PATTERN RECOGNITION IN ELECTROENCEPHALOGRAPHIC SIGNALS USING LVQ NEURAL NETWORKS

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ABSTRACT

The objective of this work is the detection of the non-averaged movement-related desynchronization (MRD) of the mu rhythm of human EEG. The MRD was produced in the contralateral sensorimotor cortex by means of two movement tasks. After amplifying and filtering, the time response of the mu band spectrum of a EEG lead was computed with the FFT and used as predicates for training and testing a LVQ neural network classifier. The performance was measured by the geometric mean of the sensibility and specificity indexes, calculated for every training epoch over test data. The best detection performance was 88% for the single movement task and 78% for repetition of movements, with an average of 66% for both tasks. Results suggests further use of this methodology for EEG pattern recognition.

INTRODUCTION

Among the several technologies developed in the last decades to aid the physically handicapped people, those that explore the electrical signals produced by the human body are the most outstanding (LUSTED and KNAPP, 1996). One of these approaches is the electroencephalographic-based communication, applied to the construction of Brain-Computer Interface (BCI) systems.

A BCI system aims at recognizing patterns in electroencephalographic (EEG) signals produced either by visual stimuli (SUTTER, 1992), specific mental activities (ANDERSON et al., 1998), movements of limbs (NASHMI et al., 1994) or imagination of movements (SCHOLOEGL et al., 1997). Further, patterns detected can be applied to the construction of an “alphabet” of commands, which, in turn, can be used to control wheel chairs, prosthetic or keyboards and devices for computer accessibility (LUSTED et al., 1996).

The movement of a limb produces changes in the EEG signal, specially in those taken in the contralateral sensorimotor cortex. Movement-Related Desynchronization (MRD) is an specific pattern that can be observed in the mu band (8-12 Hz) of the EEG leads taken in the sensorimotor region (PFURTSCHELLER et al., 1994; PREGENZER and PFURTCHELLER, 1999). In this context, the main objective of this work is the development of a classifier system capable of distinguishing the presence of MRD from the background EEG activity and, therefore, identifying a limb movement.

Experiments were conducted in such a way to evaluate two different ways of producing MRDs, using tasks that include the movement of the right hand. In the first task, a trial consisted of a single movement of the wrist, upward and downward. The second task was the repetition of the same movement during a given time.

The classifier system used in this work is the Kohonen Learning Vector Quantization (LVQ) neural network (KOHONEN, 1997). The technique used here will be further applied to implement a complete BCI system.

METHODOLOGY

The EEG was collected from the scalp of volunteers using electrodes near the C3 lead (according to the International Federation 10/20 system). The first electrode (C3a) was put 25 mm ahead of C3 and the second (C3p), the same distance before. A differential amplifier (gain 30,000 V/V) also filters the input EEG in the band 8-100 Hz. The sampling rate was 1,280 Hz, with 16 bits of resolution.

In a given signal collection session, the same task was executed in all trials (single movement or repetition). At least 50 valid trials, lasting 20 seconds each, were collected from each volunteer. Valid trials were considered those which no artifacts visually detected.

For each task, volunteers were guided by a sequence of events presented on the screen of a personal computer. For the first task (single movement), an arrow was presented in t=6s to indicate that the movement should start immediately. For the second task, the volunteer should start the movements when an arrow was presented in t=11s. This arrow was presented again 8 times in intervals of 1 second. All trials had an overall duration of 20 seconds.

In all sessions, the volunteers were sat down comfortably in a reclined chair, lights were turned off and the room temperature was lower than 25 ^{o}C. Volunteers should stay mentally and physically relaxed but awaked, staring at the computer screen.

The movement of the hand was upward and downward turning around the wrist. The task should be completed between 0.4-0.9 second, with the help of a visual timing in the screen. All volunteers were submitted to a previous training session in order to get familiarized with the procedure.

Thirteen volunteers (12 male and 1 female) took part in the experiments. They were all right-handed and had ages between 22 and 37 years old.

SIGNAL PROCESSING

Signals collected from the volunteers were processed offline. Initially, the raw signal was digitally filtered by a low-pass (128 Hz) Hanning window 128th-order FIR filter. After, the sampled signal was decimated, reducing the initial sampling rate (1280 Hz) to 256 Hz. Next, the mu band was extracted using a digital 64th-order band-pass FIR filter, in the range 7-13 Hz. Using this filtered signal, the time response of the mu band spectrum was calculated at intervals of 0.125 second (32 samples) using a 1-second window (256 samples). For each window, the FFT was computed. Therefore, the *k-th* time response *y(k)* of the mu band spectrum is defined as the average of the absolute value of the spectrum components between 8-12 Hz, taken for the *k-th* window of a given trial. In this way, the time response of the mu band was computed for every trial of each session with the volunteers.

In Fig. 1 it is shown the time response of the mu band spectrum taken as the average by session for two different volunteers. In this figure, it is seen the presence of a valley between t≈6s and t≈8s (for the single movement task) for both volunteers. This valley corresponds to the presence of the MRD of the mu band associated to the movement. In the sessions of multiple movements, for the first volunteer, the valley can be seen after t≈11s and persists until the last movement in t≈19s. For the second volunteer, the MRD disappeared soon, probably because he was too relaxed during that session, incapable of repeating the movements synchronously.

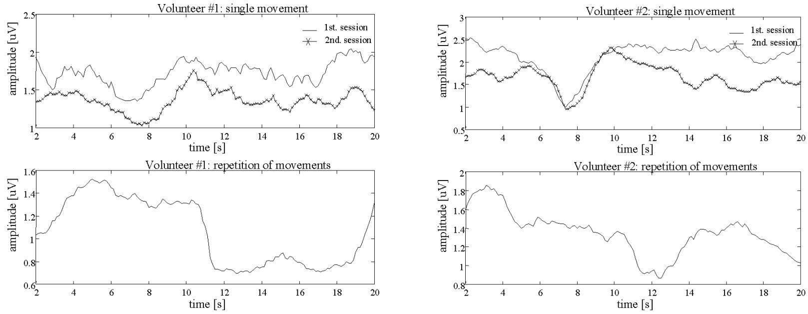

Figure 1 – Averaged time response of the mu band spectrum. Left: volunteer #1; right: volunteer #2

NEURAL NETWORK TRAINING

Vectors of 9 sequential samples, taken as windows from the time response (non-averaged) of the mu band spectrum, constituted the training and testing data for the classifier. The data set was divided into two classes, "with movement" (WM) and "background activity" (BA), where the first corresponds to the windows where the MRD was present.

For the single movement task, the windows for the WM class were taken between t=6.5s and t=7.5s and, for the BA class, after t=10s. The significance level of p>>5% was used as criterion to select the windows for the BA class. It was calculated using variance analysis (ANOVA) using the interval t=10s to t=20s as reference. A 1:3 ratio of windows (WM:BA) was used for the training / test set in all trials of a session for this task.

For the multiple movements task, the WM class windows were taken from the time response after t=11s, using the significance criteria of p≤5%. The windows for the BA class were taken in the interval t=2s to t=10s using p>>5%. In both cases, the reference was the interval with background activity, i.e., between t=2s and t=10s. For this task, a 1:1 ratio was used for the training / test set, in all trials.

After the training / test set be defined, the next step was the selection of the neural classifier. The main requirement for the classifier was to have a simple topology, capable of a fast training and adaptation. This characteristic is fundamental for a future real-time implementation. Recent literature has shown that the Kohonen LVQ (type 2) architecture (KOHONEN, 1997) is suited for this purpose (FLOTZINGER et al., 1994; PFURTSCHELLER et al., 1996; FORD, 1996), and is shown in Fig. 2.

The LVQ classifier is based on clustering with supervised learning and uses vector quantization in order to approximate the optimal decision boundaries of a Bayesian classifier (FORD, 1996). The structure of the classifier is constituted by two layers. The first one is denominated competitive layer. In this layer, the Euclidean metric (DIST module in the figure) determines the distance between the input pattern x and the $s=(n_1+n_2)$ reference vectors (R_i). The reference vectors, defined by the neural network training, are composed by n_1 subclasses representing the WM class and n_2 subclasses for the BA class. A "winner takes it all" algorithm activates ("1") a single neuron among the n_1 neurons of the WM class or among the n_2 neurons of the BA class. All other neurons are not activated ("0"). The only activated neuron corresponds to the reference vector closest to the input pattern. The second layer is linear and associates a weight "1" to each subclass of the corresponding class. Therefore, applying an input pattern x to the classifier, only one class (either WM or BA) will be activated.

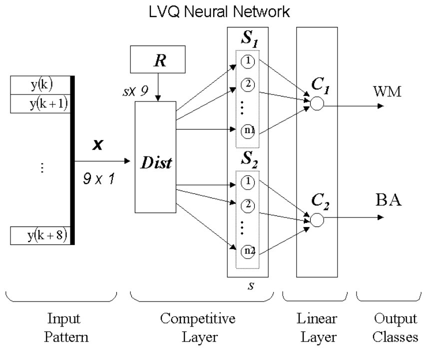

Figure 2 –Structure of the LVQ neural network

Neural networks were trained by session (or group of sessions, in the case of a given volunteer has taken part in more than one session of the same task), by task and by volunteer.

The criterion for evaluating the performance of the neural networks was defined as the number of correct classifications. That is, the number of true positive (presence of MRD; WM class) and true negative (presence of background activity; BA class) classifications relative to the misclassified cases. Common measures of performance for classifiers are: sensitivity and specificity, as defined in Eq. (1) and (2):

$$se(i) = \frac{tp(i)}{tp(i) + fn(i)} \tag{1}$$

$$sp(i) = \frac{tn(i)}{tn(i) + fp(i)} \tag{2}$$

Sensitivity and specificity identify, respectively, the proportion of cases of classes WM and BA that are correctly classified. These two measures were calculated for both the training and the testing sets. Using these measures, a performance index (*de*) of the *i-th* training epoch of a neural network was calculated using Eq. (3). This index is normalized in the range [0..1], where 0 is defined as the worst performance (0% of correct classifications) and 1 the best (100%).

$$de(i) = \sqrt{se(i) \cdot es(i)} \tag{3}$$

RESULTS

The training of a LVQ neural network requires two parameters be set: the learning rate a and the number of training epochs. According to the literature, the optimal number of epochs for training a LVQ neural network ranges between 50 and 200 times the number of subclasses considered. In this work, the best performance was found using 250 times. The learning rate was empirically set to 0.01, based on previous experiments.

The initial reference set was defined as the cluster centers determined by the fuzzy c-means algorithm. All the 36 possible combinations using 1 to 6 reference vectors for both classes (WM and BA) were tried in order to find the best combination. For all volunteers each training was repeated three times. The best results for all volunteers are shown in table 1.

Table 1 – Training results of the LVQs networks

Volunteer #	Movement	Subclasses		Performance [%]	Volunteer #	Movement	Subclasses		Performance [%]
		BA	WM				BA	CM	
1	Single	6	5	64,0	6	Single	4	3	62,1
1	Repetition	3	4	78,1	6	Repetition	4	3	59,1
2	Single	3	1	88,2	7	Single	1	3	55,9
2	Repetition	4	1	72,2	7	Repetition	2	1	70,8
3	Single	4	2	65,6	8	Repetition	2	4	60,1
3	Repetition	1	1	71,7	9	Repetition	3	2	53,8
4	Single	2	2	63,2	13	Single	5	3	73,8
5	Single	2	5	57,6	13	Repetition	5	5	60,6
5	Repetition	5	5	62,1					

Signals of some volunteers were not used in the experiment. This happened when visual inspection of the data followed by a variance analysis did not show the presence of a pattern. In such cases these signals were discarded. Data shown in table 1 is summarized in table 2, showing the average performance.

Table 2 – Comparative average performance

Movement	Performance [%]			Subclass BA			Subclass WM		
	Avg.	Max.	Min.	Avg.	Max.	Min.	Avg.	Max.	Min.
Single	66,3(*)	88,2	55,9	3,4	6	1	3	5	1
Repetition	65,4(*)	78,1	53,8	3,2	5	1	2,9	5	1

(*) – significance (p) 84%

DISCUSSION AND CONCLUSIONS

The Kohonen LVQ neural network was well suited for identifying the two classes of EEG signals, suggesting a good robustness, considering the low signal to noise ratio typical of the EEG and the biological variability. The training phase was relatively fast in comparison with other methods. This is a crucial feature for classifiers that has to be adapted in real-time, what is the case of some applications of Brain-Computer Interfaces (BCI).

. The neural network trained for both tasks achieved about the same average performance (around 65%). This means that the construction of a command set associated to the detection of movements (aiming a BCI) can be based in the single movement task. For both tasks the structure of the classifier was similar, using an average of 3 subclasses for each class (WM or BA).

The averaged time response enabled the observation of the MRD of the mu band as expected.

Results obtained in this work encourage further development of the methodology here reported, being important steps towards BCI technologies.

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