

Brain Machine Interface Based Wheelchair Control with Minimal Subject Training

Hema C.R., Paulraj M.P., S.Yaacob, A.H. Adom, R. Nagarajan
School of Mechatronic Engineering
Universiti Malaysia Perlis, Jejawi, Perlis, Malaysia
hema@unimap.edu.my

Abstract- Wheelchair control using a Brain Machine Interface based on motor imagery requires adequate subject training. In this paper we propose a new algorithm for a brain machine interface design which is implemented in real-time wheelchair navigation using minimum subject training. Classification of motor imagery for forward, stop, left and right hand movements are performed using Elman neural classifiers. Real-time wheelchair navigation is performed with trained and naive subjects to validate the proposed algorithm.

I. INTRODUCTION

People with total paralysis and severe spinal cord injuries rely on brain machine interfaces (BMI) to control electronic devices. A BMI is a digital communication system, which connects the human brain directly to an external device bypassing the peripheral nervous system and muscular system. The ability of an individual to control his EEG through imaginary motor tasks enables him to control devices. Motor imagery (MI) classification provides an important basis for designing BMI. A BMI captures and decodes the MI signals and transforms human thought into actions. The spatio-temporal pattern changes in the EEG can be recognized and associated with subject's actual hand movements, imagined movements or observation of movements. The EEG electrodes are mainly chosen to be placed on the scalp overlying the sensorimotor cortex where the recorded EEG signals are sensitive to the movements.

Motor imagery can modify the neuronal activity in the primary sensorimotor areas in a very similar way as observable with real executive movements [1, 2]. MI is the most common methodology employed by majority BMI researchers for robot control [3], virtual keyboard [4] and a simulated wheelchair [5]. This can be attributed primarily to the purely cognitive nature of these methods as opposed to the requirement of stimulus in the P300 and evoked EEG-potential methods. With proper training and motivation, majority of the subjects can learn to control the intensities of specific frequency bands, which can be used as a communication or control signal [6].

Motor imagery has been under study to translate the EEG signal into left and right movement of a computer cursor. To analyze the EEG signals different methods have been proposed in the literature [7, 8]. Our goal is to use motor imagery to control stop, forward, left and right movements of

a wheelchair.

Features are extracted from the mu and beta rhythms of the raw MI signals. An Elman classifier is used to identify the four task signals. Offline and real-time experiments are conducted to validate the performance of the algorithm.

II. METHODS

A. Synchronous Experiments

The BMI experiments are conducted in two phases first the MI signals are recorded using a synchronous protocol. The signals are analyzed offline to determine a generalized classifier model. Ten healthy voluntary subjects aged between 15 and 46, participated in the experiments. MI signals for the four tasks, relax, forward, left and right hand movements are recorded for 10 trials in a single session as per the protocol given in [9]

An ADI Power Lab amplifier is used to record the EEG with two gold plated cup electrodes placed at the C3 and C4 locations on the sensorimotor cortex area as per the International 10-20 Electrode Placement System [10], A digital band pass filter (0.5 Hz to 100 Hz) is applied to the raw signal. The EEG signals are amplified and sampled at 200 Hz. At the time of data recording the subjects are free from illness or medication. 40 EEG signals collected from C3 and C4 electrodes for the four motor imagery tasks are considered for classification. For this experiment artifacts such as eye blinks were not removed. EEG is recorded for 10 seconds for each task per trial.

B. Feature Extraction

To extract the band power features, the raw EEG signals are segmented into 0.5s windows with an overlap of 0.25s. Segmented data are band pass filtered between 8 Hz and 30 Hz using a Chebyshev IR filter to obtain the mu and beta frequencies. 195 features from five frequency components (8-10Hz, 10-12Hz, 13-15Hz, 16-18Hz and 19-30Hz) are used as the input to the neural classifier.

C. Classification Procedures

Elman recurrent neural networks (ERNN) have feedback connections which add the ability to also learn the temporal characteristics of the data set. In this study ERNN architecture

with three layers is used. The ERNN makes a copy of the hidden layer which is referred to as the context layer. The purpose of the context layer is to store the previous state of the hidden layer at the previous pattern presentation [11].

The network is trained using a back propagation (BP) training algorithm. The BP training algorithm involves three stages [12] the feed forward of the input training pattern, the calculation and back propagation of the associated weight error and the weight adjustments. The Elman network is modeled using 195 input neurons, 9 hidden neuron and 4 output neurons. The input data are normalized using a binary normalization algorithm [12]. Training is conducted until the average error falls below 0.001 or reaches a maximum iteration limit of 10000. Mean square error is used as a stopping criterion. 400 data samples are used in this experiment. Data samples are chosen randomly. 80% of the data samples are used to train the classifier to recognize the four motor tasks. The network is tested with all 100% data samples. The ERNN has an average classification accuracy of 90.87% and maximum classification of 95.5%. Figure 1 shows the training rounds versus classification accuracy plot for the ERNN and Figure 2 shows the epoch versus mean square error plot of the ERNN.

III REAL-TIME EXPERIMENTS

In the second phase of the experiments the modeled ERNN is employed for the real-time wheelchair control. The output of the classifier is translated into control signals through a BMI interface to operate a power wheelchair. The BMI wheelchair is equipped with two proximity sensors to stop when obstacles are detected. Control is passed again to the subject for further navigation. MI signals are given to the interface every 3s by the subject.

In the real-time experiments six (S1, S3, S5, S6, S7, S10) of the ten subjects participated. One naive subject (s11) who did not participate in any of the synchronous experiments also participated. Experiments are carried out in an indoor environment, the room dimensions are 15m by 5m. Obstacles on the traversable path are limited to one, with some obstacles along the walls [A to F].

The subjects are requested to follow an asynchronous protocol; two simple navigational protocols were given to the subjects; in the first protocol the subjects are required to navigate the wheelchair from location 1 to location 4 (14 m) following a clockwise sequence (see Figure 3) and in the second protocol the sequence is reversed from 4 to 1

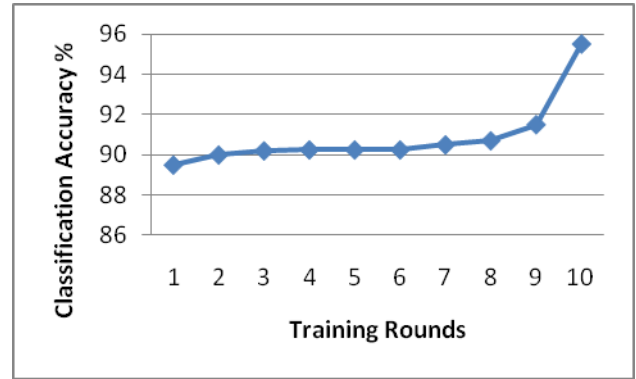


Fig. 1. Training Round versus Classification Accuracy Plot for generalized ERNN.

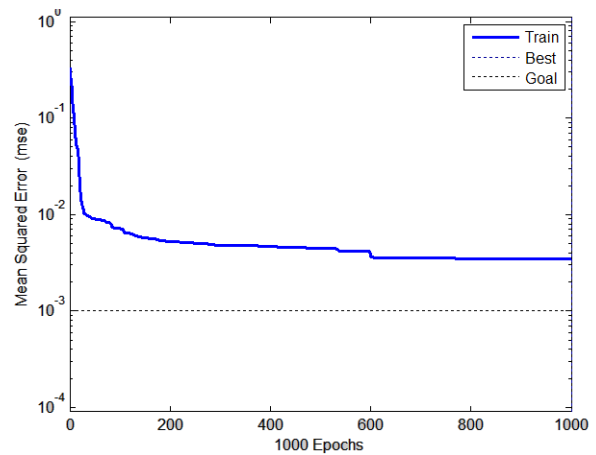


Fig. 2. Epoch versus Mean Squared Error Plot of the generalized Elman Classifier.

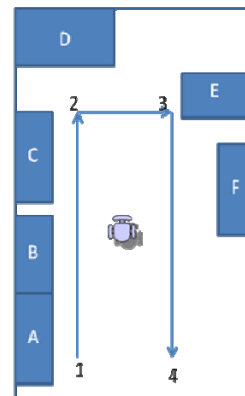


Fig. 3. Real-time experiment protocols

The task given to the subjects was to drive the BMI wheelchair avoiding the obstacles in an indoor environment showing using the two protocols. Each subject navigated the BMI wheelchair only once in a 30 minute session. From the experimental results it was observed that all the subjects were able to successfully navigate the wheelchair,

generating all the four states, stop, forward, left and right. Some subjects were not able to switch between states immediately. Three of the subjects (S3, S4 and S11) were able to complete both the protocols, with an average of 15s navigational time per protocol; subject S11 easily controlled the navigation of the BMI wheelchair, his performance was comparatively better than all the subjects who participated in the real time experiments.

IV. CONCLUSION

This paper presented an algorithm for a BMI design to control a power wheelchair. Synchronous and asynchronous experimental results are presented. Results of real-time navigation of the BMI wheelchair in an indoor environment are presented for minimal subject training and naive subjects. Subjects are able to control the navigation of a BMI Wheelchair using their motor imagery for four states for simple protocols. However more complex protocols require more subject training, moreover subjects reported fatigue after the 30 minute session.

Real-time experiments validate the proposed BMI design for real-time navigation. Though the results for real-time navigation are significant, it's also observed from the experimental results that some subjects require more training sessions to complete the given protocols. Future works will focus on real-time experimentations for more complex protocols. EEG based BMI have potential applicability beyond the restoration of lost movement and rehabilitation in paraplegics and would enable normal individuals to have direct brain control of external devices in their daily lives.

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