ARPN Journal of Engineering and Applied Sciences

www.arpnjournals.com

REAL-TIME TARGET SELECTION BASED ON ELECTROENCEPHALOGRAM (EEG) SIGNAL

Muhammad Shaufil Adha, Norlaili Mat Safri and Mohd Afzan Othman
Department of Electronic and Computer Engineering, Faculty of Electrical Engineering, Universiti Teknologi Malaysia, UTM Johor Bahru Malaysia
E-Mail: shaufil_adha@hotmail.com

ABSTRACT

Electroencephalogram (EEG)-based mobile system are getting mainstream although the true potential of EEG signals are yet to be discovered. With the help of a specific control paradigm, the success rate of a mobile system to reach to a certain location could be increased. To further extend the existed control paradigm of EEG-Based mobile robotic system, this paper demonstrated the real time target selection of a wireless mobile robot using only human mind. A unique protocol was developed to mimic a scanning process while at the same time allowing subject to make a selection. Our system utilized only single EEG channel with no subject training. We statistically verify that it is feasible to select a target by manipulating only alpha content of EEG. We also show that it is hard to achieve a stable high performance of synchronous EEG-Based BCI application in one trial with a single frequency band. However, we found that the BCI's performance in term of sensitivity is getting more stable with increase in trial.

Keywords: electroencephalogram, brain computer interface, mobile robot.

INTRODUCTION

The used of human mind rather than biological limb to drive a mobile system has fascinated a lot of research groups because it can bring back mobility to those who suffer from severely neuromuscular disorder. The system that can artificially replace and establish a direct path way between human mind and mobile system is known as Brain Computer Interface (BCI). The BCI is designed to inherent the ability of acquiring a set of features generated by human mind, translate them to digital codes and get the mobile system under its command.

The research area for EEG-Based mobile system is very broad. Some group concentrating and constrain their research in developing the algorithms for feature extraction (Po-Lei *et al.* 2012), (Xiangzhou *et al.* 2014) reducing EEG's artifact by means of preprocessing algorithms (Wu *et al.* 2009), developing a system that inherent a modality by combining various type of biological signals (Filho *et al.* 2014) – also called hybrid BCI, finding a new ways of enhancing the overall driving performance (Gandhi *et al.*, 2014) and many more. Whatever the research scope is, the main objective is to develop a stable and safe EEG-Based mobile system.

In general the EEG-based mobile system can be categorized into two types of operational mode 1) *direct control* - where the mobile system is controlled by using only EEG signals (Tanaka *et al.* 2005) and 2) shared control – a new control paradigm from combination of EEG signals and the intelligence of robotic to share the control over a mobile system (Millan *et al.* 2004). The later option is more appealing because it can increase the success rate for a mobile system to reach to a specific location. Plus with the help of robotic's intelligence system, a mobile system behave more natural compared to the first one's.

Another option to give more natural control over a mobile system is to increase the number of EEG channels. The idea is to acquire as much information as possible to be processed. However too much electrodes attached on the scalp will cause problem not only to the subjects, but also making the BCI set up more cumbersome.

Apart from that, another typical issue concerning BCI design is subject's training session. Basically a BCI that uses brain signal elicited due to mental task (e.g. imagination and problem solving) require subject to undergo training. This is needed to reduce the involvement of BCI expert while subject operating the system. Plus it has been shown that training can increase the overall driving performance of mobile system. However, training session is not without disadvantage. From devastating impaired person's perspective, long training session is not a practical solution (Neumann *et al.*2003). Some research groups attempt to reduce training session while maintaining high performance by exploiting another type of brain signal (Thulasidas *et al.* 2005). Unfortunately, this will add on another resource which is a stimulator. It is worth to mention here that if the BCI system is to be used by a patient, it ought to be portable, small and user-friendly.

From a designed perspective, any BCI can be either synchronous or asynchronous. A synchronous BCI (sometimes call cue-paced) requires a subject to only perform specific mental task at specific time interval. Even though it is easy to design, it is not as powerful as asynchronous designed in term of performance. Asynchronous design allows a subject to perform any given mental task at any time interval. The subject has a freedom to control a mobile system according to his/her instinct. The disadvantage is, this type of BCI is hard to develop.

Our long-term goal is to develop an online (sometime called single-trial analysis) synchronous EEG-Based Mobile Robot by applying shared control paradigm. The objective is to select a target's direction using only EEG signals and autonomously manoeuvring towards target by means of advanced robotics' navigation system. Plus we would like to answer a challenge of developing a mental task-based BCI with single channel EEG and without subject training. This paper serves as the first step toward our goal by developing a real time system that allows a BCI user to make a selection of an object's direction (known as 'target') by using only subject's mind. In general, before the development of BCI applications take place, it is crucial for most research group to firstly identify the scalp locations which corresponds to mental tasks. Nevertheless our previous study has succeeded in recognizing a scalp position (F_8) which corresponds to a unique mental task (Husnaini, 2014).

METHODOLOGY

Experimental setup

This section presents the experimental setup for the system. We used single EEG signals in one 10-20 international 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 bio-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 below:

- 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 manipulated using C language as our processing tool. The necessary setting for data acquisition process (e.g. sampling frequency, DAQ's I/O port and acquisition mode) was controlled by a set of appropriate C functions provided by COMEDIlib. A Zigbee-based transmitter was developed to control a mobile robot wirelessly by sending appropriate control commands.

Signal processing

EEG signals were converted into 16-bit resolution digital data after gone through sampling process at 1024Hz. The data were first segmented into several epochs where each epoch contains 1 second raw data (1024). The epochs which are time varying were then gone through a transformation process into a frequency varying (domain) by means of conventional Fast Fourier Transform (FFT). Next, the transformation results were averaged to obtain the mean for each frequency of a defined range (0Hz-120Hz). Then only alpha frequency band (8Hz-12Hz) was extracted out and normalized to the full EEG band (Equation. 1).

$$\frac{\sum Alpha_{F8}}{\sum EEG_{F8}}$$

Performance metric evaluation

In general the performance metric for brain controlled mobile system can be divided into two major categories. One is referred as task metric – it emphasis on how well the given task can be performed with the system. A used metric is system's sensitivity (Husnaini, 2014). For instance, if the BCI inherent 100% of sensitivity, we can be certain that the BCI has 100% chance to make a true detection each time a subject perform mental task. If the BCI system has low percentage of sensitivity for one or both mental task, then the mobile system may unable to locate the target's direction correctly. The system's sensitivity.

$$th = \left| \frac{max\ feature_{mental\ task\ \#2} + min\ feature_{mental\ task\ \#1}}{2} \right|$$

$$Sensitivity, se = \frac{true\ positive\ (TP)}{true\ positive\ (TP) +\ false\ negative\ (FN)}$$

Apart from sensitivity, task success can also be applied. It mainly focuses on whether a subject could accomplish given tasks for several trials. A typical result for this type of metric evaluation is right or wrong. Basically, it is more to subject-oriented performance rather than tells us more about the system's.

Another is called *ergonomic metric* – it evaluates the state of the user rather than their performance. The objective is to observe user's mental effort while operating the brain controlled mobile system. The task metric or statistical analysis (p-value) could be the tools to evaluate the user condition and effort at specific time interval.

Mobile robot

The main objective of EEG-Based mobile robot is to provide transportation for disable people provided that he/she is cognitively intact. One typical machine suitable for this purpose is an electric wheelchair. However, it is beyond the scope of this paper to discuss the architecture of EEG-based wheelchair robot in details. Interested reader may refer to (A.B.Benivides *et al.* 2011) for further information. To suit our research objective, we think that it is sufficient to apply a wireless miniaturized mobile robot with minimum integrated intelligence of

VOL. 10, NO. 19, OCTOBER 2015 ISSN 1819-6608
ARPN Journal of Engineering and Applied Sciences

www.arpnjournals.com

hardware and software components - no sensor & complex algorithm. The mobile robot was programmed to perform pre-defined tasks as enshrined in our proposed BCI protocol.

BCI protocol

In this section, we present our proposed BCI protocol. There were no initial training session provided to all 20 voluntary subjects. The control are determined by 2 mental state:

- Mind relaxation (#1)
- Imagine a 2-D star rotating in clockwise direction (#2)

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. 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 as in Figure-1. 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.

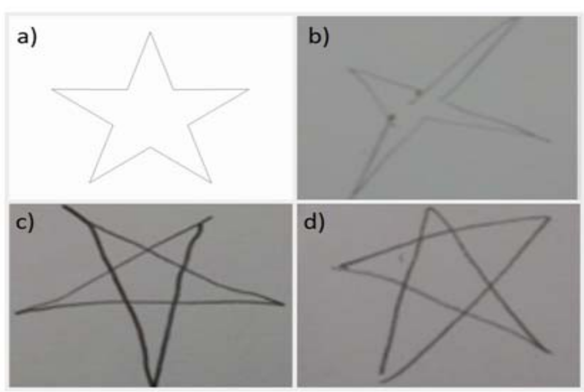

Figure-1. a) Each subject need to imagine a 2-Dimensional star rotating in clockwise direction. Figure b, c and d show drawing sample taken from three of our subject randomly. They were instructed to imagine their own drawing for 10 second.

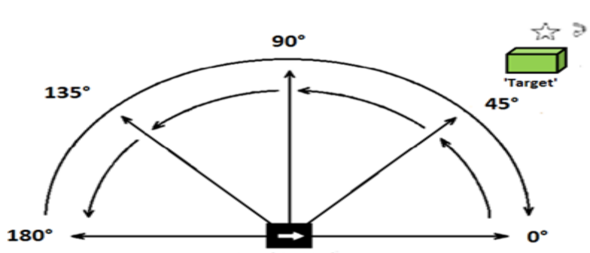

Figure-2. Illustration of mobile robot's control model. The model is divided into 5 degree-based direction where an object is placed at 45° direction known as 'target'.

The main objective of this protocol is to allow 'target' selection during a scanning process of a mobile robot. To achieve this, we divide our experimental procedure into five phases as illustrated in Figure 2. There are of five degree-based direction - 0° 45°, 90°, 135° and180°. 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 2).

Prior to first phase, the subject is required to attend his attention straight to the wall and performing mental task #1. The EEG signal is captured in 10 second duration and stored as "Control" data.

Next a triggering signal is send to mobile robot indicating the first phase has begun. Since there is no object at this direction (0°), subject is required to perform mental task #1 From this point, the EEG signal is captured in 10 second duration and stored as "Task 0" data.

Next the second triggering signal is send to mobile robot indicating the second phase has begun. The mobile robot then automatically moved itself to 45° degree to the left from current direction. Since there is a user's target at this direction, subject is required to perform mental task #2 on top of target. From this point, the EEG signal is captured in 10 second duration and stored as "Task 45" data. The mental task performed at this phase implied that the subject acknowledged there is a target he wants to select at this direction.

Next the third triggering signal is send to mobile robot indicating the third phase has begun. The mobile robot then automatically moved itself to 90° degree to the left from current direction. Since there is no object at this direction, subject is required to perform mental task #1. From this point, the EEG signal is captured in 10 second duration and stored as "Task 90" data.

Next the fourth triggering signal is send to mobile robot indicating the fourth phase has begun. The mobile robot then automatically moved itself to 135° degree to the left from current direction. Since there is no object at this direction, subject is required to perform mental task #1. From this point, the EEG signal is captured in 10 second duration and stored as "Task 135" data.

Next the fifth triggering signal is send to mobile robot indicating the fifth phase has begun. The mobile robot then automatically moved itself to 180° degree to the left from current direction. Since there is no object at this direction, subject is required to perform mental task #1. From this point, the EEG signal is captured in 10 second duration and stored as "Task 180" data.

Then the sixth triggering signal is send to allow mobile robot returning back to standby mode. It is clear that the robot's movement of 0°-45°-90°-135°-180°-135°-90°-45°-0° implied the scanning process of the robot. From this point, all the collected data is processed. Once the processed has been done, a command is send to

VOL. 10, NO. 19, OCTOBER 2015 ISSN 1819-6608
ARPN Journal of Engineering and Applied Sciences

direct the mobile robot back to where mental task #2 was performed.

RESULTS AND DISCUSSION

The real time demonstration was successfully conducted to test the online feasibility of proposed target selection paradigm. The experiment was repeated for four times for each subject. Prior to system's performance measurement, the statistical analysis for feature extraction algorithm was conducted. This is purposely done for two reasons 1) serve as verification to what have been found by previous study and 2) to observe the significance difference between each mental task perform at all direction against the control condition for all EEGs frequency bands. The probability, p value calculated from statistical t-test method was used to observe the significant level between two mental task conditions. All the statistical operation was done by using EXCEL.

The previous study has statistically shown that there was a significant difference ($p<0.001$) between mental task #1(ctrl) and #2 in normalized alpha frequency band. Table-1 shows the p values for each direction against Control condition for all EEG's frequency band. It is clear that there is difference ($p<0.0408$) between mental tasks #1(ctrl) and #2 in alpha frequency band. The results show no contradiction to the previous study's thus verifying the feasibility of proposed BCI system.

Table-1. p values for each direction against control condition for all EEG's frequency band.

	Ctrl-0	Ctrl-45	Ctrl-90	Ctrl-135	Ctrl-180
Delta	0.0202*	0.0334*	0.0154*	0.0175*	0.1596
Alpha	0.1375	0.0408*	0.0697	0.0157*	0.6123
Theta	0.0005***	0.0053**	0.0003***	0.0013***	0.0068**
Beta	0.1494	0.0358*	0.0757	0.1095	0.2982
Gamma	0.4224	0.5793	0.8574	0.3072	0.7611
HGamma	0.6983	0.5255	0.5629	0.9364	0.5212

Table-2. Sensitivity table for trial 1.

1st TRIAL						
	Total Feature	TP	TN	FN	FP	Se (%)
Non-Target (ctrl)	20	-	14	6	-	70
Target (45°)	20	8	-	-	12	40

Table-3. Sensitivity table for trial 2.

2nd TRIAL						
	Total Feature	TP	TN	FN	FP	Se (%)
Non-Target (ctrl)	20	-	12	8	-	60
Target (45°)	20	10	-	-	10	50

Table-4. Sensitivity table for trial 3.

3rd t TRIAL						
	Total Feature	TP	TN	FN	FP	Se (%)
Non-Target (ctrl)	20	-	14	6	-	70
Target (45°)	20	6	-	-	14	30

Table-5. Sensitivity table for trial 4.

4th TRIAL						
	Total Feature	TP	TN	FN	FP	Se (%)
Non-Target (ctrl)	20	-	13	7	-	65
Target (45°)	20	13	-	-	7	65

BCI performance

We are expecting to obtain as much feature as possible above the *th* while subject performing #2 and below *th* while performing #1. Tables 2, 3, 4 and 5 show the sensitivity results for trial 1, trial 2, trial, 3 and trial 4, respectively.

1st trial shows that the BCI system is more sensitive to #1 by 70% and only 40% sensitive to #2. The BCI shows rising in #2's sensitivity from previous trial which is desirable but a reduction in the #1's sensitivity both by 10%. The 3rd trial recorded the worst BCI system's ability to detect #2 compared to #1 which is only 30%. Clearly this low sensitivity occur due to the reduction in users' ability to generate high feature value for #2 (FP=14). 4th trail shows the most stable BCI sensitivity for both #1 and #2 which is 65%.

There are several things need to be pointed out from this results and will be supported by the assessment which was purposely carried out. First, the results from trial 1 reveals that it is hard to achieve a stable high performance control-based synchronous BCI application in one trial. The stability of sensitivity between #1 and #2 is not satisfactory (70%-40%), thus we are afraid that the mobile robot will falsely select wrong target's direction. If we are considering another trials, the second shows the system's sensitivity getting more stable (60%-50%). However the third shows severe reduction of #2's sensitivity compared to the first and second. The results shows that the BCI's sensitivity becomes fully stable at trial 4 but still moderate (65%). In general the increase in

VOL. 10, NO. 19, OCTOBER 2015 ISSN 1819-6608
ARPN Journal of Engineering and Applied Sciences

www.arpnjournals.com

stability over trial (1st to 2nd and 3rd to 4th) may suggest that we still need to consider training our subjects for several times before using the application but with short period of time.

Second, it is hard for the subject to control their thinking process during the mobile robot's scanning session. Most of our subjects claimed that it was easy for them to imagine a rotating star rather than relaxing their mind. It is getting harder especially after subjects performing mental task #2 at 45°. The p values of alpha frequency band in table 1 shows that there is a difference ($p<0.0157$) between control and task135. Furthermore, If we are considering the p values which is nearest to 0.05, there is also a slightly difference ($p<0.0697$) between control and task90. The difference may suggest 1) the subjects still unable to completely change their mind to relax state and/or 2) subjects still imagining mental task #2. We found that once the subjects execute mental task #2, there will be a duration of time before subjects' mind can completely change state. Statistic has shown that most subjects be able to cool down their imagination ($p<0.6123$) when the mobile robot reach 180°. This brain cooling process will take about 20 second – 10second each at 90° and 135°. Under practical situation, if the BCI system is designed without taking into consideration of this issue, the system may understand that there are two targets (45° and 135°) selected by user, which is wrong according to our BCI protocol – only a target at 45°. However, this issue comes to no surprise because under single channel BCI system, a fixed scalp position will be shared by multiple mental tasks. Thus we see that several modification and/or improvements need to be made to our protocol in handling the issue.

CONCLUSIONS

Although many researchers have developed various brain controlled mobile robots, most of them only show their feasibility in controlled laboratory environment. The main reason for this is that the BCI is not stable due to the non-stationary nature of EEG signals. If the BCI itself is not stable, a user has an option to leave the remaining tasks to robotic system. This shared controlled model is progressively under research, but still a lot of improvement and discovery must be made. Lastly, we see there is always a need to create a variety of driving techniques so that the application can inherent modularity – a system that have multiple selective driving techniques. 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.

REFERENCES

[1] Benevides A. B., Bastos T. F. and Filho T. F. 2011. Proposal of Brain-Computer Interface architecture to command a robotic wheelchair. IEEE International Symposium on Industrial Electronics (ISIE), pp. 2249-2254.

[2] Filho T. F. B., Cheein F. A., Muller S. M. T., Celeste W. C. C., del la Cruz, Cavalieri D. C., Filho M. S., Amaral P. S. F., Soria C. M. and Carreli R. 2014. Towards a New Modality-Independent Interface for a Robotic Wheelchair, IEEE Trans. on Neural System and Rehabilitation Engineering, Vol. 22, No. 3.

[3] Gandhi V., Prasad G., Coyle D., Behera L. and McGinnity T.M. 2014. EEG-Based Mobile Robot Control through an Adaptive Brain–Robot Interface. IEEE Trans. System, and Cybernetic: System, Vol. 44, pp. 1278-1285.

[4] Husnaini A. 2014. Target Selection Using Single Electroencephalogram Electrode Based On Mental Task. M.S. dissertation, ECE Dept., UTM, Skudai, Johor Baharu.

[5] Millan J. R., Renkens F., Mourino J. and Gerstner W. 2004. Noninvasive Brain-Actuated Control of a Mobile Robot by Human, IEEE Trans. on Biomedical Engineering, Vol. 51, No. 6.

[6] Tanaka K., Matsunaga K. and Wang H. O. 2005. Electroencephalogram-Based Control of an Electric Wheelchair. IEEE Trans. on Robotic.

[7] Thulasidas M. and Guan C. 2005. Optimization of BCI speller based on P300 potential, IEEE Engineering in Medicine and Biology 27th Annual Conference.

[8] Neumann N. and Kubler A. 2003. Training Locked-in Patients A Challenge for the use of Brain-Computer. IEEE Trans. on Neural System and Rehabilitation Engineering, Vol. 11, No. 2.

[9] Po-Lei Lee, Hsiang-Chih Chang, Tsung-Yu Hsieh, Hua- Tiang Deng and Chia-Wei Sun. 2012. Brain-Wave-Actuated Small Robot Car Using Ensemble Empirical Mode Decomposition-Based. IEEE Trans. System, and Cybernetics – Part A: System and Human, Vol. 42, No. 5.

[10] Wu Jin, Zhang Jiachai and Yao Li. 2009. An Automated Detection and Correction Method of EOG, International Conference on Complex Medical Engineering (ICME), pp. 1-5.

[11] Xiangzhou Wang, An Wang, Shuahua Zheng, Yingzi Lin, Mingxin Yu. 2104. Multiple Autocorrelation Analysis Method for Motor Imagery EEG Feature Extraction, IEEE 26th Chinese Control and Decision Conference (CCDC), pp. 3000-3004.