SPATIAL FILTERING IN THE TRAINING PROCESS OF A BRAIN COMPUTER INTERFACE

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Abstract- **The spatial filtering of electroencephalogram data is crucial when analyzing the brain activity. Spatial filters increase the signal-to-noise ratio, thus allowing better classification of the analyzed mental states. This study will show the evolution in the selection of the most appropriate spatial filter when subjects are training to control a brain-computer interface. Different filters -the common average reference and the estimation of the surface Laplacian both using finite different methods and spherical splines- have been adapted and evaluated for a particular configuration of electrodes, using only eight positions: F_3, C_3, P_3, C_z, P_z, F_4, C_4, and P_4.**

***Keywords*-brain-computer interfaces, spatial filtering, common average reference, surface Laplacian, spherical splines**

I. INTRODUCTION

Brain-computer interfaces (BCI) are an alternative means of communication with computers. These are systems mainly addressed to impaired people, who do not have an accurate control of their muscles, but often a clever mind. Pathologies such as spinal muscular atrophy, spina bifida, or spinal cord injury prevent from leading a normal life. But some pathologies lead to severe-motor impairments. Subjects are unable to execute any movement, the illness having spread to involve most of the body and face, i.e. people suffering amyotrophic lateral sclerosis, or particular cases of cerebral palsy.

Over the past few years some groups [1] [2] [3] [4] have demonstrated the possibility to recognize a few mental tasks from on-line spontaneous electroencephalogram (EEG) signals and have associated them to simple commands such as "move cursor up".

The main problem when analyzing EEG signals is the very low signal-to-noise (SNR) ratio (-5 dB) [5]. The classical filtering methods can increase the SNR, reducing the noise from artifacts like EMG or some ocular artifacts.

The complexity and variability of the source signals, both inter-subjects and intra-subjects, lead us to filter the data spatially. The main problem is a deblurring of the information when the ions travel from the surface of the brain to the scalp. Spatial filters try to minimize this effect by giving a more representative pattern of what is really happening at each location, substantially increasing the SNR of the EEG signals.

In this paper we investigate the most appropriate spatial filter when a small number of electrodes are considered, and the evolution in the selection of the filter when a person learns how to operate a BCI.

II. METHODOLOGY

A. Data acquisition

A commercial head-cap, with electrodes attached in the 10-20 international system of electrode placement is used for the EEG data acquisition. Each electrode is plugged directly into an amplifier to avoid problems in data transmission. Signals go to a portable electroencephalograph prototype [2]. The reference is placed in both ear lobes to have an appropriate balance between the potentials coming from the two brain hemispheres. The earth of the overall acquisition system is also applied to one of the ear lobe.

B. Acquisition protocol

The acquisition of the EEG data is done with the subject seated in a comfortable chair and spontaneously concentrates on different mental states.

The subject performs the selected task during 10 to 15 seconds, and he/she chooses when to stop doing it and the next to be undertaken. Each recording session lasts about 5 minutes. The subjects selected for this study had to mentally perform one of the following mental tasks: *relax*, *cube in rotation,* and the *imagined movement of the left hand*.

Relax state is one of the easiest, in which the subject remains with closed eyes and relaxed. For the cube rotation stage the subject remains with eyes open and imagine a three-dimensional cube spinning around one of its axis. This mental state is mainly associated with the right hemisphere of the brain, which is mainly responsible of the mentally visualization. The left-hand movement imagination is a motor related task in which the subject remains with eyes open and imagines repetitive movements of the left hand.

During the early stages of the training process, the user performs the mental states without any feedback on what is going on. This gives the user the time to get used to the different states. As soon as they start having a slight control of their thoughts, visual feedback is provided. The feedback is based on three buttons -each one corresponding to a particular mental state- that light up when the corresponding state is recognized. The brightness of the button is proportional to the accuracy in the classification.

C. Pattern detection

Data are acquired from eight positions: F_3, C_3, P_3, C_z, P_z, F_4, C_4, and P_4, covering the central part of the brain. The data are continuously acquired in blocks of 0.5 seconds. The sample frequency is 128 Hz. The frequency band analysed ranges from 8 to 30 Hz, which contains the most significant information of the brain activity required for the purpose of the present study.

Once the data are acquired the power spectrum is estimated for each channel. The averaged Welch periodogram is computed over segments of 1 s, averaging three windows of half a second with 50% overlap between segments. A Hamming window has been selected due to its appropriate balance between the peak sidelobe level and the sidelobe decade rate when windowing the EEG data.

D. Pattern classification

Detected patterns are classified using a local neural network (LNN), where every unit represents a prototype of one of the mental tasks to be recognized [6]. The LNN finds the appropriate position, and receptive field, of the prototypes in the high dimensional input space defined by the estimated power spectrum components. The basic idea is that, during training, units are pulled towards the EEG patterns of the mental task they represent and are pushed away from the EEG patterns representing other tasks.

E. Spatial filters

The current study faces the problem of spatially filtering the EEG signal using a small number of electrodes.

The spatial frequency is the variation in the scalp potential field over distance. The selection of only eight electrodes impairs the EEG accuracy due to the spatial aliasing, i.e. ghost spatial frequencies appearing as smooth patterns which are not present in the subject's scalp.

Three methods have been considered to spatially filter the EEG data: 1) the estimation of the Surface Laplacian considering Finite Difference Methods (SL_FDM), 2) the Common Average Reference (CAR) and, 3) the estimation of the Surface Laplacian on a spherical spline approach (SL_SS). The spatial filter is applied to the EEG data before the estimation of the power spectrum.

As it is referred by McFarland [7], the surface Laplacian is the most appropriate technique to filter the EEG data spatially. It provides an estimate of the local radial (normal) current density through the skull into the scalp.

Mathematically, the Laplacian method calculates the second derivative of the instantaneous spatial voltage distribution for each electrode location, and thereby emphasizes activity originated in radial sources immediately below the electrode.

Laplacian derivation acts as a high-pass spatial filter, thus enhancing focal activity from local sources, and reducing widely distributed activity, including that from distant sources (e.g. EMG, eye movements and blinks, visual alpha rhythm)

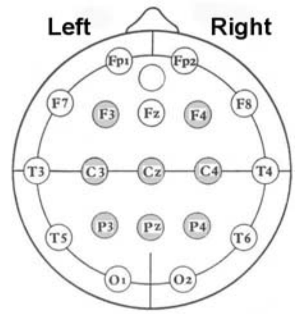

Fig. 1. Electrodes configuration.

The first method estimates the surface Laplacian using finite different methods [8]. A particular set of equations have been developed for the configuration shown in Fig. 1.

Basically, SL_FDM replace the derivatives of an unknown function by the difference quotients of unknown functions. In the configuration defined in Fig. 1, the potential function u of each electrode within a particular domain Ω bounded by a contour Γ satisfies the Poisson's equation and is subject to the Dirichlet boundary conditions as it is shown in (1) and (2).

$$\nabla^2 u = F(x,y) \quad in\ domain\ \Omega \tag{1}$$

$$u\big|_{\Gamma} = g(\Gamma)\ \ on\ boundary\ \ \Gamma \tag{2}$$

In the present case a square grid has been adopted to define the domain Ω. Considering the definition of the difference quotients, Taylor's series are used to derive the difference equation defined in (1). The general expression of the SL_FDM is shown in (3) and (4).

$$U_i^{LAP} = U_i^{ER} - \sum_{j \in Si} g_{ij} U_j^{ER} \tag{3}$$

where

$$g_{ij} = 1/d_{ij} \,/ \sum_{j \in Si} 1/d_{ij} \tag{4}$$

S_i is the set of electrodes surrounding the i^{th} electrode, and d_{ij} is the distance between electrodes i and j (where j is a member of S_i). The U_i^{ER} is the potential between the i^{th} electrode and the ear-reference, and parameter n is the number of electrodes in the montage.

The second methodology is the common average reference. CAR subtracts the common activity in the brain to the position of interest [9]. The idea under the CAR is to remove the averaged brain activity, which can be seen as EEG noise. The formula used to compute the CAR is shown in (5).

$$U_i^{CAR} = U_i^{ER} - \frac{1}{n}\sum_{j=1}^{n} U_j^{ER} \tag{5}$$

The third considered technique is the surface Laplacian transformation by using spherical splines of order 2 [10].

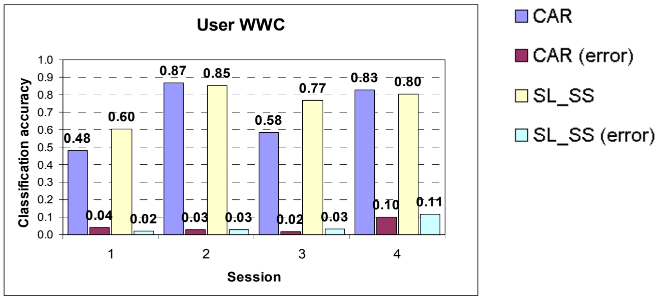

Fig. 2. Classification rates for user WWC.

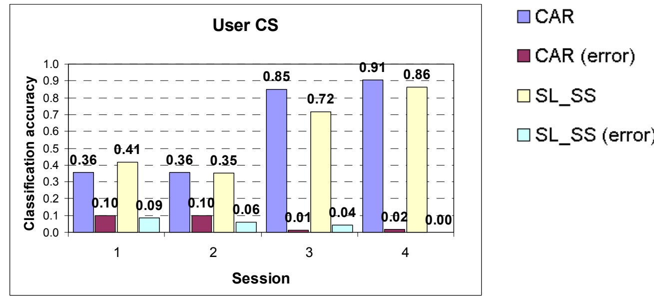

Fig. 3. Classification rates for user CS.

III. RESULTS

The small number of electrodes increases the problem of a lack of information to properly apply the different methodologies. For the configuration shown in Fig. 1 the SL_FDM has to be computed considering boundary condition for all the electrodes. For the SL_SS there are not enough electrodes to perform a good estimation of the surface Laplacian using spherical splines. Despite these theoretical considerations, appropriate estimations have been developed for each particular methodology.

The SL_FDM has been estimated for the set of electrodes: C_3, P_3, C_z, P_z, C_4, and P_4, using finite difference methods. When an electrode is missing, no brain activity is considered in that position, i.e. the potential is considered to be equal to 0. Under a theoretical point of view, the surface Laplacian calculated by using spherical splines should require at least 20 positions to represent a good estimate. Cincotti et al. [11] have demonstrated that a small number of points also achieves a good definition of the spherical spline for the estimation of the surface Laplacian.

Many training sessions have been done with a significant number of subjects –healthy people- during the last years. For the purpose of this study three different users have been selected representing our control group. The users are one female (WWC) and two males (CS and OPC). All are right-handed. They were volunteers. WWC has been selected because she was able to control the system in only one hour of training. CS represents the general finding of this study. OPC is an impair person suffering from spinal muscular atrophy.

The SL_FDM has always achieved less recognition rates for the considered mental states than the CAR and the SL_SS. For this reason and not confusing the reader, the classification rates for SL_FDM will not be considered.

The results are shown in the histograms from Fig. 2 to Fig. 4. The histogram shows the results of each session (horizontal axis) against the classification accuracy (vertical axis, where 1.0 represents 100%). Each session shows 4 bars. The first one is the recognition rate of the CAR filter, and the second bar is the corresponding wrong classifications, i.e. when the classifier has recognized mental states as belonging to a different class. The third bar is the recognition rate of the SL_SS and the fourth bar represents its percentage of wrong classifications.

User WWC is one of the best examples illustrating the evolution of the best spatial filter. This evolution is graphically illustrated in Fig. 2. Session 1 was the user's first time with the system. No feedback was supplied. The SL_SS method achieved better results (60% recognition and 2% wrong responses instead of 48% and 4%). In session 2, the user explained to us that she already had some control of the different mental states she selected, and the CAR method performed slightly better than SL_SS (87% of recognition instead of 85%).

In session 3, SL_SS achieved better performance because it was the first time the user received feedback, i.e. visual information on the recognition of her mental states. The feedback slightly affected her concentration level. A much more objective filter, not using brain activity, was more efficient (77% of recognition for SL_SS instead of 58%).

Finally, in session 4, with the user accustomed to the feedback, CAR returns to achieving a higher recognition rate (83% instead of 80%) with less wrong responses (10% instead of 11%).

The case of *user CS* is a good representation of our general findings. His data are represented in Fig. 3. In sessions 1 and 2 no feedback was provided and it was the first time the subject used the system. Therefore, in session 1 the SL_SS was the best filter. In session 2 the SL_SS could also be considered the best filter due to a lower wrong recognition rate (6% instead of 10%).

Curiously in session 3, although feedback was provided to the user, the CAR method was the best one instead of SL_SS as expected. When asked how to perform the task, the user revealed that he did not watch the screen during the session because the feedback disturbed him. In session 4 no feedback was shown and the user performed the different tasks perfectly filtered. The CAR method achieving really good recognition rates. Again it is possible to observe how the CAR spatial filter achieved the best classification rates when the users were able to control their thoughts. That is, the use of the individual brain activity to spatially filter the data is the most appropriate way to reveal the hidden patterns associated to the targeted mental states.

As a last example, another representative user has been chosen. *User OPC*, a physically-impaired person, reproduce the patterns that emerge from the previous experiments. His performance is shown in Fig. 4. In the first two sessions OPC got used to the interface and started to manage the different mental states. The performance of these mental

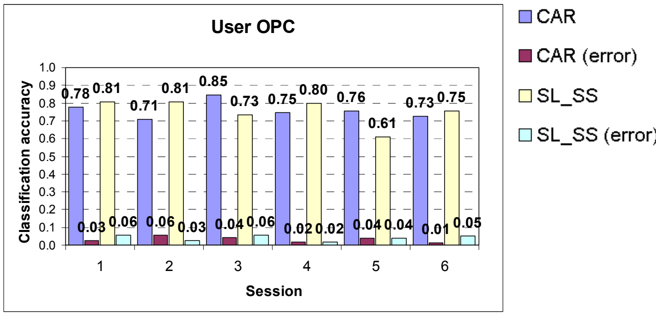

Fig. 4. Classification rates for user OPC.

states was not optimal due to the fact that it was all new to the user. At this stage, a much more objective method achieved the best classification rates, i.e. the SL_SS filter. In session 3 the user started getting used to the interface. Thus the CAR method filtered better than SL_SS (85% in front of 73%).

In session 4 the first feedback was provided, disturbing the control of the mental states. Thus the best classifications were achieved with the SL_SS method. Again, once the person got used to the feedback, the CAR filter achieved better results. In the last session although SL_SS performed slightly better than CAR in terms of number of correct classifications, CAR still achieved the lowest number of incorrect responses (0.01% instead of 0.05%).

IV. Discussion

It is a fact that the first time subjects use the system, they are more worried about the overall procedure than the performance of spontaneous-EEG signals related to the selected mental states. At this stage, spherical splines are the most convenient procedure to spatially filter the data. The splines do not required specific EEG data defining the filter but it is a filter defined using a mathematical model.

Once subjects have more confidence with the system, they perform the mental states in a more spontaneous way. They are able to balance and control their mental activity when performing the cognitive or motor-related patterns. At this stage a common average reference for filtering the EEG data is the most appropriate. CAR directly involves the brain activity resulting as a natural filter for the brain activity.

V. Conclusion

An interesting evolution in the selection of the most appropriate spatial filter of brain activity has been observed when a person is learning how to operate a BCI. The main problem defining the filter is the use of a configuration with a small number of electrodes. Only eight positions have been considered: F_3, C_3, P_3, C_z, P_z, F_4, C_4, and P_4. The estimation of the surface Laplacian based on finite difference methods is not accurate enough due to a lack of information, i.e. the filter is always under boundary conditions. The common average reference and the estimation of the surface Laplacian based on spherical splines have demonstrated the filter capabilities when few electrodes are available.

At the very beginning of the training process the users do not properly control their brain activity. This stage requires a more objective method, i.e. brain activity is not directly involved in the definition of the filter. The surface Laplacian based on the spherical spline approach achieves the best classification rates at this stage (average of 65% in front of 57%). After a period of training, when the users better balance their brain activity and are more conscious of their mental states, a common average reference defined with the present brain activity is the method achieving the best recognition rates of the mental states (83% in front of 76%).

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