A Hardware/Software Platform to Acquire Bioelectrical Signals. A Case Study: Characterizing Computer Access through Attention

Alberto J. Molina, Isabel M. Gómez, Jaime Guerrero, Manuel Merino, Juan A. Castro, Roylán Quesada, Santiago Berrazueta and María Hermoso-de-Mendoza

Departamento de Tecnología Electrónica, Universidad de Sevilla, Spain

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Abstract: This paper describes a hardware/software platform to acquire human body signals. In the field of physiological computing it is desirable to have a system that allows the synchronized acquisition of signals coming from different sources. Here is described how to unify the whole process of acquiring signals from both customized hardware and low cost commercial devices such as Neurosky's mindwave. A case study using this platform is also shown: studying the feasibility of using sustained attention to access a computer. In order to do that brain activity was measured using Neurosky's mindwave. The participants in this study were asked to keep their attention high/low for as long as possible during several trials. Experimentation was performed by 7 normally developed subjects and 3 people with cerebral palsy (CP). Our preliminary work shows that 60% of participants might be potential users of this technology. Eventually, modulating the attention to access a communication board needs a scanning period greater than 5.76s.

1 INTRODUCTION

Communication is vital for human beings. A system allowing people with disabilities to access a computer or a communication system reliably would be highly beneficial. We can find several devices on the market and scientific papers which translate user intentionality into discrete events. The simplest and one of the most extended is based on a binary switch (on/off contacts), whereby people with disabilities can use software applications, particularly those based on scanning methods. A good survey for assistive devices can be found in (McMurrough et al., 2012).

For people with severe disabilities these simple devices are still very difficult to use. For them, brain computer interfaces (BCI) could be a feasible alternative. BCI systems (Nicolas-Alonso and Gomez-Gil, 2012; Millán et al., 2010) are based on recording cortical neuronal activity, and one way to achieve this is by means of EEG (Electro-Encephalo-Graphy) which requires several electrodes placed on the scalp. One possible drawback with these systems is their cost which prevents most people with disabilities from acquiring it. Nevertheless, some companies, such as Emotiv and Neurosky have released their wireless BCI headsets (Emotiv Epoc, Neurosky mindwave,..) for entertainment uses such as brain gaming and mind monitoring with affordable prices for the consumers. Emotiv has up to 14 channels covering all the cerebral lobes and the two hemispheres and it has also studied as potential BCI system for people with disabilities (Welton et al., 2016). NeuroSky mindwave is cheaper than Emotiv epoc and it has only one channel placed at the pre-frontal left position, Fp1. In (Das et al., 2014) a comparison was carried out between both low-cost systems, to detect cognitive loads. The authors found that Emotiv provided better results but recognized the advantages of Neurosky because it is more user-friendly, easier to setup and maintain.

It is known that cognitive tasks influences signals captured from the human body in several ways. For example, stress affects brain rhythms, reducing the power of α waves in EEG (Tyson, 1987), influences the heart rate variability (Taelman et al., 2009) or produces changes in the electrodermal activity (EDA) (Villarejo et al., 2012). Attention is a cognitive process and there are several types of attention the human beings use during daily activities. One of them is the *Sustained Attention* which can be defined as the ability to focus on one specific task for a lapse of time without being distracted (e.g.: during playing a video game) (Barkley, 1997).

Training sustained attention can be beneficial for children with Attention Deficit Hyperactivity Dis-

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order (ADHD) or people with motor disabilities. In (Muñoz et al., 2015) the authors developed a videogame to train sustained attention for children with ADHD using as an action mechanism the neuromodulation of θ and β waves through an electrode located on the central part of the forehead. In (Heidrich et al., 2015) people with cerebral palsy (CP) took part in a experiment in which they had to control their attention to play with different games. In those games, the players had to reach a certain level of attention or/and to keep it over a preset value to make the game advance.

This work looks into the feasibility of modulating sustained attention to control a system in a binary way (on -high attention-, off -low attention-), such as a switch, while using cheap BCI devices. Subjects need to keep the attention low/high for a while and be volitionally able to switch between them. We have developed a software/hardware platform to receive several signals from the human body to train the modulation of the sustained attention and study how tiring this method of interaction is based on physiological signals like heart rate variability (HRV) and galvanic skin response (GSR). In this preliminary work we have just shown part of this study: the platform designed and preliminary data based only on the EEG signal.

Section 2 briefly explains the fundamentals of attention and some techniques used to measure it. Section 3 shows the devices and tools employed in experimentation, section 4 describes the methodology followed in experimentation and section 5 the results. Finally, sections 6 and 7 contain the discussion and the conclusions respectively.

2 MEASURING THE SUSTAINED ATTENTION

From a temporal point of view, attention makes EEG signals more complex, so its measurement could be based on its fractal dimension. Several works have shown the reliability of such an approach (Wang et al., 2010; Wang and Sourina, 2013; Lee et al., 2000; Siamaknejad et al., 2014). There have also been some works into the effects that attention or cognitive skills have on power bands. In general, the α band increases as the difficulty of the task diminishes or after task practice, suggesting that fewer cortical resources are required (Gevins et al., 1997). In the same work, increases in θ suggested that focusing attention or increasing the memory load require more effort. The use of the ratio between frequency bands like θ/β, known as theta-beta ratio (TBR), has also been reported as an indicator for attention deficit disorder (ADD) or ADHD people (Lubar, 1991). TBR is increased in frontocentral areas in children with attention deficit disorders.

Some papers have shown the feasibility of detecting attention using a reduced number of electrodes. In (Rodríguez et al., 2013) five different bipolar configurations of two electrodes were investigated during exercises of attention. Results showed that EEG rhythms were observed with more amplitude in two EEG channels: Fp1-A1 and FP1-T3. They adopted the configuration Fp1-A1, because those positions are free of hair which allows an easy electrodes placement (these are the positions used in Neurosky mindwave). They also found that the α, β and γ rhythms presented significant differences ($p < 0.05$) between low- and high-attention level. For this reason, they proposed an index, named Attention Power (AP), based on the sum of the power α and β bands to control a game. The 80% of the subjects found correlation between his/her attention level and the effect exerted over the game.

3 THE DEVELOPED PLATFORM

In this section we show the devices that have beenused, the designed circutis and the software made to acquire and process signals coming from different body sources.

3.1 Electrocardiogram Circuit

We have developed an electrocardiogram circuit based on the one shown in (Spinelli et al., 2001). Figure 2 shows the schematic of the implemented circuit, which uses three passive electrodes, one of them to reduce the common mode interference. The circuit has a frequency response ranging from 0.1 Hz up to 30Hz, using a one-pole high pass filter and a second order low pass filter. The former reduces the signal wandering while the latter helps to increase rejection ratio at 50Hz as well.

Signal is sampled at a 250Hz ratio by an Arduino platform which also implements a Notch digital filter to reduce the 50Hz interference (Eq. 1). Filtered data is sent to a computer by serial port at 115200 bps.

$$H(z) = \frac{z^2 - 0.618z + 1}{z^2 - 0.601z + 0.92} \tag{1}$$

An example of a 10-second filtered signal while performing an experiment is shown in Figure 2. It can be observed the main waves of a typical electrocardiogram with very low interference noise.

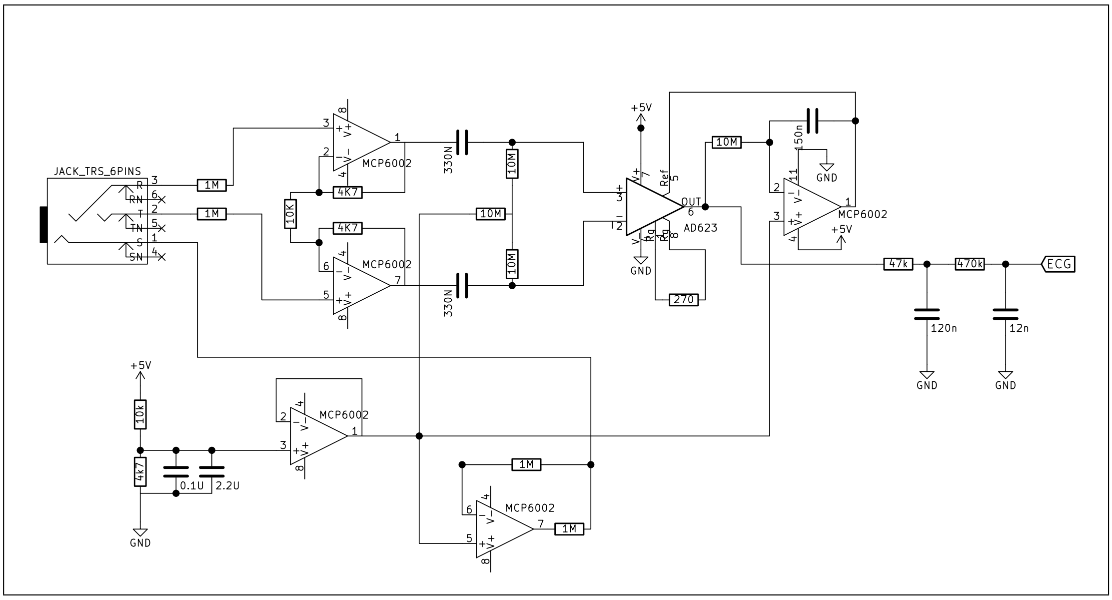

Figure 1: Electrocardiogram circuit based on the design shown in (Spinelli et al., 2001).

The ECG signal may be used to measure how stressful a cognitive task might be (Merino et al., 2014) but also to detect whether the subject is paying attention or not (Chen et al., 2010).

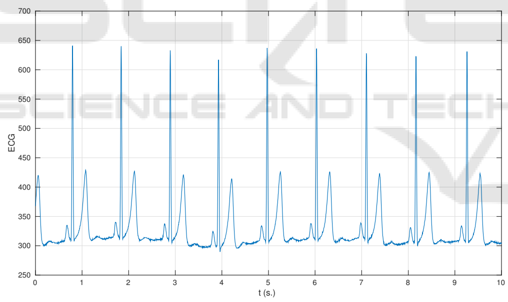

Figure 2: A ten second ECG signal after applying the notch filter.

3.2 Electroencephalogram Device

Neurosky's mindwave is a device that measures brain activity using a sensor on the forehead (Fp1) and a clip located on the left ear that acts as a ground and reference. It delivers information that we can classify in three levels of processing. From lowest to higher levels, they are: raw EEG signal (Figure 3) at a sampling rate of 512Hz and 12 bits of resolution, power bands, δ, θ, α, β and γ and eSense, which includes propietary meters for attention and meditation. Power bands and eSense signals help reduce the processing of the raw signals in external devices and allow to use digital systems with low computation resources.

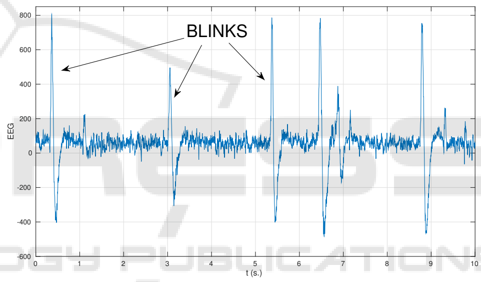

Figure 3: A segment of raw EEG signal with ocular artifacts while performing an experiment.

Neurosky's manufacturer states that attention signal has more emphasis on beta wave but the exact algorithm has not been published. Nevertheless, it has been shown that there is a positive correlation between the reported attention level of this device and the self-reported attention levels of the participants in a experiment which analyzed the Neurosky usability in an assessment exercise (Rebolledo-Mendez et al., 2009).

In this work we show the results obtained based only on the attention signal delivered by the Neurosky.

3.3 Galvanic Skin Response Circuit

The GSR circuit is shown in Figure 4. The amplifier on the left works in non-inverter mode which gain is controlled by the skin resistance. Hence, as the skin resistance increases, the gain also does. Oune electrode is powered at 0.5v, while the other is connected the the amplifier output. The second amplifier basically shifts down the voltage 0.6v and amplifies the first stage 1.5 times. A low pass filter with a cutoff frequency of approximately 5Hz filters out most of the signal noise.

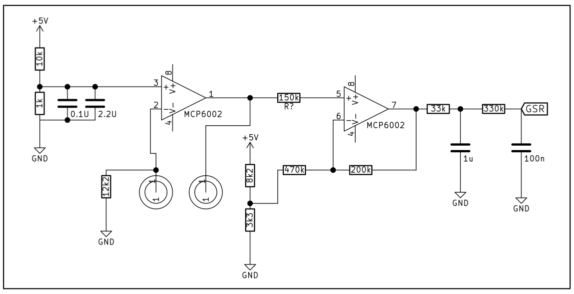

Figure 4: Schematic of the GSR circuit.

The Arduino board samples this signal at 250Hz and sends it to the computer wherein it is filtered using a 31-tap FIR low pass filter with cutoff frequency of 1Hz and, then, downsampled with a 25:1 ratio. A typical raw signal after applying these processes is shown in Figure 5.

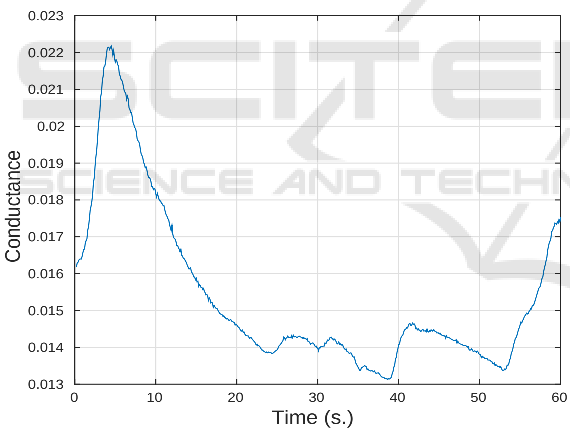

Figure 5: A segment of raw GSR signal.

3.4 Software

A Matlab©graphic user interface (GUI) was built to train subjects' sustained attention, capture information received from different sensors and store data for posterior analysis. Several functions read data coming from *Arduino* and Neurosky's mindwave, and create input streams to a synchronization software called *labstreaminglayer* (Medine, 2016). During the experiment, the software sends marks to the *labstreaminglayer* to delimit the different phases of the experiment. Another function reads and stores the output streams.

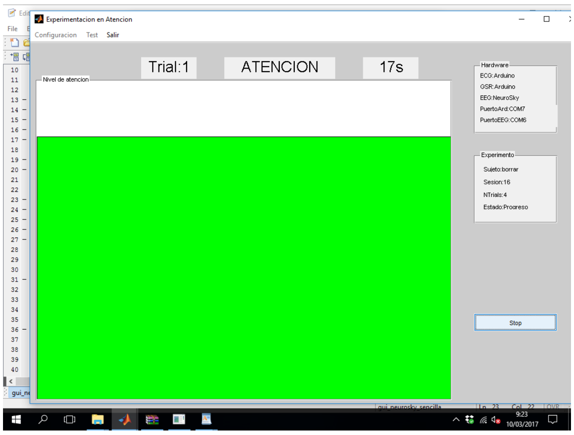

Figure 6: A screenshot of the application during a trial.

4 EXPERIMENTATION

For neuro-feedback purposes, a great part of the screen shows a bar which moves up and down changing its color according to the received attention values which ranged from 0 to 100 like a percentage. The higher the attention value, the higher the bar shown on the screen. The color of such a bar is green for an attention level over 60%, red if it is under 40% and yellow otherwise.

4.1 Participants

Seven normally developed subjects (A1,..A7) aged 36.4 ± 10.2 formed group A (control group) and three subjects with CP (B1,..B3) aged 35.3 ± 1.2 made up group B, who were recruited from ASPACE Sevilla, a non-governmental organization specialized in cerebral palsy. The recruitment into group B was done according to the following inclusion criteria:

1. The access to a computer by traditional switch-based devices is usually very hard to be carried on or almost impossible,
2. Have good intellectual capabilities,
3. GMFCS Level V (Palisano et al., 1997),
4. CFCS Level IV (Hidecker and et al., 2011).

The participants agreed to take part in the experiment and in the case of group B, their families were informed and allowed their participation. The Ethics Committee of the University of Seville also approved this experiment.

4.2 Conditions

Experimentation was carried out in a quiet room with dim lighting. The experiment was considered correct if there were no interruptions. Participants belonging to group A were told to set the environmental conditions (temperature, lighting) so that they were comfortable during the experiment. For group B subjects, experimentation was conducted by a caregiver who was always present and set the environmental conditions.

4.3 Phases in Experimentation

Experimentation consisted of two phases (see Figure 7). As explained below, in the first phase the participants had to find the strategies to control their attention. Those who would not have been able to control their mental state properly did not perform the following phase. The second phase was similar to the first with the difference that we recorded the information sent by the sensor during the attention/non-attention trials.

4.3.1 Phase 1

The main goal of phase 1, also called ”Freestyle”, was to practice and try to find the best strategies to control attention levels. Previously, they were told to follow a series of basic strategies. For instance, to practice attention we told them: ”try to perform mathematical operations”, ”try to plot an object mentally”, etc. To practice non-attention we suggested: ”try not to think about anything”, ”make your mind go blank”, etc. These suggestions were to get them going, they each had to find the best way of controlling her/his level of attention. We used the software explained above to give participants feedback about how they were performing the experimentation. The caregiver sometimes asked participants in group B to perform several attention/non-attention actions to get some feedback about their achievements.

The number of sessions in phase 1 depended on the subject but to prevent this phase from becoming too drawn out, we set an upper limit of 10 sessions of roughly 15 minutes.

At the end of each session in this phase, group A participants were asked to fill in a short questionnaire about how well they had performed the experiment. Those who admitted not having controlled attention properly in more than two out of the last five sessions, were excluded from the following phase. In group B, the caregiver was responsible for discriminating such participants.

4.3.2 Phase 2

In this phase participants performed a sequence of 5, 14 minute, sessions (one per day). Each session

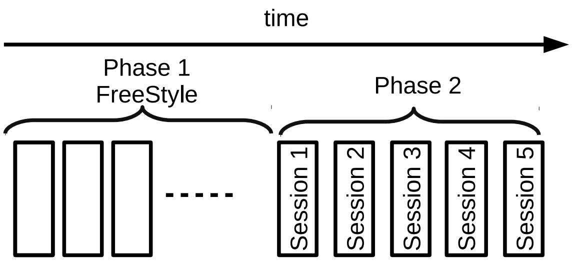

Figure 7: Experimental time sequence. Phase 1: Subjects must find the strategies to control their attention levels. A maximum of ten 15-min sessions was set. Phase 2: Five 14-min sessions with 7 attention/non-attention trials.

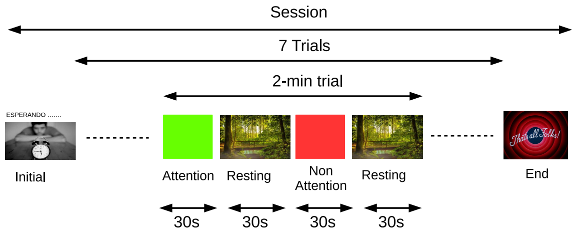

Figure 8: The temporal sequence in a experimental session.

consisted of 7, 2-minute, trials divided into four 30-second parts. In each part, subjects had to keep their attention level above/below a threshold of 50% as soon as the application requested it. In the second/fourth 30-second part of the trial the subject had to relax, and to help participants do so, the software showed an idyllic landscape on screen. Figure 8 shows the time schedule of this phase.

5 RESULTS

Data were analyzed using GNU Octave version 3.8.1 and R version 3.0.2. The first analysis was to find out how the method for identifying attentional states had worked. As the variable selected to control feedback to the user was the attention signal, the exploratory analysis was based solely on this.

Phase 1 removed four participants from group A and one for group B. Namely, participants A5-A7 and B1 were unable to control their attention level and did not go on the following phase.

Figure 9 shows boxplots containing the results of phase 2 for each subject and session, differentiating between attention trials (green boxes) and non-attention ones (red boxes). Each box contains 7 values representing the average of the attention percentages of a trial in a session.

Table 1 shows the mean and standard errors of some quantitative features which may characterize experimental results:

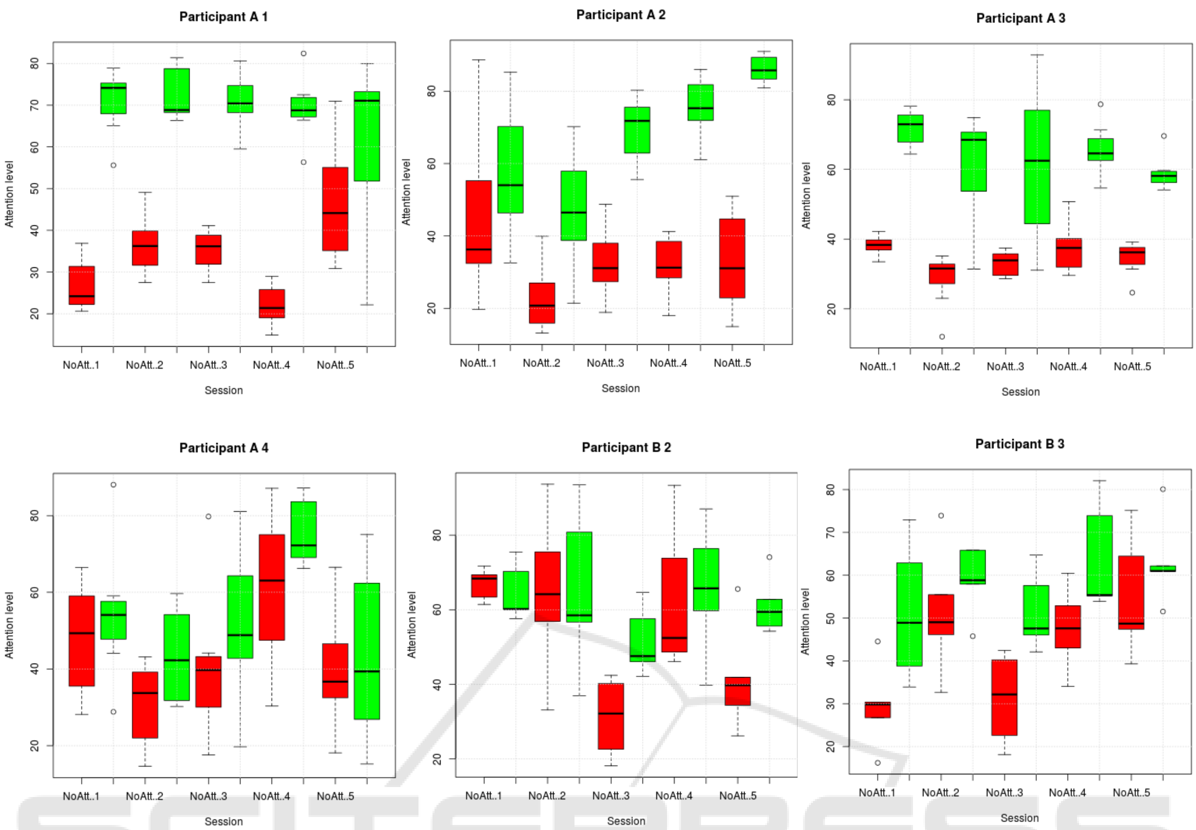

Figure 9: Attention levels for participants and sessions. Green boxes contain averaged values for attention trials; red boxes the averaged values for non-attention trials.

- The initial time, $\overline{t_i}$ or time elapsed, in average, from the beginning of the trial until the subject made the attention level go above/below the threshold in attention/non-attention trials respectively. We can differentiate $\overline{t_i}$ for attention and non-attention trials calling it t_{on} and t_{off} respectively.
- Sustained attention time, $\overline{t_s}$, shows how long, on average, the subject could maintain the attention level without crossing the threshold.

Table 1: Initial time and sustained attention time for each participant. Standard errors (SE) are also shown.

Subject	**Condition**)	$\bar{\mathbf{t}}_\mathbf{i} \pm$ **SE** (s)	$\bar{\mathbf{t}}_\mathbf{s} \pm$ **SE** (s)
A1	Attention	2.48 ± 0.87	19.3 ± 3.7
	Non-attention	2.08 ± 1.02	18.6 ± 5.8
A2	Attention	4.29 ± 1.44	18.8 ± 4
	Non-attention	2.19 ± 0.62	17.7 ± 1.9
A3	Attention	2.06 ± 0.30	16.1 ± 1.5
	Non-attention	1.69 ± 0.19	12.5 ± 0.8
A4	Attention	2.91 ± 0.66	10.7 ± 2.5
	Non-attention	4.63± 1.67	11.4± 2.0
B2	Attention	2.2 ± 0.60	12.4 ± 1.8
	Non-attention	5.0 ± 2.14	7.8 ± 2.8
B3	Attention	2.0 ± 0.46	11.0 ± 1.3
	Non-attention	2.6 ± 0.62	11.0 ± 2.5

6 DISCUSSION

Figure 9 shows that subjects A1, A2 and A3 performed the experiment rather well, as the attention boxes generally contained higher values (above the 50% threshold) than the non-attention ones (below 50%) and there was not excessive overlapping among them. It was clearly not easy to perform all sessions of the experiment perfectly. For example, participant A1 did not obtain good results in the last session; neither did, A2 in the first and second sessions nor A3 mainly in the attention trials in session 3. Participants A4 and B3 behaved differently; they did not fulfill the goals since many of their results in the attention trials were below the threshold and many of those in the non-attention trials were above it. However we should remark that for these two subjects in each session, the median values in the attention trials were higher than in the non-attention ones. Participant B2 performed similarly to A4 and B3 in the last three sessions. In the others, the subject's attention level was almost always above the threshold with non-attention mean values higher than those in attention trials. Anyway, it seems to be plausible to set a threshold, different to the 50%, which should be adjusted session by session.

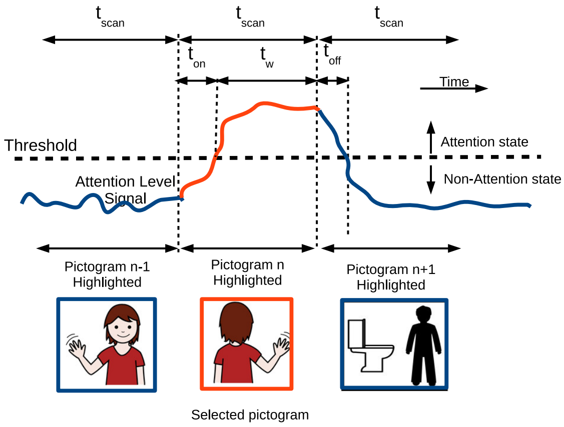

Figure 10: Temporal parameters and their relationship with scanning period. $T_{scan} \geq t_w + t_{on}$ to select one pictogram and t_w also has to be greater than t_{off} ($t_w > t_{off}$) so as not to select the following pictogram.

Initial time $\bar{\mathbf{t}}_\mathbf{i}$ and sustained time $\bar{\mathbf{t}}_\mathbf{s}$ are related to the time needed to select a pictogram on a communicator board, when accessing a computer by changing the attentional state. Firstly, a threshold establishes the border between these two states, so a subject who wants to select a pictogram has to exceed such a threshold for a time. The time $\bar{\mathbf{t}}_\mathbf{i}$ in attention trials (t_{on}) shows the average time to cross such a threshold and reach the attention state. In the same way, the time $\bar{\mathbf{t}}_\mathbf{i}$ in non-attention trials (t_{off}) shows the time taken to go back to the non-attention state. In between them, the attention level must be kept high for t_w seconds so that the system can detect the user's intention (see Figure 10). The dwell time or scanning period t_{scan} depends on such temporal parameters. For example, participant A1 took t_{on}=2.48s to move from 'resting' to the attentional state and t_{off}=2.08s to come back again. This means the scanning period, t_{scan} has to be greater than 2.48s (Eq. 2) on average and the t_w greater than 2.08s to avoid selecting the pictogram next to the preselected one (Eq. 3). The selection time, t_w is also related to sustained time, $\bar{\mathbf{t}}_\mathbf{s}$, as the latter sets the upper limit for the former. Table 1 shows that all participants were not able to maintain their attention state for more than 10.7s in group A or 11s in group B, which could be a constrain to the number of pictograms on the screen. Increasing t_w could also be a solution to the lack of control for low attentional values to reduce the number of false selections.

$$t_{scan} \geq t_{on} + t_w \quad (2)$$

$$t_{off} < t_w \leq \bar{\mathbf{t}}_\mathbf{s} \quad (3)$$

Minimal t_{scan} can be estimated by approximating $t_w \approx t_{off}$, so $t_{scan} \approx t_{on} + t_{off}$ whereas $t_w \leq \bar{\mathbf{t}}_\mathbf{s}$. According to Table 1, all users comply with Eq. 3. The minimal t_{scan} is shown in Table 2.

Table 2: Minimal t_{scan} according to Eq.2, Eq. 3 and Table 1.

Subject	$\mathbf{t_{scan}}$ (s.)
A1	4.96
A2	6.48
A3	3.75
A4	7.54
B2	7.2
B3	4.6

7 CONCLUSIONS AND FUTURE WORK

This study shows that not all participants were able to manage their attentional state well enough. Three participants from group A and one from B were not able to start the phase 2 (40%) after 150 min of training.

For the rest of participants, the control of attention to access a computer is possible, with an average t_{scan} equal to 5.76s, although further research is needed. One improvement will come from setting a classifier to discriminate between two attentional states, which allows to automatically set the threshold and increase the accuracy in classifying. Processing the raw signal, will also let us include other kind of algorithms to detect the attention. In this sense, discarding EEG segments containing artifacts is important for obtaining power bands correctly. We know that when people with disabilities used the EEG sensor, lot of artifacts where recorded due to the amount of involuntary movements the participants of group B showed. We do not know whether the Neurosky's proprietary algorithm rejects these contaminated segments.

Eventually, including other signals and psychological tests, will give us information of how tiring this kind of method of access a computer is, especially, for people with disabilities.

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