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A Two-class Self-Paced BCI to Control a Robot in Four Directions

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Abstract—**In this work, an electroencephalographic analysis-based, self-paced (asynchronous) brain-computer interface (BCI) is proposed to control a mobile robot using four different navigation commands: turn right, turn left, move forward and move back. In order to reduce the probability of misclassification, the BCI is to be controlled with only two mental tasks (relaxed state versus imagination of right hand movements), using an audio-cued interface. Four healthy subjects participated in the experiment. After two sessions controlling a simulated robot in a virtual environment (which allowed the user to become familiar with the interface), three subjects successfully moved the robot in a real environment. The obtained results show that the proposed interface enables control over the robot, even for subjects with low BCI performance.**

Keywords: Brain computer interface (BCI), virtual enviroment (VE), asynchronous, robotics.

I. INTRODUCTION

A brain-computer interface (BCI) is based on analysis of the brain activity, recorded during certain mental activities, in order to control an external device. One of its main uses could be in the field of medicine, especially in rehabilitation. It helps to establish a communication and control channel for people with serious motor function problems but without cognitive function disorder [1]. Amyotrophic lateral sclerosis (ALS), brain or spinal cord injury, cerebral palsy and numerous other diseases impair the neural pathways that control muscles or impair the muscles themselves. Some patients suffering this kind of diseases can neither communicate with the outside world nor interact with their environment. In this case, the only option is to provide the brain with a new and non-muscular communication and control channel by means of a BCI.

Most non-invasive BCI systems use brain activity recorded from electrodes placed on the scalp, i.e., the electroencephalographic signals (EEG). Different features of the EEG signals can be extracted in order to encode the intent of the user. The most common EEG signal features used in current BCI systems include [2] slow cortical potentials [3], P300 potentials [4] or sensorimotor rhythms (SMRs) [5]. SMRs are based on variations of the μ (8-12 Hz) and β (18-26 Hz) rhythm amplitudes, which can be modified by voluntary thoughts through some specific mental tasks, such as motor imagery [6]. When a person performs a movement, or merely imagines it, it causes an increase or a decrease on the μ and β rhythm amplitudes, which are referred to as event-related synchronization (ERS) or event-related desynchronization, (ERD) [7]. People can learn how to use motor imagery to change SMR amplitudes, and this relevant characteristic is what makes SMR suitable to be used as input for a BCI.

Nowadays, different BCI applications are in use, such as computer-controlled spelling devices [8] or neuroprosthesis in patients with spinal cord injuries [9]. Recently, BCI research is also targeted to rehabilitation of motion-disabled individuals, where many BCI applications based on mental task discrimination allow the user to navigate through different virtual environments (VEs) [10-12], control simulated [13] [14] or real mobile robots [15-17], and control simulated [18] or real wheelchairs [19]. In all these BCI systems, the number of navigations commands is associated to the number of classes to discriminate. For example, in [14], two mental tasks (left and right hand MI) are discriminated in order to execute two different commands ("turn left then move forward" or "turn right then move forward"). However, a higher number of commands is necessary in order to make control of the device easier. One of the options to increase the number of navigation commands is moving from a binary decision to a more diverse decision, giving a choice between more options [20], for example, by increasing the number of mental tasks. In [13, 15, 16, 18, 19] 3 mental states are used in order to provide 3 different navigation commands (move right, move left and move forward). Besides, in these BCI systems, different levels of intelligence are implemented to assist on the control task. This way, the subjects received some help to guide the robot or the wheelchair. Very recently, *Barbosa et al.* have reported an EEG-based BCI that was able to discriminate between four different mental activities related to SMRs (imagery movements of feet, tongue, left arm and right arm) to provide 4 discrete robot movements: stop, move forward 500 mm, turn left 30 degrees and turn right 30 degrees [17].

It should be noted that increasing the number of different mental tasks to discriminate is an option to increase the number of navigation commands. However, many studies have reported that an increasing number of classes resulted in a decrease of the classification accuracy [20, 21]. These studies suggest that the highest classification accuracy is achieved by classifying only two classes.

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In a BCI-driven wheelchair, for safety concerns, it is very important to guarantee a high level of classification accuracy, because choosing a wrong command due to a classification error can have important consequences, leading to very dangerous situations.

As a previous step before using a real wheelchair, in this work an EEG analysis-based, self-paced (asynchronous) BCI is proposed to control a mobile robot using four different navigation commands: turn right, turn left, move forward and move back. A self-paced BCI system distinguishes between two states: (i) a non-control (NC) state in which subjects can be involved in a mental activity other than controlling the BCI, and (ii) an intentional control (IC) state, in which subjects can control the system by specific mental tasks. Subjects voluntarily switch the state they are in. As proposed in [20] and [21], in order to reduce the probability of misclassification, the BCI is controlled with only two mental tasks (one MI versus relaxed state). The main objective of the study is to validate the usefulness of the system that lets the subjects control the robot in four directions using four low levels commands.

The final aim of this study was to test the usefulness of the proposed paradigm to control a real robot; in real conditions, it would be difficult for the users to pay attention to a graphical interface and to the robot simultaneously, so we decided to use an audio-cued interface. However, we hypothesized that it would be easier if they firstly faced a visual navigation paradigm, which could help them to become familiar with the command selection process. Therefore, we divided the experiment into two phases. After an initial training day, ,in the first phase, the subjects had to control a simulated mobile robot in a virtual environment. A similar experiment was carried out successfully in [22], where subjects had to navigate through a VE using three different navigation commands. To this end, a graphical interface was offered to the subject. The interface consisted of a circle divided into four sections, which corresponded to the possible navigation commands. A bar in the center of the circle was continuously rotating, and the subject controlled the length of the bar in order to reach the chosen command. In the second phase, the subject had to control a real robot with the only help of an audio-cued interface

II. Materials and Methods

A. Subjects and Data Acquisition

Four healthy subjects (2 male and 2 female, right-handed, age 22,5 ± 3,5), named S1, S2, S3 and S4 participated in the study. Subjects S2, S3 and S4 had previous BCI experience.

The EEG was recorded from two bipolar channels. The active electrodes were placed 2.5 cm anterior and posterior to electrode position C3 and C4 (right and left hand sensorimotor area, respectively) according to the 10/20 international system. The ground electrode was placed at the FPz position. Signals were amplified by a sixteen-channel biosignal g.BSamp (Guger Technologies) amplifier, and then digitized at 128 Hz by a 12-bit resolution data acquisition card NI USB-6210 (National Instruments) card.

B. Initial training and signal processing

Before the online self-paced experiments, subjects participated in two initial training sessions, for calibration purposes. This training was based on the paradigm proposed by our group (UMA-BCI) in [23], in which subjects, immersed in a VE, had to control the displacement of a car right or left, according to the mental task carried out, in order to avoid an obstacle. The training was carried out discriminating between two mental tasks: mental relaxation and imagined right hand movements. In the first session, the subjects did not receive any feedback, and it was used to set up classifier parameters for the second session, in which continuous feedback was provided. In this first session, subjects were instructed to carry out 3 experimental runs, consisting of 40 trials each. After a 10-15 min break, necessary time to do the offline processing, subjects participated in the second session. This feedback session consisted of one experimental run, intended to check the effectiveness of the chosen parameters and the ability of the subject to control his EEG signals. In order to increase the degree of immersion, the VE was projected on a large screen (2 x1.5 m) and subjects were placed at a distance of 3 m.

Each trial was 8-second long, its timing being shown in Fig. 1. Initially, in a scene of continuous movement, the car was being driven down the middle of three lanes. At 2 s, a puddle-like obstacle would come into view, on the left or right lane, at the end of the road. If it appeared on the left lane, subjects were to imagine right hand movements. If it appeared on the right, they were to remain in a relaxed state. At 4.25 s, the puddle was situated beside the car, starting the feedback period in which subjects were able to control the movement of the car, left or right according to the classification result, in order to avoid the obstacle (session with feedback). In sessions without feedback, the car remained in the central lane during the feedback period. At 8 s, the trial finished and started over again after a pause, ranging from 0.5 s to 3 s (randomly distributed). The VE was created with VRML 2.0, and its interaction with MATLAB was achieved using the MATLAB Virtual Reality Toolbox.

The offline processing was based on the procedure detailed in [23], and consisted of estimating the average band power of each channel in predefined, subject-specific reactive

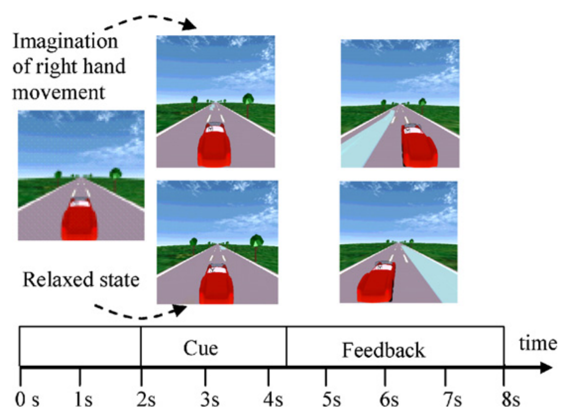

Figure 1. Timing of one trial of the training with feedback

(manually selected) frequency bands at 500-ms intervals. For the first session, an error time course was computed with a ten-time 10-fold cross-validation of a linear discriminant analysis (LDA). The extracted feature parameters of the classification time points with the lowest classification error were used to set up the LDA classifier parameters (weight vector) for the session with feedback. In the feedback session, the displacement D of the car was computed online every 31.25 ms as a result of a LDA classification. A negative/positive value of D was translated into a left/right displacement of the car, indicating that the trial was classified as a left/right trial. The same parameters as used for the feedback session were used to calibrate the system for the online experiments to control the robot. The trial paradigm and all the algorithms used in the signal processing were implemented in MATLAB.

C. *Control of the simulated robot in a VE*

The first phase of the experiments consisted of controlling a simulated robot through a group of corridors, setting up a sort of small maze. The proposed VE (and the virtual robot) is presented in Fig. 2 (left) and was designed with the same features as the real environment used during the second phase of the experiments (Fig 2-right): 70 x 95 cm; the corridors were all 20 cm wide. The virtual robot is cylindrical-shaped with a diameter of 7.5 cm and a height of 4.7 cm. It was configured to stop automatically when it approached an obstacle at 2 cm. The robot was programmed to move at a speed of 3.9 cm/s, and turned at 42.9 degrees/s. The BCI commands are translated into four different movements of the robot: turn 90 degrees to the right, turn 90 degrees to the left, move forward a fixed distance (14 cm) and move back a fixed distance. By default, when the robot moved back the distance was set to 14 cm, but if the previous movement ended up in a collision, it moved the same distance as the previous advance, in order to offer the subject the opportunity to rectify the error. The task was to drive the simulated robot from the start position to the goal as fast as possible, using the minimum number of navigation commands, trying to move always forward (the forward direction is indicated by an arrow on the top of the robot) and avoiding the collisions. The optimum solution to reach the goal would be the one shown in Fig. 2-left, been the number of the different navigation commands as follows: 2 to turn right (90 degrees), 2 to turn left, 11 to move forward and 0 to move back.

The procedure to control the simulated robot with the BCI system is similar to the one proposed in [22]. The system waits in a NC state in which an NC interface is shown. The NC interface allows the subjects to remain in the NC state (not generating any command) until they decide to switch to the IC state, where the control is achieved through the IC interface.

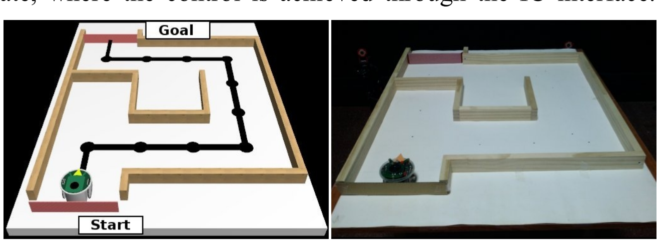

Figure 2. Simulated mobile robot in the VE (left) and the real one (right)

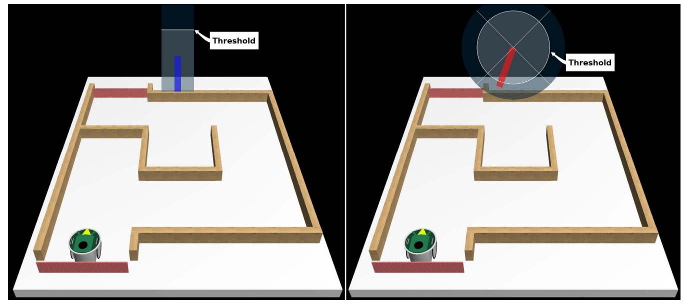

Figure 3. NC interface (left) and IC interface (right)

The NC interface consists of a semi-transparent vertical blue bar placed in the centre of the screen. The length of the bar is computed every 62.5 ms as a result of the LDA classification: if the classifier determines that the mental task is right-hand MI, the bar extends; otherwise (relaxed state), the bar length remains at its minimum size. When the length exceeds a subject-dependant selection threshold (Fig.3, left) for a given "selection" time (also chosen by each subject) the system switches to the IC state. The IC interface consists of a circle divided into four parts, which correspond to the possible navigation commands (move forward, turn right, move back and turn left), with a bar placed in the centre of the circle that is continuously rotating clockwise (Fig. 3, right). The subject can extend the bar by carrying out the MI task in order to select a command when the bar is pointing at it. The way selection works in this interface is the same as in the NC interface, with the same selection time and selection threshold. In the IC interface, another threshold is defined: the stop threshold, which is lower than the selection threshold and not visible to the subject. When it is exceeded, the bar stops its rotation in order to help the subject in the command selection. The rotation speed was fixed to 24 degrees every second, so it took 9 s to complete a turn if there was not any stop. Once a command is selected, the simulated robot starts to move and the IC interface is still shown. After the movement is completed, the position of the rotating bar takes its rotation up again from the same point it last stopped to select the command. That way, the subject can select the same command several times in a row. If the bar completes two turns without the subject selecting any command, the system switches to the NC state.

Unlike the paradigm proposed in [22], in the one proposed in this work the subjects receive audio cues while they interact with the system. When the state switches from IC to NC, they hear the Spanish word for "wait"; the reverse switch is indicated with "forward", since it is the first available command in the IC state. Finally, every time the bar points to a different command, they can hear the correspondent word ("forward", "right", "back" or "left").

Due to the main objective of the experiment being to control a real robot, the graphical interfaces used in the NC and IC states had to be replaced by the audio-cued interface. For this reason, during this first phase of the experiment subjects were trained to switch from the graphical interface to the audio-cued interface. Each subject participated in two sessions, carried out in different days, with two experimental runs each. In the first session (denoted session 1), the aim of the runs was to drive the simulated robot to the goal using the graphical and the audio-cued interfaces together. In the second session (denoted session 2), only the audio-cue interface was used to drive the simulated robot in the two runs. To increase the degree of immersion, the VE was projected on the same large screen as used during the initial training. The VE was created with OpenGL for the graphics, OpenAL for the 3D audio, and ODE for physics simulation. The C programming language was used. Interaction between MATLAB and the VE was achieved with TCP/IP communications, which allowed us to use different machines for data acquisition and processing, and environment simulation and display.

D. *Control of the mobile robot*

The second phase of the experiments consisted of controlling a mobile robot through a specific environment. The robot was an EPFL educational e-puck (www.e-puck.org). The e-puck is a two-wheeled, cylindrical-shaped programmable robot with 8 infrared sensors around its perimeter, which were configured to make the robot stop automatically when it approached an obstacle. The robot dimensions and features (movement speed, collision distance) were the same as in the VE. The real size of the environment corresponds to the one used in the simulation (see Fig. 2).

In this second phase, each subject participated in one session (denoted session 3) with two experimental runs. The aim of these two runs was to drive the robot to the goal using only the audio-cued interface.

III. RESULTS

The optimized reactive frequency bands were 11-15 Hz, 9-14 Hz, 10-14 Hz and 10-14 Hz for subjects S1, S2, S3 and S4 respectively. The minimum error rates obtained from the computer error time course during the session without feedback were 26,7%, 27,5%, 23,3% and 25,8% for each subject respectively. Finally, the chosen selection times changed among subjects, even between among sessions, in a range of 1-1.2 s.

Next, the results obtained in the 2 sessions of the simulated control and the results obtained in the session of real control are presented. Due to a number of reasons, subjects S1 did not participate in the first session and was submitted to control the simulated robot directly with the audio-cued interface. Subject S2 participated only in one experimental run to control the robot. In table I, different parameters are shown for each subject and run: the time in seconds necessary to generate the desired trajectory (T), the number of times that the robot collided with the wall (Col), the number of selected commands of each type (F: Forward, R: Right, B: Back and L: Left) and the total number of commands used to drive the robot from the start position to the goal (TC). The last row of the table shows what values should be obtained for the optimum solution (see Fig. 2).

It is interesting to notice that, out of four subjects, for three of them (S1, S2 and S3) the required average time to generate the trajectory controlling the robot (264.5 s, 286 s and 348 s for subjects S1, S2 and S3 respectively) was less than the time required to control the simulated robot in session 1 (305 s, and 366,5 s for subjects S2 and S3 respectively), and much less than the time required in session 2 (413,5 s, 476 s and 781 s for subjects S1, S2 and S3 respectively). A consequence of this is that for these subjects, in average, the total number of commands used to drive the robot (23, 29 and 21 for subjects S1, S2 and S3 respectively) were fewer than to drive the simulated robot, specifically when only the audio-cued interface was used (24.5, 31 and 33 for subjects S1, S2 and S3 respectively). The number of collisions was very small for subjects S1 and S2 in all the runs, but specially controlling the robot (0 collisions for subject S1 in both runs, and 1 and 0 collisions for subject S3 in runs 1 and 2, respectively). Subject S2 only participated in one experimental run to control the robot and collided 6 times, however, the number of collisions in session 1 was small (2 and 0 for run 1 and 2 respectively). The obtained results for subject S4 were variable between the different runs; however, run 2 of session 3 was one of the best runs carried out by this subject. It is important to notice that subject S1 is a non-experienced subject; however, his results are really promising.

In Table II, the average values obtained from each session are shown. An improvement in performance can be observed,

TABLE I. RESULTS OBTAINED FROM ONLINE SELF-PACED BCI EXPERIMENTS FOR EACH SUBJECT AND RUN

Sub.	Ses.	Run	T(s)	Col	F	R	B	L	TC
S1	1	1							
		2							
	2	1	474	0	15	6	3	6	30
		2	353	1	12	3	1	3	19
	3	1	233	0	11	4	0	4	19
		2	296	0	13	6	2	6	27
	Mean Ses1								
	Mean Ses2		413,5	0,5	13,5	4,5	4,5	3,5	24,5
	Mean Ses3		264,5	0	12	5	5	1	23
S2	1	1	430	2	11	9	4	11	35
		2	180	0	7	5	4	3	19
	2	1	497	4	13	8	3	8	32
		2	455	3	14	6	4	6	30
	3	1							
		2	286	6	9	9	6	5	29
	Mean Ses1		305	1	9	7	7	4	27
	Mean Ses2		476	3,5	13,5	7	7	3,5	31
	Mean Ses3		286	6	9	9	5	6	29
S3	1	1	469	4	16	10	12	14	52
		2	264	0	11	5	0	5	21
	2	1	650	2	15	8	4	8	35
		2	912	2	14	7	3	7	31
	3	1	450	1	13	5	3	6	27
		2	246	0	11	2	0	2	15
	Mean Ses1		366,5	2	13,5	7,5	9,5	6	36,5
	Mean Ses2		781	2	14,5	7,5	7,5	3,5	33
	Mean Ses3		348	0,5	12,5	3,5	4	1,5	21
S4	1	1	401	1	15	6	4	6	31
		2	505	6	18	25	5	5	53
	2	1	519	5	15	8	6	12	41
		2	542	1	13	8	4	12	37
	3	1	686	7	20	17	11	13	61
		2	463	3	14	8	4	4	30
	Mean Ses1		453	3,5	16,5	15,5	5,5	4,5	42
	Mean Ses2		530,5	3	14	8	12	5	39
	Mean Ses3		574,5	5	17	12,5	8,5	7,5	45,5
Manual				0	11	2	2	0	15

TABLE II. AVERAGE RESULTS OBTAINED FROM ONLINE SELF-PACED BCI EXPERIMENTS FOR EACH RUN

Ses	run	T(s)	Col	F	R	B	L	TC
1	1	433,3	2,3	14	8,3	6,6	10,3	39,3
	2	316,3	2	12	11,6	3	4,3	31
	Mean	374,8	2,15	13	9,95	4,8	7,3	35
2	1	535	2,75	14,5	7,5	4	8,5	34,5
	2	565,5	1,75	13,2	6	3	7	29,2
	Mean	550,25	2,25	13,85	6,75	3,5	7,75	31,8
3	1	456,3	2,6	14,6	8,6	4,6	7,6	35,7
	2	316	2,25	11,7	6,2	3	4,2	25,2
	Mean	386,15	2,42	13,15	7,4	3,8	5,9	30,4

in term of times, in session 1 and session 3. The obtained values are, in session 1, 433,3 s for run 1 and 316,3 s for run 2; and in session 3, 456,3 s and 316 s for run 1 and run 2 respectively.

Once a wrong command is executed, the strategy used for the subjects to turn the robot toward the correct direction was to select the opposite navigation command. For example, if the correct command is Forward but a Right command has been selected, the next command to chose would be the Left command. For this purpose, subjects must switch their mental task (to relaxed state) in order to reduce the length of the bar, allowing it to rotate. Once the bar is pointing to the Left command, subjects must carry out the MI task in order to select the new command. An example of this strategy is shown in Fig. 4, left. This trajectory is from the run 2 (session 3) of subject S1. No collision has been produced and it is possible to check how the subject rectifies the direction of the robot twice. Subject S3 carried out, in run 2, the trajectory following the optimum solution, using 15 navigation commands and avoiding collisions, as shown in Fig. 4, right.

IV. DISCUSSION AND CONCLUSION

It has been shown that the strategy used by the subjects to turn the robot toward the correct direction was to select the opposite navigation command. This strategy seems to be more natural; however, it can be more difficult to carry out, because subjects must control the changes of mental tasks. Besides, the required time can also be higher, being necessary to wait for the bar to turn. Another strategy could be to select the same wrong command three times in a row. In the same example as described in the previous section, if the correct command is Forward but a Right command has been selected, the subject can select the same Right command three more times in order to set the good direction. For this purpose, the subject has to keep carrying out the MI task in order to keep the bar extended, so he need not switch his mental task. Besides, the required time can also be lower, because it is not necessary to wait for the bar to turn to the next command.

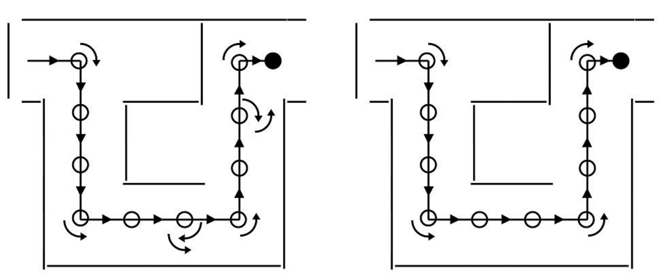

Figure 4. Trajectory of the robot during the run 1 for subject S1 (left) and run 2 for subject S3 (right).

The selection procedure could be optimized by dynamically reordering the navigation commands. In the graphical interface each section is associated to the corresponding command, and changing that association could be very confusing, but with the audio-cued interface commands can be presented in any arbitrary order. It would be interesting to investigate the likelihood of a given navigation command based on the previous sequence of movements, in order to organize the commands by probability order.

It must be pointed out that the results are worse in session 2, presumably because it is the first time that subjects face an audio-only interface;in session 3 subjects performed remarkably better.

Subject S4 is the only one that obtained worse results when using the audio-cued interface. Probably, more training sessions would be necessary for the user to adapt herself to the new interface.

In general, the results obtained in only 6 runs are remarkably good. The proposed system has proven easy to use. In some cases, such as S1 and S3, subjects executed near-perfect control. It must be noticed that the subjects were not particularly good at controlling their SMR signals- their minimum classification error percentage was not too low-, but still they were able to control the robot with almost no mistakes. The proposed interface greatly improves the navigation results. The explanation can be as follows: Subjects have not "perfect" control of their SMR signals (concerning their classification accuracy); however the subjects' intention (MI or relaxed state) determines an average, a slow change underneath the rapid changes of the bar under/above the threshold. The way the selection works, with the need of a selection time above this threshold, is analogous to the effect of a low-pass filter, thus removing the high frequency noise. In other words: A classification error in the LDA does not entail a wrong command, as the selection needs that the bar accumulates a fixed time above the threshold.

In the near future, our group plans to evaluate the performance of the system with continuous, rather than discrete, movements. A continuous system would increase the freedom of movement of the subject, but will certainly introduce new challenges regarding precision, latency and control over the interface.

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