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EVOLUTION OF THE MENTAL STATES OPERATING A BRAIN-COMPUTER INTERFACE

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Abstract: **This study analyses the location of patterns of brain activity in the signal space while a human subject is trained to operate a brain-computer interface. This evaluation plays an important role in the understanding of the underlying system, and it gives valuable information about the translation algorithms. The relative position and morphology of the patterns in a training session, and from one session to another, enable us to evaluate the performance of both the interface and the user. Thanks to these aforementioned variables we are also able to appreciate stable trajectories of the mental states during the sessions, which shows both the adaptability of the user to the interface, and vice versa.**

Keywords: **brain-computer interface, electroecephalography, local neural networks, Mahalanobis distance, linear variety.**

Introduction

A brain-computer interface (BCI) is an alternative means of communication that is of special interest for people suffering severe impairments. The interface enables a person to operate a computer or a personal device by using only brain activity.

The interface recognises different mental states that are associated with specific commands. Each mental state is represented by a set of prototypes, which are specific patterns of brain activity estimated from the user's on-line electroencephalogram.

Prototypes can be considered as points in an n-dimensional signal space, and the evolution of these points over time can be analysed when a person is in the training period to operate a BCI.

The current study presents initial evidence of the evolution of the prototypes under a geometrical point of view. Distances between prototypes in a particular training session, and from one session to another, have been analysed as well as changes in the morphology.

Materials and Methods

The mental states selected by the user to control the interface are represented by a number of patterns of brain activity in the frequency domain.

The subject had to perform mentally three of the following mental tasks: a cube in rotation, the imagined movement of the left and/or right hand, and relaxation.

Data were analysed from five subjects –all volunteers. On-line data were acquired from eight positions, which covered the central part of the brain, i.e. F_3, C_3, P_3, C_z, P_z, F_4, C_4, and P_4.

The data were continuously acquired in blocks of 0.5 seconds. The sample frequency was 128 Hz. Data were bandpass filtered from 4 to 45 Hz, i.e. the range with the most significant information of the brain activity required for the operability of the current prototype [1]. The estimated patterns were classified using a local neural network [2], where every unit represents a prototype of one of the mental tasks to be recognised.

The current study approaches the prototypes as linear varieties (LV). Each mental state is represented by a number of prototypes –up to nine. Each prototype is considered as a point in a high-dimensional space –in our case, a 96-dimensional vector space.

The linear variety V, which represents a particular mental state, is expressed in (1) as a function of the prototypes:

$$V = \{p;\ v_i\} \qquad i=1\ldots(n-1) \tag{1}$$

where p is any of the prototypes of the mental state; v_i are vectors defined from p to the rest of prototypes; and n is the total number of prototypes of the mental state.

For example, the LV of a mental state represented by the four prototypes $\{p_1, p_2, p_3, p_4\}$ is $V = \{p_1;\ v_1, v_2, v_3\}$, where $v_1=p_2-p_1$, $v_2=p_3-p_1$, and $v_3=p_4-p_1$.

The three variables used to show the evolution of the interface while training a subject are: 1) the distance between LVs in an individual training session; 2) the distance between the LV of a specific mental state from one day to another; and 3) the morphological variation of the LVs over the training. The distances are computed between the centroids c of the LV, i.e. the mean of the prototypes characterising the mental states.

Considering the two linear varieties $U=\{a;\ u_i\}$ and $V=\{b;\ v_j\}$, different distances have been tested: 1) the Euclidian distance –d_e in eq. (2); 2) the Mahalanobis distance –d_m in eq. (3); and 3) the distance between two LV –d_{LV} in eq. (4).

$$d_e = \left| c^u - c^v \right| = \sqrt{\sum_{i=1}^{n} \left| c_i^u - c_i^v \right|^2} \tag{2}$$

where c^u and c^v are the centroids of U-LV and V-LV, respectively; and n is the dimension of the input space.

$$d_m^2 = \left\| c^u - c^v \right\|^2 = \left(c^u - c^v\right)^T \cdot \boldsymbol{S}^{-1} \cdot \left(c^u - c^v\right) \tag{3}$$

where c^u and c^v are the centroids of U-LV and V-LV, respectively; and $\boldsymbol{S}$ is the covariance matrix of the corresponding mental states.

$$d_{LV} = \| a - b \|^{2} - \boldsymbol{Y}\boldsymbol{N}^{-1}\boldsymbol{Y}^{T} \qquad (4)$$

where a and b are the reference points of U-LV and V-LV, respectively; $\boldsymbol{Y}=(\langle a\text{-}b,u_i\rangle\ldots\langle a\text{-}b,v_j\rangle)_{ij}$ which is the orthogonal projection of the vector between the reference points over all the vectors defining the two linear varieties; and $\boldsymbol{N}=(\langle u_i,v_j\rangle)_{ij}$ which is the dot product between all the vectors defining the two linear varieties.

These distances have been measured both among LV in a single day, and between one day to another.

The morphological variation of the LV can be represented by both the covariances and the volume of the linear varieties.

Results

We have selected the evolutions of a representative user to show the results. Although the prototypes of each user follow different trajectories, which are related to individual performance, all of them follow the same pattern and share the evidence presented in this paper.

The distance between prototypes associated to different mental states increases significantly with the training. Figure 1 shows three curves; each one represents the Mahalanobis distance between two mental states. On the third training day, it is possible to observe a decrease in the distance, which is associated to a decrease in the classification rates of this day as well.

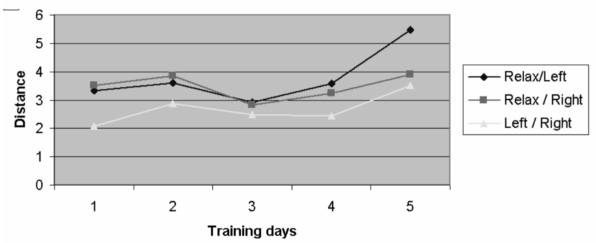

Figure 1. Evolution of the distance between LVs of different mental states.

The distance between LV of the same mental state significantly decreases from one day to another. It indicates both that the user learns to master the interface and also that the prototypes go to a certain stable point in the signal space. Nevertheless, in this example, on abscissa 4 –the distance between the prototypes from the 4th to the 5th day–, it is possible to observe a relocation of the prototypes belonging to the mental state “left”.

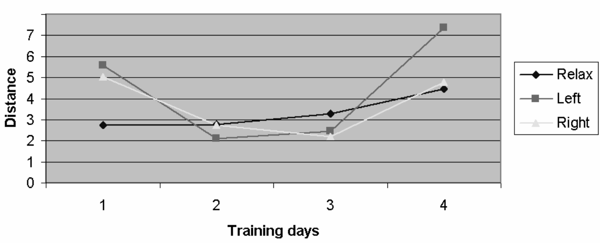

Figure 2. Evolution of the distance between LVs of the same mental state between consecutive days.

The variability of the prototypes also tends to decrease from one day to another, which indicates both the good performance of the translation algorithms, and again the adaptation of the user to the interface. Figure 3 shows a decrease in the covariance of the LVs associated to the different mental states as training proceeds.

The volume of the LV has been studied in all the analysed cases in order to look for a specific evolution. Although many tests have been carried out, there are not any definitive conclusions. But it seems that the volume decreases with training, as for the covariances.

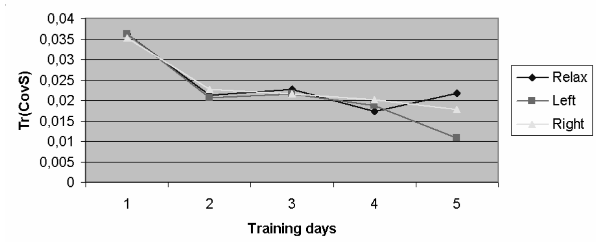

Figure 3. Covariance evolution between sessions.

Discussion

Results show interesting evidence about the trajectories followed by the prototypes, which are representative of the mental states in the signal space. Although results are in the preliminary stage, the five analysed subjects share the same evidence: 1) prototypes tend to go to stable points in the signal space; and 2) the variability tends to decrease with the training. Nevertheless, longer training periods will be necessary to validate these findings.

Conclusions

The training of a person with a brain-computer interface depends on many variables, i.e. the acquisition of good EEG data, feature extraction, and feature classification. Good performance during the training period is crucial to motivate the user to operate the interface. The current study has presented some variables to evaluate the performance of the translation algorithms. The distances between the different prototypes in the same training session, as well as from one session to another, together with their variability and morphology, increase our understanding of whether or not training is progressing correctly and is stable. These variables, and their graphical representations, may give valuable hints to the trainer on which strategy to follow to improve the brain-computer interface.

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