An ERD/ERS Analysis of the Relation between Human Arm and Robot Manipulator Movements

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***Abstract*—This work aims to analyze the relation between the movement of an anthropomorphic robotic manipulator with the brain cortex response elicited in healthy subjects for three experimental conditions. The experiment was divided in three parts: in the first one, the subject only observes the movement of the robotic manipulator; in the second part, the subject follows the robot movement with his right arm; finally, in the third part, the subject imagines the execution of the corresponding movement synchronized with the movement of the robot. Event related (de)synchronization in each of the recorded electroencephalogram (EEG) channels was analyzed. Event related desynchronization was present in alpha and beta bands in various areas of the cortex, including occipital, parietal, central and prefrontal areas. The results provided some physiological insights into human-robot interaction for future developments in brain-machine interfaces.**

***Index Terms*—ERD/ERS, brain-machine interface, human-robot interaction, assistive technologies, neurorobotics**

I. INTRODUCTION

Brain-machine interfaces (BMIs) and computer-machine interfaces (BCIs) are systems capable of extracting information from brain signals, the most direct pathway to control machines and computers, respectively [1]. BMIs (in this paper we will only use the term BMI, even when some concepts are applicable to BCIs, to avoid confusion) may become a way to allow disabled individuals to interact in society with more independence through the development of assistive technologies [2], and to improve their lifestyle through rehabilitation solutions [3], [4].

Since the publication of one of the earliest works on BMIs by Jacques Vidal in 1973 [5], extensive work on the field has brought many practical applications and a variety of features related to specific conditions have been recognized within the brain. Interfaces based in steady-state visual evoked potentials (SSVEP) [6], [7], motor imagery [6], [8], and P300 potentials [9], [10] are the most widely used. Other features are currently under research like the error related potentials (ErrRPs), which are triggered, for example, when a BMI command is wrongly recognized [10]. Hybrid BMIs that combine at least one brain signal with other biological signals have also been developed aiming to improve the performance of the system [6], [11], [12].

Generally, BMIs based in motor imagery use event related synchronization (ERS) and desynchronization (ERD) as method to classify whether a movement intention is present or not. ERS and ERD respectively reflect increases or diminutions in the power of specific EEG bands, at different instants during a movement execution or imagery. This features could then be used to identify the intention of movement and command a BMI by controlling the initiation of a task [13], [14], [15].

The interaction between humans and robots is becoming more feasible and natural thanks to the advances in robotics which enable safe and accurate control [16]. This trend seems to be growing and human-robot interaction tends to reach deepest levels as more sophisticated technology becomes available. However, the physiological basis of this interaction has not been thoroughly studied, as no research in this matter has been reported to the authors knowledge.

This work aims to analyze the effects of the interaction between individuals and an anthropomorphic robotic manipulator in three ways: the observation, execution (replication) and imagination of a movement sequence triggered by the manipulator, expecting to obtain similar responses for all the conditions [17]. The movements executed in the experiment, flexion and extension, were considered individually, and its execution was separated with no movement time intervals. The results of this work, that an ERD is present for movement execution, imagery and even observation, will be important in the design of efficient BMIs, since the user's movement intention will command the triggering of defined tasks executed by robotic manipulators, leading to intuitive human-robot interaction for assistance of individuals who suffer from motor disabilities.

II. MATERIALS AND METHODS

A. Experimental setup

Six neurologically and physically healthy male subjects (S1 to S6) participated in the study, age ranging from 23 to 32. The participants were placed in an acoustically isolated and illumination-controlled experiment room throughout the recording sessions. The participants were comfortably seated on an armchair to prevent any movement not related with the study. The experiment took place at the Biomedical Engineering Laboratory and approved by the local Ethics Committee. All participants read and signed and informed consent form.

An anthropomorphic robotic manipulator with five degrees of freedom, AX18 Smart Robot Arm (CrustCrawler Robotics, Arizona, USA), was placed within the experiment room in front of the participants. The initial position of the robot (Fig.

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1) was just below subject's straight line of sight, at about 80 cm from away from them in a way that the manipulator appeared to be a mirror of the subject's right arm. Participants remained at a safe distance outside the robot's workspace, throughout the experiment. The manipulator trajectory for the movement sequence was generated using a Jacobian based position control algorithm and dual quaternion algebra [18].

Figure 1. Experimental setup for the study

EEG was used to register the participant's brain activity. The EEG was recorded using a 36-channel BrainNet BNT-36 (EMSA, Rio de Janeiro, Brazil) biological amplifier, band-pass filtered (0.1-100 Hz) at a 600 Hz sampling frequency. EEG was registered from seventeen scalp electrodes using an EEG cap, placed according to the International 10-20 System (F7, F3, Fz, F4, F8, T3, C3, Cz, C4, T4, T5, P3, Pz, P4, T6, O1 and O2) with reference at earlobes (A1 and A2). Electro-oculogram (EOG) was recorded along with EEG (1 cm diameter Ag/AgCl electrodes).

Three conditions were explored during the experiment, all of them involving the robot movement sequence shown in Fig. 2: (1) stare at the moving robot (ST), (2) follow the robot movement with the right arm (MV), and (3) imagine that movement pattern (IM). Movement of the robot and participant's arm were recorded using a LilyPad ADXL335 accelerometer board. The movement sequence was split into two, flexion (UP) and extension (DW) movements, to look for differences in the brain responses among those conditions. All study conditions are summarized in Table I.

In order to characterize the participant's arm movement, the accelerometer was placed at the distal end of the radius, close to the wrist, and movement was performed starting in a semipronate position, with the elbow flexed at 90º.

Participants were asked to perform only an elbow flexion and extension, even when the robot performed a corresponding shoulder movement (Fig. 2), given that structural limitations prevented the robot to perform the desired elbow movements. Also, participants were asked to blink only in the interval between the movements.

Five sessions lasting 15 minutes each were performed for the study, with three minutes resting intervals between the sessions. The sequence in Fig. 2 was repeated over the session span. The first session (ST) consisted of passively staring at the robot motion. The subjects observed the robot's movement without performing any movement or imagination. The second and third sessions (MV) consisted in following the movement of the robot. Subjects were asked to perform a corresponding elbow flexion and extension of their right arm, following the robot's movement in extent and duration. Finally, the fourth and fifth sessions (IM) consisted in movement imagination. Subjects were asked to only imagine the movement the same way they executed it in the two preceding sessions, without actually performing it.

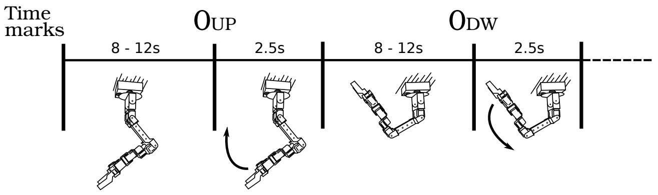

Figure 2. AX18 robotic manipulator movement sequence. 0UP and 0DW are the starting times for the movement conditions

Table I
SUMMARY OF STUDY CONDITIONS

Abbreviation	**Condition**
ST	Stare at the movement of the robot
MV	Follow the movement of the robot with the right arm
IM	Imagine the corresponding right arm movement while the robot moves
	Type of movement
UP	Flexion
DW	Extension

The order of the sessions was maintained fixed in a training fashion, that is, the movement is first executed and then imagined, given that a future goal is to command the robotic manipulator with thought. The movement observation was used as a base activity measure for comparison purposes.

B. *Data preprocessing*

ERD and ERS were analyzed in this work. Matlab® software was used for the digital data processing. EEG data from all the recorded sessions were high-pass filtered at a cutoff frequency of 5 Hz, using a fourth-order (zero phase) Butterworth filter.

Data were then split into single trials. UP and DW movements were analyzed separately. For the ST and IM conditions, the 0UP and 0DW trigger points (Fig. 2) were considered as reference. For the MV condition, the trial reference time was the beginning of the subject's movement UP or DW, registered using the accelerometer. Every trial considered the 6 seconds after and the 3.5 seconds before movement reference. Artifact rejection was applied to every trial.

We used a wavelet analysis to find the ERD/ERS bands for our analysis, based on the spectral power and time course in alpha and beta (8-30 Hz). A wavelet packet spectral analysis using a Daubechies6 wavelet at decomposition level of 6 was used because its smooth profile and its ability to represent polynomial functions up to order 6. The decomposition level of 6 provided a good compromise between spectral and temporal resolution. A mean spectrum was computed across trials for the different subjects and conditions. ERD/ERS alpha and beta bands were heuristically selected as being from 8 to 12 and 14 to 22 Hz, respectively. Frequencies over 22 Hz did not show neither a defined pattern nor an important spectral power.

C. ERD/ERS estimation

For the ERD/ERS estimation in the alpha (8 to 12 Hz) and beta (14 to 22 Hz) bands, the whole data record for every condition and every subject was band-pass filtered using a fourth order (zero phase) Butterworth filter in the respective band, and only the trials with no artifacts were used.

ERD/ERS was calculated using the intertrial variance method [19]. Mean intertrial activity was computed and removed from every trial and the variance obtained as:

$$P_j = \frac{1}{N-1}\sum_{i=1}^{N}\left(s_{i,j} - m_{s_j}\right)^2, \qquad (1)$$

where, $s_{i,j}$ is the i-th trial for channel j, N the number of trials per channel and m_{s_j} is the mean intertrial activity for channel j, calculated as:

$$m_{s_j} = \frac{1}{N}\sum_{i=1}^{N} s_{i,j}. \qquad (2)$$

In order to reduce the variability of the ERD/ERS estimative, non-overlapping windows with duration of half second were chosen and the mean power was computed for each window:

$$P_{s_{j,k}} = \frac{1}{M}\sum_{i=1}^{M} P_{j,w}, \qquad (3)$$

where M is the window length in samples, the index $k = 1, 2, ..., (N/M)$ indicates the window number and $w = (k-1)M + i$ indicates the sample of the power calculated in Eq. 1. Finally, to express the power in percentages, the mean power P_{b_j} from time -3.5 to -1.5 seconds, where neither ERD nor ERS were expected, was considered as a base measure and the percentage estimative computed as:

$$\%P_{j,k} = \left(\frac{P_{s_{j,k}} - P_{b_j}}{P_{b_j}}\right)100\%. \qquad (4)$$

The procedure indicated above was applied to each of the subject's data separately in the alpha and beta bands, for each of the study conditions (Table I). To smooth the estimative, a second order moving average filter was applied.

III. RESULTS

The available number of trials, for each UP and DW movements, were 35 for ST, and 70 for both MV and IM. The artifact rejection applied of the trials was low (about 2% of the trials) given the 5 Hz high-pass filter applied that discarded most of the blinking and body and eye movement artifacts, which are the main cause of trial rejection. For the ERD/ERS estimative, 30 randomly selected trials were used for each condition (Table I) and the grand average (average across subjects) was computed. We selected the same number of trials for all the study conditions to maintain the signal to noise ratio.

The grand average for the ERD/ERS in the alpha band is presented in Fig. 3 for UP and Fig. 4 for DW. Similar responses were obtained for both movements. For ST, ERD was spread mainly over occipital (O1, O2) and parietal (P3, Pz and P4) areas of the cortex, however, in the central (C3, Cz and C4) areas the ERD is not well defined. On the other hand, for MV and IM, ERD was present in the occipital, parietal and also in the central areas. For movement and imagery conditions, a more intense response was obtained in C3 than in C4, indicating laterality in the motor cortex as could be expected.

Responses in the beta band showed a similar profile to those of alpha band. UP (Fig. 5) and DW (Fig. 6) also presented similar responses. Furthermore, ST, MV and IM shared almost the same profile in the beta band. ERD is widely spread over many EEG channels, even in prefrontal and temporal areas, unlike the alpha band where ERD is more focused in the region comprising occipital, parietal and central areas. In both, the alpha and beta bands ERD, the more intense response is present in the parietal channels.

The widely spread ERD obtained may be the result of the complexity of the study: it involves a visual (the robotic manipulator movement), motor (the movement observation, execution or imagination) and cognitive (movement initiation, extent, duration and type) aspects. In all cases, the ERD had the same duration of the movement, approximately 2.5 seconds (Fig. 3 and Fig. 5).

Table II and Table III correspond to the correlation coefficients between the conditions of study for every channel in the alpha and beta bands, respectively. C3 and C4 presented a lower correlation for UP, between the staring (ST) condition and both, movement (MV) and imagination (IM). Furthermore, the correlation between MV and IM is high, suggesting that for ST, those motor areas are not responsive. For alpha and beta bands, DW presents higher correlations among conditions, probably because of a increased level of expectation from the subject for DW than for UP movement. Clearness of the response in the parietal area and high correlation especially in the parietal area Pz were also present. The correlation was significant ($p<5\%$) in all cases.

IV. DISCUSSION

In this study, we observed that eye movements (EOG) elicited by the observation of the robotic manipulator produced an artifact, synchronized with the movement of the manipulator, which masks the event related potential (ERP) in the EEG signals, and for that reason analysis of the ERP was not considered. Temporal subtraction, principal component analysis (PCA) and independent component analysis (ICA) were used in an attempt to extract the eye movement artifact from the ERP, without reaching its characteristic shape [20]. It is also not convenient to place the robotic manipulator far from the participant, from a BMI implementation point of view,

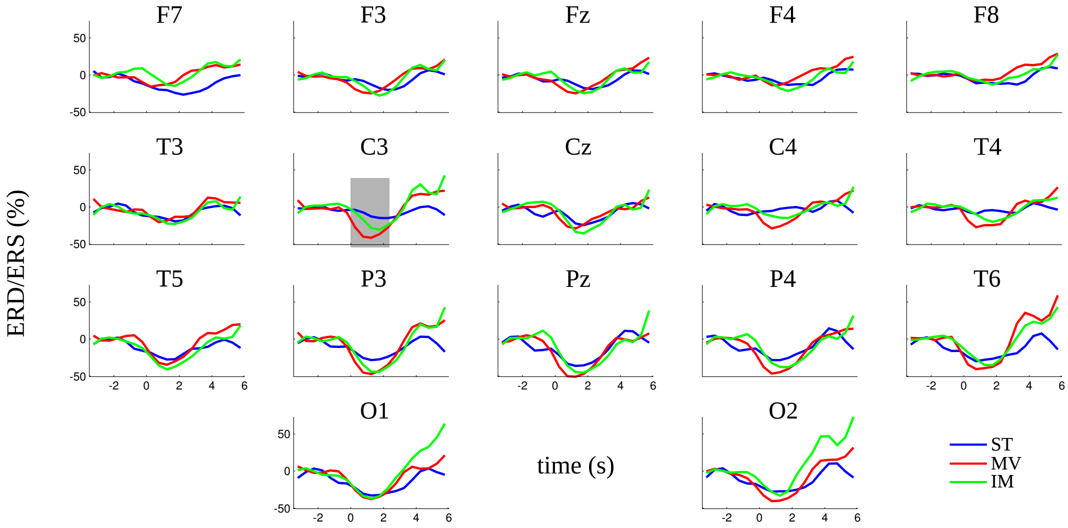

Figure 3. Grand average for ERD/ERS in the alpha band for the flexion (UP) movement. The shaded area in C3 indicates the duration of the robotic manipulator movement

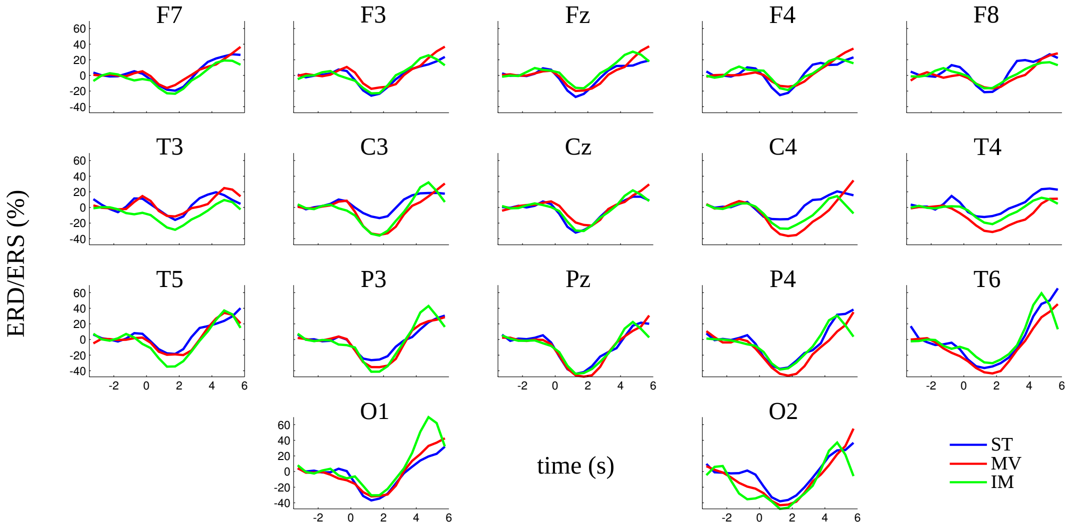

Figure 4. Grand average for ERD/ERS in the alpha band for the extension (DW) movement

given that the user must be within the workspace of the robot in order to accomplish an interactive task.

The parietal area seems to play an important role in the responses obtained for the whole experiment. This is somehow expected given that the parietal area is involved in the association of visual with sensorimotor information, and in the level of attention [21], [22]. Thus, the intense ERD present in this area may be due to the linkage between the visual information elicited by the robot observation and the motor aspects of its movement and of the subject's movement or imagination.

The results shown that in the case of movement execution and imagination, the ERD in the contralateral motor area (C3) is more intense than in the ipsilateral motor area (C4) as expected. This feature could be used for left and right arm movement discrimination, in the case of an implementation of a BMI using two robotic manipulators.

For subjects S3, S4 and S5 it was possible to perceive the alpha rhythm ERD caused by movement execution or imagination in some of the realizations of the ongoing EEG, suggesting the viability of a single trial BMI implementation [23].

In the responsive areas, the beta band presented a more defined ERD in the time interval (2.5 seconds) that the movement is being observed (ST), performed (MV) or imagined (IM), when compared to the ERD in the alpha band. Thus, this band could be used to detect the duration of an imagined movement in a more reliable way than just using the alpha band. Combining the advantages of the availability to detect laterality information of the alpha band, with the more precise movement duration profile found in the beta band, the control of a BMI would be more accurate.

The experimental setup (human-robot interaction) of this work allows to study the responses elicited by an arm movement synchronized with a visuomotor stimulus instead of only visual stimuli as light emitting diodes (LEDs) or computer screens [20], [24]. An advantage of this kind of setup (for BMIs oriented to manipulation) is that it is closer to real BMI

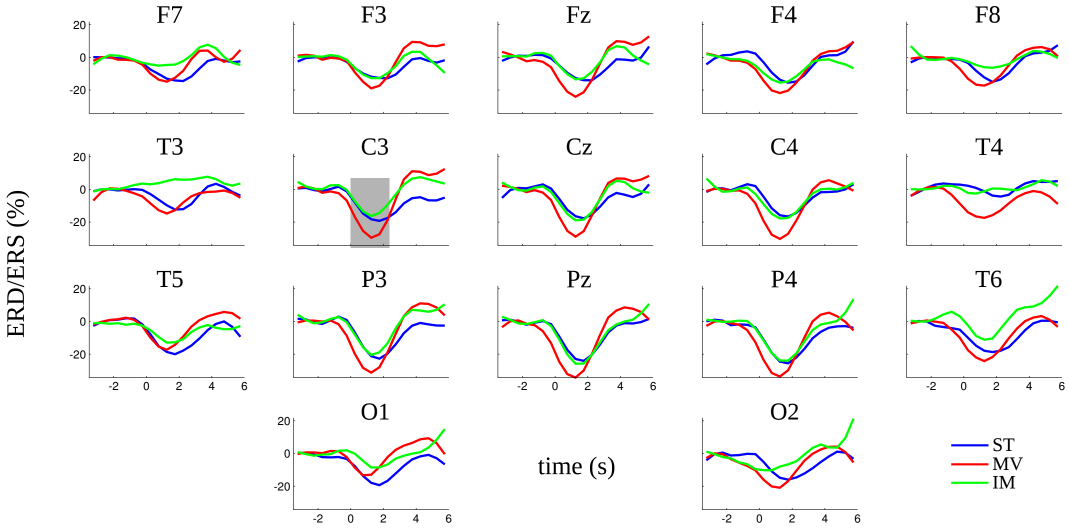

Figure 5. Grand average for ERD/ERS in the beta band for the flexion (UP) movement. The shaded area in C3 indicates the duration of the robotic manipulator movement

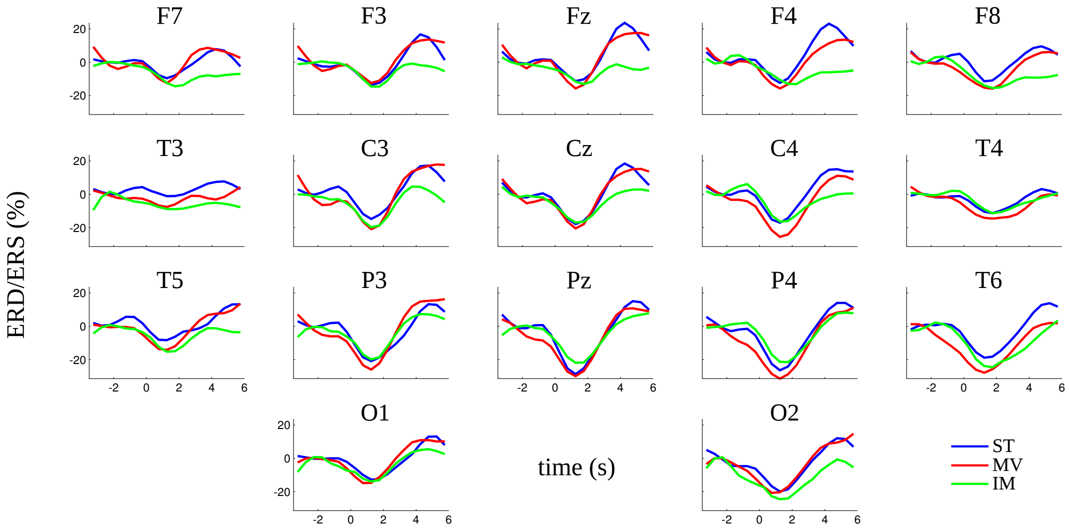

Figure 6. Grand average for ERD/ERS in the beta band for the extension (DW) movement

environment, thus permitting a data processing and analysis that may provide results that are similar to those elicited in a working BMI system.

The ERD found for ST implies that the sole observation of a movement elicits responses that are similar to those obtained for the execution or imagination, possibly affecting the control of a BMI given the close loop generated by the observation of the movement. Further studies are required to analyze these responses and the way they influence in a working BMI environment.

A future implementation of a BMI will use the ERD presence to identify the instant that a movement is being prepared and then activate the execution of a predefined robotic manipulator task. The widely spread ERD may aid in the identification process and to improve the performance of the BMI system.

V. CONCLUSION AND FUTURE WORK

This study analyzed the effects on the EEG response generated by the movement sequence of a robotic manipulator. The analysis of movement responses in the brain cortex using a visuomotor stimulus provided more spread responses when compared to responses elicited by other kind of stimulus, like purely visual [15], [24].

Studies conducted in an environment that is close to a real BMI may help to unveil brain activity patterns in a more practical way. This particular study provided results that show intense activity spread over several areas of the brain cortex, like visual, motor and association areas, suggesting a wide cognitive activity unlike other motor response studies that provide more focused results. Future works may involve the study of how the responses vary according to movement type and duration.

The next step is to test the results obtained in this study for the control of a movement-intention based BMI. Provided the

Table II
CORRELATION COEFFICIENT FOR THE GRAND AVERAGE POWER IN THE ALPHA BAND AMONG STUDY CONDITIONS

			Conditions %		
			ST-MV	ST-IM	MV-IM
EEG Channels	F3	UP	61	79	87
		DW	92	90	81
	Fz	UP	73	77	83
		DW	89	89	86
	F4	UP	65	76	73
		DW	84	84	87
	C3	UP	57	52	88
		DW	88	90	87
	Cz	UP	69	74	86
		DW	88	96	88
	C4	UP	17	-2	82
		DW	72	76	75
	P3	UP	80	72	94
		DW	96	91	94
	Pz	UP	86	73	86
		DW	96	94	93
	P4	UP	79	60	89
		DW	95	90	83
	O1	UP	82	73	88
		DW	95	85	93
	O2	UP	83	66	92
		DW	95	81	79

$p<5\%$ in all cases

Table III
CORRELATION COEFFICIENT FOR THE GRAND AVERAGE POWER IN THE BETA BAND AMONG STUDY CONDITIONS

			Conditions %		
			ST-MV	ST-IM	MV-IM
EEG Channels	F3	UP	79	82	75
		DW	92	65	56
	Fz	UP	75	69	81
		DW	93	54	60
	F4	UP	83	69	83
		DW	92	10	32
	C3	UP	67	77	97
		DW	91	90	84
	Cz	UP	78	83	93
		DW	95	89	90
	C4	UP	83	91	92
		DW	96	70	77
	P3	UP	80	85	95
		DW	90	91	93
	Pz	UP	84	97	86
		DW	97	96	93
	P4	UP	84	91	84
		DW	98	95	91
	O1	UP	67	60	50
		DW	90	88	95
	O2	UP	64	30	63
		DW	93	90	84

$p<5\%$ in all cases

possibility of single trial detection and feature extraction with low computational requirements, a high performance of the system is expected. Our purpose is to achieve a task-oriented BMI, with the user triggering the execution of a task and the robot resolving lower level aspects of that task, for example, reaching and grasping of an object. This approach would lead to intuitive human-robot interaction for assistive technology solutions through non invasive BMIs.

ACKNOWLEDGEMENTS

This work has been supported by the Brazilian agencies CAPES (Coordenação de Aperfeiçoamento de Pessoal de Nível Superior), CNPq and FAPEMIG.

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