A Cost-effective BCI Assisted Technology Framework for Neurorehabilitation

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***Abstract* –– Brain Computer Interface (BCI) controlled assistive robotic systems have been developed with increasing success with the aim to rehabilitate brain injured patients to increase their independence and quality of life. While such systems may use surgically implanted sensors, non-invasive alternatives can be better suited due to ease of use, reduced cost, improvements in accuracy and reliability with the advancement of the technology and practicality of use. The consumer grade BCI devices are often capable of integrating multiple types of signals, including Electroencephalogram (EEG) and Electromyogram (EMG), as well as basic motion-based signals, such as gyroscopic data. This paper reports the development of a framework for rolling out cost-effective BCI driven assistive technology systems and details the implementation and evaluation of a prototype robotic system to determine the efficacy of the proposed framework. The results indicate that the first stage of the framework was effective in accuracy, safety, usability, portability, adaptability and personalisation.**

Keywords - BCI; Assistive Technology; EEG; EMG; Disability; Neurorehabilitation.

I. INTRODUCTION

There are over 12.5 million people in the UK living with a neurological condition, out of which over a million are substantially disabled by their condition and a further 350,000 require help for most of their daily activities [1]. These neurological conditions cost the National Health Service in the UK (NHS) £4.4 billion in 2014 [1] (4.2% of the NHS expenditure), with the cost set to treble over the next 20 years [2]. An estimated £2.4 billion is spent on social care services alone for people with a neurological condition [1]. Given the wide range of issues that neurorehabilitation covers, as well as the success in the implementation of Brain Computer Interface (BCI) based systems using both Electroencephalogram (EEG) and Electromyogram (EMG) signals [3]-[11], it is apparent that BCI based assistive systems could become viable alternatives to traditional neurorehabilitation methods.

There is limited evidence of BCI assisted neurorehabilitation available in the literature for post-stroke disorders [3], paraplegia [4], spinal cord injury [5] and tetraplegia [6]. Cesqui et al. [10] reported an EMG based robotic system to assist in the rehabilitation of patients and Soekadar et al. [11] investigated the use of EMG as a method of post-stroke rehabilitation. However, success of such technology assisted rehabilitation largely relies on the effectiveness of integration through a process defined in a neurorehabilitation framework that is more personalized and convenient [12][13]. Development and implementation of an assistive technology has to be carefully phased out using rigorous procedures described in a framework for a system [14][15] to be better suited for patients. Availability of a framework specific to patients with more personalised needs and requirements of bespoke technologies were discussed; especially the need for a framework for the integration of BCI within neurorehabilitation context was mentioned in [5]. As a solution, non-invasive off-the-shelf portable BCI assisted systems have been popular choices due to improvement in accuracy and reliability of such systems with the advancement of technology and practicality of use [16]. This paper proposes a cost-effective BCI based assistive technology framework for the rehabilitation of patients suffering from neurological disabilities, which is an adaptation and merge of two frameworks: one [12] details the entire rehabilitation process and the other [14] details the technology lifecycle (development, selection, learning and integration). In addition to developing a framework for neurorehabilitation, this paper also investigates the efficacy of the proposed framework by developing a prototype robotic system with the help of two portable devices: an Interaxon Muse BCI (to gather brain signals) and a UFactory uArm (for robotic control), as shown in Figure 1.

Figure 1. Interaxon Muse (left) and UFactory uArm (right).

The remainder of this paper is organised as follows: Section 2 gives an overview of a proposed framework, Section 3 details the evaluation of the framework using a prototype system and its implementation. Section 4 describes the experimental scenarios to evaluate the framework. Results will be discussed in Section 5. Finally, Section 6 concludes the paper.

II. PROPOSED FRAMEWORK

We propose a new framework for BCI assisted neurorehabilitation. We consider three distinct stages of the framework lifecycle: system development, clinical trials and operational. It is critical that the end product of this system is reviewed by one or more specialists to determine whether the system has sufficient accuracy, safety, usability, portability, adaptability and personalisation.

A. System Development

The system development stage consists of four actors, adapted from Kintsch [14]; a trial group, one or more trial caregivers, a specialist and one or more developers (as listed in Table 1). While Kintsch [14] specified the required traits for each actor, this paper specifically states the role of each actor within the system.

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TABLE I. ROLES OF ACTORS IN SYSTEM DEVELOPMENT STAGE

Trial Group	Trial Caregiver	Specialist	Developer
Volunteers who trial the system. Require no prior training on the system. Gives feedback to specialist on usability of the system.	Instructs the trial user on how to operate the system. Initialises any initial parameters of the system and fits the BCI. Requires minimal training in the system.	Reviews data given by the system. Gives feedback to the developer based on feedback from system and user.	Makes changes to the system based on feedback. Ensures system safety and good coding conventions for adaptability.

This stage focusses primarily on the planning and development of the system to test the feasibility. The main criteria for suitability are the relevance to the neurorehabilitation task at hand, the cost-effectiveness for easy prototyping and overall safety of the system. If the system is not suitable, it is the specialist's decision whether further development should proceed or not. Figure 2 shows a sequence diagram of the system development stage. Once the initial proposal is being approved, the developer should strive to make the code as modular as possible to ensure that the code is easy to adapt and maintain in the future. Members of the trial group will run through the calibration and experimentation to gather data on system efficacy. Feedback from both the specialists and users is also critical to evaluate the suitability of the system in order to take it forward to the next clinical trial stage.

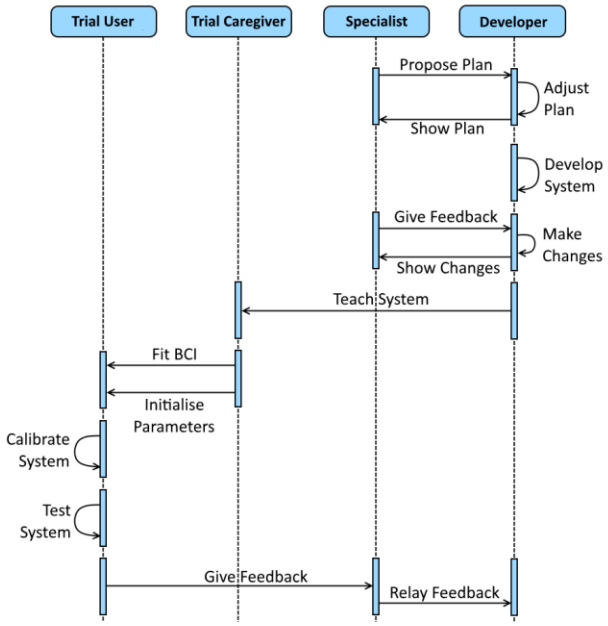

Figure 2. Sequence diagram of the system development stage.

Since the trial caregiver will be responsible for both fitting the BCI to the user's head as well as setting the experimental parameters, it is vital that the caregiver (if they are not also the developer) receives some form of training from the developer prior to carrying out any experiments. Users should carry out calibration at least once before running any experiment to filter out any unwanted artefacts. Calibration can either be run every time the experiments are to be carried out, or the data can be stored in a user profile and loaded each time the experiment is run.

B. *Clinical Trials*

Before the clinical trials stage commences, the ethical approval must be completed to try out the systems on real patients. A select group of neurologically disabled patients will volunteer to trial the system and give feedback on the system. The developer will act on this feedback and the advice of the specialist. Caregivers are likely to be nurses or family members of the patients. Table 2 shows the roles of all actors in this stage. The specialist will now be in a position to handle the training of the system to the caregivers. This is likely to be done through group training sessions where specialists train nurses. Figure 3 shows the sequence diagram of the clinical trials stage.

TABLE II. ROLES OF ACTORS IN CLINICAL TRIALS STAGE

Patients	Caregiver	Specialist	Developer
Neurologically disabled volunteers that trial the system. Require no prior training on the system. Gives feedback to specialist on usability of the system.	Either nurses or family / friends of the patients. Instructs the patient on how to operate the system. Initialises any initial parameters of the system and fits the BCI. Requires minimal training in the system.	Reviews data given by the system. Peer review through conferences in hospitals and Patient Association Forums. Gives feedback to the developer based on feedback from system and user.	Makes changes to the system based on feedback. Ensures system safety and good coding conventions for adaptability.

C. *Operational Stage*

The operational stage is the final stage of the framework, which involves regular maintenance of the system to ensure that the technology is being kept up-to-date and patched against bugs. Table 3 shows the roles of all actors in the final stage of the framework. The system at this stage is ideally to be phased out to wider group of patients who wish to make use of it. The specialist can use the data gathered from

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patients by the system to evaluate how well the rehabilitation process is going on. This evaluation can then be shared with the developer and any pertinent improvements can be justified through this process, as illustrated in the sequence diagram in Figure 4.

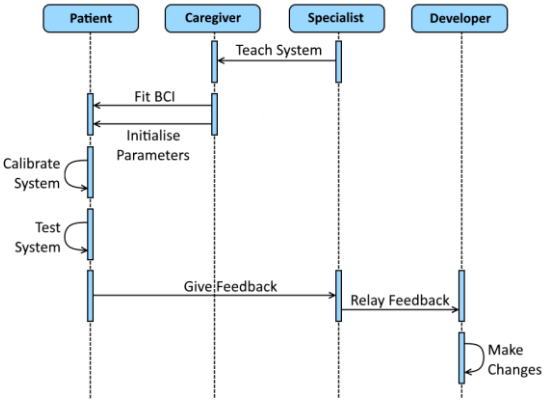

Figure 3. Sequence diagram of the clinical trials stage.

TABLE III. ROLES OF ACTORS IN OPERATIONAL STAGE

Patients	Caregiver	Specialist	Developer
Neurologically disabled patients that use the system. Require no prior training on the system.	Either nurses or family / friends of the patients. Instructs the patient on how to operate the system. Initialises any initial parameters of the system and fits the BCI. Requires minimal training in the system.	Reviews data given by the system.	Makes changes to the system as needed. Ensures system safety and good coding conventions for adaptability.

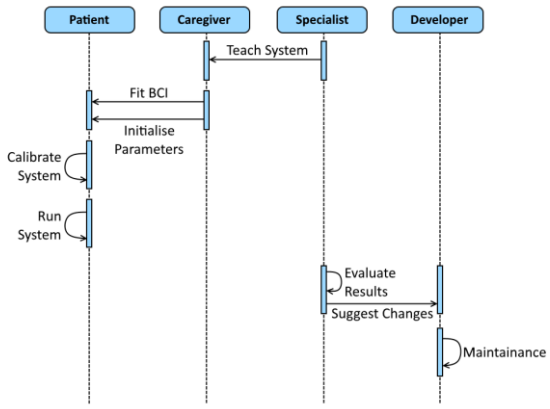

Figure 4. Sequence diagram of the operational stage.

III. FRAMEWORK EVALUATION

This section details a proof of concept of the framework proposed in Section 2, consisting of the operation of a robotic arm (as the assistive technology component) using a Muse BCI device (as the BCI component). Given the time constraints on this project, the evaluation was carried out only for the stage 1 of the framework (Figure 2). Actors involved in this stage were a developer (also acting as a trial caregiver), a specialist and a small trial group of 5 subjects. Accuracy and usability (as required by the framework) measures will be observable from the experimental results of the system, whereas the other performance measures will be discussed within the evaluation.

A. System Overview

The system hardware consists of a PC, a small portable BCI device, Muse and a portable desktop robotic arm, uArm. Viability of such low-cost portable devices as a solution to neuro-rehabilitation was discussed with a specialist at the Kent and Canterbury NHS hospital's neurorehabilitation department. Using rigorous use case scenarios both developer and specialist agreed on achievable requirement specifications for the prototype system. The overall architecture of the system is illustrated in Figure 5 and consists of two main branches: the EMG data branch and the gyroscopic data branch. More details of these steps are shown in the figure.

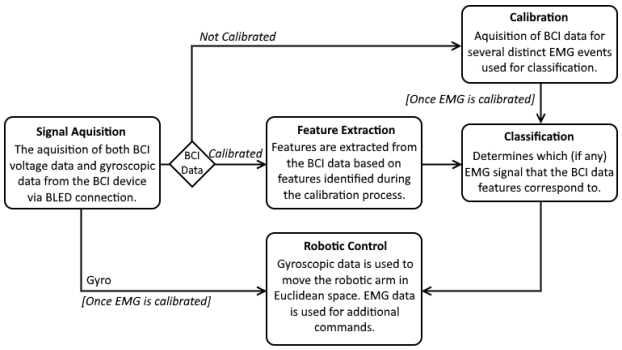

Figure 5. Overview of the system data flow.

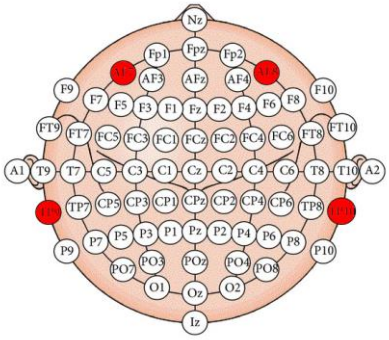

Figure 6. Muse Electrode Placement modified from [17].

B. Data Acquisition

The first step is to obtain data from the Muse BCI device, which is achieved via hosting of a Python server

leveraging the benefits of a Bluetooth Low-Energy Dongle (BLED) connection direct to the Muse device. Several sets of data are supported by this server, but the most notable are the four electrodes; AF7, AF8, TP9 and TP10 (using the 10-20 international system seen in Figure 6) at a sample rate of 256Hz as well as the gyroscopic data (at a sample rate of ~50Hz). These electrodes are able to detect electrical signals across the front of the skull, namely EMG artefacts such as blinks, winks and jaw clenches.

C. Calibration

Calibration covers the personalisation of the system, by creating separate user profiles containing information specific to each user. The user is presented with a series of prompts over the calibration process and is given a set of ten (temporally equidistant) prompts telling them to rest, which gets the baseline brain activity level. After the tenth prompt (to get a reliable amount of data), the user is given another ten prompts instructing them to blink, which gets the voltage associated with the blinking. Likewise, there is another ten prompts for left wink and then another ten for the right wink.

As an example, Figure 7 shows EMG readings over all electrodes for two different EMG artefacts (left and right winks). The figure shows that during left winks, the spike in voltage for the left electrodes are greater than the spike in voltage for the right electrodes. When there is a right wink, the spike in voltage for the right electrodes are larger than the voltage spike for the left electrodes.

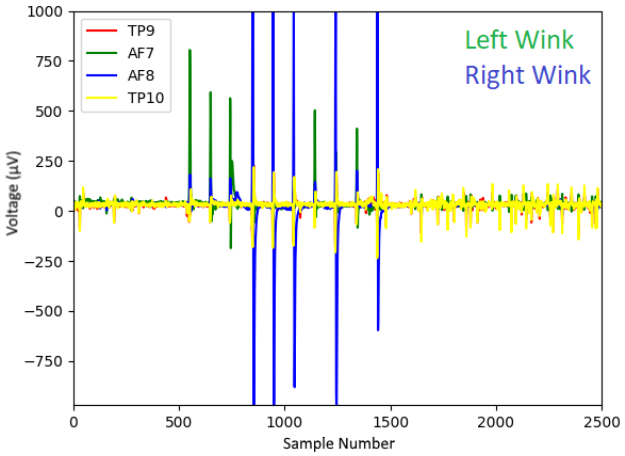

Figure 7. Differentiating between left and right wink using voltages.

Once all 40 prompts are finished, an EMG profile is built for the user. This profile consists a single threshold value, as shown in (1), calculated from the average of the maximum and average of the mean EMG values over the samples, *n=10* in (1), for every user for each of the different sets of BCI electrodes during blinks, left winks and right winks.

$$Threshold = \left(\frac{1}{n}\sum_{i=1}^{n} Vmax_i - \left(\frac{1}{n}\sum_{i=1}^{n}(Vmax_i - Vavg_i)\right) \times tolerance\right) \quad (1)$$

A tolerance value was set empirically to configure a better responsive system in relation to variation of voltage levels corresponding to EMG spikes. This algorithm ensures that a more responsive and personalised profile is set for each individual user.

D. Classification

Classification deals with the accuracy of the system. A successful and responsive classifier will yield high levels of accuracy. The classification step involves the comparison of EMG voltage data in real-time with the EMG voltage data stored in a given user's profile and applying semantics to that signal, i.e., to map a specific voltage combination to a particular EMG signal for that user.

The calibration file contains a value (which acts as a threshold) for each electrode during blinks, left winks and right winks. If both the left and right electrodes pass their respective electrode values in the calibration file, then the signal is classified as a blink. If the real-time left electrode values are greater than the left electrode's data in the calibration file and the right electrode value is less than its respective calibration value, then the signal is classified as a left wink. Likewise, if the right electrode values are greater than the calibration value and the left electrode value is less than its respective calibration value, the signal is classified as a right wink.

If none of the above criteria are fulfilled, the system returns that there was no significant EMG signal detected and therefore, no action is given to the uArm to avoid carrying out any unexpected actions by the arm. For clarity, the output of each classification is also reported back to the user.

E. Robotic Control

After calibration, the gyroscopic data can be streamed from the Muse and used to control the robotic arm, where the user moves their head in Euclidean space which corresponds to the three degrees of freedom in the robotic arm (X, Y and Z axes). The robotic arm can only move within a pre-defined "bounding box"; while this is set as an experimental parameter, is a major step to ensure system safety. Simultaneously, voltage data is being streamed from the Muse, which is used to perform a variety of actions on the uArm. Each time the program is run, it will allow users to dynamically load a control protocol, meaning that custom systems can be reused over several different experiments, or control protocols that are optimised for a specific use can be loaded.

IV. EXPERIMENTAL SCENARIO

Once the system has been sufficiently developed as described in Section 3, the next step in the framework is to teach trial caregivers how to fit the BCI and initialise the experiment parameters, system calibration and the acquisition of experimental data. After receiving feedback on the system, changes are made (if necessary). The feedback will determine the accuracy and usability of the system.

An experiment was designed to determine how usable the system is in a real-world scenario; in this case, an experiment with feeding task was set upon discussion with a specialist as a feasible task for neuro-rehabilitation. The task involves users to attempt to use EMG signals and head

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movements (gyroscopic data) to move the uArm (using a spoon as an "end effector") to a plate of dummy food (using paper balls), scoop up some of the "food" and to move it to a predefined mouth level. The process involves a user moving the uArm first using gyroscope movements and then scooping up some food. The user should then blink, which brings the food up to a predefined mouth level automatically. Once the food is being "eaten" or removed, another blink brings the uArm back down to the plate level automatically. After the trial of this task, the user should then repeat the steps for a total of three times to ensure the sufficient use of the system to be able to comment on the efficacy of the system.

Figure 8 demonstrates the control protocol of the uArm during the feeding experiment. In free mode (the initial state of the system), the subject can use gyroscopic events to move the robotic arm in the Euclidean space. If the user blinks while the uArm is not at the mouth level, the uArm moves to the mouth level and locks itself, preventing further movement. Blinking while the uArm is at the mouth moves the uArm back to the plate level and unlocks it, meaning that the user can use gyroscopic data to move the uArm again. A right wink will result in resetting the position of the uArm to its default starting position.

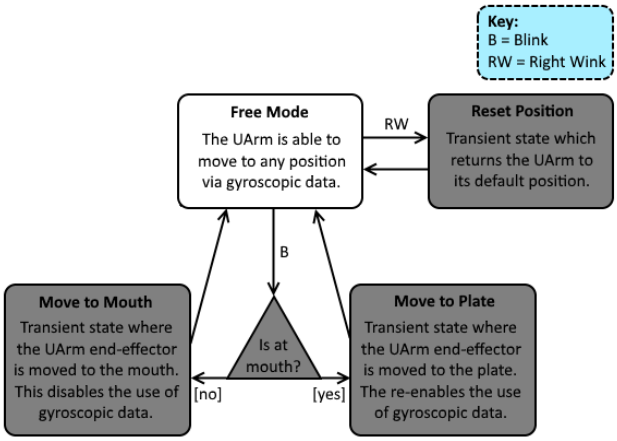

Figure 8. EMG control protocol for the robotic arm during the feeding experiment.

The objective metrics for success of this experiment are the time taken to bring the food to the user's mouth, whether the uArm successfully traversed from the plate to the mouth, the number of items dropped in this process and finally, whether the uArm successfully traversed from the user's mouth back to the plate. In addition to the objective metrics, subjective measures shall also be taken in the form of a short survey of user experience, following the system usability scale (SUS) [18] comprising of the ten questions answered on a scale of one (strongly disagree) to five (strongly agree).

V. RESULTS OF EVALUATION

This section reports the work in progress results of the evaluation of the framework's development phase using the feeding experiment as detailed in Section 4. At the time of writing this paper, in total 15 trials (Table 4) were completed to evaluate the success of the feeding task in a non-clinical setting using a trail group of five able-bodied volunteers contributed to three trials each. Performance measures of the system and the usability results were discussed in detail with a specialist at the neuro-rehabilitation centre to gain specialist's critiques on feasibility of the system if it was to be tried on real patients during the clinical trial phase of the framework.

The results of Table 4 shows that users were able to adapt to the system at varying speed. Trial times to complete the route from plate to the mouth level varied amongst users from around 7 seconds to more than 3 minutes. Even though 3 minutes seems to be longer time to complete the task, according to specialist's comments it was still a good outcome as hiring nurses or carer to carry out the same task would cost more for rehabilitation. The mean time for completion of the same task was ~45.86 seconds, with a standard deviation of ~46.55, however for one trial it took unexpectedly long (194.62 seconds) to complete the task. Discarding the outlier of 194.62 seconds, the mean completion time reduces to 35.24 seconds with a standard deviation of ~25.06.

TABLE IV. RESULTS OF THE FEEDING EXPERIMENT

		Plate to Mouth			Mouth to Plate
ID	*Trial*	*Time (sec)*	*Route Complete (Y/N)*	*Items Dropped*	*Route Complete (Y/N)*
1	1	11.51	Y	0	Y
1	2	45.49	Y	0	Y
1	3	7.20	Y	0	Y
2	1	8.32	Y	0	Y
2	2	13.09	Y	0	Y
2	3	8.80	Y	0	Y
3	1	34.30	Y	0	Y
3	2	25.36	Y	2	Y
3	3	194.62	Y	2	Y
4	1	72.58	Y	0	Y
4	2	14.82	Y	0	Y
4	3	68.29	Y	0	Y
5	1	77.00	Y	0	Y
5	2	56.97	Y	0	Y
5	3	49.47	Y	0	Y

The system managed to successfully navigate from the plate level to mouth level and vice versa in every single trial and the specialist found this to be a reliable outcome. Number of items dropped while completing the moving task from plate to the mouth level also varied amongst users depending on their efficacy of using the system after the training session. Except one user, no one dropped any item in any of the trails while moving the arm to the mouth level, showing an acceptable level of efficacy. For one user, blink event did not produce enough electrical potential to be registered as an EMG event. During the calibration stage, after checking all possible EMG events which can be detected by the system, it was found that "frowning" generates higher electrical potential for this user instead of the blink act. So, during the training session, instead of the blink act frown act was registered as an EMG control input for this user. This shows adaptation of the system control input based on specific user physiological requirements, supporting the adaptability requirement of the framework.

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TABLE V. SUS SURVEY RESULTS

Question	Average Score
I think that I would like to use this system frequently.	2.6
I found the system unnecessarily complex.	2.2
I thought the system was easy to use.	4
I think that I would need the support of a technical person to be able to use this system.	1.8
I found the various functions in this system well integrated.	3.4
I thought there was too much inconsistency in this system.	2.6
I would imagine that most people would learn to use this system very quickly.	4
I found the system very cumbersome to use.	2.6
I felt very confident using the system.	4
I needed to learn a lot of things before I could get going with this system.	2

Table 5 summaries the results of the SUS survey which was completed by users at the end of their trials. The results indicate that users found the system easy to use and they also felt confident using the system. There was strong agreement amongst users about easily learning to use the system and they also believed that most people would learn to use the system very quickly. Some users found the system cumbersome to use and inconsistent in completing the task, which was also the case in objective measures reported in Table 4, as the users completed the task in largely varying times.

VI. CONCLUSION

This paper proposed a new BCI driven assistive technology neurorehabilitation framework and reported the work in progress evaluation of the development stage of the framework. Specialist involvement in design and evaluation of the framework gave valuable insight into successful adaptation of the technology to fit better for patients' care for neurorehabilitation. The prototype system suited well within the framework with some success as observable from the results of the evaluation. While the system was deemed acceptable by the specialist, some changes to the system need to be addressed; such as more rigorous trials are required to be carried out on a larger sample population consisting of a wider variety of subjects accounting for differences in age, gender and abilities. Latency in the system should also be improved. Further experiments over a greater length of time could determine whether users can improve their performances over a number of trials. Discussion has been made already to use the framework to develop more complicated BCI assisted system, such as the BCI controlled exoskeleton, for the purpose of neurorehabilitation.

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