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Detection of movement-related desynchronization of the EEG using neural networks

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Abstract – In this work, we aimed to detect the non-averaged MRD of the mu rhythm from the background activity of the EEG. The MRD was produced in the contralateral sensorimotor cortex by means of a movement of the right hand. Thirteen volunteers took part in the experiments. They were all right-handed and had ages between 22 and 37 years old. The volunteers were asked to do one of two tasks: (a) just one movement by trial; (b) repetition of movements. The EEG signal was taken in the scalp near to C3 lead. The signal was amplified, sampled and digitally filtered off-line. The time response of the mu band was computed with the FFT. Windows of the time response was used as predicates in the training and testing of a neural network classifier. Representative samples of MRD and background activity was taken for each class. The neural networks used were LVQ and they were trained by session, by task and by volunteer. 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. For the LVQ, only 3 subclasses for every class were sufficient, and a constant learning rate of 0.01 with the number of training epochs calculated by the relation of 250 x (total number of subclasses) was enough to get the best results.

keywords: BCI, EEG, LVQ, MRD, neural networks, signal processing, pattern recognition

1. Introduction

Movements of limbs produce changes in the electroencephalographic signal, notably in the sensorimotor cortex contralateral to the limb. These changes are known as MRD (movement-related desychronization) and can be detected in the mu band (8-12 Hz) (NASHMI *et al.*, 1994; FLOTZINGER *et al.*, 1992; FLOTZINGER *et al.*, 1994; PFURTSHELLER *et al.*, 1994; PFURTSHELLER *et al.*, 1996).

The objective of this work is to develop a classifier system capable of identify the MRD from the background activity of the EEG.

Experiments were conducted to evaluate two different ways of producing MRDs, using for such, two tasks that include the movement of the right hand. The first task is a single movement of the wrist, upward and downward. The second task was the repetition of the same movement.

The work also aims to evaluate the performance of a Linear Vector Quantization (LVQ) neural network as a classifier.

The technique used here will be further applied to implement a Brain-Computer Interface (BCI) (PILLA JÚNIOR, 1999).

2. Methodology

The experimental setup used for collecting signals from volunteers is shown in figure 1.

The EEG was collected from the scalp 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 and the sampling rate was 1,280 Hz.

In a given signal collection session, the same task was executed in all trials (single movement or repetition). At least 50 valid trials, during 20 sec each, were collected from each volunteer. Valid trials were those when no artifacts were visually detected. After the session, all samples were again inspected to eliminate those with undesired artifacts.

In the screen of a personal computer a sequence of events for each task was presented in order to guide the volunteer. For the first task (single movement), an arrow was presented in the screen at t=6s to indicate that the movement had to be done immediately. For the second task an arrow was presented in the screen in t=11s to tell the volunteer that he/she had to start the movements.

This arrow was presented again 8 times in intervals of 1 s. All trials had an overall duration of 20 s.

All volunteers participate of sessions were both tasks were done.

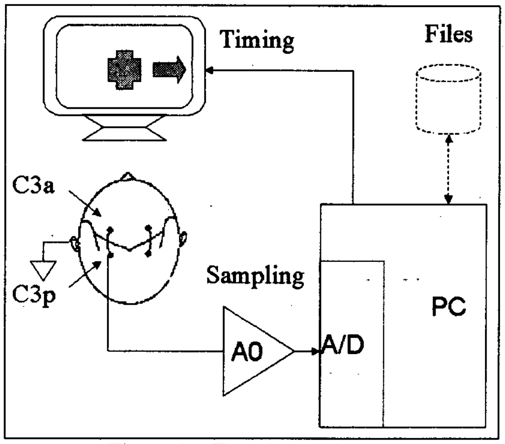

Figure 1 – Experimental setup

In all sessions, the volunteers were sit down comfortably in a reclined chair, lights were turned off and the room temperature was lower than 25 °C. Volunteers should stay mentally and physically relaxed but waked up, 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 and 0.9 seconds. (helped by 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.

3. 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 FIR filter of order 128. After, sampled signal was decimated, reducing the initial sampling rate (1280 Hz) to 256 Hz. Next, the mu band was extracted using a digital band-pass FIR filter, order 64, in the range 7-13 Hz. Using this filtered signal, the time response of the mu band was calculated at intervals of 0.125 s (32 samples) using a window of 1 s (256 samples). For every window, the FFT was computed (BOASHAH, 1992). Thus, the k-th time response y(k) of the mu band 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 the figure 2 it is shown the time response of the mu band taken as the average by session for two different volunteers. In this figure, it is seen the presence of a valley between $t \approx 6$s and $t \approx 8$s (for 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 $t \approx 11$s and persists until the last movement in $t \approx 19$s. For the second volunteer, the MRD disappeared soon, probably because he was too relaxed during that session, not being capable of repeating the movements in synchrony.

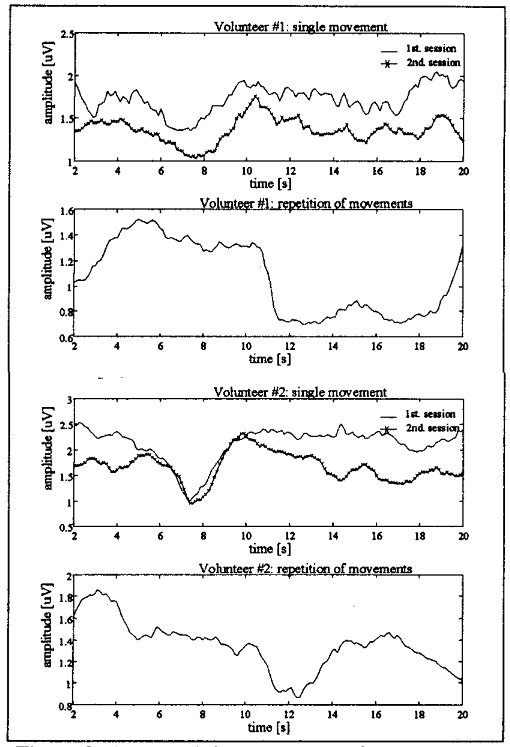

Figure 2: Averaged time response of the mu band. Top: volunteer #1; bottom: volunteer #2

4. Neural network training

Data for training and testing the classifier were constituted by vectors of 9 samples taken as windows from the time response (non-averaged) of the mu band. 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 proportion of one window of WM to three of BA was used for every trial in the session for this task for the training / test set.

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. A proportion of 3 classes WM to 3 classes BM was used for the trials in this task for the training / test set.

The classifier used was a Kohonen Learning Vector Quantization (LVQ type 2) neural network (KOHONEN, 1997), as shown in figure 3. This classifier is based on clustering with supervised learning. It uses a vector quantization architecture to approximate the optimal decision boundaries of a Bayesian classifier (FORD, 1996; FRIEDMAN and KANDEL, 1999). The structure of the classifier is depicted in the figure 3. It is constituted by two layers. The first one is denominated competitive layer. In this layer, the Euclidian 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 training of the neural network, is 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 class WM or among the n_2 neurons of class BA. 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) is activated.

Neural networks were trained by session (or group of sessions, case a given volunteer has taken part in more than one session of the same task), by task and by volunteer. Two thirds of data were used for training and one third for testing.

The criterion for evaluating the performance of the neural networks was defined as the number of correct classifications (HAND, 1997). That is, the number of true positive (presence of MRD) and true negative (presence of background activity) relatively to the misclassification cases. Common measures of performance for classifiers is the sensitivity and specificity, defined as follows:

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

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

where:

i - i-th training epoch
se - sensitivity
tp - (true positive) number of correct classifications for the WM class
fn - (false negative) number of wrong classifications for the WM class
sp - specificity
tn - (true negative) number of correct classifications for the BA class
fp - (false positive) number of wrong classifications for the BA class

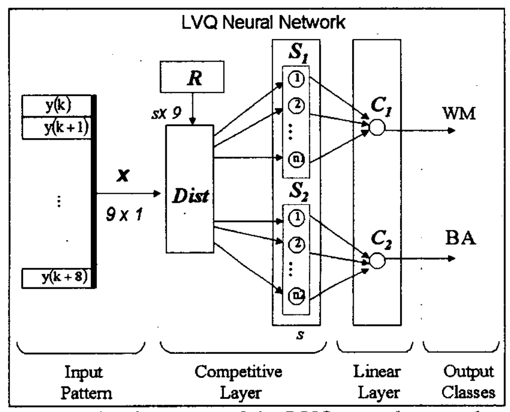

Figure 3 – Structure of the LVQ neural network

Sensitivity and specificity identifies respectively the proportion of cases of the WM class and BA class that are correctly classified as so. 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 by the following equation:

$$de(i) = \sqrt[2]{se(i)\cdot es(i)} \tag{3}$$

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%). This index facilitates the analysis of the neural network training since it uses both sensitivity and specificity.

5. Results

The parameters to be adjusted in a LVQ neural network training are: learning rate α and the number of training epochs. The training aims to find the best reference vectors for each class. 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, it was found that 250 times the number of subclasses was enough to reach the best performance.

The learning rate was empirically set to 0.01, since previous experiments have shown that better results were obtained with α within the range of 0.005 to 0.02 than outside it.

All the 36 possible combinations using 1 to 6 reference vectors for each class (WM and BA) were tried in order to find the best combination. Each training was repeated three times for all volunteers. The best results for all volunteers are shown in table 1

Table 1 – Training results of the LVQs networks

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

In table 1 it can be seen that not all volunteers have their signals 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 [%]		
	Average	Max.	Min.
Single	66,3(*)	88,2	55,9
Repetition	65,4(*)	78,1	53,8
Movement	**Subclass: BA**		
	Average	**Max.**	**Min.**
Single	3,4	6	1
Repetition	3,2	5	1
Movement	**Subclass: WM**		
	Average	**Max.**	**Min.**
Single	3	5	1
Repetition	2,9	5	1
(*) – significance (p) 84%			

6. Discussion and Conclusions

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

The classifiers (LVQ neural network) trained for both tasks achieved about the same performance (around 65%), in average. 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 is similar, being necessary an average of 3 subclasses for each class (WM or BA).

The Kohonen LVQ neural network was suited for identifying the two classes of electroencephalographic signals approached in this work. This suggests that the classifier is robust enough for such applications, considering that the EEG samples used were very noisy. 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 results obtained in this work encourages further development of the methodology here reported, being important steps towards BCI technologies.

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