HUMAN-COMPUTER ADAPTATION FOR EEG BASED COMMUNICATION

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Abstract Brain-computer interface (BCI) systems allow the user to interact with a computer by merely thinking. Successful BCI operation depends on the continuous adaptation of the system to the user and on the user motivation. This paper presents a model of continuous adaptation using kernel based dynamic data characterization. Additionally, the adaptive capabilities of the brain are engaged by providing feedback to the user who can modulate her mental activity so as to make the BCI accomplish her intents.

Keywords – Direct brain-computer communication, electroencephalography, brain-computer interface, adaptive learning, kernel methods.

I. INTRODUCTION

Automatic systems capable of understanding different facets of human communication will be at the heart of human-computer interfaces (HCI) in the near future. An HCI which is built on the guiding principle: “think and make it happen without any physical effort” is called a brain-computer interface (BCI). Indeed, the “think” part of this principle involves the human brain, “make it happen” implies that an executor is needed (here: a computer) and “without any physical effort” means that a direct interface between the brain and the computer is required.

BCIs are mainly intended for people with motor disabilities in order to provide them with new communication channels [1]. Also, BCIs can be used as a complement to other HCI devices to enrich the interaction between humans and computers [2].

To make the computer interpret what the brain intends to communicate necessitates monitoring of the brain activity. Among the possible choices, the scalp recorded electroencephalogram (EEG) appears to be an adequate alternative because of its good time resolution and relative simplicity. Furthermore, there is clear evidence that observable changes in EEG result from performing given mental activities (MAs) [3]. Here, we study an EEG based BCI, hereafter called a BCI. This BCI is subdivided into three units, namely EEG acquisition, processing and output (Figure 1).

The EEG acquisition unit is composed of an electrode array arranged according to the 10-20 international system and a digitization device [4]. The acquired signals are often noisy and may contain artefacts due to muscular and ocular movements.

The processing unit is subdivided into a preprocessing unit, responsible for artefact detection, and a feature extraction and recognition unit that identifies the command sent by the user to the BCI. The output subsystem generates an action associated to this command. This action constitutes a feedback to the user who can modulate her mental activity so as to produce those EEG patterns that make the BCI accomplish her intents.

Figure 2 illustrates the scheduling of the BCI. The BCI period is the average time between two consecutive actions and the EEG trial duration is the duration of EEG that the BCI needs to analyze in order to generate an action.

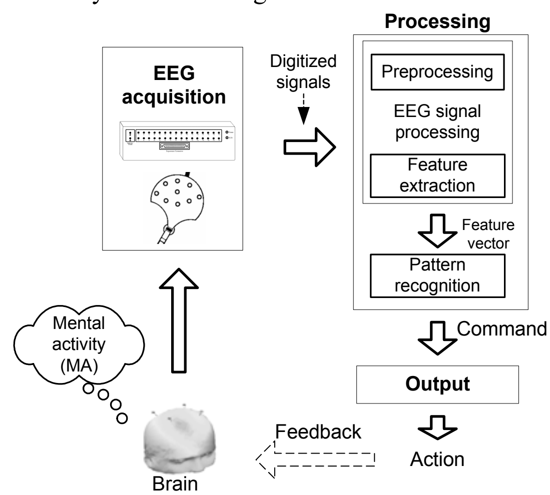

Figure 1. BCI architecture.

Successful BCI operation depends on system design factors (feature extraction, MA recognition algorithm, communication bit-rate and feedback strategy) as well as on the user motivation.

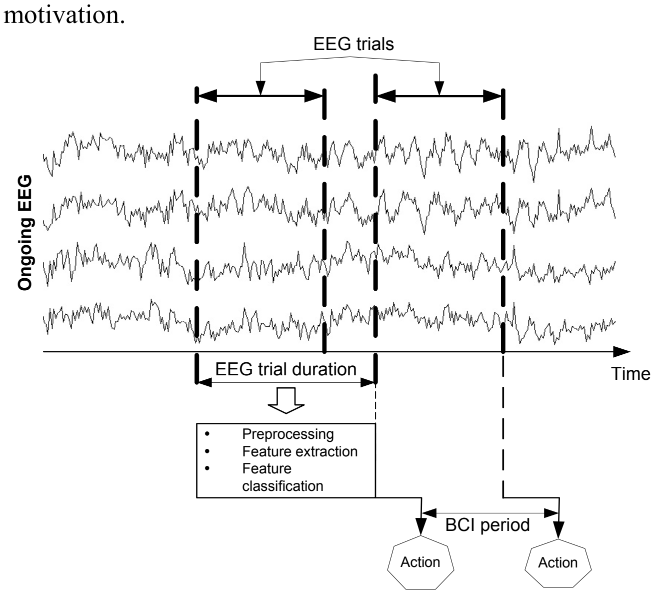

Figure 2. BCI scheduling.

As mentioned in [1] effective BCI systems adapt to each user on three levels. First, when a new user accesses the BCI the system adapts to that user's signal features. In the second level of adaptation periodic adjustments are carried out to reduce the impact of EEG variations. The third level of adaptation accommodates and engages the adaptive capacity of the brain.
In this paper we focus on the second and third adaptation levels and briefly introduce the first in Sect. II (detailed information on this first level can be found in [5]).

II. EEG FEATURE EXTRACTION

An EEG trial is a multivariate signal composed of the signals recorded at each electrode. In order to extract a feature vector from an EEG trial, a set of space-frequency filters are established during a first training session where the user is asked to perform the MAs that she will use to control the BCI. These filters give as a result a feature vector that is composed of the averaged powers associated with each space-frequency "direction". This vector belongs to $\mathbb{R}^M$ where M is the number of space-frequency filters.
The filters coefficients are determined for each MA and adapted to each user so as to maximize the discrimination between the targeted MA and the rest of mental states that can take place in the brain.
The optimal durations of the EEG trial and BCI period were set depending on the recognition error. According to the results in [5] the EEG trial and BCI period durations were both set to one second.

III. BCI MODEL

We consider a BCI that is commanded by N_A MAs. A_0 is the neutral action (i.e. the BCI does not execute anything).
The following model is proposed to address the second and third adaptation levels (Figure 3).
Every BCI period the brain produces a feature vector $V(k)$ which is drawn from a probability density function (PDF) that depends on the action at time (*k-1*): $A(k-1)$ and extra-system factors that can be external (noise and environmental conditions) and internal (user's state of mind).

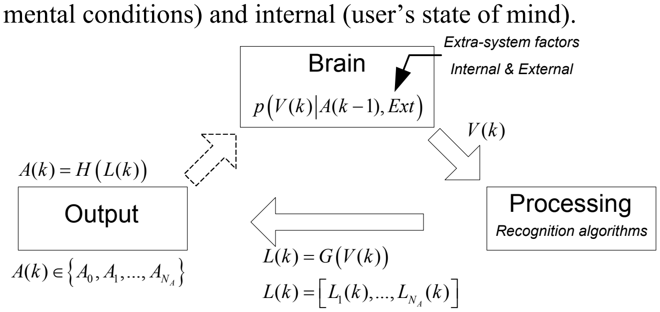

Figure 3. BCI model.

The result of the processing unit is a vector $L(k)$ containing N_A scores which are related to the likelihood that $V(k)$ belongs to each MA. The computation of such scores is explained in Section IV.
The action produced by the output unit depends on $L(k)$ (likelihood vector). This action can be noticed by the brain who adapts its activity so as to make the output unit produce the desired actions.
While external factors can be easily controlled, internal factors cannot, even by the user herself.

IV. DYNAMIC CHARACTERIZATION OF THE PDF ASSOCIATED WITH AN MA

The role of recognition algorithms is to dynamically characterize the probability density function associated with each MA under different extra-system conditions. The characterization for the MA_q is noted Φ_{MA_q} . This characterization is carried out during several training sessions and continuously updated. We assume that external conditions are constant during each training session.
The first characterization $\Phi_{MA_q}(0)$ is determined in an open loop modality (training without feedback) where the user is asked to perform MA_q while the produced feature vectors are recorded. The next characterizations are updated in a closed loop modality (training with feedback) in which the user is asked to perform MA_q and feedback is provided to him. The feedback is positive if the system successfully recognizes MA_q and negative otherwise. The feedback of a session results from the description that was established in the precedent session.
The characterization Φ consists of a set of vectors that are located at the boundaries of the probability density function. This set is built using the approach in [6] for novelty detection.
We consider the set S_q composed of those vectors recorded during the performance of MA_q and its complement $\overline{S}_q$.
A transformation F_H that maps the feature vectors into a space H (of infinite dimension) is defined through a Kernel function that is the internal product in H and can be expressed in terms of the dot product in the original space $\mathbb{R}^M$.
Here, we used a Gaussian Kernel function as it was more appropriate for our application[6].
If x and y belong to $\mathbb{R}^M$ the Gaussian Kernel is given by

$$K(x,y)=\exp\left(-\frac{x\cdot x-2x\cdot y+y\cdot y}{\sigma^2}\right) \tag{1}$$

The width parameter σ is determined through cross-validation.
We assume that the vectors belonging to S_q are inside a sphere of radius R and centered in Ω (in the space H) whereas the vectors belonging to $\overline{S}_q$ are outside this sphere. The values of R and Ω can be found solving an optimization problem which consists in minimizing the radius R.

Nonetheless, some of the vectors can be in the wrong set (training errors) because of possible perturbations during the measurements or the user's lack of concentration. As a matter of fact, some of the users of our system reported that they not always performed what we asked them to do. In order to take it into account we introduced lack variables into the optimization problem. The problem then becomes:

$$\text{minimize}\left(R^2 + C_1\sum_i \xi_i^{(x)} + C_2\sum_j \xi_i^{(y)}\right) \tag{2}$$

under the constraints

$$\begin{aligned} &\|u_i - \Omega\|^2 \le R^2 + \xi_i^{(x)} \;;\; u_i = F_H(x_i) \;;\; x_i \in S_q \\ &\|v_j - \Omega\|^2 > R^2 + \xi_j^{(y)} \;;\; v_j = F_H(y_j) \;;\; y_j \in \overline{S}_q \\ &\xi_i^{(x)} \ge 0 \;;\; \xi_j^{(y)} \ge 0 \end{aligned}$$

The index i is used for vectors (or transformed vectors) associated with S_q while j is used for elements in $\overline{S}_q$. C_1 and C_2 are penalization constants whose values are determined as explained later in the text.

Using Lagrange multipliers, the optimization problem (2) is equivalent to minimize

$$\begin{aligned} \Lambda_P = {} & R^2 + C_1\sum_i \xi_i^{(x)} + C_2\sum_j \xi_j^{(y)} - \sum_i \gamma_i^{(x)}\xi_i^{(x)} - \sum_j \gamma_j^{(y)}\xi_j^{(y)} \\ & -\sum_i \alpha_i^{(x)}\left(R^2 + \xi_i^{(x)} - \|u_i - \Omega\|^2\right) - \sum_j \alpha_j^{(y)}\left(\|v_j - \Omega\|^2 - R^2 + \xi_j^{(y)}\right) \end{aligned} \tag{3}$$

$$\alpha_i^{(x)} \ge 0 \;;\; \alpha_j^{(y)} \ge 0 \;;\; \gamma_i^{(x)} \ge 0 \;;\; \gamma_j^{(y)} \ge 0$$

Taking derivatives of Λ_P with respect to $R, \Omega, \xi_i^{(x)}, \xi_j^{(y)}$ and setting them to zero results in

$$\sum_i \alpha_i^{(x)} - \sum_j \alpha_j^{(y)} = 1 \tag{4}$$

$$\Omega = \sum_i \alpha_i^{(x)} u_i - \sum_j \alpha_j^{(y)} v_j \tag{5}$$

$$C_1 - \gamma_i^{(x)} - \alpha_i^{(x)} = 0 \Rightarrow 0 \le \alpha_i^{(x)} \le C_1 \tag{6}$$

$$C_2 - \gamma_j^{(y)} - \alpha_j^{(y)} = 0 \Rightarrow 0 \le \alpha_j^{(y)} \le C_2 \tag{7}$$

when (4), (5), (6) and (7) are substituted in (3) we obtain the dual problem,

Maximize:

$$\begin{aligned} \Lambda_D = {} & 1 - \sum_{i1,i2} \alpha_{i1}^{(x)}\alpha_{i2}^{(x)} K\left(x_{i1}, x_{i2}\right) + 2\sum_{i,j} \alpha_i^{(x)}\alpha_j^{(y)} K\left(x_i, y_j\right) \\ & -\sum_{j1,j2} \alpha_{j1}^{(y)}\alpha_{j2}^{(y)} K\left(y_{j1}, y_{j2}\right) \end{aligned} \tag{8}$$

Furthermore, the Karush-Kuhn-Tucker conditions [6] imply that

$$\alpha_i^{(x)}\left(R^2 + \xi_i^{(x)} - \|u_i - \Omega\|^2\right) = 0 \tag{9}$$

$$\alpha_j^{(y)}\left(\|v_j - \Omega\|^2 - R^2 + \xi_j^{(y)}\right) = 0 \tag{10}$$

The value of $\alpha_i^{(x)}$ determine the position of u_i with respect to the sphere.

$$\text{if } \begin{cases} \alpha_i^{(x)} = 0,\ u_i \text{ is inside the sphere} \\ 0 < \alpha_i^{(x)} < C_1,\ u_i \text{ is in the boundary of the sphere} \\ \alpha_i^{(x)} = C_1,\ u_i \text{ is outside the sphere (false negative)} \end{cases}$$

Similar results are found for the $\alpha_j^{(y)}$'s and their corresponding v_j 's. From the above results and (4) we can state that

$$C_1 < \frac{1}{\text{number of } u\text{'s outside the sphere (false negatives)}} \tag{11}$$

$$C_2 < \frac{1}{\text{number of } v\text{'s inside the sphere (false positives)}} \tag{12}$$

Thus, C_1 and C_2 for a given training session can be set according to the quality of that session. In our experiments, we set these values depending on the number of positive feedbacks multiplied by a factor which sets the amount of new knowledge that is acquired in the session.

The characterization Φ is composed of the vectors that are in the boundary of the sphere.

In the next session, the new characterization is obtained adding the characterization set of the precedent session to the new vectors and solving the optimization problem (Eqs. (2) to (10)).

It can be shown that if the boundary of the PDF change, the characterization Φ adapts to that change. In this way we can achieve the second level of adaptation.

As feedback is provided during the training sessions, (except the first one) the brain can adapt itself in order to produce the right MAs.

For an unknown vector z the score with respect to an MA characterization is computed as the ratio between the distance from $F_H(z)$ to the center of the sphere Ω_{MA} and the radius R_{MA} . If the score value is smaller than 1 then $F_H(z)$ is inside the sphere.

The output of the processing unit for z is a vector $L(z)$ (called likelihood vector) composed of the scores associated to each MA.

V. Output unit

The action produced in the output unit depends on the likelihood vector. This vector contains scores whose values are positive real numbers.

If we assume that each MA is associated with an action and if that action can be executed with certain intensity, it is possible to build a function mapping the score to the intensity. Such a function should be monotonically decreasing for score values ranging from 0 to 1 and zero for score values larger than 1.

VI. Results and discussion

Two male healthy subjects aged 24 (S1) and 27 (S2) participated in eleven training sessions where they were asked to perform two MAs namely MA1 (imagined right hand movement) and MA2 (mental counting). The EEG signals at electrodes F7, F3, F4, F8, T3, C3, C4, T4, T5, P3, P4, T6, O1 and O2 [4] were analyzed.

The false positives and true positives percentages for each MA and each subject are reported from session two to eleven in Figures 4 and 5.

The learning curve of S1 (Figure 4) shows that the true positive rate globally increased for both MAs over the sessions and the final true positive rates for MA1 (81.7%) and MA2 (79.8%) are closer. Instead, the final false positive rates for MA1 (23.8%) and MA2 (31.2%) are quite different. Also, the learning curve exhibits an irregular evolution of the results corresponding to MA2. This indicates that, depending on the BCI application, S1 can need more training to produce MA2 more accurately.

The importance of the false positive rate depends on the application (e.g. to command a wheel chair could require a low false positive rate in order to avoid abrupt movements).

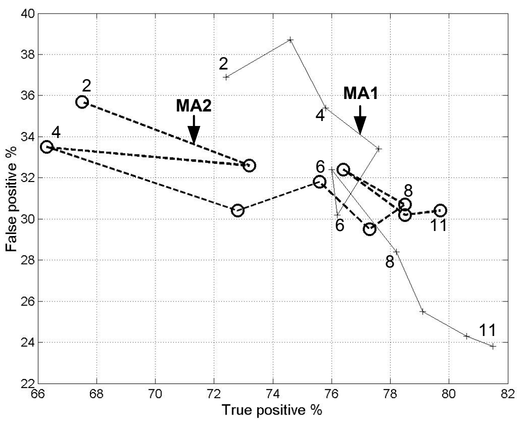

Figure 4. False positives versus true positives percentages for subject S1 for session two to eleven.

The learning curve of S2 (Figure 5) exhibit a more regular evolution of the results associated with both MAs. Globally, the true positive rates increased and the false positive rates decreased over the sessions. The final values of the true positive rates (74.6% for MA1 and 78.6% for MA2) and false positive rates (22.4% for MA1 and 26.0% for MA2) are not very different as in the case S1.

While the false positive rates are better than those of S1, the true positive rates are smaller when compared to those of S1.

Again, the importance of the true positive rate depends on the application (e.g. in a game application a low true positive rate can produce frustration in the user).

VII. Conclusions and Future Work

The three adaptation levels of a BCI and a model that can implement those levels were presented. The first adaptation level is achieved by setting a set of space-frequency filters whose parameters are determined for each user and each MA. The resulting feature vectors are then characterized by a set whose elements are those vectors that are at the boundary of the probability density functions associated with each MA.

Such characterization is periodically updated using an efficient algorithm which easily integrates the "knowledge" gained in a training session in the next session (second adaptation level).

The obtained results show that the user performance tends to improve through the training sessions because of the feedback. This implements the third level of adaptation as it engages the adaptive capabilities of the brain.

Additional work is necessary in order to establish a feedback strategy that efficiently reinforces the user learning. This part should be achieved by taking into account physiological and psychological aspects.

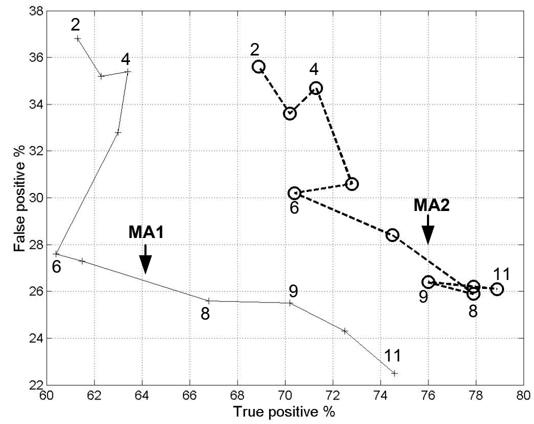

Figure 5. False positives versus true positives percentages for subject S2 for session two to eleven.

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