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Controlling Robot Motion by Blinking Eyes: an Experience on Users Training

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Abstract

This article aims to describe a system designed to control the movement of mobile robots by blinking eyes. It is based on the use of a Brain Computer Interface and a particular control architecture. The paper addresses the key aspects that allow simplifying users-robot interaction and proposes a control strategy that facilitates a fast learning of robot handling. In this sense, the main advantage of the approach is the short period of time required for users' training. The article details a methodology aimed to evaluate this feature, presents experimental results that confirm this fact and also discusses about the influence of interacting with a real or a simulated robot. Particularly, it analyses if a previous training with the virtual robot helps to improve the interaction with the real robot or vice versa. *Copyright © CEA.*

Keywords:
Human Robot Interface, User Training, Robot motion Control, BCI, Blinking, Neuro-Feedback.

1. Introduction

The study of Human-Robot Interfaces (HRI) has focused the attention of the scientific community in the last decades (Adams, 2002), (Kofman *et al.*, 2005). Human-Robot interaction has traditionally been implemented by the motion of certain parts of the body: from the use of hands (moving a mouse, touching a screen, etc..) to others parts of the body with enough mobility to be registered (Goodrich and Schultz, 2008). It is also worth mentioning the incorporation of voice for interacting with robots (Lv *et al.*, 2008). However, there are still people who, due to their movement and voice limitations, can not use these devices efficiently.

With the arrival of Brain-Computer Interfaces (BCI) the opportunity to help these people to interact with electronic systems appeared. Especially new challenges arose to face the integration of these devices within the control mechanisms of the robot (Ibáñez *et al.*, 2009). In this sense, different devices that are able to capture electrical signals produced by the interaction of neurons in the human brain have been developed: (Ibáñez *et al.*, 2011), (Elsawy *et al.*, 2017). Moreover, numerous applications have been developed by using BCI systems (Choi *et al.*, 2017), (Barios *et al.*, 2017), (Ubeda *et al.*, 2017). Though the accuracy of these devices is not high enough for clinical use, it can be used for neurofeedback purposes (Salabun, 2014), providing a direct communication between the brain and an external system. Through their use, researchers have attempted to control various types of robotic platforms, from basic applications (such as virtual simulations, mouse pointer control, etc.) to more complex applications in which robots (manipulators or wheelchairs) are managed (Sudarsanan and Sasipriya, 2014), (Escolano *et al.*, 2012), (Hortal *et al.*, 2015A).

This technology is hopeful for the assistance of elderly or disabled people with mobility and voice restrictions, since it will allow them, in day life, to interact freely with different devices, and overcome their limitations of movement. Almost 15 percent of the world population has a disability. In Spain, this number reaches 3 million people, among them those having limited physical mobility represent a high percentage. So the development of this technology must be considered as an ethic compromise for researchers and engineers.

A BCI system suitable for controlling a robot is a closed-loop control system that uses brain signals in combination with surrounding environment feedback in real-time. The collected brain activities must be decoded to identify human mental activities and to generate commands for robots to execute an action or a particular task. The design of such a system must also take into into account kinematics and dynamics of the robot, as well as the control architecture and the robot behavior (Ferreira*et al.*, 2008), (Hortal *et al.*, 2014), (Hortal *et al.*, 2015B).

The possibility of brain-computer communication based on the electroencephalogram (EEG) was discussed almost four decades ago. The acquisition configuration usually consists of evoking sources to generate specific brain activities, measuring

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brain signals with a BCI sensor, analyzing data and possibly controlling objects. Major techniques for this challenging process has been developed by the use of three main EEG paradigms and their hybrids (Mao *et al.*, 2017): event-related desynchronization or synchronization (ERD/ERS), steady-state visual evoked potential (SSVEP) and event-related potential (ERP). ERD/ERS are generated by Motor Imagery (MI), when the user makes a mental representation of a motor act. SSVEP is a steady-state physical response to outside periodic stimuli, when the user selects a target by means of an eye-gaze. ERP is generated when a specific stimulus acts on the sensory system of the brain or some mental factor occurs, this bias stimulus is called target stimulus when the subject reacts to it. The P300 component, for instance, is observed in 300ms after the target stimulus appears.

Although these methods exhibit high reliability, are very expensive in terms of equipment and, mainly, in users' training time. So, in order to achieve an efficient development of this technology, it is necessary to reach a trade-off solution that takes into account efficiency, cost and users learning facility. This is the reason why this paper propose the use of blinking eyes for control purposes. Blinking is one of the most natural motion of human being. Even people with a paralyzed whole body can blink. Blinks can be easily identified, when ECC signals are recorded. Moreover, as will be shown, blinking action can be easily trained, so user can quickly acquire an adequate ability to control then.

This paper approaches the development of a platform that allows to teleoperate a mobile robot through blinking signals registered by a commercial BCI. The BCI processes the brain waves and characterizes the level of attention or meditation of the user. These signals are complemented by an associated signal, also generated by the BCI, which in this case is the strength of the user blinks. By using this information, the system implements a control methodology that allows users to operate the robot by controlling the strength of the blinks. This methodology avoids the use of the traditional paradigms, using a simple visual feedback. With respect to previous works, the time for training user's ability to maneuver the robot is improved (from days to few hours or minutes, depending on the objective to achieve), and all of this is implemented with an usable, portable, and accessible technology.

The article describes the main features of the system, the control strategy and some experimental results that show how non-expert users are capable of achieving outstanding results without a previous training. Experimental results also compare the result of operating with a real o a virtual robot.

The paper is organized as follow. In section 2 a description of the system and its components is drawn. Section 3 details the control strategy. Section 4 is devoted to illustrating the experimental setup and describing the method for organizing the experiments. Section 5 is dedicated to analyzing the results. Finally, the article ends with some conclusions.

2. Using blinking for controlling robots

This work aims to develop a platform that allows controlling simple movements of a mobile robot without the interaction of hands, voice or any of the traditional mechanisms to transfer the user's command to the robot. The design is based in the spirit of finding a practical and economical solution for robot operation by avoiding the use of complex and costly devices. Authors hypothesized that using blinking eyes could be an easy way to achieve these objectives, and that user training will be easier than in other alternative methodology, allowing them to handle the robot in a short periods of time without much training and specific technical knowledge. The approach is based on the use of three basic elements: an accessible BCI, the MindWave BCI developed by Neurosky (NeuroSky, 2009), a mobile robotic platform, and a resident application on a personal computer (PC).

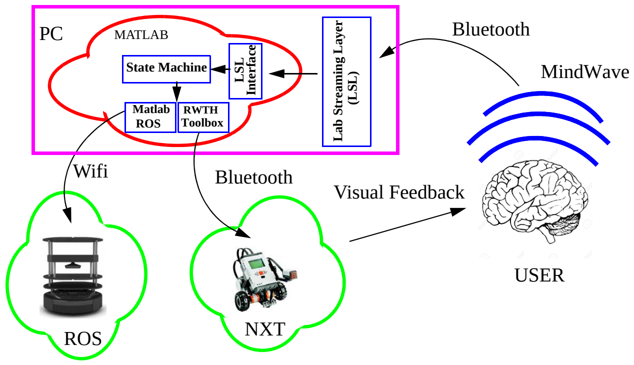

Figura 1: System Architecture.

2.1. System Architecture

The architecture of the developed system is shown in Figure 1. It is noteworthy that the three elements are connected wirelessly, giving some freedom of movement to the user. The core of the system is an application developed in Matlab 2015b, that interacts independently with the BCI MindWave's controller and the robot.

On the one hand a specific software has been programmed in C# to read the data captured by the BCI and to format them correctly. This program aims at overcoming Matlab limitation to manage more than one serial port at the same time. It is based on the Lab Streaming Layer (LSL) (C. Kothe *et al.*, 2005), which uses the UDP protocol to create different data streams that are synchronized by adding time stamps to them. The Matlab application also includes an LSL interface to receive and store the data streams created by the controller. On the other hand, the control application implements an algorithm that eases the task of driving. The user has a visual feedback of the behavior of the robot and through the control of the signals provided by the BCI he should be able to move the robot from a specific point to another initially established.

2.2. Neurosky Mindwave

MindWave BCI is able to estimate the state of attention and meditation (among other parameters) of the user. The attention and meditation signals are established by the behavior of certain brain waves. In particular, alpha waves are dominant when the meditation is high and beta waves predominate when the level of attention is high. Mindwave records these waves, and set the levels of attention and meditation using only two sensors, which is an important advantage compared to other more complex and difficult systems, that requires more than 24 electrodes. Together with this reduction, it should be noted as an advantage that the electrodes work in dry, which improves the precision in the measurement of brain wave.

Specifically, MindWave provides attention and meditation states using the so called attention and meditation algorithm eSense, property of NeuroSky, along with the registered waves and information on the frequency bands of the brain wave, which is provided by the proper NeuroSky technology, ThinkGear. This technology includes the contact sensor, touching the point of the head front, the contact reference in the ear clip and the integrated circuit that processes all the data.

The shapes of brain waves and the eSense measurements (attention and meditation) are calculated in this circuit by amplifying the signal of brain waves, removing ambient noise and muscle movement. eSense algorithm is then applied to the remaining signal resulting in values that can be interpreted. Keep in mind that the values of the measured eSense levels do not describe an exact number, but the ranges of the activity of the subject. Each different type of eSense value is reported on a relative scale of 1 to 100. In this scale, a value from 40 to 60 is considered *neutral* and is similar in concept to the *baselines* established in conventional brainwave measurement techniques (although the method used by ThinkGear for determining a baseline is proprietary and may differ from conventional methods).

A value from 60 to 80 is considered *slightly elevated*, and can be interpreted as levels of attention or meditation which may be considered greater than normal for a particular person. The values from 80 to 100 are considered *high*. Similarly, at the low end of the scale, a value from 20 to 40 indicates *low*, while a value from 1 to 20 indicates *very low* levels. These levels may indicate mental states of distraction, agitation, or an anomaly.

The reason to have spread ranges of values for every possible interpretation is that some parts of the algorithm of eSense learn dynamically, and, sometimes, some slow adaptation algorithms are used, so it fits to the fluctuations and trends of each user in a natural way. This represents the fact that brain waves in the human brain are subject to fluctuations. For this reason, the ThinkGear sensors are able to operate within a wide range of individuals under an extremely wide range of personal and environmental conditions at the time that they provide a good accuracy and reliability.

Additionally, the Mindwave system is capable of capturing another signal called 'eye blink strength', which advises the user's eye blink intensity. Its value ranges from 1 to 255 and is provided when a blink of the eyes is detected. The value indicates the relative strength of a blink without units. The front sensor of the Mindwave must be very tight in order that spurious blinks were avoided. These blinks are ranged usually in an intensity value from 30 to 40, the same that occurs with the natural eye blink.

The Mindwave transmits the data to the PC wirelessly, through the use of a Bluetooth USB adapter specific for the BCI used in this experiment.

2.3. *Application running on the personal computer*

The general scheme of the applications obeys to the flow chart shown in Figure 2. It can be observed how two programs (control and BCI reading) are running in parallel. Control application has been implemented under the Matlab environment, whereas the BCI reading program runs under the control of the Operative System. In both cases, after the phase of variables initialization and ports configuration, an iterative loop is executed until finishing after a given time.

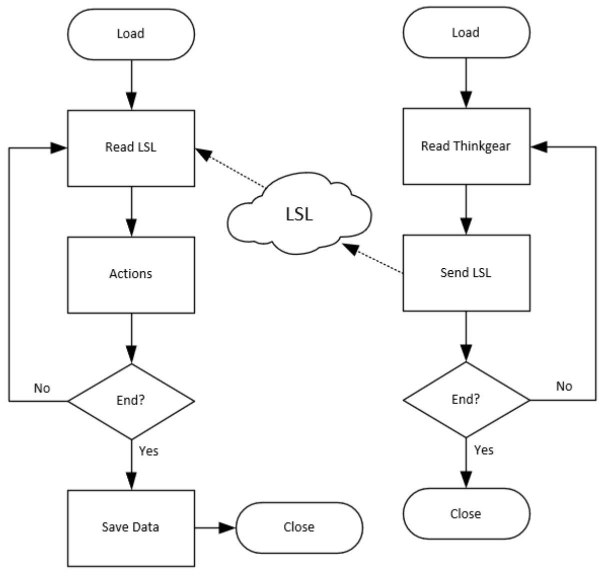

Figura 2: Software workflow. Matlab application scheme on the left and the MindWave data acquisition controller on the right.

ThinkGear components deliver their digital data as a series of asynchronous-byte sequence. This sequence must be analyzed and interpreted as ThinkGear packages in order to extract the data values correctly and process them on a computer. Neurosky provides a specific library that helps the programmer to establish a communication between Mindwave and the PC in an easy and simple way. By using this library, it is possible to access the data package and extract the values of attention, meditation and eye blink strength values. This way, the acquisition application reads data from the BCI, formats them conveniently, and sends data packets to Matlab in its own LSL stream through an UDP port.

Withing the loop of the control program, the following is executed sequentially: reading data from the UDP port, evaluating a state machine that determines the actions the robot must perform, and sending the control instructions to the robot. As the algorithm is simple, Matlab can work nearly in real time.

2.4. *Robotic platforms*

Two different robotic platform have been used for experimental purposes: a robot built with the Lego's Mindstorms NXT kit, and a Turtlebot robot. The first one represents a practical option; due to its small size it is easily transportable and adaptable to any experimentation scenario. The second is a less easily transportable but more sophisticated option, since it has a more precise optometry and capacity to incorporate advanced sensory systems. This option seems more appropriate for the development of applications in which accuracy is necessary.

On the one hand, the Toolbox RWTH - Mindstorms NXT has been used to control the behavior of the Lego robot from Matlab. This toolbox is a project developed by the University of RWTH Aachen (RWTH, 2017). This software has been developed to control the robot kit using Matlab via a Bluetooth wireless connection or via USB. This software is an open source product and is subject to the GNU General Public License (GPL). With this software it is possible to interact with the robot using MATLAB commands via Bluetooth.

On the other hand, TurtleBot is connected using the Matlab ROS interface. This Robotics System Toolbox enables you to interface with ROS and use ROS functionality in Matlab and Simulink (Matlab, 2017). You can connect to a ROS network, collect data, send and receive your own messages, and deploy code to a standalone system. With this software it is possible to interact with the robot using Matlab commands via Wifi.

The main part of the mobile robot control lies in a state machine that takes the levels of the signals provided by the BCI as input values, and evolves by activating and deactivating a set of states that are associated with the different ways of moving that the mobile robot has. This state machine together with the general control strategy are illustrated in the following section.

3. Control Strategy

The approach presented in this paper are based on a simplified version of the methodology detailed in (López de Ahumada *et al.*, 2017). There, the control strategy was based on the combination of attention signals, and eye blink strength to determine the intentions of the user. However, the present approach addresses the possibility of controlling the robot by just considering the capability of user for training eye blinking strength. Thus, the state machine that controls the robot will only respond to the changes of this signal to evolve from one state to another.

The idea presented in this paper is to control the movement of the robot by two parameters, the linear velocity (v_l) and angular velocity (w). Although more complicated strategies can be used, the illustrated experience is based on the switching between two behaviors: forward movement (L_M: v_l enabled and w disabled); rotating movement (R_M: v_l disabled and w enabled).

To make the state machine evolve, an input variable will be taken into account: eye blink strength (I_b). The machine has two states. One activates the L_M behavior and the other activates the R_M behavior. The switching between one behavior to another takes place when the intensity of the eye blink I_b is higher than a certain threshold.

This simple strategy allow user to move the robot in an easy way, just switching from forward to rotating motion. The implementation of a more sophisticated strategy, allows the realization of turns to the right and to the left, as well as more complex maneuvers with forwards and backwards movements (López de Ahumada *et al.*, 2017). However the time for users' training required by that approach is larger than the period required by the present work.

4. Experiments Setup

The objective of the experiments was to verify that users without previous training could handle the robots and reach certain proposed goals. In addition, the study aimed at figuring out whether the interaction with a real or virtual robot, or with both, influences the success of users in achieving the goals.

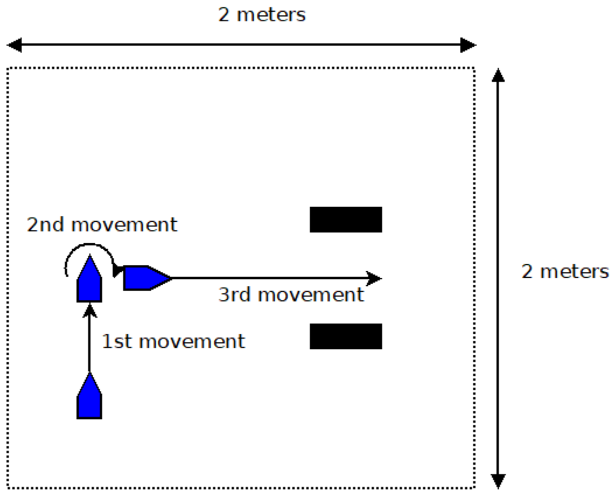

Figura 3: Working area of the experiment with the real robot, including the optimum route

4.1. *Evaluation tests*

The experiments analyzed below were carried out during the celebration of the Week of Science at the University of Huelva. Eighteen boys and fifteen girls between 14 and 16 years old participated in the experiment. The kids could interact with the robot, controlling its movement, either in a real or a virtual environment.

Participants were split into two groups in order to check the system usability and test different hypotheses. The first one, or hypothesis H1, aims at verifying if the user experience is better, or not, with a virtual or a real robot. The second one, or hypothesis H2, looks for studying the existence of any other effect in the interaction with virtual and real robots or, in other words, if starting using the virtual robot helps them improve the interaction with the real robot or vice versa. Then, both groups were split, in turn, into two subgroups. For H1, one of them only played with the real robot while, the other, only with the virtual one. For the H2, one half of the participants started using the virtual robot to later interact with the real one, whereas the remainder inverted the order of playing.

For both hypothesizes, two dependent variables were analyzed: number of achieved targets (N_{at}) and number of blinks per target (N_{bpt}). These variables quantify, in some extent, the task completeness and the difficulty in maneuvering the robot respectively.

The objectives the students had to achieve were different depending on whether they were interacting with the real or the virtual robot.

4.2. *Interacting with a Real Robot*

The working area of the experiments with the real robot is represented in Figure 3. It consists on a flat surface of 4 m^2 in the ground where the robot could move freely. Two objects were located at a distance of 20 cm between them. Figure 4 shows a snapshot of the experimental session. The objective set for the students was to drive the robot until it moved between both objects, as many times as possible.

In each experiment, the robot was initially located perpendicularly to the objects, in the same relative position, so that

Figura 4: A snapshot of the experiments during the Week of Science

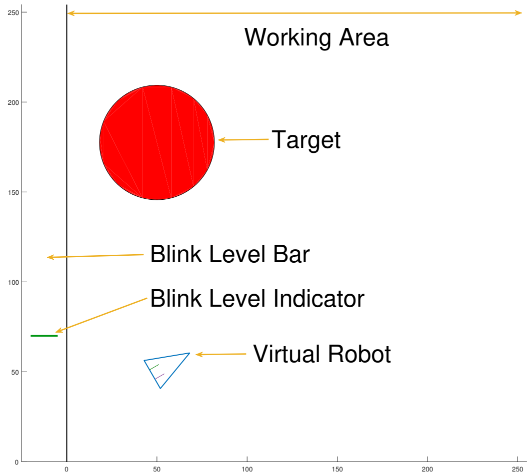

Figura 5: Virtual Robot Interface.

the optimum route to achieve the objective would consist of three different motions (as illustrated Figure 3): firstly a forward displacement, secondly a rotational motion and a thirdly a forward movement. If the objective was achieved, the student had to drive the robot to another point of the working area and start manoeuvring again. Experimenter manually annotated the number of achievements in each session, whereas the other variable, N_{bpt}, was obtained from the analysis of the recorded data.

4.3. *Interacting with a Virtual Robot*

A Matlab application was built to simulate the movements of the robot on a computer screen. The virtual robot appears as a triangle (Figure 5) that can move ahead and rotate, as the real robot does, using the same control algorithm. In the R_M state, the robot spins around at a frequency of $\pi/6$ rad/s and, in the L_M state, it moves along the panel at a velocity that allows the target to be reached several times during the session. Such a target is shown as a red circle, with a size that is one eighth of the working area side, and a position that randomly changes as soon as the robot touches it. Once the target is placed on a new position, the robot appears away from it at a distance of one half of the working area side and with a relative angle that is a multiple of $\pi/6$. This allows users to reach the target by performing only one blink.

Additionally, the user interface contains a lateral panel wherein a blink level indicator, for feedback purposes, is also shown. The blink indicator, the robot rotation movement and the finite state machine are all updated every second, as the software receives a new data package from the NeuroSky headset. The target position, EEG signal, received blinks and robot location was all continuously recorded for further analysis.

5. Experimental Results

The first objective was to show that the proposed methodology facilitates user robot interactions, by analyzing the percentage of students that achieve, at least, a target during their first experimentation. In the case of participants interacting with the real robot, the percentage of user achieving a target was 40 %, while this percentage increase to 92 % for users playing with the virtual one. Later, authors proposed to analyze differences in the interaction with the real and the virtual robot by considering hypotheses H1 and H2.

5.1. *Hypothesis H1*

Table 1 summarizes the results obtained by participants when maneuvering the robot in a virtual or a real scenario. As can be seen, the percentage of people who could properly drive the robot towards the target, and reached it in at least one occasion, was higher with the virtual robot (87.5 %) than with the real robot (37.5 %). Besides, the average number of blinks per target was 5.9 with the virtual robot, less than with the real, 8.5. Note that N_{bpt} is not considered when the robot did not reach the target.

Figures 6 and 7 depict the boxplots for N_{at} and N_{bpl} respectively. Their median values (plotted with a red line in the boxes) show that the use of virtual robots seems to be better for obtaining a slightly higher number of achievements, N_{at}, and needing a lesser number of blinks for the robot guidance towards the target, N_{bpl}. The Mann-Whitney-Wilcoxon test (MWW), a nonparametric statistical test that does not need previous knowledge of the sampling distribution and can be applied to unequally-sized observation groups, shows that there exists an effective influence of robot model on N_{at} (p=0.03), but not on N_{bpt}, p-value of 0.46.

5.2. *Hypothesis H2*

Here, we investigated any order effect on the variables of interest, collected in Table 2. Five people (subjects 25-29) followed the virtual-real robot sequence in a double-round experiment, whereas the four other subjects (30-33) performed a reversed sequence. The table also includes the incremental values, ΔN_{at} and ΔN_{bpt} which have been calculated by subtracting the results of the first round from the second one. Thus, a negative/positive ΔN_{at} means that the number of final achieved targets decreased/increased with respect to the first round figures.

On the one hand, the percentage of achievements in the first round was 100 % and 50 % respectively for those subgroups, higher and lower respectively than the results obtained in H1, but with non statistically significant differences between them ($p > 0.4$ according to MMW). On the other hand, the average number of blinks per target was 8.5 and 14.5 for virtual and real

	Subject	N_{bpt}	N_{at}
Virtual	1	13	1
	2	8.5	1
	3	11	1
	4	1	2
	5	3.5	1
	6	1	1
	7	3.5	1
	8	-	0
Real	9	-	0
	10	10	1
	11	-	0
	12	-	0
	13	-	0
	14	-	0
	15	-	0
	16	6	1
	17	-	0
	18	-	0
	19	1	2
	20	16	1
	21	-	0
	22	-	0
	23	5	1
	24	13	1

Tabla 1: Results for hypothesis H1. Subjects 1-8 used only the virtual robot while subjects 9-24 drove the real robot.

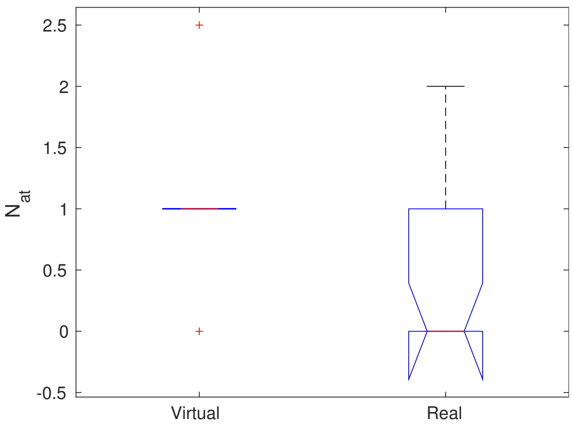

Figura 6: Number of achieved targets with the virtual and the real robot.

robot at the first round. Both higher than the values in H1, but without significant differences either ($p > 0.3$ in both cases).

Figures 8 and 9 respectively depict the boxplots containing the incremental variables ΔN_{bpt} and ΔN_{at} for H2. Following the same procedure as above, the statistical analysis turned out a p-value higher than 0.4 for both variables, meaning that the order does not exert any significant influence on them.

It is remarkable that the variable N_{bpt}, in the second round with the real robot, showed a significant increase ($p=0.016$) with respect to the first round, performed with the virtual robot, suggesting that the former was perceived as more difficult to control.

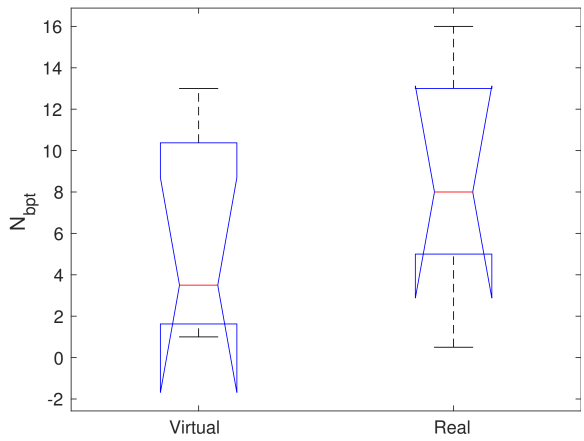

Figura 7: Number of blinks per target with the virtual and the real robot.

	1-Virtual		2-Real			
Subject	N_{bpt}	N_{at}	N_{bpt}	N_{at}	ΔN_{bpt}	ΔN_{at}
25	12	1	-	0	-	-1
26	7	1	14	1	7	0
27	5	1	19	3	14	2
28	9	3	63	1	54	-2
29	10	2	18	2	8	0
	1-Real		2-Virtual			
Subject	N_{bpt}	N_{at}	N_{bpt}	N_{at}	ΔN_{bpt}	ΔN_{at}
30	-	0	-	0	-	0
31	15	1	-	0	-	-1
32	-	0	-	0	-	0
33	14	2	8	2	-6	0

Tabla 2: Results for hypothesis H2. Subjects 25-29 used the virtual robot and then the real robot, while subjects 30-33 inverted the order. Incremental values are also shown.

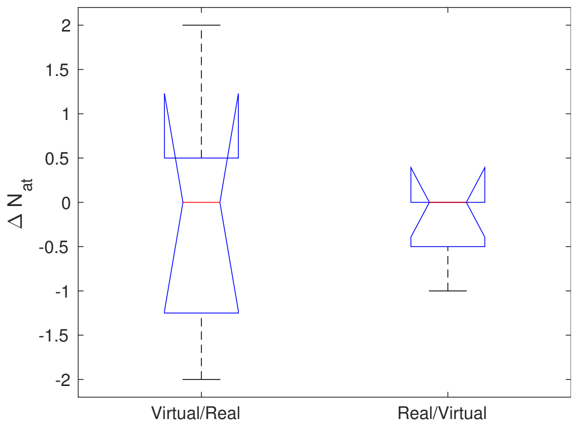

Figura 8: Differences in the number of achieved targets according to the experimental sequence.

5.3. Discussion

The analysis of the results presented above demonstrates that this approach can be considered as a user-friendly methodology for interacting with real or virtual robot. A success rate between 40 % and 60 % in a first interaction, without a prior training and

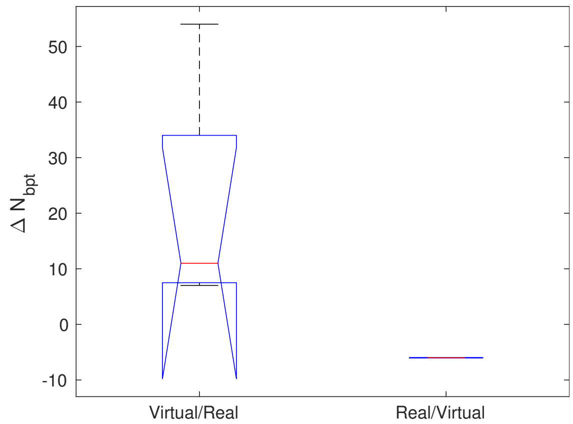

Figura 9: Differences in the number of blinks per target according to the experimental sequence.

considering a evaluation period of 60s, indicates that the participants quickly acquire an efficient ability to handle the robot.

Another question is: which environment, real or virtual, facilitates user's learning the most? Virtual environments and the use of robots have shown several advantages in areas like Medicine. In (Riener, 2012), authors proved the benefits of virtual environments in rehabilitation, showing even better performances than real environments when comparing motor learning in people with disabilities (Holden, 2005). Other studies have demonstrated the feasibility and effectiveness of an assistive robot system to engage elderly users in physical exercise (Fasola *et al.*, 2013), enhance manual performance of individuals with cerebral palsy (Nooshin *et al.*, 2017) or promote social interaction (Gómez-González *et al.*, 2016).

When comparing virtual or physical robots, some works have showed that tangible agents or physical robots resulted in more favorable responses from participants during a human-computer interaction (Li, 2015), or in promoting longer exercising times compared to virtual agents (Schneider *et al.*, 2018). In contrast, our results have shown more effectiveness for virtual robots according to the statistical significance in the number of achieved targets. Several reasons may justify this, some of them related to how the interaction was carried out, which slightly differed from the physical robot in two main aspects. Firstly, if the virtual robot gets too close to the working area border, it automatically switches into the rotation state. Secondly, as soon as the target is reached, another target is generated, the virtual robot is placed at a specific distance from it and the control algorithm returns again to the rotation state. These reasons together give enough spare time for subjects to achieve more targets during the session. Moreover, the dynamics of the real robot has special influence in the interaction with users. For instance, robot's inertia is particularly responsible for the lack of precision during motion switching and reorientation manoeuvres. Similarly, Bluetooth communication between computer and robot adds delays that in the case of the simulated system do not exist. These reasons could explain a larger number of successes (N_{at}) in the experiment with the virtual robot and a greater the number of blinks per target (N_{bpt}) in the case of the real robot.

Another aspect concerns the high number of blinks needed to complete the task, when, as explained above, it might have been possible with just one blink. A possible explanation yields in the proprietary blink detection algorithm supplied by NeuroSky. Some studies have highlighted its low accuracy, close to 50 % (Maskeliunas *et al.*, 2016), which may cause a lack of response in the robot to the subject's signal at the appropriate time. To address with this issue, it is necessary to include another method that guarantees a much higher blink recognition rate, as for example, with the algorithm proposed in (Molina-Cantero, A. *et al.*, 2017a) or (Molina-Cantero, A. *et al.*, 2017b) which reaches an accuracy over 98 %. Additionally, the control variable itself, eye blinking, affects the robot guidance when involuntary blinks make the robot switch among states, modifying its trajectory and, then, requiring more blinks to complete the driving task. To avoid that effect, new methods for discriminating between voluntary and involuntary blinks must be included. In this sense, the development of a new algorithm that allows determining more precisely the intensity of blinking would help to develop more efficient applications.

By comparing H2 to H1, additional information can be explored. On one hand, for those who used the real robot in the second round in H2, the mean of achieved targets was 1.4. This figure improves the result obtained by subjects 9-24 in H1 in average (0.44), who only used the robot. This may suggest that a previous training with a virtual robot benefits the control of a real robot. Indeed, the statistical analysis showed that this procedure was near to be significant (p=0.055). However, the reduced number of subjects limits the power of the statistical analysis and, hence, it must not be concluded the existence of such an effect. On the other hand, those who played in the second round with the virtual robot, experienced a decrease in the N_{at} with respect to subjects 1-8 in H1 (from 1.13 down to 0.5) but, as similarly as above, such differences were not conclusive (p=0.12). Future work will try to reduce the differences between the virtual and the real robot to determine if these results are due to this or other reason.

6. Conclusions

This article describes the architecture of a system aimed to control the movement of a robot by blinking eyes. The system is based on the use of a BCI that registers the intensity of blinking, and a control architecture that allows transforming intensity changes into motion commands for the robot. By means of this approach the training time that users need to learn to drive the robot is very short, obtaining a high rate of success in a period of 60s. The article presents experimental results that confirm this fact and also discusses about the influence of interacting with a real robot or with a virtual one. The results indicate that with the proposed configuration users handle the virtual more easily than the real robot. The article also studies if a previous training with the virtual robot helps to improve the interaction with the real robot or vice versa. The results indicate that experimenting first with the real robot helps to improve the results with the virtual robot, nevertheless the same does not happen in reverse. As future works we propose the development of a particular algorithm that improves the estimation of the blinking intensity and the application of other types of algorithms in order to enhance the discrimination of natural blinks.

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