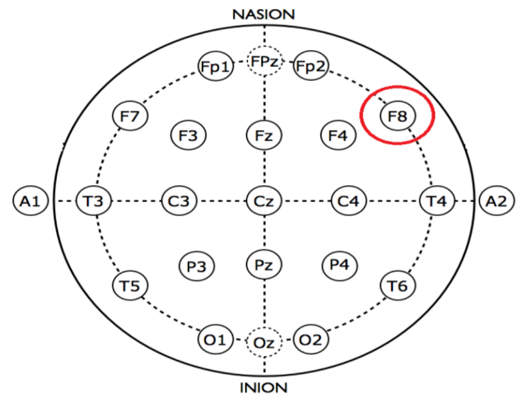


Figure 1 EEG's international 10-20 standard showing single channel electrode placement (F_8) for proposed BCI system

2.0 METHODOLOGY

2.1 Experimental Setup

This section presents the experimental setup for the system. We used single EEG signals of 10-20international standard location (F_8). The reference potential position was placed at the right ear lobe. An EEG paste was used to increase the electrode conductivity. The channel was directly connected into BMA-400 EEG-amplifier which provides specific gain constant for bio signal amplification.

The EEG signal was digitized using National Instruments (NI)-PCI-6229 Data Acquisition Card (DAQ) which was connected into Peripheral Component Interconnect (PCI) slot of a personal computer's (PC) motherboard. All necessary specification of a PC in used are listed here:

- 2.50 GHz i5-2520M Intel® Core™
- Fedora 8 RTAI Linux-kernel-2.6.23-42-fc8
- COMEDI's pci-6229 device driver

Control and Measurement Device Interface (COMEDI) is a collection of device drivers for a variety of common data acquisition plug-in boards (e.g. NI-PCI-6229 DAQ card). The system was designed to acquire a single signal of EEG and was exploited using C language as our processing tool. The necessary setting (e.g. sampling frequency, DAQ's I/O port and acquisition mode) for data acquisition process was controlled by a set of appropriate C functions provided by COMEDIlib.

2.2 Experimental Procedure

In this section, we present the experimental procedure for data collection. 10 subjects were voluntarily participating in this experiment. There were no initial training session provided to all of them.

Based on previous study by [4] two mental states were used as below:

- Mind relaxation (control condition).
- Imagine a 2-D star rotating in clockwise direction (target condition).

The subjects were required to sit on a chair comfortably and facing towards a mobile robot which was located about 2 meters from their feet as shown in Figure 2. Before the experiment took place, all subjects were given a briefing session regarding the experimental procedure for about 5 minutes. Each subject was then required to draw a 2-D star and was given 5 second to glare at the star. Simple assessment was carried out after the experiment session. All subjects had no previous experience with meditation and specific mental illness record. Subjects were in a healthy condition during the experiment period.

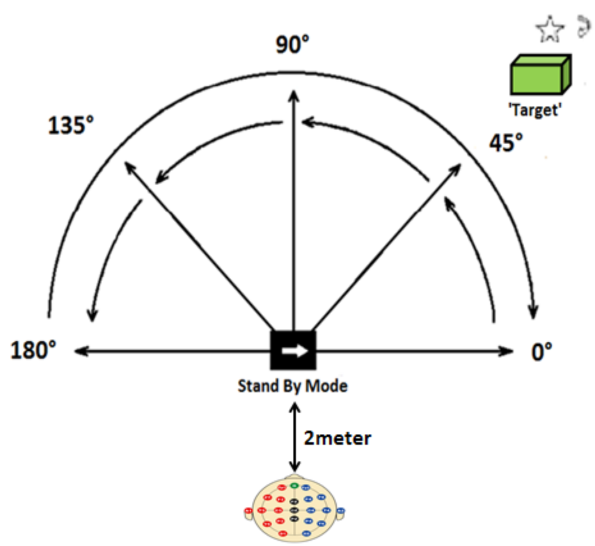


Figure 2 Illustration of control scheme. A box is placed at 45° serve as target to be selected by imagining a start rotating clockwise direction on top of it for 10 second

The procedure was developed to allow 'target' selection during scanning process of a mobile robot. The control area was divided into five degree-based direction - $0°45°$, $90°, 135°$ and $180°$. The robot is initialized to standby mode - face towards $0°$ direction to the right. An object is placed at the direction of 45° where it serves as a target to be selected. Figure 3 shows a control flow chart of synchronous process between direction, mental state and time.

2.3 Extraction Process

EEG signals were digitized into 16-bit resolution data at 1024Hz sampling rate. The *n* second raw data (10sec in our case) were first segmented into several epochs, *j* (*j* is integer) where each epoch *j* contains 1024 data points. The PSD of each epoch were then estimated using Fast Fourier Transform (FFT).

One possible solution to characterize EEG is to create several sets of feature [18]. Some studies use R, [18-20] while other use normalized R, [4, 12] as defined below:

$$R_k^j = \frac{\sum_{i=x}^{y} p_i}{\sum_{i=0}^{120} p_i} \quad (1)$$

where:
j = epoch
x = minimum frequency component of band *k*
y = maximum frequency component of band *k*
p = Instantaneous power
k = delta(δ), theta(τ), alpha(α), beta(β), gamma(ς) and high gamma(ћ)

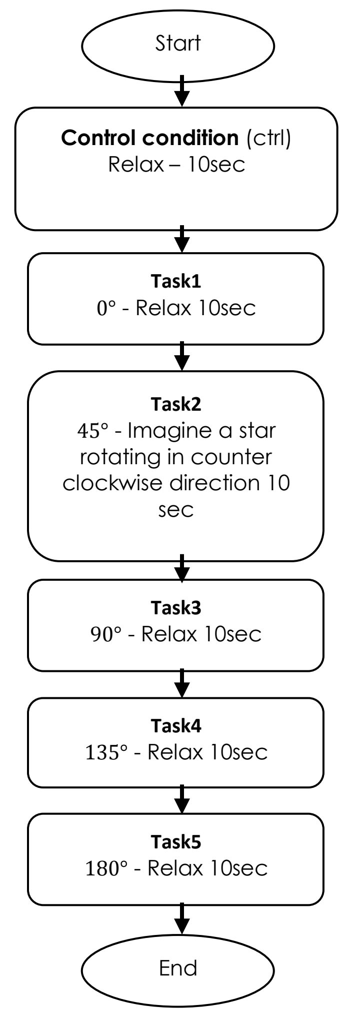


Figure 3 Flow chart of control procedure

Here R is defined as the area under spectral density curve for six frequency band (delta, theta, alpha, beta, gamma and high gamma).For *k* no. of

EEG bands, there are 2^k possible feature sets of summation of normalized power value as shown in Table 1. For 6 frequency bands, there will be 64possible combination of summation between frequencies in a single task

Table 1 possible feature sets of summation of normalized power value

i^{th} feature set	Set representation
0	{null}
1	$\{R^1_\delta, R^2_\delta \dots R^z_\delta\}$
2	$\{R^1_\tau, R^2_\tau \dots R^z_\tau\}$
…	…
7	$\{R^1_{\delta,\tau}, R^2_{\delta,\tau} \dots R^z_{\delta,\tau}\}$
…	…
63	$\{R^1_{\delta,\tau,\alpha,\beta,\varsigma,\text{Ђ}}, R^2_{d\delta,\tau,\alpha,\beta,\varsigma,\text{Ђ}} \dots R^z_{\delta,\tau,\alpha,\beta,\varsigma,\text{Ђ}}\}$

In our case, for 1epoch/sec, 10 sec of time period, 4 trial and 10 subjects the total number of epoch, z in each possible combination of feature set (Table 1) is:

z = 1epoch/sec x 10sec x 4(trials) 10(subjects)
= 400epoch (2)

Two sets which is a null set (contain all zero) and last set (contain all 1) is ignored. For six different tasks (each at five directions includes control condition) there will be $6(2^k - 2) = 372$ number of feature sets is created.

Next, for each created feature sets, histogram, *H* is developed where *m*is the number of bin and is estimated using square root choice:

$$z = \sum_{i=1}^{m=\sqrt{z}} H_i \quad (3)$$

For each histogram we were only considered to retain the highest probability bin (elements inside bin) while eliminating the rest. Since we have 372 bins left, a possible of 62 (372 bins/6 tasks) distribution model was developed as shown in Figure 4.

The main purpose of the model is to observe the tasks' behavior (either the distribution go to the left or right correspond to low and high power respectively). According to Azmi and Safri (2013), the normalized alpha power were observed to increase and decrease when subjects were imagining a star rotating in clockwise direction and relax respectively with p value less than 0.001. Based on this knowledge, we defined model selection criterion as: *the right most distribution must come from task2.*

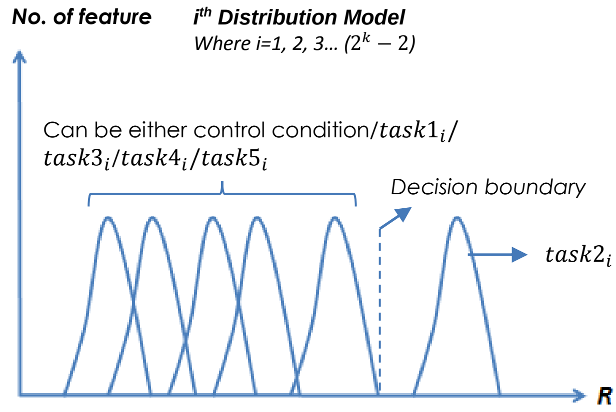


Figure 4 Expected Distribution Model that meets the defined criterion. In general decision boundary is a line that discriminates between two mental classes – relax (left) and star imagination (right)

3.0 RESULTS AND DISCUSSION

3.1 Target Selection

At the end of control procedure, a mobile robot is given a task to select the direction where the target is located at (in this case 45°). A limited analysis performed on a subject basis for every i^th models in Table 2 (z=400) would yield poor selection result. This is mainly due to the inconsistency in generated i^th models where feature set for each subject varies with time and the number of feature in use [18]. In other word, the statistics of brain signal keep changing from time to time.

To observe the effect of using different number of epoch on distribution model, the value of z was varied. Table 2 illustrates the problem for z=200, 300 and 400 where a different set of ith models were generated. For instance, if we vary the value of z from 1 to 400 we would have 400 different set of i^{th} models that meet the model's criterion. Thus it is hard for us to draw a concrete conclusion which i^{th} model needs to be selected to be used in real time scheme.

One possible solution is to use probability measure to select a target. The idea is, if we have 400 set of i^{th} models that meet the criterion, we can build a frequency table to observe which i^{th} model is the most active (appear in every i^{th} model) - in case of Table 2, 15^{th} model is the most active.

To do this, the extraction process was iterated for z times. Each iteration would generate a set of i^{th} models that meet the criterion and recorded (as Table 2). This process is repeated five times where each repetition defines a different model selection criterion: *the right most distribution must come from task i (i=1, 2, 3, 4 and 5).* Figure 5 shows flow chart of the process.

To calculate the probability value, frequency table for six recorded i^{th} models corresponding to their tasks (direction) were developed (Table 3).

Figure 6 shows sample distributions taken from 15th model (τЋ). In the distribution space, the control condition is assume to be reference for relax state. Thus, theoretically the distribution mean for control condition, 1, 3, 4 and 5 should be approximately the same. In practice this is not the case.

Our preliminary result statistically shown there is a possibility that subjects accidently imagine a star rotating at135°. Most of them having no difficulties to imagine a star rotating at 45° but they have difficulties to suppress their imagination at 90° , 135° and 180°.

Table 2 The ith Models that meet the criterion (task2). For instance, at (z=200) model no. 2,3,15,60 and 61 corresponding to τ, α,τς,δτβςЋ andδαβςЋ respectively were observed to meet the criterion

ith models (z=200)	ith models (z=300)	ith models (z=400)
2	4	4
3	5	6
15	11	11
60	15	15
61	16	18
	30	20
	31	30
	32	34
	33	37
	40	40
		42
		62

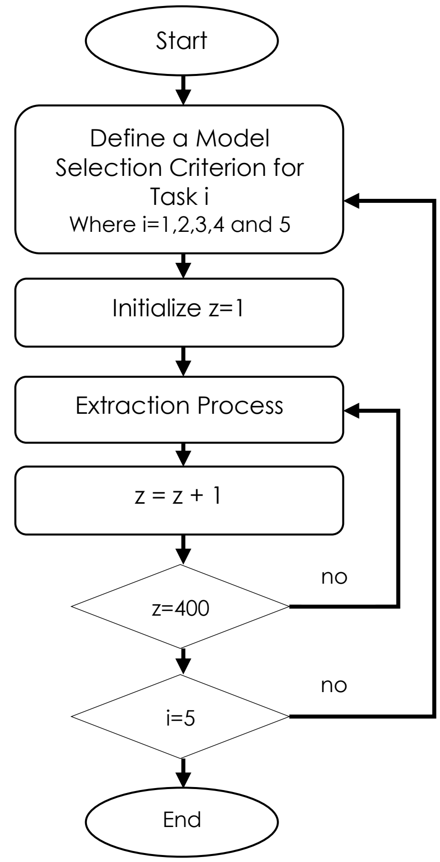


Figure 5 Flow chart for extended process

Second, there is always chances that signal is affected by various source of artefact (eye blinking and unknown physiological state). A simple assessment was conducted after experiment for each subject. Most of our subject claims that it is hard for them to keep their mind in relax state for a given duration of time.

Recall that in previous section, for a histogram we were only considered to retain the bin with highest number of elements inside it. This in under assumption that the elements inside the bin have highest probability of occurrence for a given period of time and regard the rest as noises (unwanted information). In this case, we care less about the probability value of the bin but the behavior of elements inside it. Figure 7 shows a comparison of distribution behavior of elements (feature) between before and after we apply a PDF technique. Notice that, it is hard to differentiate between control condition and start imagination's distribution if we do not consider removing some unnecessary elements (the eliminated bins). After a PDF process it is observed that the normalized power value for star imagination is higher compare to control conditions' as expected.We found that theta activity (2nd model) was increased (95%) and suppressed during star imagination and relaxation respectively.

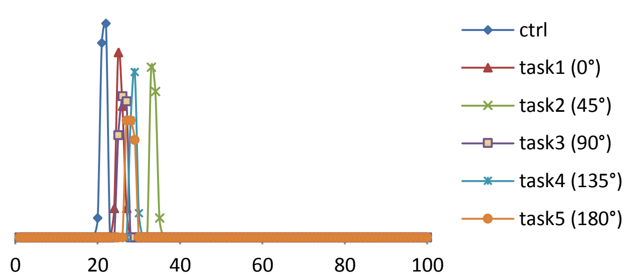


Figure 6 15th distribution model (z=400) of normalized power (all subject) for each task correspond to specific direction respectively including control condition as main reference for relax state

Table 3 Frequency table of ith models up to 6th model for all five tasks (success rate, probability in percent)

ithmodel	Task1	Task2	Task3	Task4	Task5
1	134(33%)	3(0.75%)	53(13%)	343(85%)	236(59%)
2	0(0%)	**381(95%)**	13(3%)	143(35%)	146(36%)
3	0(0%)	123(30%)	209(52%)	133(33%)	173(43%)
4	66(16%)	45(11%)	0(0%)	255(63%)	344(86%)
5	254(63%)	66(16%)	174(43%)	46(11%)	3(0.73%)
6	28(7%)	0(0%)	14(3%)	320(80%)	372(93%)

4.0 CONCLUSION

We have shown the feasibility of PDF to extract highest probability of occurrence and observe their behavior. It is hard to draw a concrete conclusion which frequency band can be used to discriminate between mental classes. The speculation of theta and alpha activity during relaxation is inconsistence in various research papers. The increase in theta activity during relaxation as reported by Jacobs and Freeman (2004), are focusing more in temporal, central, parietal and occipital region. No significant activity of theta in frontal region as what we found. There still a lot of works need to be done in the future and more rooms for improvement. This has become the scope of current research.

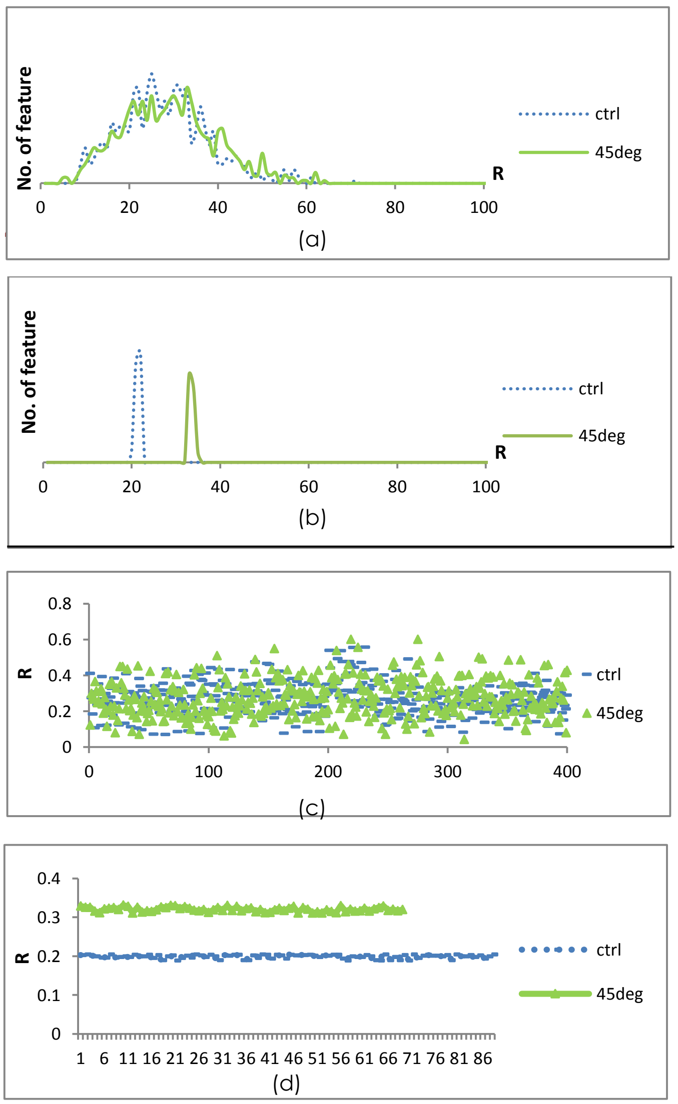


Figure 7 15thDistribution models between control condition and star imagination: a) before PDF, b) after PDF. The scatter version of elements: c) before PDF, d) after PDF

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