Motor Imagery EEG-EOG Signals based Brain Machine Interface (BMI) for a Mobile Robotic Assistant (MRA)

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***Abstract*—Assistive devices for disabled individuals provide the support to fulfil their activities of daily living. The proposed mobile robotic assistant (MRA) in this paper is capable of providing both mobile and manipulation support for users. The MRA, which consists of an electric wheelchair and a custom developed 5DOF robotic manipulator is controlled by a Motor Imagery (MI) Electroencephalography (EEG) and Electrooculography (EOG) based Brain Machine Interface (BMI) which is proposed in this paper. A custom developed Graphical User Interface (GUI) is utilized to interact with the users and users are able to control either the wheelchair or the robotic manipulator based on a combination of left and right hand MI-EEG signals and EOG signals via this GUI. A Multilayer Perceptron (MLP) Neural Network based classifier is developed to classify the EEG signals of left vs right vs rest. EOG signals (eye-blinks) are used to activate the task on the GUI menu. A set of experiments have been carried out with healthy subjects and the results show the effectiveness of the proposed methods.**

***Index Terms*—Brain Machine Interface, Motor Imagery, Electroencephalography, Electrooculography, Mobile Robotic Assistant, Multilayer Perceptron Neural Network.**

I. INTRODUCTION

Brain Machine Interface (BMI) is a promising technology for assisting people who suffer from physical disabilities due to amyotrophic lateral sclerosis (ALS), brainstem stroke, brain or spinal cord injury, cerebral palsy, muscular dystrophies, multiple sclerosis, and numerous other diseases which impair the neural pathways that control muscles or impair the muscles themselves [1]. Electroencephalography (EEG) signals are one of the non-invasive bio-signals which can be used to measure the brain activities and develop BMIs. Many research work has been successfully carried out for BMI-controlled wheelchairs [2], [3] and other type of assistive devices throughout the past two decades. Most of such cases, the proposed solutions have been limited only for mobile applications or manipulation tasks such as meal feeding assistant [4], home appliance control [5] assistant etc. On the other hand, assistive systems which are capable of providing assistance to both mobile and manipulation activities are less. One of the possible reasons is the challenging nature of implementing a BMI with required number of distinct brain signals/potentials as input signals. However, many EEG signals based BMIs have been developed based on different brain potentials such as Steady State Visual Evoked Potentials (SSVEP), P300 or Motor Imagery (MI) [6].

A research group from Peru has developed a mobile robotic assistant [7] using SSVEP based BMI. However, in a typical SSVEP approach, because of the light bulbs/visual sources used as stimuli, subject can suffer from eye fatigue [8], [9]. Similar visual approach P300 also inherits the issues pertain in SSVEPs based approaches. As an alternative method, many researches have been carried out to explore the possibility of using MI-EEG signals for developing MI-based BMI though it is challenging. One of the major challenges in MI based BMI is the classification of MI-EEG. In order to tackle this problem, complex mathematical models have been proposed including machine learning techniques [10]. Support Vector Machines (SVM) and Neural Networks [11] are commonly used machine learning techniques for MI-EEG classifications. Attempts from several research groups [12], [13] reflects that the NNs are a successful classifier for EEG based MI classifications though avenues for improvements are still available.

In this paper, a MI-EEG and Electrooculography (EOG) signals based BMI for a Mobile Robotic Assistant (MRA) is proposed as shown in the fig.1. The proposed MRA is capable of providing both mobile and manipulation support. The MRA, which consists of an electric wheelchair and a custom developed 5DOF robotic manipulator can be controlled based on a combination of left and right hand MI-EEG signals

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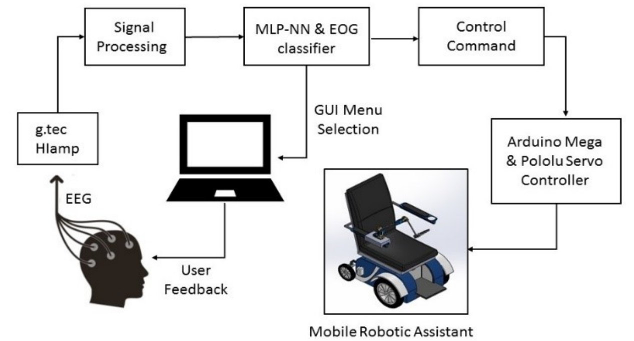

Fig. 1. Overview of the System: The system consists of an EEG acquisition system, a Laptop for data processing, mapping and displaying the GUI, a wheelchair mounted custom developed 4DOF robotic manipulator with controllers.

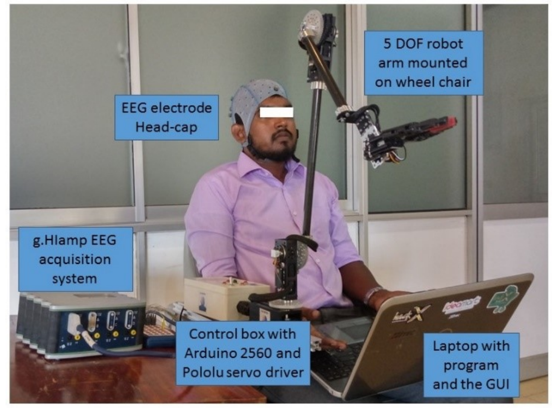

Fig. 2. Hardware system of the MRA

and EOG signals via custom developed GUI. A Multilayer Perceptron (MLP) Neural Network (NN) is used to classify the EEG signals of left vs right vs rest. At the initial stage, EEG signals generated during left and right hand movements of the users are recorded. Then the recorded EEG data are pre-processed and fed into the proposed MLP-NN for training. After a complete training of NN, the real-time MI-EEG data are fed into the NN for classification. When the MI - EEG signal is classified by the BMI, output of the classifier is used to change the selected position of the GUI menu. After the selection, the task can be activated by providing an EOG signal (double eye blinks) to the BMI. Integrated EOG feature based threshold classifier is implemented to classify the double blink related EOG signals. A set of experiments with healthy subjects are carried out to validate the proposed system and the results are presented.

The structure of the rest of the paper is as follows. The section II describes the method and the implementation of BMI for the control of MRA. Experiments and results are presented in section III. Finally, section IV concludes the paper with potential future directions.

II. METHOD

A. Hardware System of the Mobile Robotic Assistant(MRA)

The MRA is equipped with a DC motors driven wheel chair and a wheel chair mounted 5 DOF robotic manipulator which communicates with the laptop via Bluetooth as in fig.2. Arduino Mega 2560 micro-controller is used as the low level controller. The robotic manipulator can operate in two different modes. The Cartesian arm mode to move the manipulator to a finite amount of distance and the pre-defined task mode to perform a manipulation task such as pick and place. Six channel Pololu servo driver is used to control joint angles of the robotic manipulator which were obtained using a kinematic analysis. Manipulator is equipped with a two jaw gripper end effector. In the wheelchair mode, the wheelchair can be moved to a finite amount of distance to 4 directions including left, right, forward and backward. g.tec HIamp, High Density EEG signal acquisition system is used for MI-EEG acquisition which is placed on a container behind the wheel-chair seat.

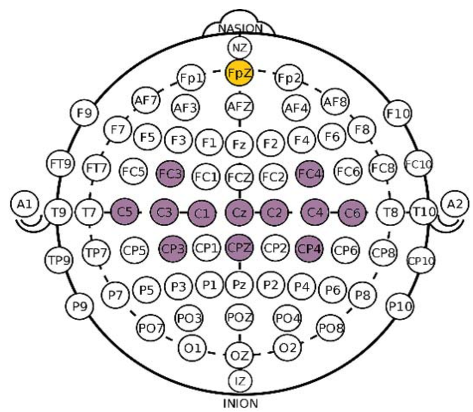

Fig. 3. Electrode head cap arrangement with 12 electrodes 4 electrodes were placed around both C3 and C4 electrodes

B. Development of MI-EEG and EOG signals based BMI

MI-EEG signals within 0-30Hz were recorded for offline classification with a sample rate of 256Hz. The head cap was consisted of 12 electrodes (C3, C4, C1, C2, C5, C6, CP3, CP4, FC3, FC4, CZ and CPZ) placed as depicted in fig.3 focusing on C3 and C4 electrodes where the MI-EEG features are prominent [11], [14]–[16]. Ground electrode was placed on FPZ. In experimental protocol, the time frame for single trial was selected as 4 seconds as shown in fig.4 based on the observations of pre-experiments (as per the literature, the single trial time frame windows are typically ranging with 2-15 seconds for motor tasks [15], [17]). A custom developed GUI was displayed to the subject and the subject performs the motor task according to the displayed instruction on the screen. Out of 4 seconds, only one second was instructed to perform the task while rest of the seconds remain at rest state. Researches has been carried out for different type of motor tasks for hands. For an example, a research group

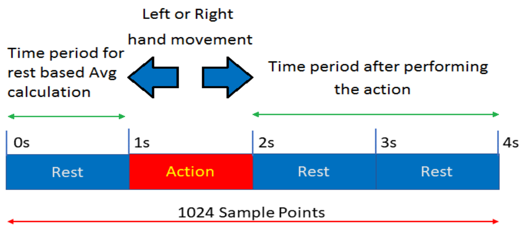

Fig. 4. Time frame of the experiment protocol used for EEG acquisition and NN training, offline and real-time classification

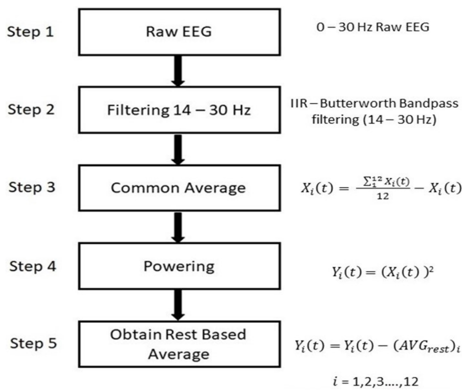

Fig. 5. Preprocessing steps and the algorithms implemented in the proposed method

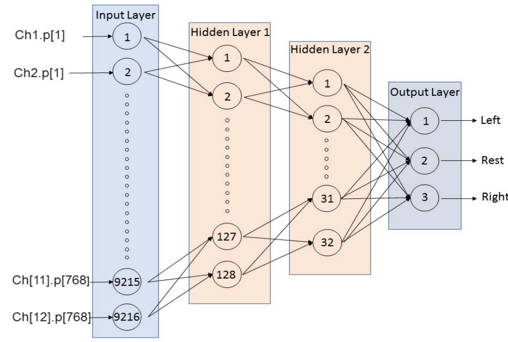

Fig. 6. Multi-layer Perceptron Neural Network (MLP-NN) structure developed in the proposed method

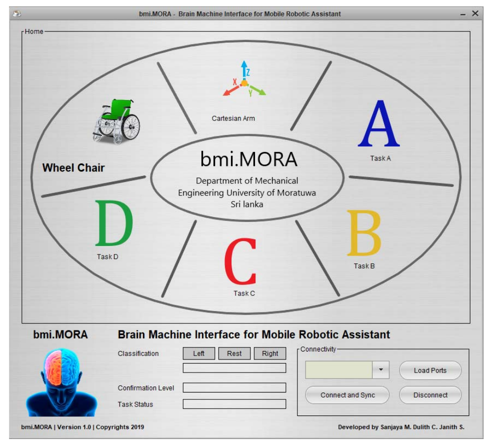

Fig. 7. Developed GUI for Home Window: The user can navigate this GUI via real time classified MI-EEG signals. EOG signals of eye blinks is used for activating the task displaying on the GUI.

from University of Minnesota decoded and mapped right hand movements including Flexion, Extension, Pronation and Supination [18] in their research. The motor task which was performed in this experiment was lifting the left and right hand. Once the EEG signals are recorded, they were pre-processed in order to enhance the features of the signals.

As shown in fig.5, first the recorded signals were filtered using Butter-worth band-pass filter in order to isolate the beta region(14-30Hz) by using an open source Java filtering library. The common artifacts and the noises were removed using common average algorithm. As the next step, the power value was obtained by squaring up the all recorded EEG data points. Subsequently, the average was taken relative to the rest state of each recorded EEG signal. After that, the pre-processed data points of 3 seconds (action, rest, rest) were fed into a NN for training. A Multi-layer Perceptron (MLP) - NN was implemented as the neural network which was consisted with 9216 input neurons (256*12*3) and 3 output neurons (left, right, rest). The structure of the implemented MLP-NN is depicted in fig. 6. The NN was consisted with two hidden layers with 128 and 32 neurons respectively as in fig.6. For the development of MLP - NN java neuroph (version 2.92) open source machine learning library was used. The MLP-NN was trained using Momentum Backpropagation learning rule with a fixed learning rate of 0.1 until the mean squared error (MSE) converged to 0.01. Sigmoid function was used as the transfer function in between all layers inside the MLP - NN. 300 MI-EEG samples were used as for the training purpose and 120 samples were used to validate the trained NN. Average time taken for a training was below 30 minutes and once NN is trained, it is used in the real time application for the real-time EEG classification.

C. Development of GUI

All GUIs were developed using NetBeans IDE (version 8.2). A Home window consists with six menus for predefined tasks as shown in fig. 7. Inside the wheel chair menu, the user can select the required direction to drive the wheel chair. In the Cartesian mode menu of the robot manipulator can be moved to a finite amount of distance to the directions of Up, Down, left and Right. These developed GUIs are operated through the real time classification signals of MI-EEG. The real time pre-processed signals are fed into the trained NN while the application is executed inside a thread written in Java and for each second, the classified output was obtained. Depending on the output, menu in the GUI is selected. The user have to change the selection of the menu using MI-EEG. There is back option in wheel chair and Cartesian mode to return to home menu. In order to confirm the selection in GUI, EOG

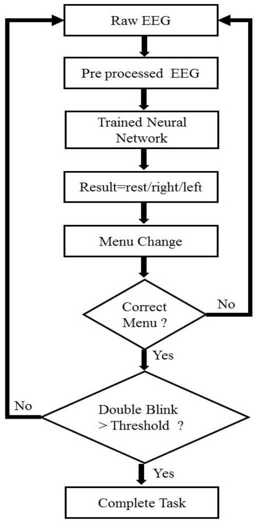

Fig. 8. Flowchart of the GUI menu navigation and task selection using proposed MI-EEG and EOG signals based BMI

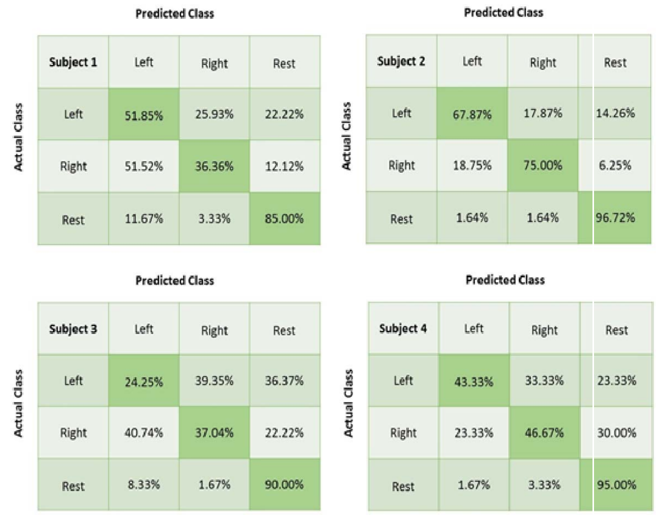

Fig. 9. Confusion matrices of classification accuracies of trained MLP-NN for each subject

TABLE I
DETAILS OF HEALTHY SUBJECTS

Subject	Gender	Age	Previous experience in conducting EEG experiments
1	M	24	No
2	M	25	Yes
3	M	24	No
4	M	24	No

TABLE II
OVERALL ACCURACY FOR ALL 4 SUBJECTS

Subject	Overall Accuracy(%)
1	64.17
2	84.30
3	60.00
4	70.00

signals generated by the double eye blinks are used. It is classified using a simple threshold (Integrated EOG feature based threshold) based classifier. Once the EOG signal exceeds this predefined threshold value, the selected menu is activated. A flowchart of this process is shown in fig. 8.

III. EXPERIMENTS AND RESULTS

Experiments were carried out to validate the system with four healthy young subjects(see table I for subject details). First, the EEG data were recorded from the selected subjects as described in the method section. Then the MLP-NN was trained for each subject. The trained MLP-NN accuracy was tested using a new data set of each subject. Subject 2 has followed the EEG acquisition protocol more than 10 times while the other subjects participated for the experiment as for their first time. The accuracy for each subject, per class is shown in the fig.9 as confusion matrices. Based on these results overall accuracy is calculated per each subject (see table II). As in the result, subject 2 showed the highest overall accuracy of 84.30% (refer fig.9). Therefore subject 2 was selected to conduct the real time experiments with MRA.

Real-time experiments were conducted in an open space with less background noise for all 3 different modes of the MRA with subject 2. In the predefined mode, the subject 2 was asked to perform a manipulation task, eg: moving the bottle from cage A to cage B as depicted in fig.10. Average time taken for initiate one manipulation task was 58.7 seconds with a deviation of 27.5 seconds. As shown in fig.11, experiments were conducted for mobility tasks using wheelchair mode. Average time taken for one movement of wheelchair is 35.75 seconds with a deviation of 20.6 seconds. For left and right turns the wheelchair is turned for 30 degrees of angle. In the Cartesian mode as in fig.12, to perform one movement for any direction average time of 40.5 seconds were taken with a deviation of 15.4 seconds.

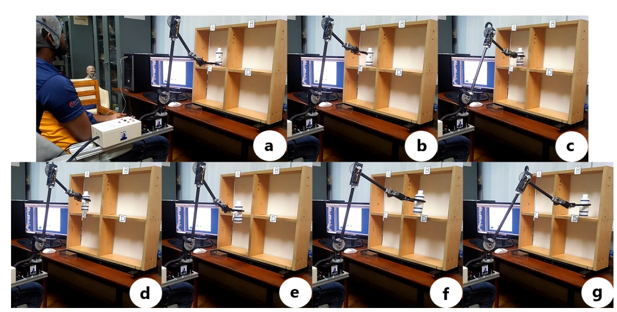

Fig. 10. Subject 2 is performing a manipulation task on a book shelf. A manipulation is done using pre-programmed positions of the robotic manipulator

Fig. 11. Wheelchair movements taken from roof mounted camera

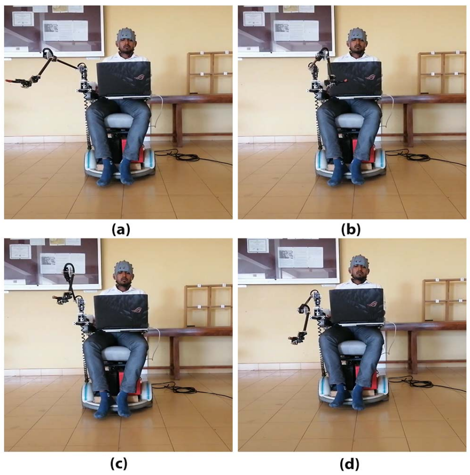

Fig. 12. . Controlling the manipulator in Cartesian mode (a) moving the arm in right, (b) left, (c) upward and (d) downward

IV. CONCLUSIONS AND FUTURE DIRECTIONS

This research proposed a novel assistive system called MRA which is capable of providing both mobile and manipulation support for users which is controlled by a MI-EEG and EOG signals based BMI. The proposed BMI was able to manipulate the robot arm mounted on the wheelchair effectively along with the wheelchair movements. The implemented GUI shown to be effective for the subjects and the obtained results reflected that the MLP-NN is an effective classifier for MI-EEG classifications. For all the subjects, the rest state classification percentage was higher compared to left and right classification. In the real time implementation of the system, the noises in the background affected for the classification of MI-EEG signals. Less noisy environment was desirable for efficient task selections(subject 2 feedback). More researches can be carried out to adopt the system to noisy environments as a future improvement. The performance of the MLP-NN can be improved further by changing the neurons and the learning rate. However, to implement the proposed system in real life scenarios with real end users or disabled people, more testing and validations are required. The BMI proposed for MRA in this research only classified the MI-EEG of left, right hand movements and rest state of the brain. Furthermore, in order to enhance the number of control commands, the left and the right leg movements can also be attempted to classify so that the EOG signals can be eliminated from the system and the proposed MRA can be controlled using only MI-EEG signals.

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