Article

Project MindReader: Reading Using Affordable BCI

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Abstract:

"Although Brain computer interface (BCI) devices are beginning to aim at the consumer level, their cognitive usability is still limited, especially for a physically-disabled person. To improve usability of BCI interfaced devices, we employed the Emotiv Epoc, a low-priced electroencephalography (EEG) headset, to design and build a proof-of-concept document reader system that allows users to navigate the document without the need of physical actions. Our prototype has been implemented and evaluated with 12 participants who were trained to navigate documents using brain signals acquired by Emotive EEG. In addition to testing cognitive actions of participants, we also proposed an automata theory based benchmark to model the participants' behaviours. Furthermore, our framework is also able to identify every software bottleneck and to provide future ways for improvement."

Keywords: Brain Computer Interface; Document Reader; Affordable; BCI

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1. Introduction

BCIs produce a way of communicating brain activity, which can help physically disabled people make use of more common assistive technologies. When an individual thinks of an action they wish to make, such as pushing a mouse device, electrical activity produced by the brain penetrates the skull and can be measured on the scalp using electrodes. This is called electroencephalography (EEG). Different actions (and specifically action intents – which is the intention or desire to stimulate an action) are associated with different patterns of electrical activity. These associated patterns of electrical brain activity, enable the actions or intent of the user to be interpreted without the physical action occurring.

Affordable brain-computer interface technology has only recently become accessible to users with limited and experimental software. This subject therefore, although emerging, has only seen limited (yet promising) research. The effects of affordable brain computer interface technology being integrated into people's lives can have a positive impact in the way that both non-disabled and disabled people interact with their surroundings through technology. This social aspect has not yet been researched. Inclusive design such as this can allow individuals to live better, more comfortable and productive lives, enabling them to interact better in society. Beyond the affordable physical interaction, the research can play a positive psychological, social and emotional role for disabled people. The applications of a brain computer interface is primarily to introduce another level of multimodality to a user. The work is therefore not limited in findings to those individuals with disabilities but rather produces a basis and foundation that will ultimately be used to enable those people within the disability spectrum.

In this paper we propose a framework using an affordable, non-intrusive method to investigate cognitive control usability for EEG enabled BCI devices. Firstly an affordable prototype is implemented to investigate the efficacy of allowing quadriplegic patients elementary control over a document reader thus reinstating autonomy to the individual without the need for assistive care. By detecting EEG activity from a brain computer interface (BCI) and mapping the cognitive functions to physical actions, users are able to navigate through a document without any movement from their limbs. The initial phase of testing is to improve the validity of our framework using an in-suited software (see details in section 3). In future we will improve the prototype to make it easier for users which then will be tested by paraplegic and quadriplegic individuals.

The work presented in this paper is organized as follows: The background and related work section describes the required background knowledge of BCI devices; The prototype and the user study description is then outlined; The results and discussion regarding to user actions with a mathematical automata based theory language are presented a) to create a foundation for visual inspection, b) to evaluate action impacts and improvements c) to increase the ecological validity of the findings by therefore allowing wide communication of the work to other disciplines.

2. Background and Related work

A brain computer interface (BCI) devices provide a new channel for communication and control, which can offer a new range of assistive and rehabilitative applications for people who suffer from motor impairment [1, 2]. Traditionally the BCI area related research is based on expensive and complex prototypes such as the Graz brain-computer interface II [3, 4]. The cost for conducting research using EEG based BCI devices was still relatively high for individuals and require a number of specially trained people to set up[5,6].

During the last decade, more affordable/consumer BCI devices have been released and used for academic research purposes. These include: the Neurosky Mindset headset[1], used to enhance cognitive functions and increase satisfaction within a game called 'Neuro Wander' [7]; the Myndplay Brainband, used to elicit different mind states of participants viewing emotional videos [8]; and the OpenBCI system, used for investigating optimal electrode placement for motor imagery applications [9].

The Emotiv Epoc[2] device is inexpensive, commercially available and has been used extensively in the past for similar types of research with good results [10-15]. This device is used to measure the engagement level of users using the physiological reading method [10] and is an innovative approach that aims to enhance the user's learning experience by measuring the engagement of the user. Stytsenko et al reported that Epoc was "able to acquire real EEG data which is comparable to the one acquired by using conservative EEG devices" [16]. Their research team also used this device for measuring and evaluating user experience [11]. These measures were used as part of a simulation where the users were controlling the movement of a simulated robot. The engagement data showed that each test provided a different kind of experience for users and an unbalanced experience between the users. Epoc was also used for evaluating if a low priced commercial device can be used as an interface for users with no impairments for controlling assistive technology devices with their thoughts [12]. The results supported this as all of the participants achieved positive success rates at the end of the training period.

Duvinage et al's work reported a high signal-to-noise ratio problem of Emotive Epoc, but they demonstrated that Epoc was capable of recording EEG [15]. They warned that the device would be more suitable for non-critical applications rather than prosthetics or rehabilitation as it may cause serious consequences if the control fails or lacks accuracy [15]. Furthermore, Taylor et al produced results which "found the system to perform significantly better than chance for all mental actions, and improve over time with additional training data" [17].

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[1] http://neurosky.com/biosensors/eeg-sensor/ - Accessed March 2016

[2] https://emotiv.com/epoc.php - Accessed March 2016

3. Materials and Methods

3. 1 Prototype

The prototype system architecture consists of four key components. These are:

1. Emotiv Epoc EEG Headset
2. EmoKey Software
3. Epoc Control Panel
4. MindReader Software

The **Emotiv Epoc Headset** is used to receive raw EEG data and brain patterns from the individual and send the signal to the Epoc Control Panel. The BCI contains 14 channels (See electrodes AF3, F7, F3, FC5, T7, P7, O1, O2, P8, T8, FC6, F4, F8, AF4 in Figure 3) and 2 reference points (In the CMS/DRL noise cancellation configuration P3/P4 locations). It uses a sequential sampling rate of 2048 Hz, a bandwidth of 0.2 – 43Hz, digital notch filters (at 50Hz and 60Hz) and a dynamic range of 8400 μV(pp). The P300 evoked potential causes a 300ms delay after a relevant sensory stimulus.

The **Control Panel** then clears the noise and separates distinct and recognizable pattern actions such as "think push", "think pull", "think lift", "smile" and "Clench". Upon detecting on of the selected patterns that constitute a specific action, the control panel then triggers the (customized) Emokey Software.

Emokey Software translates the thought actions to physical keyboard keystrokes. In turn, keystrokes are detected by the MindReader Software which instigates navigational actions on the document reader.

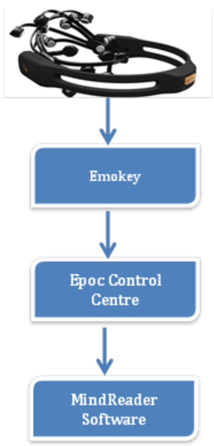


Figure 1. Key Components to Operate MindReader System

Our prototype software **MindReader** is written in C# through WinForms under the .NET framework. The specific release (Beta V.01) presented in the paper and used for the user testing comprises of a document reader that loads a series of documents that have been translated to images from PDFs. Although the MindReader code is not open source yet, we are plan to publish the source code in near future.

In this work, MindReader software produces a two page reading format (See Figure 2) for the user but can be adapted beforehand to a single page view. The software currently in its beta stage allows for user testing controls; namely, the investigator can imitate a "start task" trigger which will take readings such as location, navigation speed and user intent (actions performed). The software is also able to use simple key strokes or buttons to move between the pages but these are only visible as an addition for future work involving the integration of eye-tracking equipment with BCI devices. Users should be able to navigate forward and backward one page at a time, controlled by the Emotiv Epoc.

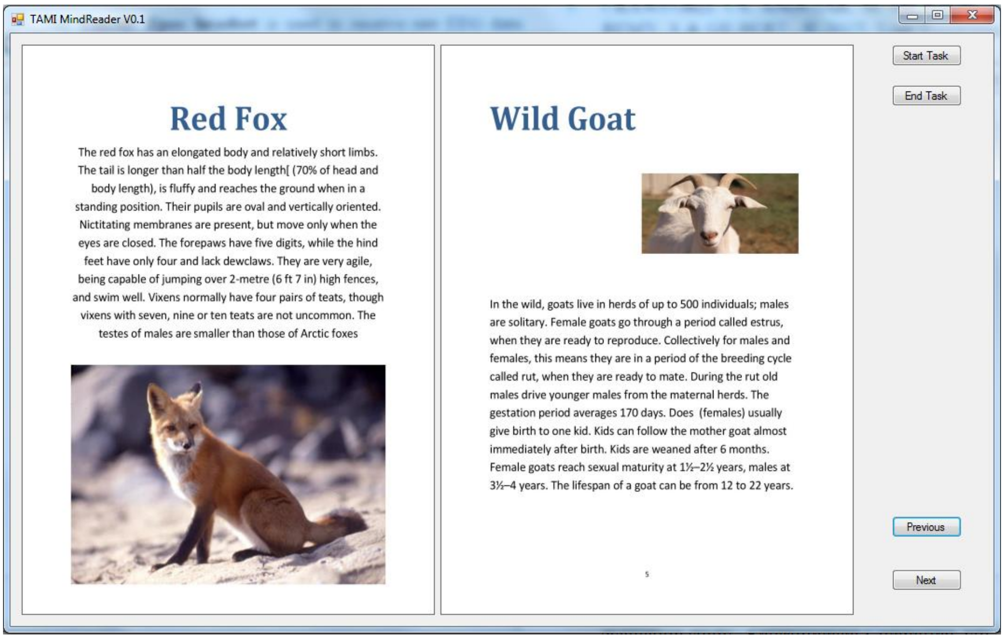


Figure 2. MindReader Beta Version 0.1

Code snippets of the navigating algorithm can be found below (C#):

```
// initialise timer and record at 100ms
aTimer.Elapsed += new ElapsedEventHandler(OnTimedEvent);
aTimer.Interval = 100;

// append all details of time to file when state changes
hour = DateTime.Now.Hour;
min = DateTime.Now.Minute;
sec = DateTime.Now.Second;
TimeSpan time = new TimeSpan(hour, min, sec);
File.AppendAllText(file_times, time.ToString());
File.AppendAllText(file_times, ",");

// append all details of location to file during all intervals
File.AppendAllText(file_pages, pageisat.ToString());
File.AppendAllText(file_pages, ",");

// change page state when EEG pattern indicates next page
if (e.KeyCode == Keys.R)
{
Next.PerformClick();
}
pageisat = pageisat + 1;
pictureBox1.Image = WindowsFormsApplication1.Properties.Resources.Page5;
pictureBox2.Image = WindowsFormsApplication1.Properties.Resources.Page6;
```

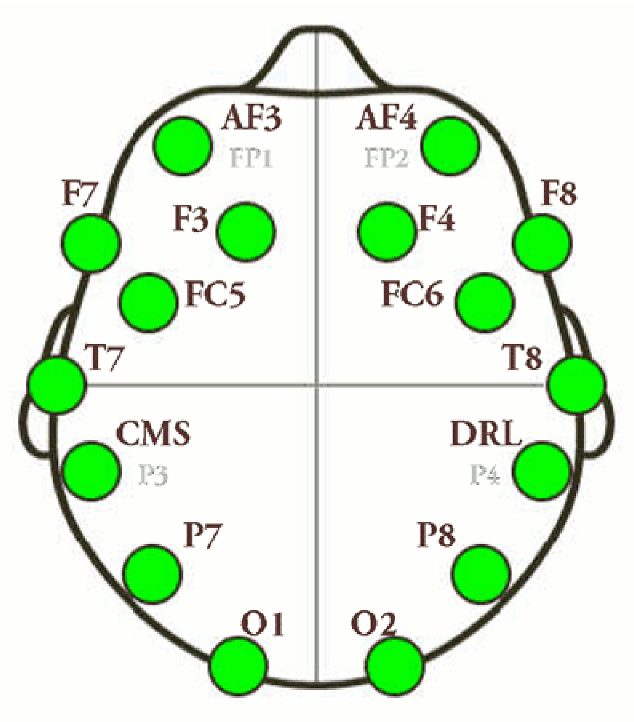


Figure 3. Emotiv Epoc Electrode placements from [20]. CMS and DRL are ground and work as reference point in our experiment.

3.2. Experiments

To test the prototype we chose 14 participants to take part in our study. 2 of the participants were asked to be pilot subjects to fine tune the testing variables such as the amount of saline solution needed on the BCI pads, time required per test and the sensitivity settings on all the software that needed to communicate.

The 12 main participants (5 female – 7 male) were given a short description of the experiment and each was given a choice of actions that they could choose from in order to calibrate the forward and backward actions. Specifically, participants could choose from Think Push, Think Pull, Lift, Clench and Smile. Once the participant had chosen a set of actions, they would then be calibrated to the specific individual, a process that took no more than 5 minutes per participant (See Figure 3).

'Signatures' classify user EEG input into mapped expressions and intentions. A default signature is known as the universal signature and is an average estimation of the predicted readings that any user would produce in terms of brain activity for a given action. For our calibration we rejected the universal signature in place for a per participant, trained signature. These are called baseline signatures. In order to create the baseline signatures performance metrics require the user to train the system by performing the desired action before it can be detected.

All 14 electrode placements were placed on the users' head with 2 noise cancelling points (See Figure 3 - CMS and DRL). Motor action thoughts were prevalent with readings elevated on the primary motor cortex and supplementary motor area during training. The Premotor cortex also spiked in activity during the training exercises. The algorithm used to capture each user's individual signature is internal to the custom software from the BCI headset and is beyond the scope of this study. In future we will refine the individual electrode readings to allow us to focus on specific electrode readings only and work towards our own universal signatures.

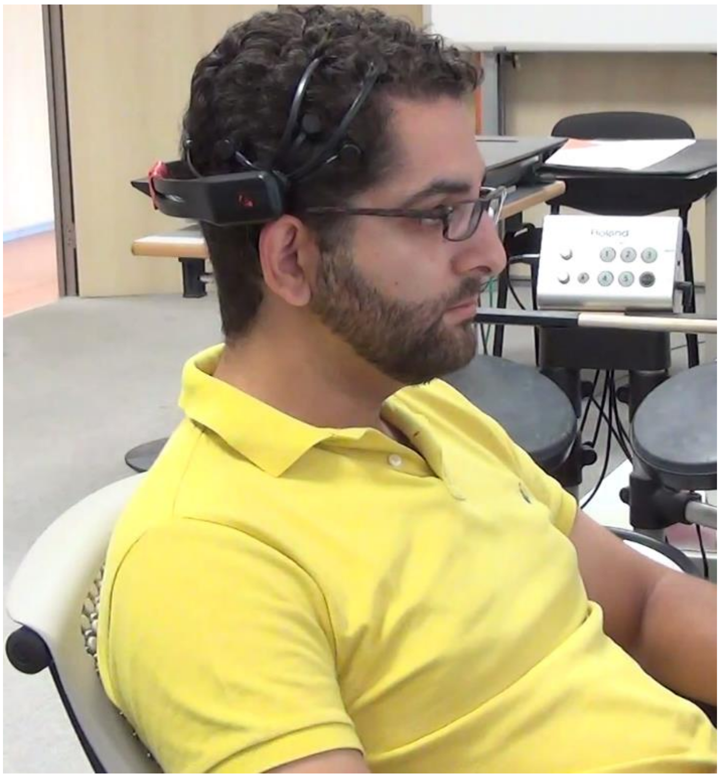


Figure 4. User Interacting with MindReader

Once the BCI connection was established and calibrated, our prototype software MindReader was loaded with a document containing 16 pages in a two page view (book style view) and the participants were then given a set of tasks to complete. These tasks were:

TASK 1 – Navigate to the Contents Page – this was page 1

TASK 2 – Navigate back to the beginning (page 0)

TASK 3 – Navigate to Page 6

TASK 4 - Navigate back to the beginning (page 0)

TASK 5 – Navigate to Page 12

TASK 6 - Navigate back to the beginning (page 0)

TASK 7 – Navigate to the last Page

TASK 8 - Navigate back to the beginning (page 0)

TASK 9 – Answer the question: How many babies do female goats give birth to? (the answer is on page 2)

TASK 10 – Feel free to browse the magazine. (For the qualitative feedback)

No think–aloud comments were permitted. After the tasks a semi-structured interview was conducted for qualitative feedback.

4. Results

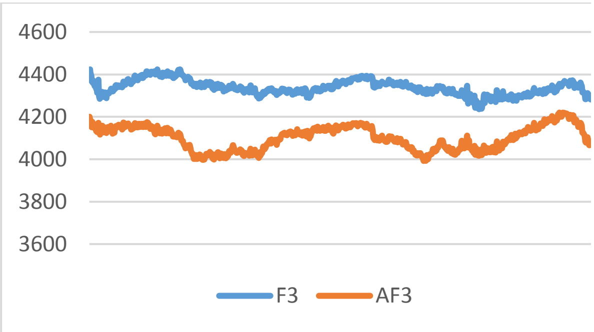
To test the validity of our work, raw data samples of EEG activity were recorded. It was used to establish a baseline of the actions that the users were able to select EEG level in terms of a specific action their chosen. The users were recorded in a 'neutral state' and then their EEG activity was recorded with five options: Smile, Clench, Pull, Push and Lift. Afterwards a statistical t-test was used to identify elevation in EEG between neutral states and action states. Most of the actions produced statistically significant changes in the readings from the majority of the electrodes (See Figure 5).

	AF3	F7	F3	FC5	T7	P7	O1	O2	P8	T8	FC6	F4	F8	AF4
Smile	< 0.01	< 0.01	< 0.01	< 0.01	< 0.01	< 0.01	< 0.01	< 0.01	**0.343301**	< 0.01	< 0.01	< 0.01	< 0.01	< 0.01
Clench	**0.89134**	< 0.01	< 0.01	< 0.01	< 0.01	< 0.01	< 0.01	< 0.01	< 0.01	< 0.01	< 0.01	< 0.01	< 0.01	< 0.01
Pull	< 0.01	< 0.01	< 0.01	< 0.01	**0.392256**	< 0.01	< 0.01	< 0.01	< 0.01	< 0.01	< 0.01	< 0.01	< 0.01	< 0.01
Push	< 0.01	< 0.01	< 0.01	< 0.01	< 0.01	< 0.01	< 0.01	< 0.01	**0.343301**	< 0.01	< 0.01	< 0.01	< 0.01	< 0.01
Lift	**0.654926**	< 0.01	< 0.01	< 0.01	< 0.01	< 0.01	< 0.01	< 0.01	< 0.01	< 0.01	< 0.01	< 0.01	< 0.01	< 0.01

Figure 5: T-Test of neutral state verses actions states of electrode EEG readings ($p < 0.01$ $n = 1200$)

We can report on the high level of noise that occurs from the different regions of the EEG activity but can verify that the F3 and F4 regions associated mostly with motor actions produced also significant differences which can give evidence towards the successful use of motor intentions EEG to control the virtual actions of our software [18].

We also checked specifically for EMG contamination [19] from testing the active readings between the F3/F4 and AF3/AF4 electrodes during active thoughts by the participants. An example can be seen in Figure 6 - Left. We wanted to check for elevation of the F3/F4 electrodes closer to the motor cortex. The results can be seen in Figure 6 - Right. All the tests were statistically significant with a t-test revealing $p < 0.01$ ($n = 1200$). All the results were statistically significant to the 0.01 level with 1200 samples for all actions.



	F3 - AF3	F4 - AF4
Smile	< 0.01	< 0.01
Clench	< 0.01	< 0.01
Pull	< 0.01	< 0.01
Push	< 0.01	< 0.01
Lift	< 0.01	< 0.01

Figure 6: (left) Readings (in µV microVolts) of an active state of the user thinking 'Lift' of the F3 and AF3 electrodes. (Right) statistical difference in F3/F4 and AF3/AF4 electrodes during action thoughts $P < 0.01$, $n = 1200$.

In this section we present the raw data and make observations based on the performance of the participants via visual inspection. Tasks 1,2,5,6,7 and 8 are reported on. The remaining two tasks (3 and 4) do not produce data that adds to the findings and therefore were not included in the results. Figure 7 presents an overview of the tasks and the time taken, as well as the errors that were made in taking the tasks.

Task	Number Error Free	Number Errors	Minimum Time (seconds)	Maximum Time(seconds)
1	9	1	2	8
2	7	5	2	7
5	8	9	8	29

6	8	4	7	41
7	8	18	8	40
8	11	1	8	50

Figure 7. Data Overview (including time and errors)

Task 1

Figure 8 shows the results obtained when the participants were asked to navigate from the first to the next page. Clearly there are great variations in the times taken, the minimum time being 2 seconds, and the maximum 8 seconds. Only one participant made the error of moving onto the second page, the others navigated to page 1 directly.

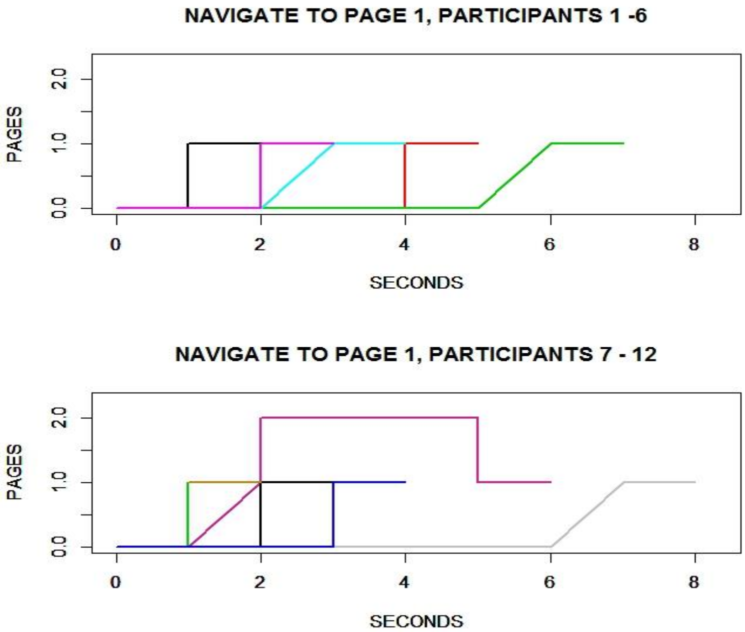


Figure 8. Task One Results

Task 2

Figure 9 shows the results obtained when the participants were asked to navigate from the second page to the start. Again there are great variations in the times taken, the minimum time being 2 seconds, and the maximum 7 seconds. Seven of the ten participants completed the task without error. Two participants made 2 errors each. The remaining participant did not attempt the task.

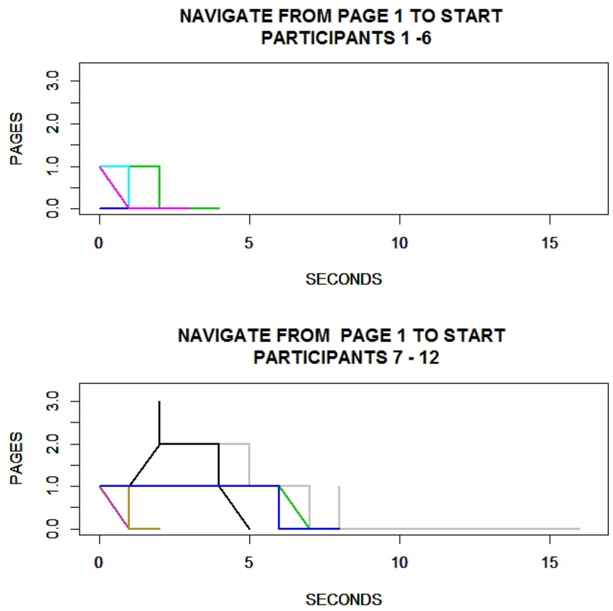


Figure 9. Task 2 Results

Task 5

Figure 10 illustrates the patterns taken by the twelve participants when asked to navigate to page six. Clearly there is great diversity, 8 of the 12 participants navigated to page 6 without error, but the time taken to do this varied from 8 to 29 seconds. The number of errors made by the other 4 participants varied from 1 to 5. There is no evidence of a relationship between the number of errors made and the time taken to complete the task, and it would appear that errors are equally likely to occur at any stage of the task.

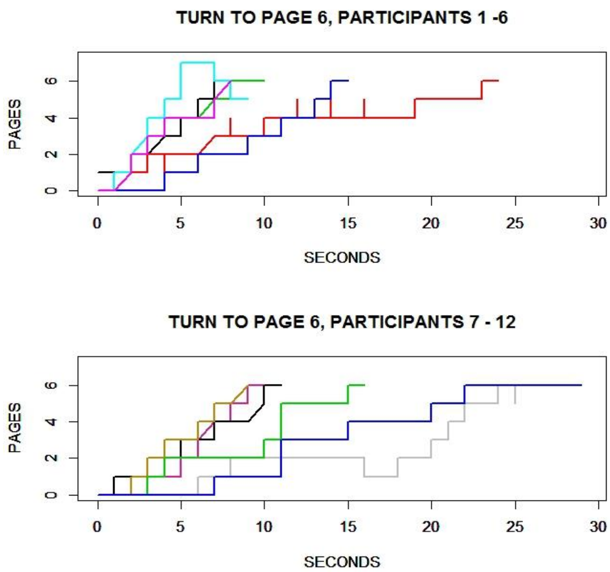


Figure 10. Task 5 Results

Task 6

Figure 11 illustrates the patterns taken by the twelve participants when asked to navigate from page six back to the start. Again there is great diversity. 8 of the 12 participants sucsessfully navigated from page 6 to the start without error, but the time taken to do this varied from 7 to 41 seconds, the other 4 participants each made exactly one error. Times varied between 9 and 41 seconds, and there appears to be little or no relationship between errors being made and completion time.

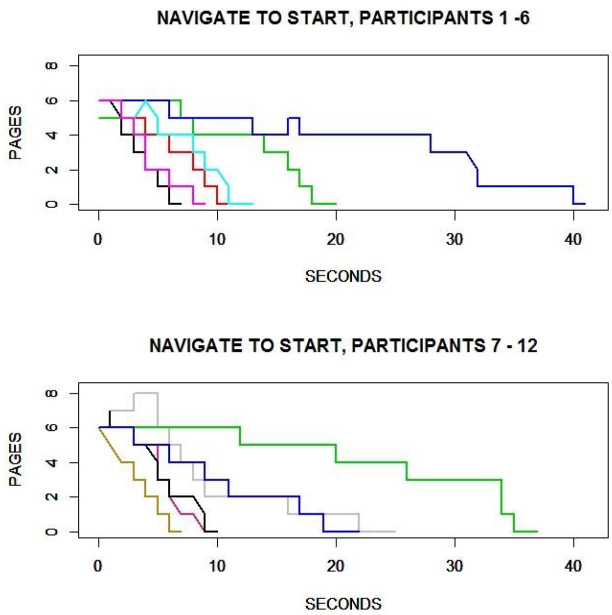


Figure 11**.** Task 6 Results

Task 7

Figure 12 illustrates the patterns taken by the twelve participants when they were asked to navigate from the start to the end (page 8). Unsurprisingly, the results are similar to those of task 5, where participants had to navigate to page 6. Eight of the twelve participants navigated to page 8 without error. One participant failed to commence the task and the other three made 2, 6 and 9 errors. Completion times, (excluding the person who failed to start) varied between 8 and 40 seconds.

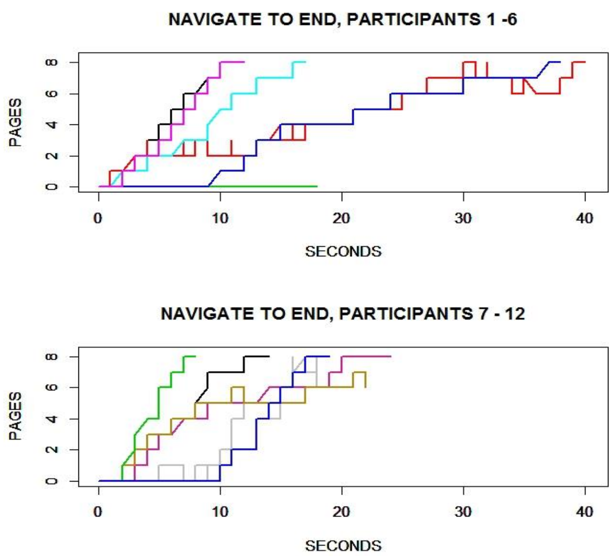


Figure 12**.** Task 7 Results

Task 8

Figure 13 illustrates the patterns obtained when the participants were asked to navigate back to the start from the end. One participant (represented by the green line of the top diagram) appears not to have properly attempted the task. All of the remaining participants completed the task without error, in times varying from 8 seconds to 50 seconds.

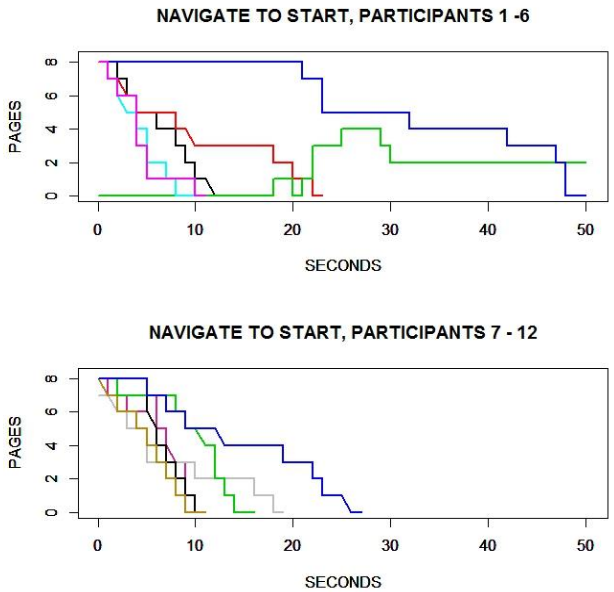


Figure 13. Task 8 Results

Task 9

In this task, participants were asked to `` Answer the question: How many babies do female goats give birth to?'' The answer was on page 2. It would appear that there was confusion about the nature of this task as few participants navigated to page two and stopped (See Figure 12).

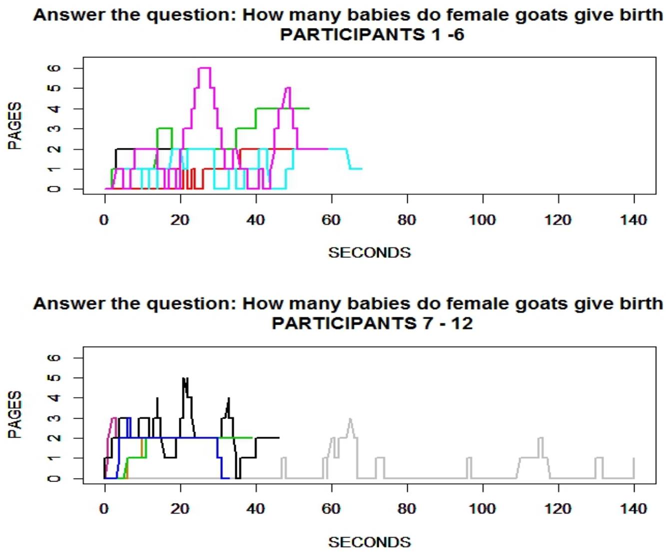


Figure 14. Task 9 Results

5. Automata Theory Based Evaluation Model

In addition to testing the validity of our document reader prototype system, we also presented a framework to analyse user actions. Our aim is to describe a universal framework which can be modified and applied to a variety of situations. We introduce

a collection of tools and techniques based on Automata Theory, an area on the boundary of theoretical computer science and mathematics. Automata Theory is often used to model computation, but in this work we demonstrate how it can be used to model the human behavior [21]. A finite automaton can be pictured by a directed graph called a state transition diagram with nodes representing states and arrows labeled by letters of the alphabet.

We use states Q= {0,1,2,3,4,5,6} corresponding to the pages. If a participant is at page q , his/her movement can either to page q+1 via transition R or to page q-1 via transition L. The initial state in the model is state *s* which does not correspond to a page in the document. It serves as a start state only. Each task begins by moving via an empty transition ε from state *s* to the required start page. Then the task is accomplished by a sequence of transitions from the start state to the accepting state. In the initial model (See Figure 15) it is possible to make an empty transition to every state and ever state is classified as an accepting state.

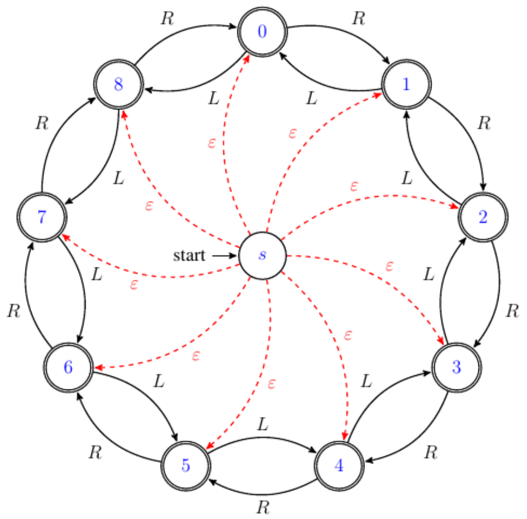


Figure 15**.** Total Transition Model

To carry out a task we restrict the possibilities for empty transitions and we restrict the set of accepting states (See Figure 16).

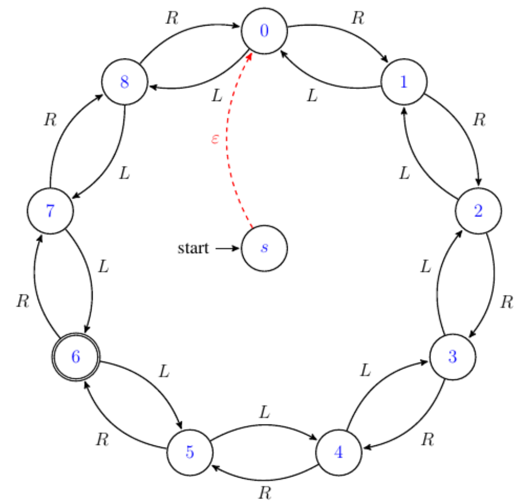


Figure 16. Single Transition Possibility Model

There is only one empty transition available; from state s to state 0. The task terminates successfully when the participant navigates to page 6. Thus the only accepting state is now state 6. The restricted model from the overall model above for tasks 1,2,5,6,7 and 8 are shown in Figure 17.

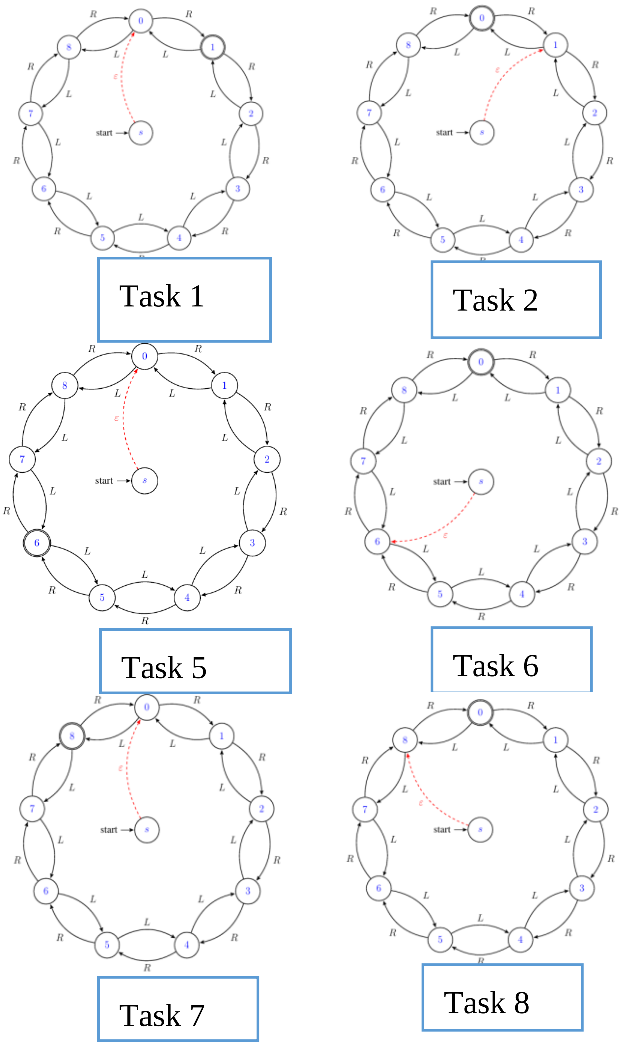


Figure 17. Restricted Model Variations Based on the Assigned Tasks

A notion of optimality exists in the above tasks. For example, task 6 requires the user to navigate from page 6 to page 0. The optimal solution here is to perform the sequence of transitions LLLLLL. In task 7 the optimal sequence of transitions is RRRRRRRR. The variety if terms of sequences of transitions used by the participants is summarized in the graphs in the previous Section.

6. Conclusions and Future Work

We described the prototype of document reader to identify the efficacy in using affordable brain computer interfaces to control elementary functions. This work included with a) creating a prototype document reader which could be controlled with affordable commercial BCI equipment b) testing with 12 participants to identify the successful use of the software in order to improve cognitive usability.

Our experiment results demonstrate that participants can navigate through the pages of a document reader in order, although minimal calibration is needed and errors were present (such as overshooting pages). We have also modelled the user behavior for further identifying software bottlenecks and transfer the finding into other software with navigation capabilities.

We present our results as a pilot testing. The main aim of the study was to show reasonable evidence of the efficacy of using affordable BCI equipment to control basic actions of a document reader. The number of participants (12) means that there is limited scope in this study for in depth comparisons. In future, an experiment with a much larger participants will be conducted. Specifically the future work will include with (a) reducing errors through improving the software algorithms and by testing further hardware variations; (b) answering behavioural and interactivity questions such as "Is getting further in the magazine of proportional effort to getting to an earlier page?" The sequential nature of the experiment means that it is likely that participants "improved" as they progressed from task to task. These learning effects can be minimized by randomizing the tasks in future experiments. "Do different tasks seem to give more difficulties than others and why?" This can be tackled by changes test variables such as assigning longer tasks.

Furthermore, we will also introduce our improved document reader assistive system to quadraplegic patients. We also plan to include further compliments to the setup that will give further autonomy and freedom to users, such as pairing the BCI with an eye-tracker for gaze / fixation recognition. Further software, such as internet browsers are also being developed based on the same principles.

Acknowledgments: ANON

Author Contributions: ANON

Conflicts of Interest: ANON

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