Human Machine Interaction via Brain Activity Monitoring

D. Wijayasekara, M. Manic
University of Idaho,
Idaho Falls, Idaho, USA,
wija2589@vandals.uidaho.edu, misko@uidaho.edu

***Abstract.* Brain Computer Interfaces (BCI) are becoming increasingly studied as methods for users to interact with computers because recent technological developments have lead to low priced, high precision BCI devices that are aimed at the mass market. This paper investigates the ability for using such a device in real world applications as well as limitations of such applications. The device tested in this paper is called the Emotiv EPOC headset, which is an electroencephalograph (EEG) measuring device and enables the measuring of brain activity using 14 strategically placed sensors. This paper presents: 1) a BCI framework driven completely by thought patterns, aimed at real world applications 2) a quantitative analysis of the performance of the implemented system. The Emotiv EPOC headset based BCI framework presented in this paper was tested on a problem of controlling a simple differential wheeled robot by identifying four thought patterns in the user: "neutral", "move forward", "turn left", and "turn right". The developed approach was tested on 6 individuals and the results show that while BCI control of a mobile robot is possible, precise movement required to guide a robot along a set path is difficult with the current setup. Furthermore, intense concentration is required from users to control the robot accurately.**

***Keywords*: Brain Computer Interface, Emotiv EPOC, EEG, Differential Wheel Robot.**

I. INTRODUCTION

BRAIN Computer Interfaces (BCI) are direct functional interactions between a human brain and an external device [1-2]. BCI have recently gained a new interest as a practical Human Machine Interface (HMI). Although early BCI was proposed in the late '70s [3] wide spread use was limited due to equipment cost and complexity [4]. However, recent technological advantages have enabled the development of low cost BCI devices that are aimed at the mass market. The Neurosky Minwave [5] device and the Emotiv EPOC headset [6] are examples of low cost BCI devices.

BCI is performed by measuring the brain activity of a user and then identifying the thought pattern or desired action using of the user. Brain activity is measured by detecting minute voltage changes in specific areas of the brain [7]. This can be done in three ways: 1) invasive, where electrodes are placed on the brain itself, 2) partially-invasive where electrodes are placed in the skull and 3) non-invasive where electrodes are placed on the scalp [8]. Electroencephalography (EEG) is the only currently available non-invasive brain activity measuring method and therefore it is the most widely used [7]. It has been shown that using EEG is a viable method of BCI [9], [10].

Many researchers have focused on remote tele-operation of robots via BCI [8], [11-13]. BCI has also been extensively investigated as a feasible method of HMI for physically impaired individuals [9], [14-15]. BCI can enable such individuals to interact with machines without using any motor skills to physically touch a HMI device. BCI have also been investigated in medical and commercial applications such as physiotherapy [7], [16] and measuring brain activity of individuals to stimuli [17-18]. Researchers have also focused on BCI technology for the gaming industry where users can manipulate their environment via thought or facial muscle movements [4], [19-20]. Another application of BCI is steady state visual evoked potential (SSVEP) feedback. SSVEP uses brain activity of the user to detect where the user is focusing on [19-20]. Also, since BCI bypasses conventional motor output pathways comprising of muscles and nerves [21], it is possible that signals can be passed to the device faster. Furthermore, BCI can be used as a secondary input device that complements already existing input devices, and increase the accuracy and responsiveness of the control input.

Typical BCI equipment that utilize EEG to measure brain activity is expensive and require expert knowledge to setup and use. However, recently developed low price BCI devices that are aimed at the mass market, are more user friendly. One of the more recent and very well documented BCI devices is the Emotiv EPOC Neuroheadset [6]. The Emotiv EPOC headset utilizes 14 strategically places sensors to measure brain activity of the wearer. Furthermore, simple interface and wireless connectivity enables the user to use the headset without expert knowledge or supervision [22]. Thus, the Emotiv EPOC headset is used as the BCI device in this paper.

This paper presents: 1) a BCI framework using low cost EEG devices aimed at a real world application, 2) the control actions of the presented framework are entirely based on thought patterns, 3) the strength of the thought patterns are linearly transferred into control actions of the robot and 4) a quantitative analysis of the performance of the system that can identify usability and limitations of the system.

An implementation of a differential wheeled mobile robot that is controlled by identifying brain activity of the user is presented in this paper. The mobile robot was controlled by using 4 commands: “neutral”, “move forward”, “turn left” and “turn right”. These commands were identified by measuring the brain activity of the user at a given time. Performance of the mobile robot over a given path was measured. The BCI implementation was experimented on 6 different users and the results show that while BCI control of a mobile robot is possible, precise movements required to guide the robot along a set path is difficult. Furthermore it was observed that intense concentration was required by the user and even minor distraction will divert the path of the robot.

The rest of the paper is organized as follows. A survey of related literature is performed in Section II. Section III describes the hardware used for the proposed implementation. Section IV presents the proposed implementation of the BCI framework. Section V presents the experimental results and Section VI concludes the paper.

II. Related Work

In [9] and [23] Philips et al and Millan et al proposed the use of EEG for control of a wheelchair. This work was aimed at physically impaired individuals and used EEG to identify thought patterns and classify intended actions. Furthermore the final decision of motion was made by observing the surrounding environment for improved obstacle avoidance.

In [5], [11] and [16] the authors focused on using EEG to control robotic arms which will aid physically impaired people. Palankar et al proposed a methodology that was able to control a 9-DOF control arm using EEG [16]. In [11], the authors used Emotiv EPOC headset to control a robot arm using facial expressions. The authors found that while the EPOC headset compares well with higher grade equipment, and that facial expressions can sometimes be difficult to differentiate [1]. A robotic arm that will aid physiotherapy for disabled and paralyzed individuals was proposed in [5], where the authors used EPOC headset and showed promising results.

Significant research has been done on BCI for gaming and virtual environment interaction in the past [4], [12], [19-20]. In [4] the authors proposed the use of low cost EEG devices for mobile gaming applications and concluded that while there is a significant advantage, more research needs to be conducted on this area. Vliet et al investigated the use of consumer grade equipment using SSVEP interaction for gaming and concluded that for this application consumer grade equipment shows good results [19]. A similar experiment was performed by Chumerin et al using Emotiv EPOC headset in [20]. In [4] the authors used Emotiv EPOC headset for the control of a virtual environment and suggested that classification of intended activity of the user needs to be improved.

BCI systems for mobile applications were proposed in [4], [16], [24] and [25]. In [16] the authors proposed the use of low cost wireless EEG devices for measuring brain activity and displaying the results using mobile devices. A methodology where emotions are detected to aid speech recognition software in mobile devices was suggested in [24]. Campbell et al [25] proposed the use of EEG headset for interaction with a mobile phone.

Vourvopoulos and Liarokapis proposed the use of low cost EEG devices for control of mobile robots in [8] and [13]. The authors used Emotiv EPOC headset and Neurosky Mindset to control a Lego NXT mobile robot. The work presented in [8] and [13] is different to the work proposed in this paper in several ways: 1) robot control in [8] and [13] is performed via a combination of thought and facial expressions, while in this paper the control is performed entirely using thought. 2) In this paper we use the strength of the thought signal and linearly transfer it to the robot motion whereas in [8] and [13] it was not. And 3) [8] and [13] focus on a qualitative analysis and does not show any performance details, whereas in this paper we perform a quantitative analysis based on the intended actions of the user and movement of the robot.

Other related work in the literature include: classification of objects using EEG signals [21], identifying consumer responses to various stimuli [17], [26].

III. Hardware Setup

This section elaborates the hardware setup and used for the BCI framework presented in this paper.

A. Emotiv EPOC Neuroheadset

The Emotiv EPOC Neuroheadset is a low cost easy to use BCI device (Fig 1(a)). It is able to measure brain activity of the wearer by utilizing 14 sensors (Fig. 1(b)). Each of the 14 sensors is an electrode which is hydrated using a saline solution. This is necessary to increase the

(a)

(b)

Fig. 1 Emotiv EPOC Neuroheadset (a) and sensor pad (b)

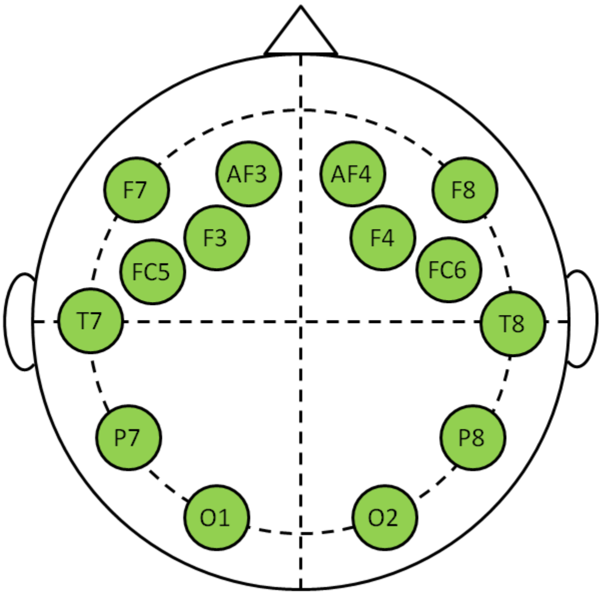

Fig. 2 Emotiv EPOC Neuroheadset sensor placement according to the international 10-20 standard [27]

TABLE 1. EMOTIV EPOC NEUROHEADSET SPECIFICATIONS [27]

Parameter	Value
Number of channels	14 Channels
Sampling Rate	2048 Hz
Sampling Resolution	14 bits
Sampling Method	Sequential. Single ADC
Bandwidth	0.2 – 45 Hz
Dynamic Range	8400 μ V(pp)
Connectivity	Wireless 2.4GHz band
Battery	LiPoly
Battery Life	~12 Hours

conductivity of the contact pad and thus increase the sensitivity of the reading.

These sensors are placed according to the international 10-20 system [27]. Fig. 2 shows the locations utilized by the Emotiv EPOC headset according to the 10-20 system electrode locations. The sampling rate of the EPOC headset is 2048 Hz with 14 bit resolution. This enables fast and precise data collocation. Additionally, gyroscopic sensors are located in the headset that can detect the orientation of the headset. Table 1 lists the specifications of the EPOC headset.

It has been shown that the Emotiv EPOC headset compares well with high grade research level equipment and the information retrieved is reliable and sufficient for most applications [19], [22].

The wireless design and low comparable weight enables users to wear the EPOC headset for longer durations of time, compared with more sophisticated EEG devices [5], [20], [22]. Furthermore, the comparatively low preparation time enables regular use [24].

B. *Differential wheeled robot*

A differential wheeled robot is a mobile robot with 2 or more wheels. Two wheels on either side of the robot body are driven separately and this governs the movement of the robot [28]. Fig. 3 shows the diagram of the differential wheeled robot used in this paper. The third wheel is a free

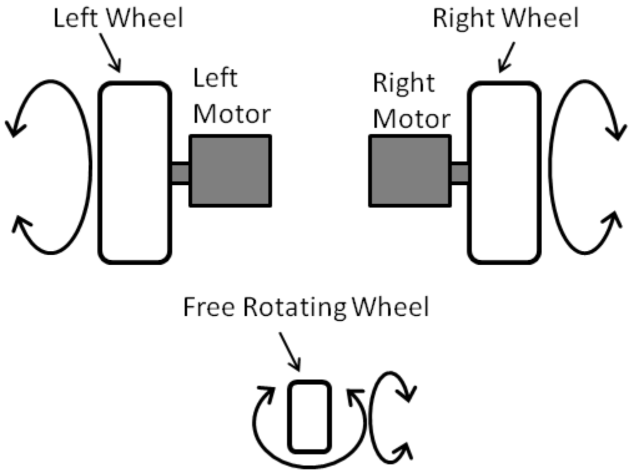

Fig. 3 Differential wheeled robot setup

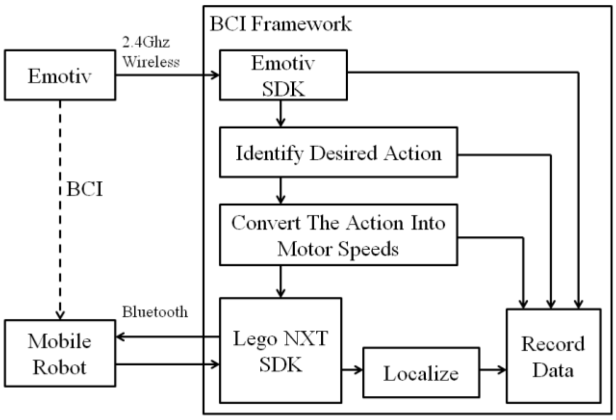

Fig. 4 BCI Framework block diagram

turning wheel used to balance the robot. A differential wheeled setup was used in this paper because of the ease of control and ease of dead reckoning [28].

The differential wheeled robot shown in Fig. 3 was implemented using Lego NXT [29]. This enables the communication between robot and a computer wirelessly via Bluetooth. Furthermore, the rotation of the motors can be controlled using integer values between -100 and +100, and an accurate measure of the number of turns each motor performed can also be acquired.

IV. PROPOSED BCI FRAMEWORK

In order to implement the BCI, Emotiv SDK [6] and Lego NXT SDK [29] was used. A Graphical User Interface (GUI) was implemented in the C++ environment that combines the processed signals from the Emotiv SDK and the control outputs to the mobile robot. The implemented GUI provides the seamless connection required between the brain activity and the motion of the robot.

Since the brain activities of individuals are different, each thought pattern corresponding to an action has to be identified for different individuals. The Emotiv SDK enables the training of the system to different individuals. Thus, before a new user can successfully control the mobile robot, training must take place. The required training process can also be performed using the implemented GUI.

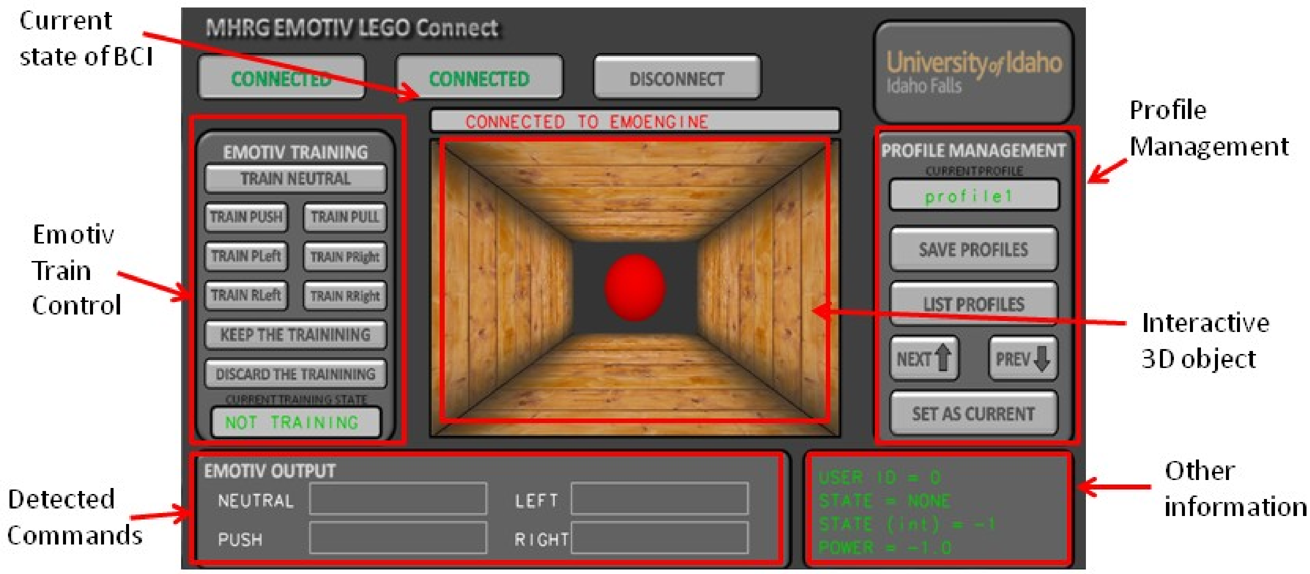

Fig. 5 Emotiv control GUI implemented for the presented BCI framework

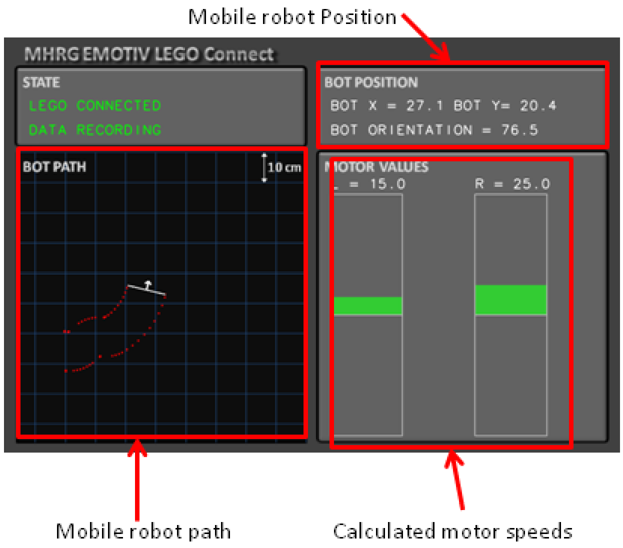

Fig. 6 Robot information GUI implemented for the presented BCI framework

Once the training is complete the Emotiv SDK is able to identify the intended action using the brain activity of the user. For this application 4 different actions were used: "neutral", "move forward", "turn left" and "turn right". Power of each action is returned from the Emotiv SDK as a value between 0 and 1. Using the values of these actions the desired speed of each motor is calculated using:

$$M_{LEFT} = f(E_{NEUTRAL}, E_{PUSH}, E_{LEFT}, E_{RIGHT}) \quad (1)$$

$$M_{RIGHT} = f(E_{NEUTRAL}, E_{PUSH}, E_{LEFT}, E_{RIGHT}) \quad (2)$$

where, M_i is the speed of the motor i and E_j is the power of the action j. The function $f()$ is a linear function that directly converts the power of intended action to the motor speed.

The calculated motor power is then used to control the mobile robot. Fig. 4 shows the block diagram of the BCI implementation.

The implemented GUI consists of 2 windows. The first window, shown in Fig. 5, extracts the EEG data and converts it into an action (neutral, push, turn left or turn right). Different users can be added to the BCI environment using the implemented profile management. The required training for different users can also be performed using this window. In order to aid the training and controlling process a 3D object that can be manipulated by thought is displayed on this window. Once training is completed a user profile can be saved and retrieved at a later time.

The second window, shown in Fig. 6, provides the user with information about the mobile robot. The robot path is shown including a history of the motion. The calculated speeds of the motors are also displayed as well as the position and orientation in space.

V. Experimental Results

The BCI system presented in Section III was implemented for the experimental phase. A simple route, made up of 60cm of straight section a 90 degree turn to the left and another 60cm straight section was set up for the robot to follow. The objective was to use the implemented BCI and move the robot along the path from the start to the finish.

Six different users were tested and the results were compared to identify the limitations of using such a system. Each user was given 30 minutes to train the system and familiarize themselves with the system. Afterwards each user was given 30 minutes to complete as many runs as possible. Since the training time for users vary significantly and users take time to get used to the system the run with least error from each user was selected for comparison.

The total error and average error of the robot trajectory compared to the objective path was calculated as well as the time for the completion of the route. The total error, T_E, was calculated using:

$$T_E = \sum_{i=1}^{N} \min_j \sqrt{(x_{bot,i} - x_{path,j})^2 + (y_{bot,i} - y_{path,j})^2}, j = 1,2,...M \quad (3)$$

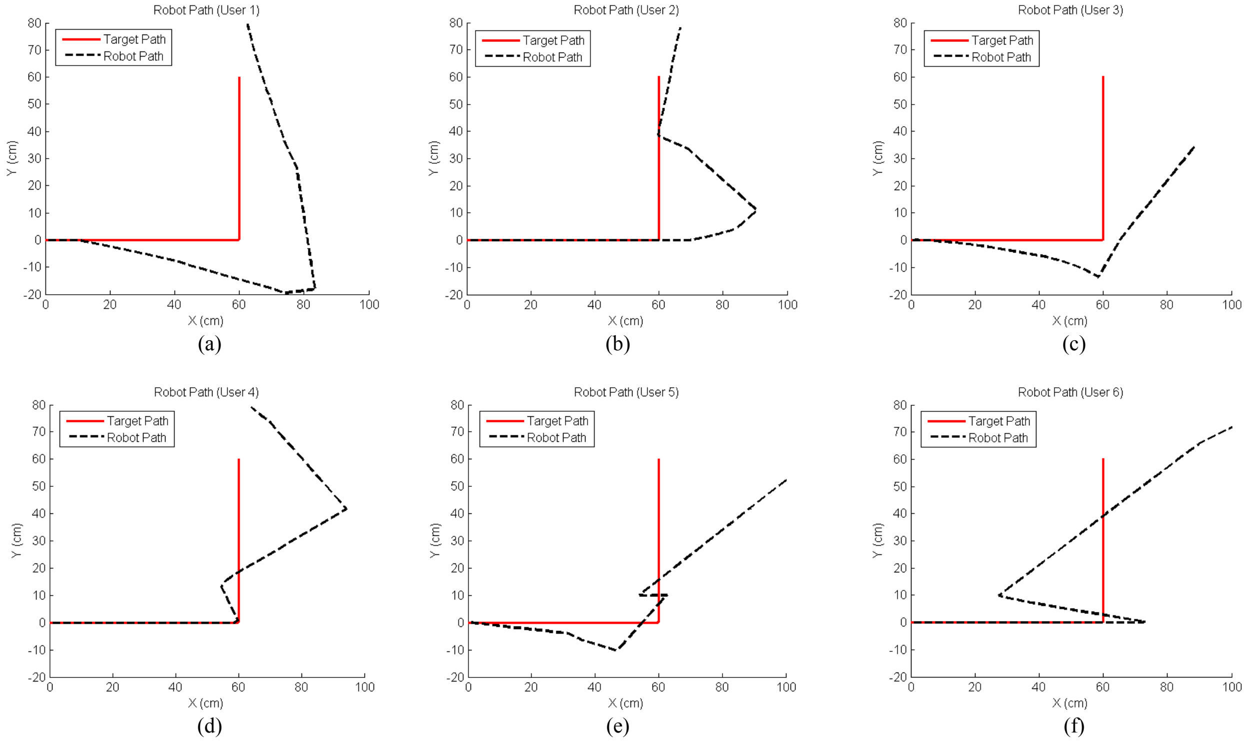

Fig. 7 The path of the mobile robot for each user compared to the set path

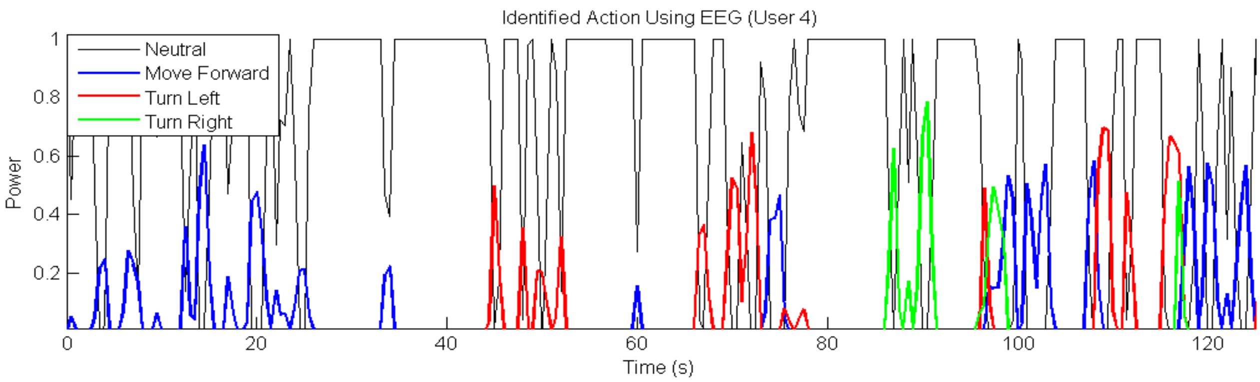

Fig. 8 Identified actions and intensity using EEG for User 4

TABLE 2. PERFORMANCE OF EACH USER

User	Total Error(cm)	Average Error(cm)	Maximum Error(cm)	Time to Complete (s)
User1	2839.8	18.44	29.92	76.5
User2	2215.7	12.17	30.73	90.5
User3	917.3	10.31	29.01	44
User4	1677.5	6.55	34.45	127.5
User5	1324.6	10.86	59.01	60.5
User6	1154.1	85.48	57.61	67

where N is the set of all recorded robot positions during the run, $(x_{bot,i}, y_{bot,i})$ is the location of the robot at the i^{th} recorded time. M is a set of discretized locations of the preset path, and $(x_{path,j}, y_{path,j})$ is the location of the path at the j^{th} discrete step. The average error, T_A, was calculated using:

$$T_A = \frac{T_E}{N} \tag{4}$$

Figs. 7(a) to 7(f) show the selected robot trajectories for each user. Table 2 shows the errors and time to complete the route for each user. Fig. 8 show the actions that was identified by the BCI system for User 4. The experimental results show that even after extensive training the BCI system show significant deviation from the intended path.

The results show that while thought patterns regarding certain actions can be correctly identified, the precision and accuracy required to guide the robot along the path is lacking. Further, Fig. 8 shows that even with intense concentration, it is difficult to maintain a thought pattern for a long period of time. Fig. 9 shows the distance travelled by the robot (User 4) elaborating the non-smooth operation of the robot. Thus, the experimental results show that while BCI mobile robot control is possible, significant improvements to the presented BCI system need to be made to make it more usable in real world scenarios.

The sub-optimal results may be due to the classification algorithm used to detect intended action of the user. An improved classification that is tailored to the control of a mobile robot might yield better results. The training time is

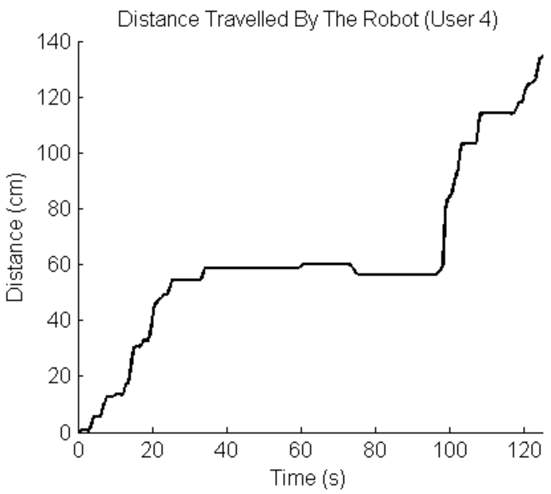

Fig. 9 Distance travelled by the robot for User 4

also major factor in correctly identifying the intended action of the user. More training time may lead to a better classification and thus better control of the robot. Furthermore, the highly varied results show that certain individuals perform better compared to others. This may be due to different levels of concentration, or that the thought patterns of certain individuals are easier to classify

VI. CONCLUSION

A BCI setup that uses a low cost widely available EEG device was implemented in this paper. Five different actions were identified using the thought patterns of the users. These actions were used to control a differential wheeled robot. Several performance measures were recorded to investigate the feasibility and limitations of a BCI interface.

It was shown that although the presented BCI system using a low cost EEG device is possible, significant improvements to the detection and classification algorithms need to be made to make the system more usable. Furthermore, it was observed that the intense concentration required to operate the system was taxing on the users and even minor distractions may lead to unwanted behavior.

As future work a more improved method of classifying intended actions using advanced machine learning techniques is suggested. Furthermore, a BCI system that complements conventional HMI techniques, that may increase the accuracy and responsiveness, will be investigated.

REFERENCES

[1] Dietrich D, Lang R, Bruckner D, et al (2010) Limitations, possibilities and implications of Brain-Computer Interfaces. In Proc of IEEE Conference on Human System Interactions (HSI), pp. 722-726
[2] Bobrov P, Frolov A, Cantor C, et al (2011) Brain-Computer Interface Based on Generation of Visual Images. In PLoS ONE 6 (6):1-12
[3] Vidal JJ (1977) Real-time detection of brain events in EEG. In Proceedings of the IEEE 65 (5):633- 641
[4] Coulton P, Wylie CG, Bamford W (2011) Brain interaction for mobile games. In Proc. of the 15th International Academic MindTrek Conference: Envisioning Future Media Environments, pp. 37-44
[5] Neurosky Mindwave: http://neurosky.com/Products/MindWave.aspx, Accessed 10 February, 2013
[6] Emotiv Website: http://www.emotiv.com/, Accessed 10 February, 2013
[7] Webb J, Xiao ZG, Aschenbrenner KP et al (2012) Towards a portable assistive arm exoskeleton for stroke patient rehabilitation controlled through a brain computer interface. In Proc. of 4th IEEE RAS & EMBS International Conference on Biomedical Robotics and Biomechatronics (BioRob), pp.1299-1304
[8] Vourvopoulos A, Liarokapis F, (2012) Robot Navigation Using Brain-Computer Interfaces. In Proc. of 11th International Conference on Trust, Security and Privacy in Computing and Communications (TrustCom), pp. 1785-1792
[9] Philips J, Millan JdR, Vanacker G, et al (2007) Adaptive Shared Control of a Brain-Actuated Simulated Wheelchair. In Proc. of IEEE 10th International Conference on Rehabilitation Robotics, (ICORR 2007), pp. 408-414
[10] Rodrigues JP, Migotina DG, da Rosa AC (2010) EEG training platform: Improving Brain-Computer Interaction and cognitive skills. In Proc of IEEE Conference on Human System Interactions (HSI), pp.425-429
[11] Ranky GN, Adamovich S (2010) Analysis of a commercial EEG device for the control of a robot arm. In Proc. of IEEE 36th Annual Northeast Bioengineering Conference, pp. 1-2
[12] Loska A, (2012) BCI and virtual collaboration. In Proc. of the 3rd International Conference on Cognitive Infocommunications (CogInfoCom), pp. 89-94
[13] Vourvopoulos A, Liarokapis F (2011) Brain-Controlled NXT Robot: Tele-operating a Robot through Brain Electrical Activity. In Proc. of International Conference on Games and Virtual Worlds for Serious Applications (VS-GAMES), pp. 140-143
[14] Krishnaswamy K, Kuber R (2012) Toward the Development of a BCI and Gestural Interface to Support Individuals with Physical Disabilities. In Proc. of ACM SIGACCESS conference on Computers and accessibility, (ASSETS '12), pp. 229-230
[15] Gonzalez AR (2010) System of communication and control based on the thought. In Proc of IEEE Conference on Human System Interactions (HSI), pp. 275-280
[16] Palankar M, De Laurentis K, Dubey R (2009) Using biological approaches for the control of a 9-DoF wheelchair-mounted robotic arm system: Initial experiments. In Proc of IEEE International Conference on Robotics and Biomimetics, pp. 1704-1709
[17] Khushaba RN, Wise C, Kodagoda S, et al (2013) Consumer neuroscience: Assessing the brain response to marketing stimuli using electroencephalogram (EEG) and eye tracking," in Expert Systems with Applications, (in printing), 2013.
[18] Stopczynski A, LarsenLyngby JE, Stahlhut C, et al (2011) A smartphone interface for a wireless EEG headset with real-time 3D reconstruction. In Proc. of International conference on Affective computing and intelligent interaction (ACII'11), pp. 317-318
[19] van Vliet M, Robben A, Chumerin N, et al (2012) Designing a brain-computer interface controlled video-game using consumer grade EEG hardware. In Proc. of Biosignals and Biorobotics Conference (BRC), 2012 ISSNIP, pp. 1-6
[20] Chumerin N, Manyakov NV, van Vliet M, et al (2012) Steady State Visual Evoked Potential-based Computer Gaming on a Consumer-grade EEG Device. In IEEE Transactions on Computational Intelligence and AI in Games, (in printing)
[21] Esfahani ET, Sundararajan V (2012) Classification of primitive shapes using brain–computer interfaces. In Computer-Aided Design, 44 :1011-1019
[22] AlZu'bi HS, Al-Zubi NS, Al-Nuaimy W (2011) Toward Inexpensive and Practical Brain Computer Interface. iin Proc. of Developments in E-systems Engineering (DeSE), pp. 98-101
[23] Millan J, Galan F, Vanhooydonck D et al (2009) Asynchronous non-invasive brain-actuated control of an intelligent wheelchair. In Proc of IEEE International Conference of the Engineering in Medicine and Biology Society, pp. 3361-3364
[24] Perakakis M, Potamianos A (2012) Affective evaluation of a mobile multimodal dialogue system using brain signals. In Proc. of IEEE Spoken Language Technology Workshop (SLT), pp. 43-48
[25] Campbell AT, Choudhury T, Hu S et al NeuroPhone: Brain-Mobile Phone Interface using a Wireless EEG Headset. In Proc. of ACM SIGCOMM workshop on Networking, systems, and applications on mobile handhelds, pp. 3-8
[26] Khushaba RN, Greenacre L, Kodagoda S et al (2012) Choice modeling and the brain: A study on the Electroencephalogram (EEG)

of preferences. In Expert Systems with Applications, 39 (16): 12378–12388
[27] Emotiv EPOC Neuroheadset Specifications: http://www.emotiv.com/epoc/download_specs.php. Accessed 10 February 2013
[28] Dongkyoung C, (2010) Tracking Control of Differential-Drive Wheeled Mobile Robots Using a Backstepping-Like Feedback Linearization. In IEEE Transactions on Systems, Man and Cybernetics, Part A: Systems and Humans, 40 (6):1285-1295
[29] Lego Mindstorms: http://mindstorms.lego.com/, Accessed 10 February, 2013