A Novel BCI-Controlled Pneumatic Glove System for Home-Based Neurorehabilitation

Aodhán L. Coffey[1], Darren J. Leamy[1] and Tomás E. Ward[1]

Abstract — **Commercially available devices for Brain-Computer Interface (BCI)-controlled robotic stroke rehabilitation are prohibitively expensive for many researchers who are interested in the topic and physicians who would utilize such a device. Additionally, they are cumbersome and require a technician to operate, increasing the inaccessibility of such devices for home-based robotic stroke rehabilitation therapy. Presented here is the design, implementation and test of an inexpensive, portable and adaptable BCI-controlled hand therapy device. The system utilizes a soft, flexible, pneumatic glove which can be used to deflect the subject's wrist and fingers. Operation is provided by a custom-designed pneumatic circuit. Air flow is controlled by an embedded system, which receives serial port instruction from a PC running real-time BCI software. System tests demonstrate that glove control can be successfully driven by a real-time BCI. A system such as the one described here may be used to explore closed loop neurofeedback rehabilitation in stroke relatively inexpensively and potentially in home environments.**

I. Introduction

Stroke is one of the leading causes of long-term motor disability among adults. Weakness on one side of the body is common post-stroke, affecting roughly 85% of survivors. An estimated 55% to 75% of survivors suffer from upper limb impairment lasting more than 6 months post-stroke [1,2]. In terms of recovery, even in the absence of any specific treatment intervention the brain demonstrates an innate capacity to recover lost function – a phenomenon called spontaneous recovery. The neural basis for this recovery of function is a complex set of processes (comprising molecular, genetic and anatomical aspects) which together have been described as neuroplasticity. This rewiring of the brain can take place over relatively short windows and in fact in the case of motor function, the largest changes in recovery of which occur in the first 30 days. However, for severe patients, recovery processes beyond 90 days is also apparent. The post-lesional changes to the motor map are however not always adaptive as full recovery is not always attained. In many cases, the rewiring process can be considered maladaptive in that the patient is left with residual abnormal motor patterns and function. Fortunately, from a therapeutic perspective, evidence is mounting that the reorganization process during the sub-acute plasticity window may be guided through appropriate behavioral training [3]. Fundamental research particularly through studies in animals have demonstrated that reorganization is not driven simply by increased use and that expansion of cortical representations requires skill-dependent motor learning behavior. Other studies have demonstrated the importance of appropriate stimulation. For example a study of the long term plasticity in mouse sensorimotor circuits provides evidence that passive stimulation of whiskers induced plasticity of subsequent whisker-evoked cortical responses [4]. These fundamental results are changing clinical rehabilitation perspectives on the role of therapy in promoting recovery. As a result, motor therapy comprising task-specific, repetitive, prolonged movement training with learning, often guided by a therapist who assists in the completion of movement tasks [5], may have significant impact on recovery. However, in the case of severe impairment where motor skills have been highly affected there is often little or no movement available with which the therapist can work with. Patients with such severe disability then have few if any therapy options for the required type of motor rehabilitation.

In such cases the application of a brain-computer interface (BCI) may provide an alternative approach for neurorehabilitation [6]. A BCI can serve a number of rehabilitation purposes for recovering stroke patients, for example a BCI can be used to substitute for loss of neuromuscular functions by using brain signals to interact directly with the environment. Another mode of application is to provide a means by which a severely disabled patient can engage in activities that may help restore function. In such an application coincident activation of sensory feedback loops and primary motor cortex may reinforce previously dormant cortical connections through Hebbian plasticity and thereby support functional recovery [7]. A BCI can help achieve this through a neurofeedback process in which measures of motor program engagement can be detected with appropriate feature extraction and machine learning to produce a control signal which is then used to close the feedback loop through triggering of appropriate feedback [8]. Recently this feedback is being incorporated into robotic or haptic rehabilitation systems. Such an approach may have tremendous utility in providing closed loop neurorehabilitation to patients with severe deficits. Current approaches however require sophisticated, expensive mechanical systems which require supervision from technical operators. While these systems represent the state of the art in clinical rehabilitation and are capable of

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[1]A. L. Coffey is with the Department of Electronic Engineering, National University of Ireland Maynooth, Ireland acoffey@eeng.nuim.ie

[1]D. J. Leamy is with the Department of Electronic Engineering, National University of Ireland Maynooth, Ireland dleamy@eeng.nuim.ie

[1]T. E. Ward is with the Department of Electronic Engineering, National University of Ireland Maynooth, Ireland tomas.ward@eeng.nuim.ie

fine measurement and performance, they are however unsuitable for home deployment given their costs, complexity and technical operation requirements. Advocates of home-based stroke rehabilitation suggest that there are several advantages to moving towards home based rehabilitation; there is an opportunity to facilitate the swift transition of care for patients from hospital to home, reduced risks of nosocomially acquired illnesses and distress from prolonged stay as an inpatient [9].

In this work we describe a compact, inexpensive solution for home-based motor-neurorehabilitation comprising an EEG-based BCI and simplified haptic feedback system based on a pneumatic glove solution. Easy to deploy in a home environment it can be considered as complementary to approaches in clinical BCI-mediated robotic systems.

II. Methods

A novel pneumatic-controlled finger extension system was developed to provide haptic feedback to subjects. The complete system is described here in detail.

A. Pneumatic Glove

We repurposed a pneumatic exercise glove which utilizes low air pressure to provide assistance of digit extension. The glove consists of strategically placed air bladders that run the length of each finger. Additional air bladders are situated between the fingers to encourage lateral movement. The forearm, wrist and individual fingers are affixed to the glove with velcro straps, as shown in Figure 1. The development of a similar pneumatic glove, the PneuGlove, has been described elsewhere [10].

B. Pump and Valve Control

A custom control system, shown in Figure 2, was designed to facilitate the inflation and deflation of the glove through a computer-controlled interface.

Figure 1. Glove at minimal inflation (top) and at full inflation (bottom)

A 12 V DC diaphragm vacuum pump (Airpo-D2028B, Ningbo Forever Electronic Appliance Co., China.) supplies both pressure and vacuum to our system. Inflation and deflation of the glove is determined by control of two electro-mechanic 3/2 solenoid valves (SMC Corporation, Japan. S/N: VDW250-6G-1-01F-Q). The valves exhibit binary control allowing for the selective routing of air from their input port to one of their two output ports. For both valves, the input port is connected to the vacuum pump, one output port is connected to the glove and the other is connected to the atmosphere. Configuration is presented in Figure 3.

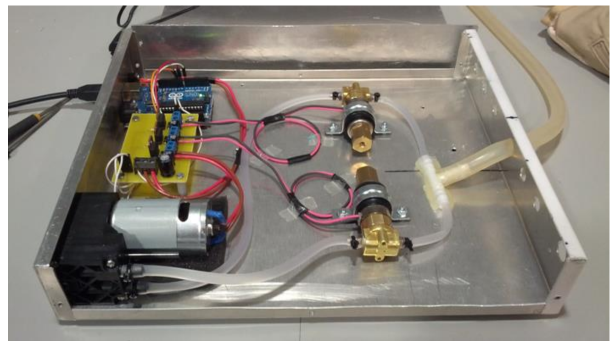

Figure 2. Custom pneumatic control system

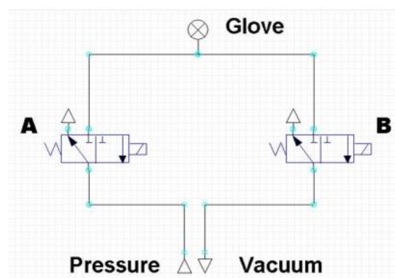

Figure 3. Pneumatic system

The system incorporates two independent power supplies: 5 V DC supplied by USB to power the Arduino platform and 12 V DC to power the pump and solenoid valves. In order to safely control the higher voltage components using 5V logic, additional electronics are required, as shown in Figure 4.

The inflation time taken for the glove to move the subject hand from minimal to maximal deflection was 12 seconds. The time to deflate the glove back to its initial state was 10 seconds. Therefore, total time for inflation then deflation of the glove, producing maximal range of hand motion, was 22 s.

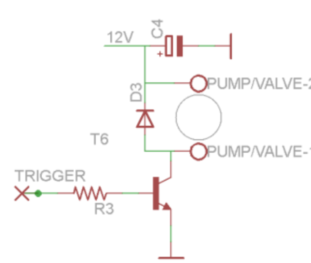

Figure 4. Circuit for controlling 12 V components with 5 V logic

C. Arduino

An open-source prototyping platform, the Arduino Uno (Arduino, Ivrea, Italy), acts as a mediator between the BCI and pneumatic glove system. The Arduino receives instructions over a serial communication link from the PC and carries out appropriate control of the pump and solenoid valves. Thus, inflation and deflation of the glove is controlled via serial communication with the PC.

D. Brain Computer Interface

Electroencephalogram (EEG) was recorded from 27 Ag/AgCl electrodes placed over the motor and central areas according to the 10/20 system of electrode placement. Data was recorded using a g.USBamp system (g.tec Medical Engineering GMBH, Austria) at a sample rate of 256 samples per second. We used a modified version of g.tec software to implement a real-time two-class Common Spatial Patterns (CSP) based BCI [11], which was used to send appropriate control signals to the Arduino.

CSP is a popular BCI method which produces a set of spatial filters based on recorded EEG and event data. These filters are then used to decompose real-time EEG into new CSP signals. The variances of these new CSP signals can be used to optimally discriminate between two classes of activity [12,13].

All sampled EEG was band-pass filtered in the 0.5-30 Hz frequency range and had a 50 Hz notch filter applied. EEG was further filtered to the 8-30 Hz range before the CSP stage of processing. g.tec software [14] was used to remove artifact-affected trials and noisy channels, carry out CSP analysis, produce CSP filters and train a Linear Discriminant Analysis (LDA) classifier for real-time testing.

During real-time testing, EEG was filtered as before, decomposed by the trained CSP filters and classified by the trained LDA classifier. The classifier output was smoothed with a moving-average filter of length 0.5 seconds. At a specific time after instruction onset (determined during BCI training), the smoothed classifier output was sampled. The control signal sent to the Arduino was based on this sample value. An overview of the entire system is presented in Figure 5.

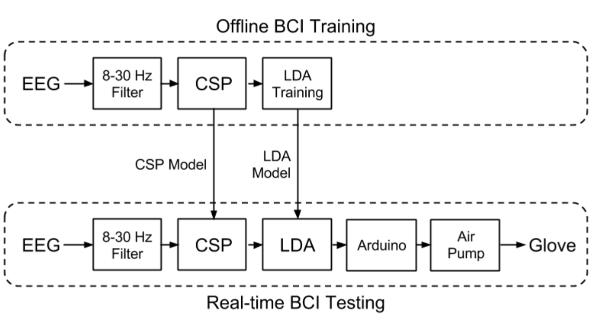

Figure 5. BCI system overview

E. Subject

Three subjects (all male, aged 24 - 28) participated in a system test. Subjects were all self-reported right handed and gave oral consent before participation. Subjects were recruited from National University of Ireland Maynooth.

F. Experimental Protocol

To demonstrate the operation and feasibility of our stroke rehabilitation BCI platform, subjects participated in the training and testing of an overt movement BCI. During training and testing sessions, subjects were seated in a comfortable chair, had their hand affixed to the glove and followed instructions presented on a PC monitor in front of them at eye level. The subjects wore the glove during both sessions. 20 rest trials and 20 active trials were presented in a randomized order in each session. During an active trial, the subject was instructed to perform self-paced dominant-hand digit contraction and extension, as this action resembles the movement induced by glove inflation and deflation.

For the training session, each trial lasted 8 seconds. At 0 s, the screen went blank. At 2 s, a fixation cross appeared on-screen. From 3 s to 4.5 s, an instruction arrow appeared, pointing right to indicate a movement instruction or pointing left for a rest instruction. From 4.5 s to 8 s, the fixation cross remained on-screen. The subjects were instructed to perform the action (rest or movement) as soon as the arrow appeared. For each subject, the recorded EEG was analyzed to produce optimal CSP filters, train the LDA classifier and determine the optimal delay after instruction onset to sample the smoothed classifier output.

For the test session, each event lasted 30 seconds. Instruction presentation was the same as before except that the fixation-cross remained on-screen from 4.5 s to 30 s. During these 25.5 s, feedback of the classifier output was also presented on-screen in the form of a bar extending to the left or right of the centre of the screen. The sign of the sampled classifier output determines the decision to inflate then deflate the glove or to let it remain deflated. A positive sample value indicates movement classification while a negative sample value indicates rest classification. As inflation and deflation of the glove takes 22 seconds, there is sufficient time per trial for full range of hand movement induced by the glove.

III. RESULTS

A table of classification accuracy results of the BCI test sessions is show in Table I. Presented in Figure 6 is a representative section of the time course of classifier output with timings for active and rest instruction onset, classifier sample times, classifier sample points and an illustration of the changing air pressure in the glove over time as it reacts to the classifier output.

TABLE I. SYSTEM TEST RESULTS

Subject	*Classification Accuracy*
A	92.5%
B	90.0%
C	80.0%

IV. DISCUSSION

The main goal of this paper is to report on the development of a simple, affordable and accessible neurorehabilitation system which could fulfill the need for home-based motor therapy with somatosensory feedback. The focus is the novelty of the system as a whole and not the results of classification as the BCI software used here is quite basic and available commercially. The system presented here uses a basic form of CSP, simple classification with LDA and a relatively easily-classifiable EEG pattern of overt movement activity. Any stage of the BCI could be replaced by a more sophisticated design and implementation. For example, there are many improvements to the CSP algorithm which could be used, a more advanced classification method such as Neural Networks or Gaussian Process classification could be utilized. Additionally, an imagined movement-based protocol could be used to explore BCI-based stroke rehabilitation methods [15].

Current clinical approaches to BCI-based neurofeedback rehabilitation involve sophisticated mechanical devices that can accurately administer precise movements with high fidelity and control. While these machines represent the state of the art in rehabilitation efforts they are largely inaccessible due to their operation requirements. Home rehabilitation with a system such as the one presented here allows for great flexibility by allowing patients and their therapists to tailor a program of rehabilitation without disruption to the patient's normal routines. The major disadvantage of home-based rehabilitation programs is the current lack of specialized equipment and insufficient data as to their efficacy. Unfortunately this lack of data makes it difficult for companies which might provide BCI-driven robotic systems to justify the investment required to make this technology widely available. This, in turn, makes collection of the required evidential data even less likely to happen. We believe that the relatively inexpensive, albeit very simple, BCI-driven haptic system described here is an example of the type of approach which may help "bootstrap" the process of creating the necessary studies which can build evidence as to the effectiveness and utility of home-based BCI rehabilitation systems. Our future work involves the testing of the platform with a number of sub-acute stroke patients.

Many considerations were made while developing this platform. The pneumatic glove used is comfortable to wear and uses adjustable velcro straps, allowing it to fit different size hands. It is easy to don and doff therefore it is entirely possible for a family carer or even the user to use the system without technical assistance. The glove design inherently minimises movement restrictions placed on the user as there are no stiff mechanical parts. The pneumatic control system was designed with portability in mind, weighing less than 2 kg and is housed in a compact case. The system can be used with any PC, requiring only installation of the software.

We advocate the replication of our system in the hope that it might enable other researchers to experiment with a neurorehabilitation-based approach to enhancing motor function recovery after stroke using simple robotic systems.

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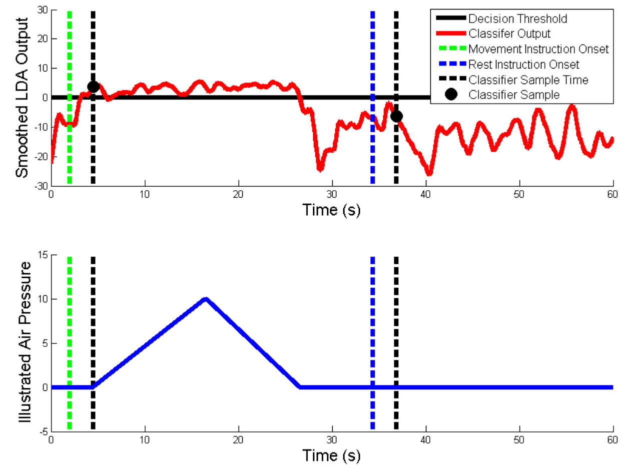

Figure 6. LDA classifier output with event timings (top) and illustrated air pressure in the glove (bottom)

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