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Brain-computer interface: Proposal of a shaping-based training

Leandro da Silva-Sauer*, Luis Valero-Aguayo, Francisco Velasco-Álvarez, Ricardo Ron-Angevín, Salvador Sancha-Ros

Abstract **Introduction:** *Persons affected by certain motor disabilities such as amyotrophic lateral sclerosis can evolve with important motor and speech difficulties in communication. A BCI (Brain Computer Interface) is a system that allows interaction between the human brain and a computer, permitting the user to control a communication channel through his or her brain activity. It is based on the analysis and processing of electroencephalographic (EEG) signals to generate control commands. The present study focuses on the subjects' capability to improve the way they learn to control a BCI system.* **Methods:** *Two training procedures were compared: standard and progressive shaping response. Six volunteers participated in a reversal single-subject ABAC design.* **Results:** *The study showed that both procedures are equally effective in producing a differential responding in the EEG signals, with no significant differences between them. Nevertheless, there were significant differences when distinguishing two neuronal responses (relax state and hand-movement imagination). Also, in the analysis of individual signals, an adaptive process for the shaping process and a lower error rate in the idle response appeared.* **Conclusion:** *Both proposed training procedures, standard and progressive shaping, are equally effective to achieve training of differential responses (imagination of hand/relax) in the interaction with a BCI.*

Keywords *Brain computer interface, BCI, shaping, learning.*

*e-mail: sauer@uma.es
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Braz. J. Biom. Eng., 29(2), 123-132, June 2013

Introduction

Those who are affected by a number of neurological disorders can also be affected by physical disabilities. In some cases, motor deficiencies can become quite severe, even to the extreme of producing a loss of total control of the muscles that are responsible for voluntary movement of the body, including the movements of the eyes and the muscles involved in respiration. People who suffer from such deficiencies lose all possibility of exterior communication; this means that the only possible alternative for these individuals would be to present the brain with a new, non-muscular, channel that would permit them to send messages and orders to the outside world. A BCI system allows communication between the brain and an external device. The system provides an additional channel of communication, transforming brain signals into commands that are interpreted by the machine but without any muscle movements. BCI systems can help people affected by severe motor disabilities such as amyotrophic lateral sclerosis to express themselves, and thus provide greater autonomy in their daily lives (Wolpaw *et al*., 2002).

These interfaces are considered one of the most important applications in the future of neurorehabilitation, creating a communication and a control channel for those individuals with serious handicaps in their motor functions, but who do not show disorders at the cognitive level (Birbaumer, 2006). Nowadays, the studies which are presently being carried out are focused on the investigation of algorithms to process EEG signals. However, there are some aspects that still have not been studied with the intensity they deserve. In particular, those aspects related to the person, his or her behavior, and the psychological aspects involved in the interaction between the person and the computer. The training required to control a BCI requires a considerable effort. Sustained attention, motivation, fatigue, distraction (Neumann and Kubler, 2003), concentration and attention (Silva-Sauer *et al*., 2011), are some of the factors that need to be taken into account when establishing a protocol of training that guarantees efficient learning.

One of the peculiarities of this kind of interface is its ability to determine a general neuronal state from the available EEG signals, thus providing the user with a minimal communication alphabet, essentially as activation/deactivation of a given brain area or wave frequency. In order to achieve this purpose with certain success, it is necessary for the system to discriminate between at least two different bioelectrical signals. The EEG signals in the BCI system can be obtained by performing different mental tasks, such as imagining given activities or situations (Hassan *et al*., 2008; Keirn and Aunon, 1990; Neuper *et al*., 2009). The extraction of the required EEG signals for a BCI system may be invasive (by surgical procedures – electrocorticogram) or non-invasive (obtained from the bioelectrical potentials that are generated in the brain, and can be detected with electrodes applied on the scalp).

The basic structure of a BCI system is based on acquisition (amplification), digitalization and processing of the EEG signals. The final stage is the output, where the signals are transformed in order to generate control commands. The subject perceives a feedback indicating his or her performance (Figure 1).

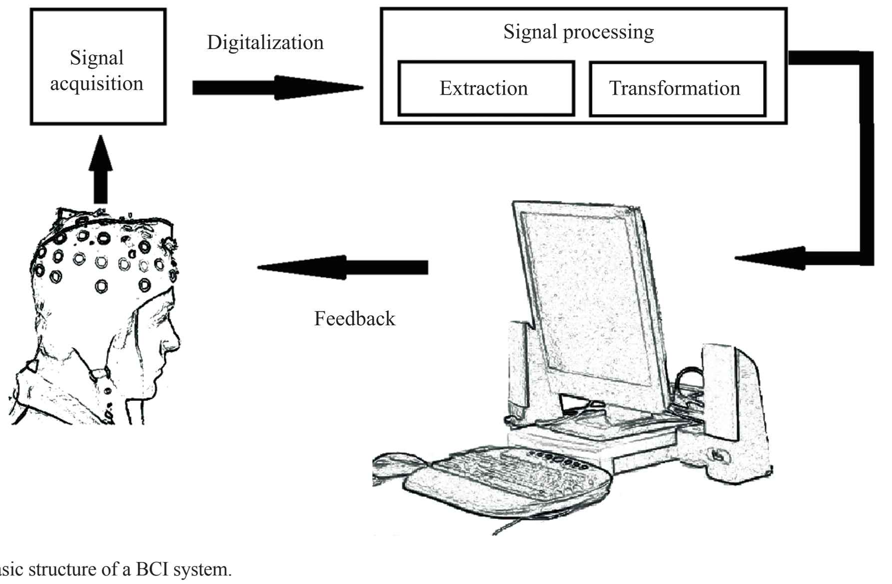

Figure 1. Basic structure of a BCI system.

The EEG signals coming from the user may be classified as endogenous, where the modulation stimulus comes from the person, or exogenous, where the modulation stimuli are external to the person. Among the endogenous are the Sensorimotor Rhythm-based BCIs (SMR-BCI), which are based on the changes of μ and β rhythms. These rhythms correspond to specific features of the EEG signals, characterized by frequencies that can be modified by voluntary thoughts. When a person performs a movement, it causes a synchronization/desynchronization in his or her brain activity (event-related synchronization/desynchronization, ERS/ERD), which involves a rhythm amplitude change (Wolpaw *et al*., 2000).

The advantage of SMR-BCI systems is that they provide the user with intentional changes, which enable a greater control over the devices. In particular, the μ and β rhythms have the characteristic that when the subject performs or imagines a motor action, the amplitude of such rhythms is modified, thus making it possible to assign control commands to those characteristics of the signal. Brain rhythms have been used to provide the user with control over a number of devices which allowed him/her to manipulate his/her environment (Millán *et al*., 2004), communicate (Obermaier and Müller, 2003) or operate computer programs (Muller *et al*., 2008; Pineda *et al*., 2003).

The learning process aims to modulate the EEG components by trial and error. This is provided by feedback, in most cases visual, that provides the subject with an image of his/her performance. Training to control a BCI system requires a considerable effort, and it depends, beyond proper acquisition and signal processing, on the degree to which the neuronal activity can be controlled by the subject. This implies that most papers on BCI are made with single-subject studies or very small groups, as the procedure to obtain control on the desynchronization of the rhythms entails a great amount of tests and time (Ron-Angevin and Díaz-Estrella, 2008).

Considering that the BCI system is an interface between an organism and a computer, a subject of study could be the "interaction", the reciprocal action between both of them; that is, the "behavior" of the person in front of the computer stimuli. One of the methods used in psychology to improve the learning process for new behaviors, with minimum errors and in a progressive way, is the shaping by successive approximations procedure (Domjan, 2009; Skinner, 1975). This technique consists of differentially reinforcing small approximations to a final behavior; that is, guiding the subject's behavior through the rewards towards the desired behavior. In that case, we presented reinforcing consequences in the visual feedback after small changes in the subject's brain rhythms, in such a way that when those behaviors' remove variations increase, the intensity of the feedback is reduced, so that the learning process is progressive and with fewer errors (Malott *et al*., 2003). Using this strategy, the intention is that the individual would gradually learn a discriminative response that was originally very complex and out of his repertoire.

We present a study aimed at testing the effectiveness of a psychological learning technique, namely shaping by successive approximations, using feedback with differential reinforcement over the behavior, in order to achieve an improvement in the training for a BCI system. We seek to improve the learning process, with fewer errors and shorter learning time, comparing it with a standard BCI training procedure proposed by Ron-Angevin and Díaz-Estrella (2009), in which the movement of a car is presented as a feedback associated to two mental tasks.

Methods

Participants and design

Initially, eight participants volunteered, all of them students from the School of Psychology at the University of Málaga, without previous experience on BCI. Only six of them were included in this experiment: two men and four women, with an average age of 22.7 years. The inclusion criterion was to obtain a minimum amount of control (more than 70%) in the first session.

A reversal single-subject design, with single-subject condition control and counter-balancing of the order of such conditions among subjects, was used. The subject serves as his/her own control, rather than using another individual/group. These designs are sensitive to individual organism differences versus group designs which are sensitive to averages of groups. Thus, both procedures were compared for the same participant (ABAC or ACAB), where A, B and C indicate the three possible stages (each stage consisted of two sessions): A = base line without feedback, B = sessions with the shaping procedure and C = sessions with the standard procedure. In the shaping procedure (B) is applied differential reinforcement of successive approximations that modifies the feedback received by the user (explained in more detail later). In the sessions with the standard procedure (C), the feedback is the same proposed by Ron-Angevin and Díaz-Estrella (2009), the car movement corresponds directly to EEG processed. This design was repeated with six participants distributed randomly, in pairs,

Rev. Bras. Eng. Biom., v. 29, n. 2, p. 123-132, jun. 2013
Braz. J. Biom. Eng., 29(2), 123-132, June 2013

where the order of the conditions was standard first and then shaping, or vice versa.

Training protocol and signal acquisition and processing

Each session consisted of 4 sets of 40 tests. In the first session all subjects were explained what the experiment consisted of, and were urged not to move during the tests, as any body movement would cause noise on the signal. The 40 tests of each set were randomly divided in 20 tests for each mental task, with a rest period of 1.5s between the tests. One of the two mental tasks to be carried out was the imagination of the movement of the right hand; the another mental task was the maintenance of a relaxed state. The intervals between sets ranged between three and five minutes.

The virtual environment showed a car moving in a three-lane road, where at a given instant visual stimulus of a puddle of water came up on either side of the road. This cue indicated what mental task subjects should carry out in order to skip the puddle: imagining the right hand movement would move the car to the right and keeping the relaxed state would move it to the left.

Each test was eight seconds long, starting with the car moving down the central lane. After two seconds the puddle became visible and, depending on its position, the subject was to perform one of the two mental tasks that were being discriminated, and maintain it continuously up to the 8th second. In the sessions with feedback, the feedback was presented after the first 4.25 seconds, moving the car farther to the right or the left according to the signal classification. After the eight seconds the test ended, and there was a 1.5s pause (with the car stopped) until the next test started (see Figure 2).

In stage A, sessions one and four, there was no feedback; subjects only had to perform one of the two mental tasks matching the visual stimulus that was presented. Besides serving as "neutral" or control stages, they were used to update the parameters of the classifier. In stages B and C the visual feedback of the car moving was presented, as provided by the real-time extraction and classification of the EEG patterns. During the shaping by successive approximations (applied in the B stage) the reinforcement of the visual feedback was modified according to the results in the previous set of tests.

For the development of the BCI system the following instruments were used: The EEG was recorded from two bipolar channels using gold electrodes placed 2.5 cm anterior and posterior to electrode positions C3 and C4 (right and left hand sensorimotor areas, respectively) according to the 10/20 international system, as in previous experiments (Iturrate *et al*., 2009). The ground electrode was placed

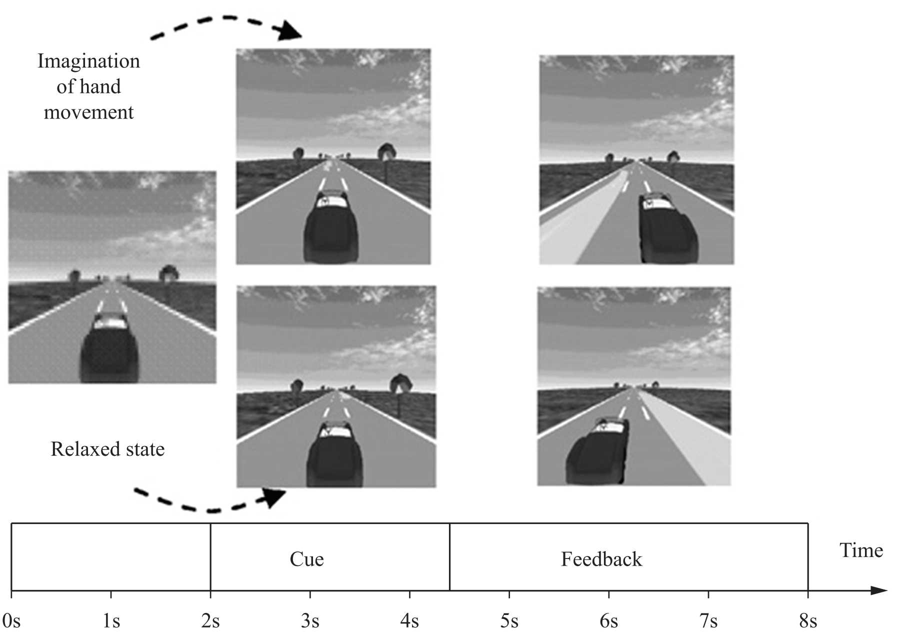

Figure 2. Car movement paradigm and timing of the tests. The feedback is in the form of a car movement. The cue stimulus, between 2 and 4.25 s, consists of a puddle-like obstacle which appears in the left or right lane and which comes into view at the end of the road. Between 4.25 and 8 s, the subject controls the movement of the car to the right or left, according to the mental task required in order to avoid the puddle.

at the FPz position. Signals were amplified by a 16 channel biosignal g.BSamp amplifier and then digitized at 128 Hz by a 12-bit resolution data acquisition NI USB-6210 card. For analysis, a MATLAB program was developed that allowed for both online and offline study of all the signals and subsequent statistical comparative study in SPSS.

Signal processing in the BCI system implied extracting the characteristics of the EEG signals and classifying them. Such processing was based on that proposed by Guger *et al*. (2003), without artifact detection. Extraction of characteristics consisted of estimating the average power of the signal in 0.5s windows in a subject-specific reactive frequency band, which was manually identified by comparing the power spectra of two traces in two different 1-second intervals: one in which the subjects were not performing any mental activity, and other one in which they were. For each session, we obtained a curve for the error rate, *e(t)*, averaged over the 160 tests, as a result of a LDA (Linear Discriminant Analysis) classification, following the procedure proposed by Guger *et al*. (2001).

After stage A, the parameters of the classifier were updated with those of another LDA calculated for the samples of the instant in which the *e(t)* curve reached its minimum. In the feedback sessions (B and C), calculation of the average power for each of the two EEG channels, and the result of the classification, were obtained in real-time. The LDA classification was then translated online into the length L of the feedback displacement of the car, according to the following Equation 1:

$$L(t) = w_1 P^{C3}(t) + w_2 P^{C4}(t) + w_0 \tag{1}$$

Length L was updated on the screen every four samples; that is, every 32ms, to make feedback as continuous as possible. A negative/positive value of L was translated into left/right displacement of the car. Thus, classification consisted of a simple linear combination of the power from each channel (PC3 for C3 and PC4 for C4), with the classification weights (W1, W2 and W0) obtained in the first session (stage A). A deeper explanation of this procedure can be found in Ron-Angevín and Díaz-Estrella (2009).

Adapted shaping

Shaping consisted of modifying the visual feedback, reinforcing correct behavior (avoiding the puddle) and attenuating errors. Reinforcing a correct behavior meant, in this case, moving the car a greater distance than the actual one (corresponding to the subject's performance in the standard procedure); attenuating an error meant making such distance shorter. This modification was implemented with a function that obtained the shaped distance (L^S) from the unshaped distance (L). In the standard procedure (stage C), this function was the straight line $L^S = L$; that is, no shaping for hits or errors, the distance the car moved on the screen and the real one were equivalent. In stage B, the shape of the function was a curve, so in case of a hit $|L^S| > |L|$; that is, the car moved more than the detected neuronal response, and in case of an error $|L^S| < |L|$, which means that the car moved less than the neuronal response. A greater curvature of the function (curve farther away from the straight line $L^S = L$) means greater reinforcement. This way, the effect of reinforcement is maximized over the hits and minimized over the errors. This effect can be observed in Figure 3, in an example of a curve corresponding to the right-hand mental task. When the relax task is requested the curve is symmetrical to the former about the origin of coordinates.

The technique of learning by shaping actuates as reinforcement over the adequate neuronal response, thus maximizing the effect of visual feedback, and successively approximating to the desired behavior.

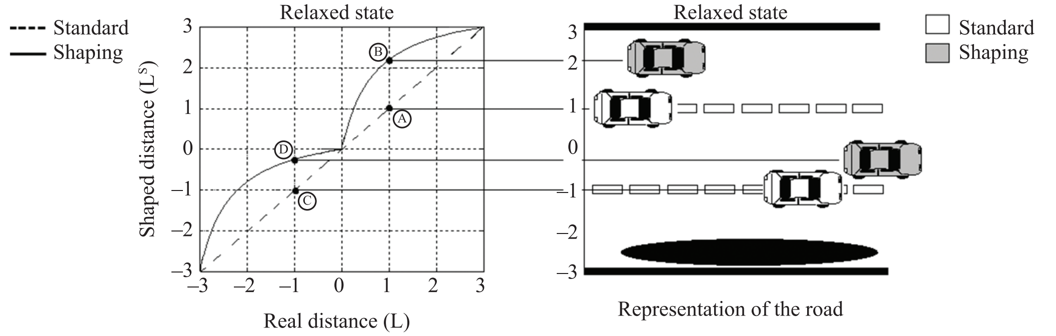

Figure 3. Example of two curves: the dashed one corresponds to the standard procedure (no shaping), and the continuous one to the procedure that modifies the visual feedback. A hit that would have a 1m displacement in the standard procedure (A) would be represented by more than 2m (B) when using shaping, which implies positive reinforcement. In case of an error with a displacement of 1m in the standard procedure (C), the represented displacement with shaping would be 0.3m (D), thus attenuating the consequences of the error.

In the case of the present BCI system, the behavior to shape consists of the subject's control of their brain rhythms, because these rhythms are responsible of the control of the system. The variability and dependence of these behaviors on the previous execution is reflected on the choice of different reinforcement curves. Because of this, each subject started out with an initial reinforcement curve that depended on their control, determined by the minimum of the error rate obtained as an average of the e(t) for the 160 tests of the previous A stage. The successive approximations in stage B were expressed in variations of the shaping curve as long as the subject obtained positive results (analyzed every 40 tests), so their progress had an effect on the choice of a curve in which reinforcement was smaller. In case their results were negative, no modification was made to the curve. In this study we decided to establish 10 thresholds for the error rate (0% to 50%), associated to 10 shaping curves (see Figure 4).

In the previous paragraph, reference was made to positive or negative results of the subject's performance; it is necessary to detail what criterion was used to make this choice. We defined as "displacement area" the region between the central line of the road and the trajectory of the virtual car in each test. This way, a balance can be established between areas linked to hits and errors, both for right and left, according to the movement of the car. To calculate these areas we used the Equation 2:

$$A_H = \sum_{i=136}^{256} |L_H(i)| \quad A_{E'} = \sum_{i=136}^{256} |L_E(i)|$$
$$L_H = \begin{cases} L(i) & \text{hit} \\ 0 & \text{error} \end{cases} \quad L_E = \begin{cases} L(i) & \text{error} \\ 0 & \text{hit} \end{cases} \tag{2}$$

The used indices correspond to the feedback period (from instant $t_1 = 4.25$ seconds to $t_2 = 8$ seconds). The variable "right balance" (BR) was calculated as the difference between the accumulation of all the hits areas (AH) and the error areas (AE) in the tests in which a movement to the right was requested. The variable "left balance" (BL) was defined analogously. Depending on the performance of the tests, these variables held positive or negative values. The "total balance" (B_T) is the sum $B_R + B_L$. This variable determines the possible switch to the next curve in stage B of the experiment.

In stage C (standard procedure) behavior reinforcement was not applied, so the received feedback corresponded to the subject's real performance. This way, learning in this stage produces trial-and-error, giving large displacements of the car in both directions, until they stabilized as the number of tests increased.

As dependant variables to compare the performance during the usage of the BCI in both procedures, we used several parameters obtained and processed simultaneously to the task, and processed *a posteriori* from the EEG data acquired by the system. As real-time variables we used the following: B_R, B_L and B_T.

The *a posteriori* variables considered were: i) minimum error rate (*MER*), defined as the minimum of *e(t)*; ii) right- and left- hit rate (HR_R and HR_L respectively), the number of hits, divided by the total number of tests, for each mental task. In order to calculate the latter two variables, a test was considered a hit or an error depending on the result of the classifier only in the instant were the minimum *e(t)* was produced.

Results

The results of three sets from Subject 1 were not validated due to the poor quality of the signals. Consequently, the same three sets from the next stage were removed for purposes of statistical validation. Eventually, a total of 90 sets among all subjects were considered, 45 from stage B and 45 from stage C. In Table 1 it is possible to observe the reactive frequency band for each participant.

Table 1. Reactive frequency band for each participant.

Subject	Frequency band (Hz)
S_a1	10-12
S_a2	10-13
S_a3	9-12
S_a6	10-13
S_a8	9-12
S_a9	10-14

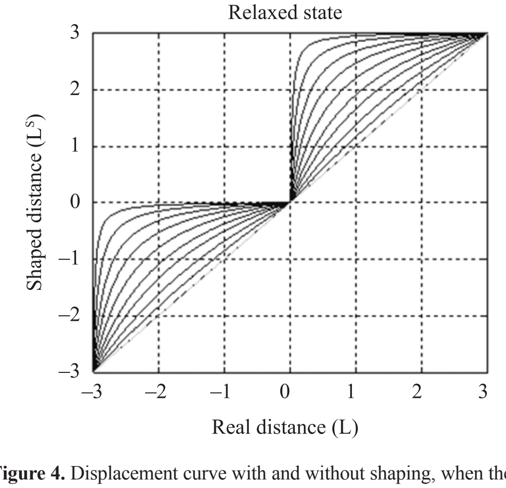

Figure 4. Displacement curve with and without shaping, when the subject is requested relaxed state. The curves start at 0% of the error rate (straight line, corresponding to the standard procedure), with increments of 5% up to 50%.

No significant differences are observed between the two procedures in most of the studied variables, using the t test for related samples for repeated measures (see Table 2). A significant difference appears only in the global parameter B_T of the virtual car ($t(44) = 2.20$; $p < 0.05$), averages can be seen in table 2. In this case, the obtained displacement with the brain responses in the standard procedure is more extreme or variant than during the shaping. In the variables obtained offline we observed that both procedures achieve control of the virtual car, but no improvement or manifest superiority of one over the other appears (see Figure 5).

There is a difference between right and left task because mold a mental task force (right hand) appears to be more effective than a mental task consisting do/think anything (relax state)

When the graphs of these data are observed, this global analysis over the equality of both procedures can be confirmed. Nevertheless, with regard to the B_T of the virtual car, where there is significance, it can be appreciated that the responses are more extreme (B_T), or even negative (B_L) in the standard procedure, whereas they vary less and they are always positive in the case of the shaping procedure (see Figure 6).

Table 2. Average of the BCI variables in both procedures.

	Shaping				Standard				
	N	**Sets**	**Mean**	**DT**	**Mean**	**DT**	**t**	**gl**	**Sig.**
HR_R	6	45	17.84	3.24	17.60	3.01	0.415	44	0.680
HR_L	6	45	13.20	2.47	13.64	2.29	–0.980	44	0.332
MER	6	45	20.26	6.35	20.11	6.37	0.206	44	0.838
B_R	6	45	0.1025	0.0157	0.1692	0.0395	–1.809	44	0.077
B_L	6	45	0.0170	0.0151	–0.0129	0.0233	1.004	44	0.321
B_T	6	45	0.1195	0.0141	0.1562	0.0224	–2.207	44	0.033*

*p < 0.05 **p < 0.01.

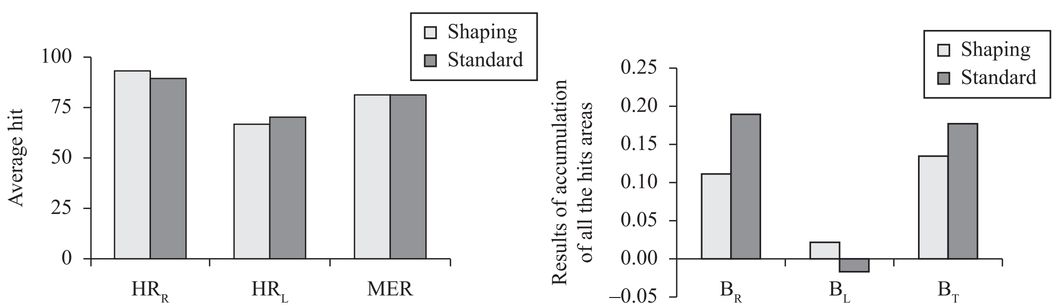

Figure 5. At the left, the graph for the "hit" percentage (identification of the requested mental task, at the optimum second of the test) general in both procedures in an *a posteriori* analysis. At the right, the graph for the total average of displacements among all subjects, subtracting negative values from positive ones, for both procedures. Values greater than 0 are correct movements, and lower than 0 are wrong.

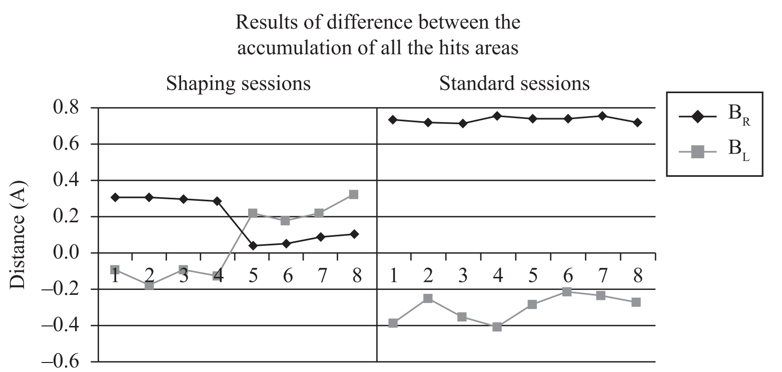

Figure 6. Average of RB and LB as measured in each set of 40 tests during both stages, corresponding to subject 6. Zero indicates the center of the road. Positive values mean the subject was performing the appropriate task, this moving towards the correct side. Negative values mean the subject was not managing to move towards the correct side.

Rev. Bras. Eng. Biom., v. 29, n. 2, p. 123-132, jun. 2013
Braz. J. Biom. Eng., 29(2), 123-132, June 2013

If the acquisition graphs of these "right" (HR_R and B_R) and "relax" (HR_L and B_L) are analyzed during the whole procedure as a single case design, in several subjects differentiated curves appear as those shown in Figure 6. It can be observed that, in the standard procedure, both responses are completely separated and differentiated, with very positive values in the first one that indicate adequate movements of the car (the right hand is properly imagined), but with negative values in the situation of "relax"; that is, more errors are made or negative distance of the car when trying to stay relaxed. However, in the shaping procedure a progressive change is seen, as intended, where both tasks approach each other; that is, an intermediate positive displacement point is modeled in both mental tasks.

Significant differences have been found between HR_R and HR_L in the shaping procedure ($t(44) = 7.43$; $p < 0.001$) as well as between B_R and B_L ($t(44) = 3.11$; $p <0.01$); but the same significant differences have also been obtained in the case of the standard procedure in HR_R and HR_L ($t\ (44) = 7.42$; $p < 0.001$), and B_R and B_L ($t(44) = 7.98$; $p < 0.05$) (see Table 3).

This implies that both procedures achieve well differentiated neuronal responses. When the number of hits in the optimum second is analyzed, significant differences are found too, which means that in that instant the participant was managing to execute the proper mental task to avoid the puddle. The mental task of right hand imagination obtains greater averages in all the variables, which indicates better execution and control with that movement imagination, but imagination of relax seems more difficult to achieve.

Discussion

In this paper we have shown that both proposed training procedures, standard and progressive shaping, are equally effective to achieve training of differential responses (imagination of hand/relax) in the interaction with a BCI. As the effectiveness of shaping in creating new behaviors and increasing other progressively is known, we started with the hypothesis that the shaping technique might be superior. In total scores, errors and discriminating capacity, it is as effective as the standard. Nevertheless, a general process has been observed as the training was performed, so that errors or deviation in the "relax" responses are notably reduced.

A difference is clearly observed between the subject's control with one mental task and the other, being significantly better in the case of right hand imagination. It is possible that herein resides the key for a better shaping procedure, as the presented study progressively changes the response of both tasks simultaneously, so learning one is affected by the progress of the other. In this case, it has been observed that the task of relaxation would have needed different shaping curves from the right one, given the general difference in performance. In other words: relaxation needed more help, and it did not receive it because performance with the right-hand task was higher. This made the improvement in this task mild. On the other hand, the right-hand tasks would have needed curves that implied a smaller reinforcement of the feedback; as it did not happen, excessive reinforcement made the subject continuously perceive his right-hand performance as excellent, so it is possible that the subject progressively reduced their efforts to achieve control. Future research which has already started in our group, aims to obtain a differentiated response for each task.

It was observed that control of the relaxed mental state is more unstable, so one of the possible ways to improve control should be to promote the capacity to hold that state, as shown by several studies (Eskandari and Erfanian, 2008; Mahmoudi and Erfanian, 2006; Tan *et al*., 2009). The reliability of this control is the key to develop more complex asynchronous interfaces with a greater freedom of movement.

All in all, BCI system and all the aspects of psychological interaction implied in them constitute an inexhaustible source of new research; it is an ongoing process. The present study is the result of a research project in which two fields collaborate: Engineering and Psychology. People from different departments are working together in order to make progresses both in the system's efficiency and the

Table 3. Average of all the variables in the differential responses of "right" and "idle" in both procedures.

	Right				Left				
	N	*Sets*	*Mean*	*DT*	*Mean*	*DT*	*t*	*gl*	*Sig.*
MER with shaping	6	45	17.84	3.247	13.20	2.473	7.437	44	0.0001***
MER standard	6	45	17.60	3.011	13.64	2.298	7.412	44	0.0001***
B_T with shaping	6	45	0.1025	0.1059	0.0170	0.1014	3.116	44	0.003**
B_T standard	6	45	0.1692	0.2655	–0.0129	0.1567	7.986	44	0.005**

**p_ < 0.01. ***p_ < 0.001.

user's performance. The final aim of our research is not only to develop a BCI-controlled wheelchair, but to provide the potential users with a proper training procedure as well.

Acknowledgements

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Authors

Leandro da Silva-Sauer*, Francisco Velasco-Álvarez, Ricardo Ron-Angevín, Salvador Sancha-Ros
Departamento de Tecnología Electrónica, Escuela Técnica Superior de Ingeniería de Telecomunicaciones, University of Málaga, Spain.

Luis Valero-Aguayo
Departamento de Personalidad, Evaluación y Tratamiento Psicológico, Facultad de Psicología University of Málaga, Spain.