UNIVERSIDADE FEDERAL DE LAVRAS

LUCAS FIORINI BRAGA

CONTROLE DE AMBIENTES INTELIGENTES POR COMANDOS MENTAIS USANDO EEG

LAVRAS – MG

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Monografia apresentada à Universidade Federal de Lavras, como parte das exigências do curso de Ciência da Computação, para a obtenção do título de Bacharel.

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Dedico este trabalho aos meus queridos pais Roberto Alves Braga Júnior e Vanessa Mesquita Braga, meus avós Délcio Mesquita, Celma Maria Mesquita, Roberto Alves Braga e Dorothy Aparecida de Souza Braga.

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RESUMO

O último Censo Brasileiro revelou que o número de pessoas com deficiência física no Brasil em 2010 girava em torno de 6,7 % da população. A interação cérebro-computador com sensores de eletroencefalograma tem mostrado bom potencial para permitir a interação de pessoas com deficiências que limitam seus movimentos e capacidade de controlar dispositivos interativos. Este estudo teve como foco um estudo exploratório para investigar a usabilidade de um equipamento baseado no reconhecimento de abstrações mentais, usando um eletroencefalograma sem fio para controlar um ambiente doméstico inteligente. As avaliações envolveram 30 estudantes brasileiros sem deficiência física ou intelectual diagnosticada, como um primeiro estudo para investigar a usabilidade da abordagem, precedendo testes futuros com pessoas com deficiência física. Este estudo teve como objetivo analisar a usabilidade de uma abordagem em que comandos mentais manipulam um bloco virtual como proxy para o controle de eletrodomésticos. O método incluiu a análise de problemas de usabilidade, precisão, dificuldade da tarefa, satisfação e reações emocionais durante as tarefas. Os participantes do estudo mostraram um alto nível de aceitação em relação à dificuldade e precisão. O estudo também revelou várias limitações do hardware, sendo sua especificidade de usuários ótimos, como pessoas com menos ou mais cabelos finos e a delicadeza dos eletrodos. Com os resultados, pudemos identificar como grande parte das variáveis interfere nas métricas e o impacto positivo na comunidade de acessibilidade.

Palavras-chave: EEG; Eletroencefalografia; Casas Inteligentes; Acessibilidade; Usabilidade

Article

Usage of EEG for mental commands at home assisted environments

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Abstract: Brain-computer interaction with electroencephalogram sensors has shown good potential to enable interaction for people with disabilities that limit their movements and ability to control interactive devices. This study focused on an exploratory research to investigate the usability of an application based on recognition of mental abstractions, using a wireless electroencephalogram to control a smart home environment. Evaluations involved 30 Brazilian students with no physical disabilities diagnosed, as a first study to investigate the usability of the approach, preceding future tests with people with physical disabilities. This study aimed to analyse the usability of an approach in which mental commands manipulated a virtual block as a proxy to control house appliances. The method included analysing usability problems, accuracy, task difficulty, satisfaction and emotional reactions during the tasks. Study participants showed a high acceptance level concerning difficulty and precision. The study also revealed several limitations of the hardware, being its specificity of optimal users like people with less or thinner hair and the delicacy of the electrodes. With the results, we were able to identify how most of the variables interfere in the metrics and the positive impact on the accessibility community.

Keywords: EEG; Smart Home; Assistive Technology; Usability; Electroencephalography;

1. Introduction

Advances in Internet of things (IoT) technologies have boosted the availability of technological solutions to support activities in people's daily lives. Among these technologies are the Ambient Assisted Living (AAL) systems and Smart Homes [2]. Smart homes seek to automate everyday tasks to provide facilities for domestic activities [11]. Among the tasks that this technology can perform is the control with more ease of equipment, features, and appliances present in the environment.

AAL systems seek to support older people and people with physical disabilities in their daily routine. Its main objective is to promote autonomy and security in these people's daily lives in the domestic environment [7]. These systems are often composed of several sensors to monitor users present in the environment and offer medical care remotely [16].

For the control of smart homes and AAL systems, there are various modes of interaction in the area [21]. The use of voice commands and intelligent sensors allow the user to interact with the system. This diversity of interaction modes enable different types of users to take advantage of smart home technologies, including people with different kinds of disability. However, the main focus is disabilities such as quadriplegics, paraplegics or people with similar injuries. For example, this group of people may find it more suitable to use interactions by voice commands to perform tasks in the home environment more efficiently (such as turning on lights, turning on appliances, among others) [5]. Thus, the use of AAL systems proves to impact accessibility, autonomy, and independence significantly for people with different levels of limitations [25]. These characteristics are essential for the quality of life of these users [5].

Even though these technologies provide significant assistance, people with motor disabilities may have many more complicated challenges dealing with how they interact with their home environment. For example, in more severe cases, people who are paraplegic or quadriplegic may need different interaction mechanisms, such as eye-tracking[22] and brain-computer interaction [15].

Mental commands as data entry for systems are a fundamental approach to allow interaction. The use of this mode of interaction is very present in assistive technologies for people with motor disabilities. A good example is the research of wheelchairs controlled by mental commands [13, 20, 10]. By mapping brain signals, it is possible to assign an action to be performed by the equipment/system/technology in question.

The application of mental commands for the control of smart homes by people with motor disabilities is another solution to give autonomy and independence to these people in the home environment.

This study aimed to analyze the usability of an approach in which mental commands manipulated a virtual block as a proxy to control house appliances. The method included analyzing usability problems, accuracy, task difficulty, satisfaction and emotional reactions during the tasks. As the versatility of electroencephalography is paired with many doubts about being intrusive or invasive, this study brings metrics obtained though assessments and detailed video analysis which reinforces not only the technical issues found but also the usability perceived by the users.

The remainder of this paper is organized as follows. Section 2 presents the main concepts related to Brain-Computer Interaction, Smart homes and Ambient Assisted Living and related work. Section 3 presents the main methodological aspects. Section 4 presents the results obtained, which are discussed in Section 5. Finally, Section 6 presents conclusions and future work.

2. Theoretical Background

2.1. Brain-Computer Interaction (BCI)

Brain-computer interfaces (BCI) referees to a technology aimed mainly to aid the communication and independence for neuromuscular impairments via the electrical potential information from the brain[28]. This potential that is further on translated to usable information, is acquired at the cortex of the brain, the closest layer from the scalp. BCI have had significant growth in research interest. This type of interface corresponds to systems that incorporate algorithms that translate input from users into commands to control devices [28]. Electroencephalography has been widely used to enable BCI, and it is evolving with more sophisticated models, causing it to be widely used across medicine.

As described by Lin *et al.* [14], (EEG) equipment is a powerful tool for capturing and understanding the multiple variations of cognitive states of its users without the need to maintain the head in a fixed state, being able to give researchers valuable data like feelings, alertness and attention [8]. That is mainly due to its non-invasive and non-intrusive properties provided by attributes like the lack of wires for using a battery, lightweight, and facility to wear. This brain-imaging equipment functions by placing electrodes over some strategic regions of the scalp, calculating the electrical potential generated by these areas. A measurement of an electrical pulse derived from a dense mass of neurons can only measure the information from this area and not from individual neurons. This process is also exposed by the interference caused by the different conductivity of surrounding tissues between the neurons and the electrode [17]. Some studies like [29] and [24] work on signal processing algorithms to predict and classify the patterns.

The signal quality and accuracy measured when there is a change in mental state, response to internal or external stimuli and directed attention can be attenuated not only by physical barriers. For example, eyes opened or closed can lead to different values caused by visual input [3]. Personal traits from each individual and the current state during its use (level of attention and amount of external interference) can make the task of providing a reliable solution even more delicate. So the biggest challenge, according to Mihajlovi *et al.* [17], is finding a solution smart enough that provide a superior signal quality and, at the same time, a comfortable and convenient for the user.

This technology can be found more consistently in hospitals for predicting epilepsy occurrence [18] and even understanding better the brain recovery after traumas or procedures. This equipment is also found in clinics that perform exams such as polysomnography. However, the process of installing EEG equipment may be cumbersome for users. They need to go through a skin-clearing which involves sometimes abrading it, followed by gel application used for sticking the electrodes and also increases the current flow between the equipment and the user's head [27]. All these procedures make the process intolerable and uncomfortable for the user, leading to biased and noisy results, bearing the need for equipment with better overall usability.

2.2. Smart homes and Ambient Assisted Living

With a low cost and a wide variety of ways to control an intelligent environment, smart houses are have attracted increased research attention. Some authors may describe it as a house that can capture information, control its appliances and also be flexible enough to fit several ways of controlling it[2]. What makes it possible is a noticeable growth on the Internet of Things (IoT) field. It allows a cost-effective way to exchange information and interconnect equipment to share information and to work simultaneously. It is more feasible to assemble an Ambient Assisted Living (AAL) that suits multiple disabilities in this given context.

Those types of Smart Homes can offer, with particular ease and precision, ways to control it that covers many physical impairments. For example, Bempong [12] discusses ways to modify a smart ambient in ways that it notifies deaf and hard-of-hearing users when it produces a sound. Oliveira *et al.* [19] in other hand produced, by screen-reading technology, a method that aid people with vision-related disability to be able to control its environment. Another inclusive mechanism for special needs would be electroencephalography-based control. This one can support serious motor disability users to be more independent when controlling their surroundings, such as interacting with the television and turning on or off other home appliances.

2.3. Related Work

The usage of EEG equipment can bring a layer of ease when it comes to task automation for complex mechanical disabilities. Architectures that involve EEG signal processing for this purpose are more widely available, with the widespread use of IoT technology. Partha *et al.* [24] used the Emotiv EPOC+ to obtain brain signals and try to use predictive models to extract information from them. This study tries to use this method mentioned above to turn on and off a light bulb.

The same type of study was conducted by Wenchang[29] who also worked at the back-end part acquiring and processing data with artificial intelligence methods from EEG signals. Moreover, when it comes to home automation targeting disabled people, the studies focus on approaches that still require the user to leave its physiological state to interact with it. At this point, studies like the ones performed at [14] or [15] target the house interaction with the lowest effort possible mainly because of the designated audience composed of elderly people or severely disabled people. In the study conducted by Luo *et al.* [15], the EEG chosen was the same as this study, the Emotiv EPOC. Differently from the studies that deal with back-end signal processing. Here was opted to use the processing system developed by Emotiv's company themselves and translated the acquired signals to the house commands. Another study that addressed the life quality and greater independence for people with severe physical problems using BCI was Ullah [26]. The goal was to build a single-channel EEG with self-made electrodes and produce a tool for communication with no need for physical interaction. Aiming at low costs and easy setup, the software aid the communication for those targets via SMS and got an 87% rate of accurate typing.

Other usages of BCI can be contemplated by Rebsamen [23] and Craig [6], who developed a mental command-based system to manipulate a wheelchair. Another example can be the usage of EPOC embedded gyroscope to control a robotic arm proposed by [1]

Partha *et al.* [24] proposed an in-depth study on the BCI field for home automation while focusing on testing a custom-made machine learning model described as a combination between Long Short-Term Memory (LSTM) and classical Random Forest Classifier (RFC), and also discuss the data retrieved from different areas of the brain. Using a commercial solution, the EPOC+ was the EEG solution to gather data for future usage into the classification methods. Hereafter, the testing procedure was conducted in two phases using eighteen healthy users with 20 to 25 years old with no records informed about the existence of prior knowledge about EEG systems. The final intention was to test the accuracy of the classification method aforementioned in acting on turning on and off a lamp.

The test setup was conducted under the following circumstances, a well-lit and quiet room where the instructions were given through audio and video from a computer there placed. The first phase consisted of showing an image of a glowing bulb and asking the subject to give mental commands for 14 seconds to turn it off while limiting the body movement and maintaining the eyes closed. After that, in the second phase, the user maintained a relaxed state of mind with the equipment still recording for 15 seconds to represent the *no-command* state, then repeated the training for turning on the bulb. With the data acquired, it went through denoising, digital filter, cleaning, and a parameter-based pre-processing to be feed into the hybrid model proposed. With no possibility of interaction with the image and any user feedback presented, it was not possible to track the emotions and the user-perceived precision.

Finally, to calculate its efficiency, no questionnaires focused on user experience. Therefore, there were no data on difficulty or emotional reactions. Instead, the data acquired was used to train, validate and test the model accuracy. The proposed model performed better than a Support Vector Machine used for comparison reasons, and, using the optimal electrode setup, its accuracy was 68.36%. After all, the limitations concentrated on discovering more detailed information about the behavior of some regions of the brain and a better method of gathering features with more precision.

Another solution for smart home automation with BCI was designed by Luo et al. [15]. Here, the equipment was the same as the previous one, Emotiv EPOC+ and there was also developed an Android system to enhance the accuracy of control. Unlike many previous papers mentioned, in this study, the signal was not processed in a custom way. The data acquired from the users was processed by the Emotiv software itself and sent the results to a control unit. After passing the control unit, the micro-controller unit (MCU) coordinates environmental objects such as TV, air-conditioning, curtain, door, and light. The study counted with five users being two of them already familiarized with the technology, average age of 21 years old, two females, and no further information on special physical needs. The environment had no declared condition pattern for the tests and no specification on how the users performed the training. The tests involved six actions, turning on and off air-conditioning, light and opening and closing curtain, and for each one, the recording occurred five times. The accuracy metric was related to the Up command, which is to move the block upwards at the Emotiv Control Panel software. Therefore, the success rate was the number of successful attempts to control a subject divided by the total attempts. No information about the user experience was obtained, neither the overall emotional reactions related to the actions performed. There were two rounds of tests, the first one without the Android software to control the command stability and the second one. The first one got an average accuracy of 29.6%, being the lowest 13.33% and the highest 33.33%. Now with the Android software, the results raised to 84%. Barriers encountered by this study were the lack of stability of the EEG signals, transmission delay, chock in communication among some parts, and the memory overflow at the central control system.

Like aforementioned, the studies covers mainly the technical aspect related to EEG usage and application. Also, at some of them, the main focus was to identify an accurate model to classify the information gathered by EEG. In other hand, other researches focused on building cheap equipment or to integrate it into other solutions instead of home usage. But, the main problems when, it comes to EEG solutions, are the usability aspects. This is why this study gave a lot of attention for this part, which as missing in the literature and is so important.

3. Method

3.1. Study design

The study aimed to perform a usability evaluation of a smart home resource control prototype with control by mental commands and facial movements, evaluating the reactions and user experience with the commands.

For the usability evaluation, an intra-participant design was chosen so that all participants will be exposed to the test conditions with a set of mental commands and facial movements for a series of actions to be carried out on the smart home prototype, operating a TV and a lighting system. The movements and commands chosen were defined through a previous analysis whose objective was to select those that require less effort.

After each action, participants assigned ratings for aspects measured by the Self Assessment Manikin - SAM [4], with variables of satisfaction, motivation, and feeling of control. Also, participants were asked to complete a questionnaire on the use of technologies and demographic data.

Before each evaluation, users were informed about the research objective, in addition to the privacy policies for the use of data and the analysis and publication of results.

Participants were completely voluntary and could withdraw participation at any time during the evaluations. The university's Research Ethics Committee approved the usability assessment protocol with id: CAAE 66819517.3.0000.5148. All participants signed a consent form authorizing the collection and use of data.

3.2. Application evaluated

To develop an interface between the Smart Environment and the electroencephalogram, the EEG tool was first chosen. The Emotiv EPOC+ is a model that counts on fourteen channels for complete brain sensing. The fourteen channels used to retrieve data using the sequential sampling method are AF3, F7, F3, FC5, T7, P7, O1, O2, P8, T8, FC6, F4, F8, AF4, as shown in Figure 1. It uses a saline-based compound to connect the electrode over the scalp better, enhancing the signal retrieved by the electrical potential at these areas. This model connects via Bluetooth, which increases mobility and supports the non-invasive and non-intrusive principles. Another favorable feature brought by this model is the ease to install it over the user's head due to a mild amount of connectors and lack of wires, making the setup faster and less meddling.

The software that comes with the drivers and enables several interfaces to interact with its functionalities, called Emotiv Xavier Control Panel v3.5.1, can help the user identify if the electrodes are correctly positioned and working appropriately. After the setup, which also includes a user profile that saves training progress, the used areas for this study were only the Facial Expression and the Mental Command sections. Other functions like Performance Metrics that measure specific emotions and Inertial Sensors that detect head movements were not used in this study.

With the EEG ready, there was a code integration between two sources. The first one, no longer available, was the EPOC+ developer Java code made available by Emotiv developers. The second code part was obtained by previous studies on Assistive Homes found at [19]. As described in Figure 2, the EPOC+ Figure 2 (3) was connected via Bluetooth with the computer Figure 2 (4) was the application caught the information received by this equipment, translated that mental command input to the mapped action associated with it and sent it over an MQTT(Message Queuing Telemetry Transport) protocol. Once the server subscribed to that topic, a micro-controller like Arduino or Raspberry Pi Figure 2 (8) would receive the information and translate it to events at the environment connected to it, for example, turn on or off the TV Figure 2 (9).

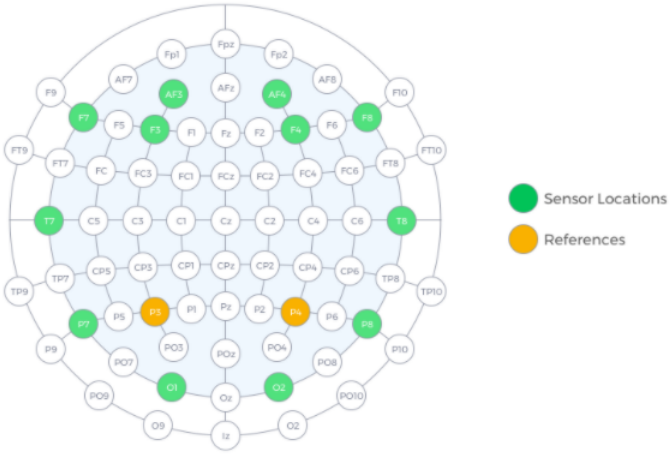

Figure 1. Emotiv EPOC+ connection points [9]

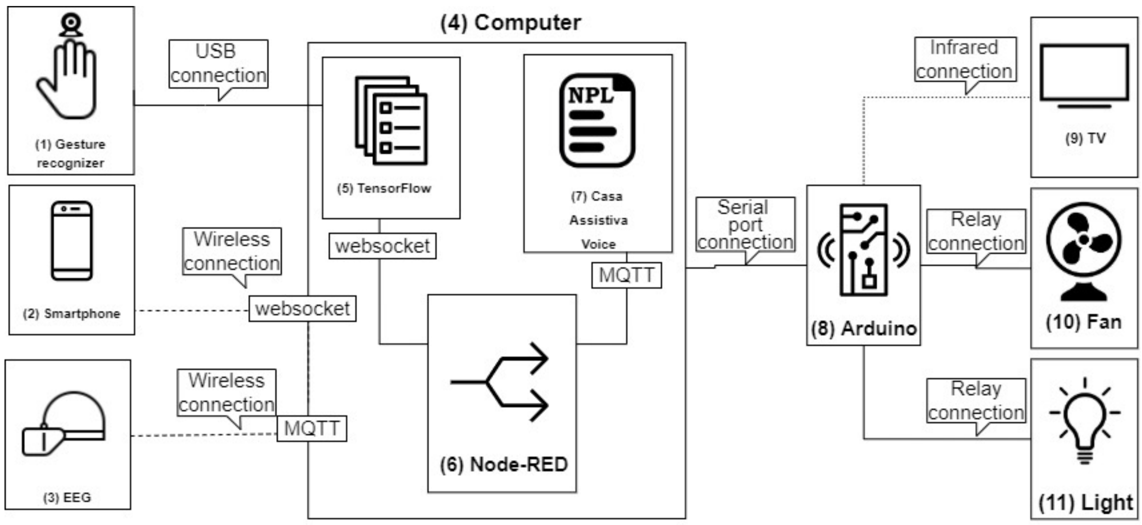

Figure 2. Smart House Architecture (OLIVEIRA 2020)

The possible signals received from the electroencephalography equipment were the PUSH, LIFT, and SMILE. The first one was a task based on pushing a virtual block to the end of the scenario Figure 3. It was translated into a turning the TV command Table 1. The second was relatively the same as the first one, but the command was lifting the block, which was translated to changing the TV's channel. Finally, the third captured the smile facial expression made by the user. This command would represent turning off the TV.

Command	Code	Action
Smile	T1	Turn TV Off
Lift	T2	Change TV Channel
Push	T3	Turn TV On

Table 1. Mental command mapping

The choice of translating those signals from mental commands to actual actions in the smart environment was to mitigate the complexity of thinking about such abstract commands. Turning on television is a simple task, but it is not as easy to materialize its action mentally as pushing a virtual block. This approach saved time during the testing, which is a significant matter for performing a less invasive and tiring process to the user, and helped improve the overall accuracy of the tasks by making them think only about the block in front of them.

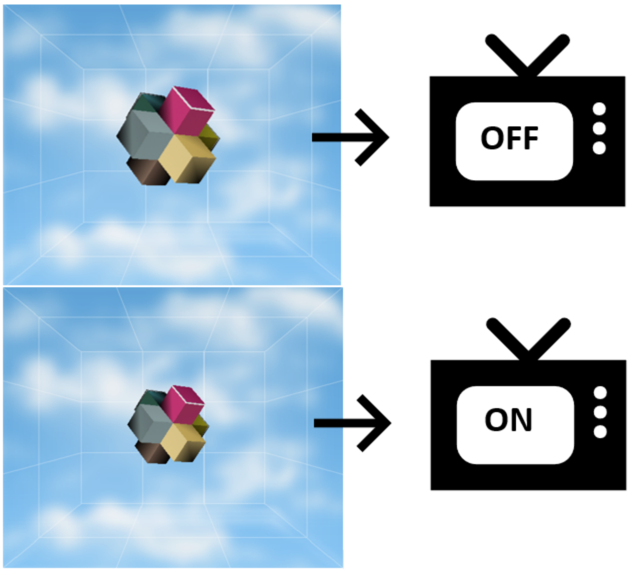

Figure 3. Emotiv Xavier 3.5.1 mapping to assistive home command

3.3. Evaluation Procedures

The procedure started by explaining to the user the primary motivation of the study and how the equipment works. Further on, the test moderator explained the privacy policies for using their image only by the researchers and the possibility of giving up at any given time due to excessive discomfort. After setting the system up and ready to start, the user was asked to follow the Think Aloud protocol during the whole experiment. Therefore, it would enable the researchers to re-watch the tests and comprehend in-depth details that could not be noticed first. That step also improves the ability to understand the cognitive process used by the users. Meanwhile, the video was also recorded to identify facial expressions that could lead to discomfort, excitement, confusion, or other traits of feelings that could emerge. After those statements were clear, the main focus was to clarify how the test would be conducted before it got started. This way, there would be no interference on the recording.

After the setup and preliminary explanations, the user was asked to focus as much as possible on a neutral mental state where he/she was supposed to think about nothing or to focus on a certain spot to prevent any sort of distraction for thirty seconds. At this moment, the participants often tended to do it with their eyes closed, which showed a significant increase in the precision of this type of command. Afterwards, three more neutral state training exercises were performed to increase the accuracy captured by the equipment. The moderator made it clear that at these, they were supposed to perform the same focus routine as they performed at the thirty seconds one to maintain the consistency. When the neutral training was over, the same was executed with the other two actions. One of them was to concentrate on lifting a block that appeared on the screen for seven seconds and the other on pushing that block forward. Both of them needed at least four iterations to achieve a significant accuracy (above seventy per cent).

The actions performed were guided by the software, where the block moved, so the user could better understand how it should move and give them better confidence. Therefore, after all, training steps were finished, the system started to run, and meanwhile, he was asked to stay in a neutral state and as soon as the tester asked to perform one of the actions previously seen, the software should capture it and translate to one of the house tasks such as turn on the TV for the mental command push and next channel for the lift action.

Tests aimed at evaluating mental commands and one command based on facial expressions to turn off the TV in the assistive environment. In this case, the expression was the smile. For this phase, similar to the previous one, a neutral facial expression was captured for thirty seconds and three more times for seven seconds, Figure 4. Later on, the smile expression was captured at least three times to get the desired precision to be able to go on to the test on the actual smart house.

Finally, the evaluation of each task also had a score assigned by participants from one to nine to rate their satisfaction, motivation, and feeling of control. Before answering the questions, the moderator explained that satisfaction was supposed to be evaluated considering how challenging the tasks were and how complicated it was to understand. For motivation, participants should also consider the mental overload throughout the test, and a feeling of control was referred to as the perceived accuracy.

Figure 4. User performing neutral facial expression training

3.4. Participants

The study recruited participants who were undergraduate university students from any course with no intellectual or physical disabilities, considering that the study was a pilot evaluation to assess the mental commands' usability before the actual evaluation with disabled users. The metrics obtained would be less likely to have any noise derived from these conditions and represent more precisely the conditions observed from the equipment.

3.5. Data Analysis

The analysis involved a content analysis, which involved watching the videos produced to extract details of the sessions, including usability problems and emotional reactions. Among those details, it can be pointed facial expressions of traces of feelings like excitement or confusion. The amount of training required for each task, its precision, the level of confidence noticed, and other variables that could be interfering were noted to be evaluated.

We also observed whether the eyes were open or closed during the whole time or partly. This factor was observed in another study conducted by Barry *et al.* [3]. This detail can change the precision of the task completely, being important to note.

The next step was to require the user to evaluate each task. Participants rated each task on scales from one to nine on the level of confidence, the feeling of control, and the motivation scores. These data were cross-tabulated with the videos' data and related the events observed with the scores pointed.

4. Results

4.1. Participants profile

The thirty participants were graduating students with no restriction on which course and with no physical disabilities. The mean age of the participants was around 22 years old (Figure 5), and the majority were men due to a problem encountered while testing with women. Such a problem happened due to a poor or absence of connection between the scalp and the electrodes.

To avoid biased results, all the users did not know how the EEG worked and never used this sort of technology before. That circumstance supports the theory that any person with no previous background in that technology category can come up with good results out of its usage.

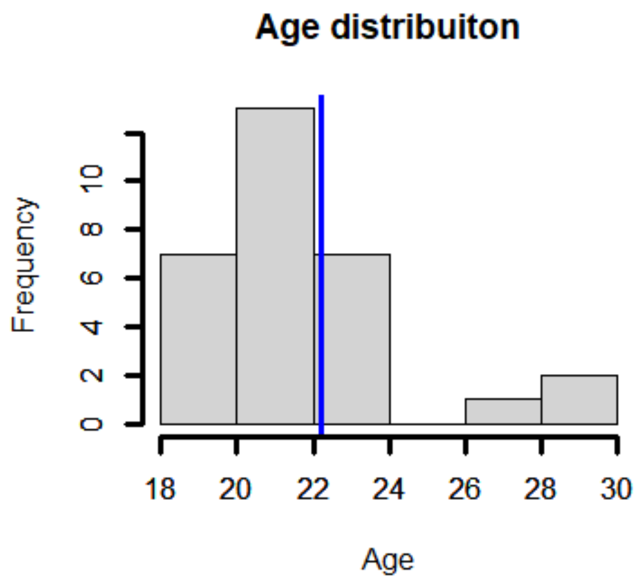

Figure 5. Participants age distribution

4.2. Usability problems encountered

One of the main problems with the EEG was the fragility of its sensors. Massive maintenance was required to keep them plugged correctly at the helmet structure without a thick layer of oxidation under the hydrated sponge that prevented the electrical signals from flowing correctly. Another significant barrier to the test was the amount of hair. The user could not have a thicker hair type because it would make the headset unable to connect correctly, leaving a poor connection of less than half of the electrodes or even no connection at all. That issue also propagated to female participants due to its considerable likelihood of having a longer and thicker hair layer between the scalp and the electrode sponge.

Before the usability test was carried out, many tests were performed with the EEG. A significant threat to the complexity and duration of the test was with joining two or even more commands together at one single user profile. That user profile is a form that Emotiv Xavier uses to separate user training info that was labeled to a certain person or command. So, for the same user, there can be used multiple profiles, so in each one the software will be able to identify the specific trained commands only.

It means that the equipment would need to differentiate between two or more states at the same time. That configuration required more time to perform more training and required more effort to maintain the precision. Therefore, we opted to split in one profile per command. Therefore, the equipment would need to split between only two states making the ease to identify higher. Table 2 presents a list of the main types of usability problems encountered and the number (N) of users who encountered those problems. The following subsections present a characterization of these problems.

Table 2. Categories of problems encountered.

Categories	**Occurrences**	**N# of users**
Training and execution of actions require a lot of user effort	20	15
Distractions affected training drastically	9	8
Different actions require different efforts	2	2
Command inaccuracy in relation to desired action	10	9
User shyness or anxiety hinder training	7	6

4.2.1. Training and execution of actions require significant user effort

Among the found problems during the testing, the most critical ones were related to a considerable effort during the training procedure. As it requires much attention, the repetitive tasks used to train the equipment could get cumbersome for at least half of the users. They complained that it was hard to focus enough, so the EEG performed precisely what they were willing to do.

For example, at the push statement that required the user to focus on pushing a virtual block to the bottom of the environment it was placed, the user needed to perform this mental command for seven seconds non-stop around four times, so the equipment could record the mental state at those seven seconds. This problem was mainly encountered due to reports after spending seven seconds training that they had used much concentration on it. Because for the first seven seconds of training, the block moved by itself to induce the user to understand better its mechanics. After that, with this option turned off, they realize how concentrated they need to be to push the block to the bottom and maintain it there during the training.

4.2.2. Distractions affected training drastically

Another problem encountered in the evaluations was the high level of attention needed. Even though numerous electrodes are available, compared to other base models, distractions still play a significant role in performance. During the operation, the users that distracted the most got the worst results or took longer to obtain a correct spot where the device knew the differences between neutral and non-neutral states. The way the EPOC+ works is by switching between trained phases. For example, if there are two trained states, the neutral one representing the absence of specific thoughts and the pushing one that makes a virtual block goes to the end of a corner. Therefore, the user is either neutral or pushing a block. Even though they are confounds, anything between those two states is assigned to one of the trained tasks. So, if the user performs the neutral state talking, thinking about something, or even distracting with ambient noises, the system is more inclined to associate that neural activity to a task that involves greater activation (push) instead of neutral that is associated with a more clear state of mind. Consequently, the participant will see the block moving when it was not supposed to and decrease the accuracy points perceived on the SAM ratings.

To prevent the user from distracting as much as possible, before starting the process, concentration is essential. Therefore, the participant was orientated not to pay attention to the test applicator and put away his cellphone.

According to Table 2, and regarding what was said about distractions during the test, in some cases it is possible to relate the inaccuracy to the lack of focus. However, problems with the connection between the user and the equipment sometimes happened and made the data from the electrical pulse more noisy or weak, causing the same problem.

4.2.3. Different actions require different efforts

As stated by Figure 6, the three actions that were chosen to compose the test required different amounts of training to obtain good precision. To reach that point of accuracy required, the metric Overall Skill Rating Figure 3 given by the Software was used. It indicated in percentage how precise the command was. In this context, the required precision level was above seventy per cent.

Until the user makes it to the precision mark, we observed that each test had a different mental workload. The Push command, even though it has the same range of training times, it has a slightly bigger median, and it has a more significant outlier associated with it. It can be justified by relating that this command was always the first, which means that the user's first contact with the workflow of the test can lead to some extra training. Therefore, the Lift command was started with more understanding and more user confidence, causing it to need less training to get a good precision range.

The command Smile did not have a performance metric to indicate how precise the action was. To identify the precision of it during the test, the user was asked to smile and come back to the neutral facial expression, and if it recognized at least three times straight, that command was considered precise for that user. As noticed in Figure 6, the median is significantly smaller than the previous commands, and the feeling of control associated with it was high in Figure 10.

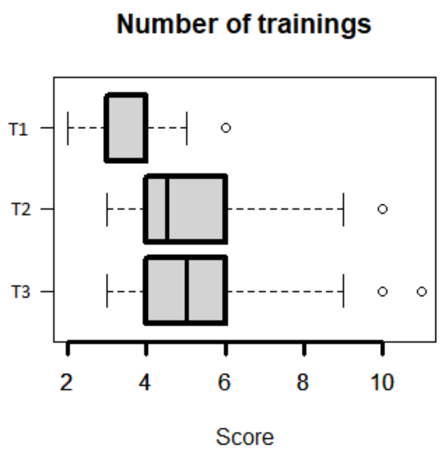

Figure 6. Number of training's required to get a good precision

4.2.4. Command inaccuracy in relation to desired action

Inaccuracy was a common problem found during training. Even with the minimum required precision to continue the test, one-third of the users dealt with a partial or a complete lack of accuracy. An attention lapse can cause that situation during the testing, the number of electrodes working (which could vary throughout the test), and the protocol break by acting differently from how it was trained.

For example, users who focused on the wall with their eyes opened to record the neutral state or decided to stay with the eyes closed to reduce one stimulus for the neutral state should reproduce this same state every time it was requested to stay at such state. However, when the user tried to see the block feedback while it was supposed to maintain its eyes closed, the feedback was not precise, and the user was requested to restart the command performing exactly how he trained, leading to the perception of low precision.

4.2.5. User shyness or anxiety hinder training

Before the beginning of the test, some users demonstrated some level of shyness or anxiety. This phenomenon can be related to the lack of knowledge about EEG's and the disbelief in their performance. That event could happen before the test, as soon as the goal was explained and, less common, during it. Another factor that might create tension and, therefore, shyness was the usage of the camera to capture more information out of the test for further analysis.

To create an ideal circumstance for the user and avoid this situation, before any hardware setup, a conversation was carried to ensure that the videos would be seen exclusively by the testers. Another critical topic brought during this conversation was that the intention behind this test was strictly to evaluate the hardware accuracy and usability, showing that his/her performance would not be evaluated individually.

4.3. Emotional Reactions

Several emotions were identified during the test application and video analysis. The main ones depended on the circumstance where the neutral and excitement happened the most. In the beginning, a neutral expression was the most common. Users had doubts about the efficiency of what was being tested. As soon as the first command was successfully executed by the user, usually the push command, the frequent reaction of surprise and excitement were recorded. Since the predominance of positive test outcomes, both of these reactions were recurrent, and each time easier to identify the transition between them.

To measure the feelings and impressions throughout the test, users were requested to fill a form based on self-assessment manikin (SAM). This method contemplates a visual quiz based on images representing a scale. As shown in Figure 7, the first row contains an image scale that goes from a happy place to an apathetic one to represent the motivation dimension. The second row, represented by a sacred figure to a relaxed one, measures the satisfaction. The final question intends to measure the precision or how much control of its environment the user feels. According to Bradley [4], the SAM instrument represents an easy and quick way to measure effective responses after experiments and can be related to several benefits. Benefits include the reduced amount of data extracted and the ease to apply over populations like kids or elderly due to its lack of linguistic abilities.

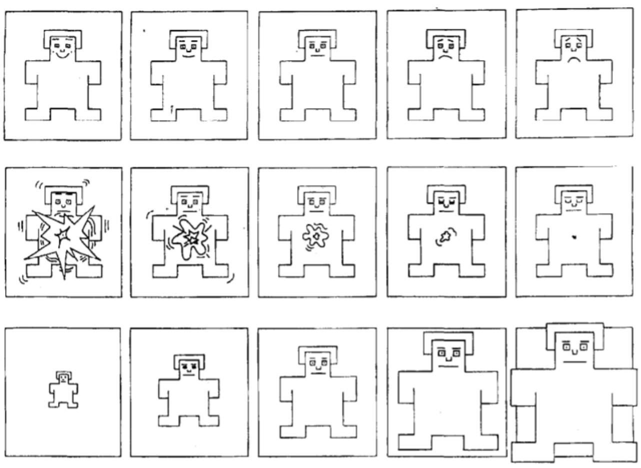

Figure 7. Self-Assessment Manikin test used to measure Motivation, Satisfaction and Feeling of control

The results are shown in Figure 8, Figure 9 and Figure 10 can demonstrate the median and the minimum or maximum values obtained after all the test procedures. For the Push command, it is possible to see that the Motivation and Satisfaction indicators were higher than the Control Precision one. This can be explained by the number of confounds encountered during testing. But, despite those confounds, the median kept above the threshold.

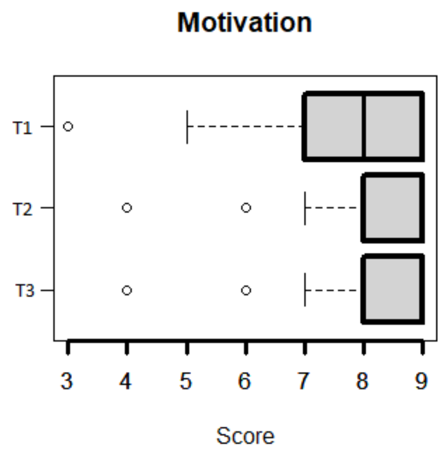

Figure 8. Motivation metric score

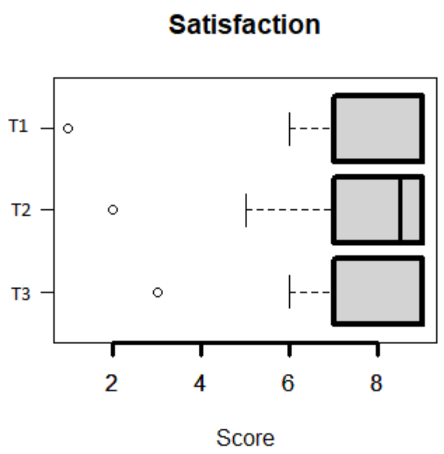

Figure 9. Satisfaction metric score

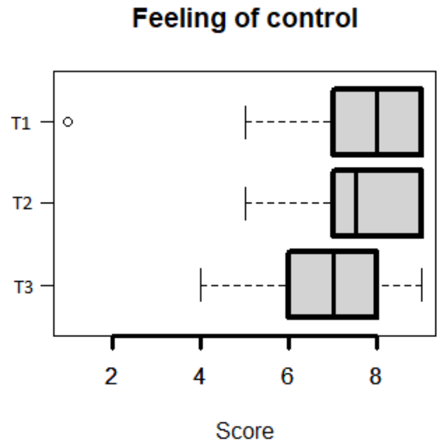

Figure 10. Feeling of control metric score

We performed related-samples Friedman's tests to verify if there were significant differences between the scores of motivation, satisfaction and sense of control for the commands smile, lift and push. No significant difference was found between the motivation scores for the commands push, lift and smile (χ^2_r = 0.45, N=30, p-value = 0.79852). No significant difference was found between the satisfaction scores for the commands push, lift and smile (χ^2_r = 1.3167, N=30, p-value = 0.51771). No significant difference was found between the feeling of control scores for the commands push, lift and smile (χ^2_r = 2.6, N=30, p-value = 0.27253).

According to the analysis made on the recorded videos of each training, there was considerable positive feedback. Most of them were related to the mental command portion of the training Figure 11, instead of the facial expression, which might explain the higher score on motivation for those commands Figure 8.

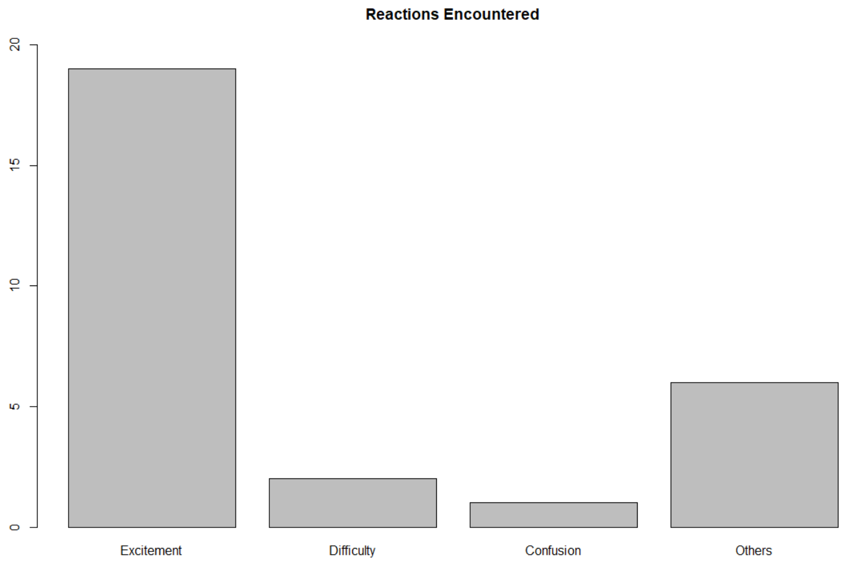

Figure 11. Emotional reactions encountered

In Figure 11, the emotions captured during the training were separated into four categories. The first one, called Excitement, represented positive feedback. These were accounted for when the user demonstrates statements or gestures such as Excitement, astonishment, or enthusiasm. The difficulty referred to the category of discomfort, pain, or tiredness. The third one was assigned to confusion. For example, the user could not perform was asked, needed further explanation, or demonstrated a lack of comprehension during the test. The last one, Others, was related to confounding reports. These reports included concentration deficits during the testing, requests to train an action again, or precision complaints.

According to the graph shown in Figure 11, the most frequently captured emotions were positive. Most of them were related to users being astonished by the successful mental command performed. It can be explained by the fact that any of the participants have had no previous experience with EEG technology. Yet not as common as the above mentioned, the E4 reactions were present in a suitable recurrence, indicating that the experiment can be fragile to confounds like distractions and concentration insufficiency at certain moments.

5. Discussion

The results indicate that implementing a brain-computer interface for the interaction with smart homes is feasible due to the high accuracy found during the test. To support that statement, at Figure 10 can be noted a high level of acceptance from the users when it comes to precision which can be correlated with Figure 8 that demonstrates that users kept motivated during the test. In that context, those results yield a good non-invasive and non-intrusive environment. Also, the duration of the whole test landed in between twelve and twenty-four minutes. Thirty users surpassed the studies from Partha [24] and Luo [15] in the number of participants and also with none of the users being familiarized with the technology like in [15].

Using non-static objects to train the subjects, unlike Partha [24] who displayed an image of a bulb, yielded good metrics of motivation. That fact is observed in Figure 11, where excitement emotions when the user saw the object moving due to its mental commands were frequent.

The methodological choices were constrained by having users with short hair due to the poor contact with the scalp, caused by a thick layer between the electrodes and the skin. At Luo *et al.*'s [15] study, there were women among the test users, and there were no records shown related to a poor connection due to the hair layer. Also, it is beyond the scope of this study to test with disabled users. Therefore, the generalizability of the results may be limited for that circle of people too.

Along with the procedures, the overall quality of the equipment decayed. Electrode fixation points broke, forcing frequent maintenance and electrodes blackout. Moreover, that fixing process involved leaving the electrode permanently attached to its headset base, making the whole equipment even more fragile to minor impacts. Still, on the electrodes, the saline solution required to enhance the connection caused over time a thick coat of rust, leading to bad connection problems that were only solved when opened and grated.

Another complication, also found by Luo [15], was the delay between the equipment and the computer. As the data is sent over Bluetooth, the distance between both parts and any blockage may cause a delay on the commands. Moreover, as this study used interactive training, sometimes, that delay created a more significant impact when the user was trying to lift or push the object, and it kept still for a moment before it started moving. In this situation, the user sometimes tried to restart the command, and as soon as he stopped thinking, the previous commands started reflecting and moving the object. The whole situation can confuse the user and also decrease its sense of precision.

The training needed to be sliced into profiles that contained only one command because the usage of one single profile that condensed all actions resulted in lower precision. Again, it would require more time to practice and train commands and a higher level of focus, leading to a more invasive procedure. By dividing the profiles, the software only demanded distinguishing between two phases, the neutral and the command itself. Even though the neutral state training needed to be repeated at every profile, the overall time still lower than the other approach, in which a big volume of training per command was mandatory to reach the same accuracy.

As important as measuring the numeric feedback, the user experience and feelings are also important. With these sorts of information, it is possible to understand not only if the model or the equipment is accurate like Luo [15] and Partha [24] did, but also how the users feel about it throughout the entire process. A big concern about EEG technology is finding a good ratio between precision and the need to be invasive to achieve it. We can infer that the overall ease between facial expression and mental commands is slightly lower with the obtained results. That is because the number of training required to obtain a good precision is lower at facial expressions Figure 6. It might occur because smiling, for example, does not require a mental overload as significant as mental commands. However, the motivation associated with facial expression skewed more to the lower end of the score axis than the Push or Lift commands. The positive feedback of excitement can explain that phenomenon obtained multiple times when the user realized that his mental command controlled the environment according to his thoughts Figure 11, something that lacked for the smiling training.

This study, used as subjects healthy and young people, but for users with some disability the scenario could be different. Impairments, such as a stroke, can lead to blacked out areas of the brain. Or even other types of limitations could lead to worse signal quality, therefore, this technology would not be usable for some cases. Furthermore, some disabilities may cause difficulty on memorizing the proxy commands, turning it into a complication that con lead to home control problems and even the disability to control at all. For example, if a user has severe brain damage that has one of its side effects as memory loss, a wrong command could lead to turning something off or leveling up the volume of a TV too much. Also, the SAM applied to each participant, did not cover the difficulty of relating the proxy to the command. Neither the test tried to identify the complexity of using all of them in a mixed order to verify how well would the users perform when it comes to remembering each command.

6. Conclusion and Future Work

Intending to create a non-invasive and straightforward setup method that controls a smart house for severely disabled people, the brain-computer interface using EPOC+ was adequate to implement the prototype and to enable the usability evaluations. The research study provided relevant contributions showing the usability benefits and limitations of employing an object-based abstraction to perform mental commands with EEG-based interaction and the precision of such commands.

The main limitation that constrained the study was the feeble attachment between the electrode and the scalp for users with thick hair. Also, the low quality of the fits for the electrodes, that delayed the testing as a result of below twelve well-attached points on the head.

Regarding training, multiple actions combined at one profile resulted in more extended practice and more significant focus, leading to a significantly larger mental overload. However, when separated into one profile for each command, the training was faster and more accurate. Here, the usage of interactive objects provides more motivation as the user realizes that he/she is controlling something. Also, that concept helps the subject execute actions linked to a physical movement instead of an abstract thought such as turning on a TV.

Based on these conclusions, future research should consider using more stable equipment and ways to overcome physical limitations with the sensors. Other studies should also build upon the findings from the present study to continue the design and perform user evaluations involving disabled people.

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