A similitude-based BCI system for Communication

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Abstract

This work describes a procedure to design a similitude-based brain computer interface system for communication. Five healthy subjects and two patients with disorders of consciousness took part in the study. A support vector machine classifier applied to EEG data was used to detect answers to simple yes/no questions, while reducing the number of required electrodes. Just using ten electrodes we obtained a mean classification accuracy of 83.5% (SD 12%) for healthy subjects and 90% (SD 14.1%) for patients.

1 Introduction

One of the major concerns in recent studies is the discrimination between vegetative and minimally conscious state (Georgiopoulos, et al., 2010). The correct discrimination between these two conditions has major implication in subsequent rehabilitation of patients. In particular, establishing a communication with them would be advantageous and desirable. Several techniques, including functional magnetic resonance imaging (fMRI), cognitive event-related potentials (ERPs) and quantitative EEG analysis (qEEG), are currently developed to assess patients correctly and to attempt the communication with them (Monti, et al., 2010) (Cruse, et al., 2010) (John, et al., 2011). This work describes a procedure to investigate a subject's pattern of activation during mental imagery tasks. It aims to design a brain computer interface system for communication. Healthy subjects and patients with different levels of disorders of consciousness underwent EEG recording during yes/no personal questions. The first aim of the study was to develop a procedure of features selection in order to reduce the number of electrodes required. The second aim was to design a classifier that, after the training with two questions with known answers, is able to forecast the third unknown answer.

2 Methods

2.1 Subjects

Five healthy subjects (HS) (age 26 to 37) and two patients (P) took part in the study. The first patient was a 21-year-old female and her level of cognitive functioning (LCF) was 7. The second patient was a 28-year-old female and her LCF was 3. The etiology of the injury was traumatic for both patients.

[*] Collected and analysed the data and created the first version of this document
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2.2 Protocol

The experiment consisted of a Communication Trial. Simple yes/no personal questions, with known answers, were asked to the subjects (e.g. "Are you married?"). Subjects were instructed to imagine for 30 seconds a movement of the right hand for an affirmative answer and a movement of the right foot for a negative answer. The Trial comprised six questions which were repeated six times for HS and twice for P. The experiment was repeated on two consecutive days (sessions) for HS only. No feedback was provided to the subjects.

2.3 EEG recording and signal processing

The EEG was recorded from 31 electrodes positioned according to the international 10-20 layout using a Neurowave System (Khymeia, Italy). EEG signals were band-pass filtered between 3 Hz and 60 Hz and underwent manual identification and rejection of artefactual segments. For each section, the epochs after the fourth second were eligible for the classification process. Power spectral density (PSD) was extracted from two seconds epochs without overlap. A modified periodogram method, based on FFT-algorithm and Blackman Harris window, was used. Subsequently, we averaged 5 values of the extracted PSD with a six seconds overlap, thus obtaining one PSD for every 10 seconds. The power in four frequency bands was extracted: theta (4-8 Hz), alpha (8-13 Hz), beta (13-25 Hz) and gamma (25-40 Hz). For each subject, each session and each answer, 31 (electrodes) × 4 (bands) × n (repetitions) sets were collected. Each value of the variable described above was labelled with the corresponding imagery task. The first aim of the study was to choose the Best 10 common Electrodes (BE) for all HS using a similitude criterion between equal answers. After the BE selection procedure we listed the subject-specific most significant features, in terms of Band-Electrodes Couples (BEC) for each HS and each P. The feature selection procedure used the same similitude criterion of the BE search. A certain number of BEC will be used in the classification process. For each HS, each P and each session we divided the dataset into two parts. The first one includes the 31 (electrodes) × 4 (bands) × n (repetitions) sets of the first half of the Communication Trial and it was used to select the BE and the BEC. The second includes the 10 (BE) × 4 (bands) × n (repetitions) sets of the remaining half of the Trial and it was used to classify the answers of HS and P.

2.4 Search of the Best Electrodes and Band-Electrode Couples

For each subject, on the basis of the given answers, all the sequences of three answers, with the first and the second one different (one hand and one foot movement imagery), were identified in the first part of the dataset. We will call these sequences of three answers sub-sessions. The number of sub-sessions was different from subject to subject. Considering the data of each HS and each sub-session, we computed a similitude index $s_{i,j,k}$:

$$s_{i,j,k} = \frac{\sum_k \frac{P3_{i,j,k} - P1_{i,j,k}}{P2_{i,j,k} - P1_{i,j,k}}}{n}$$

where i is the electrode index, j the band index, k the repetition index, n the number of repetitions, and $P1$, $P2$ and $P3$ are the power of the first, second and third answer of the triple, respectively. If the third answer is the same as the first one, s tends to zero, while if the third one is equal to the second, s tends to 1. Using s we calculated the similitude between equal answers and we selected the 10 BE that optimize s for all HS. The classification of the third answer is performed using the following conditions:

$$\begin{cases} -0.5 - sd\left(s_{i,j}\right) < mean\left(s_{i,j}\right) < 0.5 - sd\left(s_{i,j}\right) \quad \& \quad sd\left(s_{i,j}\right) < 3\left|mean\left(s_{i,j}\right)\right| \quad P3 = P1 \\ 0.5 + sd\left(s_{i,j}\right) < mean\left(s_{i,j}\right) < 1.5 + sd\left(s_{i,j}\right) \quad \& \quad sd\left(s_{i,j}\right) < 3\left|mean\left(s_{i,j}\right)\right| \quad P3 = P2 \end{cases}$$

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The aim of this preliminary selection on the HS was to reduce the problem dimensionality. After this selection, we applied again the same criterion for each HS and each P separately, with the aim to find a list of BEC according to the similitude criterion.

2.5 Classification Performance

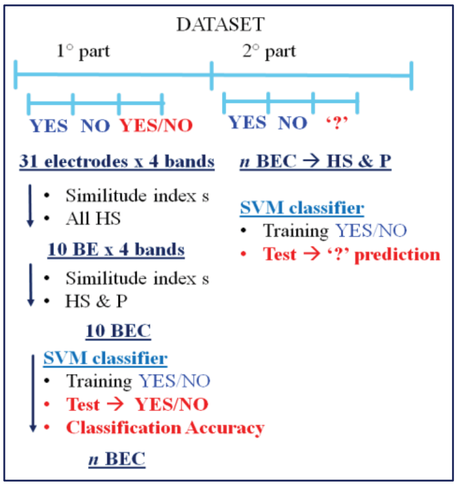

Figure 1: Selection and Classification

The second aim of the study was to establish a mean of communicating with the subject by detecting his/her answer to simple yes/no questions. We designed a classifier trained with two questions with known answers that was able to forecast the third unknown answer. After each sub-session of three questions, the classifier will be retrained with new data. We used the first part of the dataset to select the number of BEC to be considered. For each HS, each P and each session, a linear SVM classifier (SVMc) was used to train and to test all the triples of the first half of the dataset using a variable number, from 1 to 10, of BEC from the ordered list. The classification accuracy was computed and the number of BEC with the higher accuracy was selected. Subsequently we considered the second half of the dataset. For each HS, each P and each session we trained and tested all the triples using the number of BEC previously selected. The first and the second answers were used to train the SVMc and the third one was used to test it (Figure 1). Each answer having a different number of repetitions, the class of attribution was decided by counting yes/no responses.

3 Results and Discussion

3.1 Search of the Best Electrodes and Band-Electrode Couples

Considering all HS and all sessions, the ordered list of the ten BE was: PO3, Fc2, C3, O1, Fc1, Cz, Fz, P3, PO4 and T6. We found that the BE are mainly located in the fronto-central and parieto-occipital cortex. This confirms the results of previous studies demonstrating activation of motor cortex and parietal cortex during the execution of motor imagery task (Ishizu, Noguchi, Ito, Ayabe, & Kojima, 2009) (Lebon, Lotze, Stinear, & Byblow, 2012). Using the BE we searched, for HS and P, a subset of subject-specific and session-specific BEC optimizing the similitude index *s*. Table 1 lists the BECs selected for the classification process for each HS, each P and each session.

3.2 Classification Performance

The mean of the classification accuracy was 83.5% (SD 12%) for HS and 90% (SD 14.1%) for P. The random level of classification is 82.6%. Table 1 shows the results for each subject and each session. The table shows a predominance of the lower frequency band for P and a predominance of the higher frequency bands for HS (De Lange, Jensen, Bauer, & Toni, 2008). The preliminary selection of the ten electrodes in HS, proved suitable also for patients, thanks to the further selection of subject-specific subsets, and guaranteed a good accuracy in the classification of their answers. The proposed procedure allowed us to fix a robust common subset for all subjects (BE), but we also considered the inter and intra-subject variability by selecting a subject and session specific subset. In a

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future practical application of our protocol, each communication session will be preceded by a brief configuration session in which the classification algorithm selects the optimum electrode subset from the fixed BE. Furthermore it will be necessary to train the classifier with two known questions. Even if the procedure is long and repetitive, it guarantees an high classification accuracy for the patients.

Table 1: The table shows, for each HS, each P and each session (S), the best couples electrode-band (BEC) selected using the similitude index *s* and the related classification accuracy (CA).

	S	BEC				CA	Mean±SD
		θ	**α**	**β**	**γ**		
HS 1	1	O1	Cz-PO4	C3-Cz-PO4		90 %	**83.5±12%**
	2			P3-Fc1-T6	PO3-O1-T6	90 %	
HS 2	1	C3- T6-PO3	O1-PO3-P3		O1-PO4	80 %	
	2	P3-PO4		C3	Fz-T6-Fc1-P3-O1-PO3	80 %	
HS 3	1				Fz-C3	100 %	
	2	Fc1-Fc2	PO4		C3	75 %	
HS 4	1	Fc2		C3	Fc2-PO3	80 %	
	2	Cz			O1-PO3	60 %	
HS 5	1		C3	Fz		100 %	
	2	Fc2-Fz	O1-Cz-PO3-P3-PO4		O1	80%	
P 1	1	PO3-C3	Fc1-P3	Fc2	PO4	80%	**90±14.1%**
P 2	1	PO3-C3	C3-P3			100%	

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