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Advances in Non-Invasive Brain-Computer Interfaces for Control and Biometry

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1. Introduction

During the last decade many advances in a number of fields have supported the idea that a direct interface between the human brain and an artificial system, called Brain Computer Interface (BCI), is a viable concept, although a significant research and development effort has to be conducted before these technologies enter routine use. The conceptual approach is to model the brain activity variations and map them into some kind of actuation over a target output through the use of signal processing and machine learning methods. In the meantime, several working BCI systems have been described in the literature using a variety of signal acquisition methods, experimental paradigms, pattern recognition approaches and output interfaces, and requiring different types of cognitive activity (Allison *et al.*, 2008; Bashashati *et al.*, 2007; Berger *et al.*, 2008; Leeb *et al.*, 2007; Millán, 2008; Müller-Putz & Pfurtscheller, 2008). Nowadays, the principal reason for the BCI research is the potential benefits to those with severe motor disabilities, such as brainstem stroke, amyotrophic lateral sclerosis or severe cerebral palsy (Bensch *et al.*, 2007; Birbaumer *et al.*, 2007; Nijboer *et al.*, 2008; Pfurtscheller *et al.*, 2008). However, the most recent advances in acquisition technology and signal processing assert that controlling certain functions by neural interfaces may have a significant impact in the way people will operate computers, wheelchairs, prostheses, robotic systems and other devices.

A very effective way to analyze the brain physiological activity is the electroencephalogram (EEG) measurements from the cortex whose sources are the action potentials of the nerve cells in the brain. The theoretical and the application studies are based on the knowledge that the EEG signals are composed of waves inside the 0-60 Hz frequency band and on the fact that different brain activities can be identified based on the recorded oscillations (Niedermayer & Lopes da Silva, 1999). Over the last years, the interest in extracting knowledge hidden in the EEG signals is rapidly growing, as well as their applications. EEG-based BCIs for motor control and biometry are among the most recent applications in the computational neuro-engineering field. Despite the proof of concept and many encouraging results achieved by some research groups (Marcel & Millán, 2007; Millán *et al.*, 2004; Palaniappan & Mandic, 2007; Pineda, 2005; Pfurtscheller *et al.*, 2006; Vidaurre *et al.*, 2006), additional efforts are required in order to design and implement efficient BCIs. For example, reliable signal processing and pattern recognition techniques able to continuously extract meaningful information from the very noisy EEG is still a high challenge.

The project behind this chapter aims to initiate a long-term multidisciplinary research by combining developments in relevant fields, such as computational neuro-engineering, signal processing, pattern recognition, brain imaging and robotics. In the middle-term, the main objective has been the design and development of BCIs to exploit the benefits of advanced human-machine interfaces for control and biometry. In this line of thought, this chapter will present recent advances towards the development of two BCI systems that analyzes the brain activity of a subject measured through EEG. The former tries to find out the user's intention and generates output commands for controlling an appropriate output device (Bento *et al.*, 2008). The later explores the possibility of using the brain electrical activity during visual stimuli for implementing an EEG biometric system (Ferreira *et al.*, 2010).

The remainder of the chapter is organised as follows: Section 2 presents an overview of the activity at the IEETA (Institute of Electronic Engineering and Telematics of Aveiro) research unit. Section 3 explores the application of beamforming techniques in EEG source analysis from a simulated dataset. Section 4 describes the main advances in the development of an EEG-based BCI for biometry. Section 5 concludes the chapter and outlines the perspectives of future research.

2. Framework of the research at IEETA

The development of non-invasive BCIs for control and biometry are the research focus of the IEETA Computational Neuro-engineering research group and among the most recent applications based on personal EEG data. In spite of sharing the same basic components, a BCI to provide an alternative control channel for acting on the environment and a biometric system for identification or authentication reveal significant differences. While the BCI technology has been focused on interpreting brain signals for communication and control, the requirements of an EEG-based biometric system are entirely different: they require no interpretation of the brain signals, but use the unique brain´s response to stimuli as the identification method. The identified person is exposed to a stimulus (usually visual or auditory) for a certain time and the EEG data collected over this time is input to the biometry system. It has been shown in previous studies (Paranjape *et al.*, 2001; Poulos *et al.*, 1999) that the EEG can be used for building personal identification systems due to the unique brain-wave patterns of every individual. At the same time, the frequency band segmentation is a key concept in the area of EEG-based BCIs. Current implementations for motor control are based on the special frequency range termed sensorimotor rhythm mu which is related with imagery subject movements. As for the EEG-based biometry, the concept of Evoked Potentials (EP) and Visual Evoked Potentials (VEP) of the brain electrical activity play a major role. EP are transient EEG signals generated in response to a stimulus (*e.g.*, motor imagery or mental tasks) and VEP are EP produced in response to visual stimuli generating activity within the gamma band.

From the viewpoint of brain-computer interfacing for control, a major concern has been considered to structure the research, which is: how to improve the BCI's performance by solving the EEG inverse problem for the localization of the brain activities underlying recorded EEG. Source-based BCIs have been exploited with encouraging results by achieving improved spatial accuracy, as well as by providing additional biophysical information on the origin of the signals (Grave de Peralta *et al.*, 2005; Grosse-Wentrup *et al.*, 2009; Kamousi *et al.*, 2005; Noirhomme *et al.*, 2008; Qin *et al.*, 2004). In line with this, the problems of head models in EEG source analysis, the generation of the simulated datasets, the estimation of original sources signals using beamforming and the optimization of certain

parameters with influence in the system's performance will be addressed as the central topics of this chapter. The insights gained with this study can be relevant when optimizing the design and implementation of a practical source-based BCI.

In what concerns the EEG-based biometrical scenario, we aim at focusing on several open problems related with: i) design a feature model that belongs to a certain person and design a personal classifier with a respective owner, ii) study on the type and the duration of the evoked potentials (visual or auditory) that would enhance the identification/ authentication capacity; iii) post-processing techniques on the classifier output as averaging or sporadic error correction would improve the identification/ authentication capacity, and iv) optimization of the evoked potential duration (EPD) in order to implement the paradigm in an on-line scheme.

3. Beamforming in brain-computer interfaces

In brain imaging, the EEG inverse problem can be formulated as follows: using the measurements of electrical potential on the scalp recorded from multi-sensors, the idea is to build a reconstruction system able to estimate the time course of the original source signals or some of them with specific properties. The problems of reconstructing the original source waveforms from the sensor array, without exploiting the *a priori* knowledge about the transmission channel, can be expressed as a number of related blind source separation (BSS) problems. Choi *et al.* (2005) present a review of various blind source separation and independent component analysis (ICA) algorithms for static and dynamic models and their applications.

Nowadays, beamforming has also become a popular analysis procedure for non-invasive recorded electrophysiological data sets (Baillet et al., 2001; Fuchs, 2007). The goal is to use a set or recording sensors and combine the signals recorded at individual sites to increase the signal-to-noise ratio, but focusing on a certain region in space (region-of-interest, ROI). In that sense, beamforming uses a different approach to image brain activity: the whole brain is scanned point by point. In general, when this approach is applied to EEG recordings the objective is to estimate the magnitude, locations and directions of the neural brain sources, by applying a spatial filter to the data. This spatial filter is designed to be fully sensitive to activity from the target location, while being as insensitive as possible to activity from other brain regions. This is achieved by constructing the spatial filter in an adaptive way, i.e., by taking into account the recorded data. More concretely, the beamforming is carried out by weighting the EEG signals, thereby adjusting their amplitudes such as that when added together they form the desired source signal.

The primary motivation for our study is the potential of application of beamforming in brain-computer interfaces. In spite of some encouraging results (Grosse- Wentrup *et al.*, 2009; Kamousi *et al.*, 2005; Noirhomme *et al.*, 2008; Qin *et al.*, 2004), only recently the concept of source-based BCI was adopted in literature. Therefore, additional research efforts are needed to establish a solid foundations aiming at uncovering the driving force behind the growth of source-based BCI as a research area and to expose its implications for the design and implementation of better systems.

This section proceeds as follows: first, an EEG dataset is created by simulating the neural activity in specific locations modelled as current dipoles. The spatiotemporal patterns that would be measured by the recording system are the superposition of these brain sources. Second, some basic concepts on beamforming are presented before the EEG dataset used to estimate the source activity is processed. Finally, several simulations are performed in order to evaluate how certain parameters affect the performance of the reconstruction system.

3.1 Simulating the electric activity in the brain

The human brain consists of neuron cells that communicate by means of short bursts of electrical activity called action potentials. Neurons that have relatively strong potentials at any given time tend to be clustered in the brain. Thus, the total electric potentials at any given time in such an activated region may be large enough to be detected on the scalp by EEG electrodes. Bearing this in mind, the current distribution in an activated region will be modelled by an equivalent current dipole within the conductive brain tissue. Further, the EEG dataset is simulated assuming that the electrical activity of the brain, at any given time, can be modelled by only a small number of dipoles.

A three-concentric spherical model consisting of a central sphere for the brain and two spherical shells for the skull and scalp was used to approximate the head volume. This is a simplification that preserves some important electrical characteristics of the head, while reducing the mathematical complexity of the problem. The different electric conductivities of the several layers between the brain and the measuring surface need to be known. The skull is typically assumed to be more resistive than the brain and scalp that, in turn, have similar conductivity properties (Lai *et al.*, 2005).

Once defined the source and head models, the computation of the scalp potentials given by known electrical dipoles sources requires the solution of the forward problem. If there are M active dipoles and N sensors, the measured activity at the sensors $x(t)$ is the sum of the individual contributions of each individual dipole $y_m(t)$ as follows:

$$x(t) = \sum_{m=1}^{M} L_m y_m(t) \tag{1}$$

Here, $L_m \in R^{N \times 3}$ is the lead field matrix for dipole m. In the spherical three-layer model, an analytical expression for the forward model can be derived as function of the dipole location, electrodes positions and head geometry (Salu *et al.*, 1990). The three columns in the forward model contain the activity that will be measured at the sensors due to a dipole source with unity moment in the x, y, and z directions, respectively, and zero moment in the other directions. The development of a forward model is also the first step in building the beamformer filter. This model is needed because its inverse describes how the brain activity can be estimated from sensor measurements, which is the purpose of beamforming.

Throughout this section, all simulations are based on the following assumptions: (1) the scalp electrodes record the superposition of both brain sources and non-brain sources related to, for example, movements of muscles, (2) the reference is at an infinite distance with zero potential, (3) the location of the target dipoles are known; (4) the distribution of the electrodes on the scalp is made by selecting spherical coordinates θ and ϕ from uniform distributions. Fig. 1 illustrates a realistic head model and the hemisphere model (top view) where an array of 64-electrodes is arranged. Their coordinates are defined with respect to a reference frame whose origin is located at the centre of the sphere.

3.2 Beamforming: generic concepts

The basic idea behind beamforming is to estimate the time course of a current dipole $y(t)$ at location r and direction d using the measurements of electrical potential on the scalp recorded from N sensors located at the surface of the head. The beamformer filter consists of

weight coefficients w_m that when multiplied by the electrode measurements give an estimate of the dipole moment:
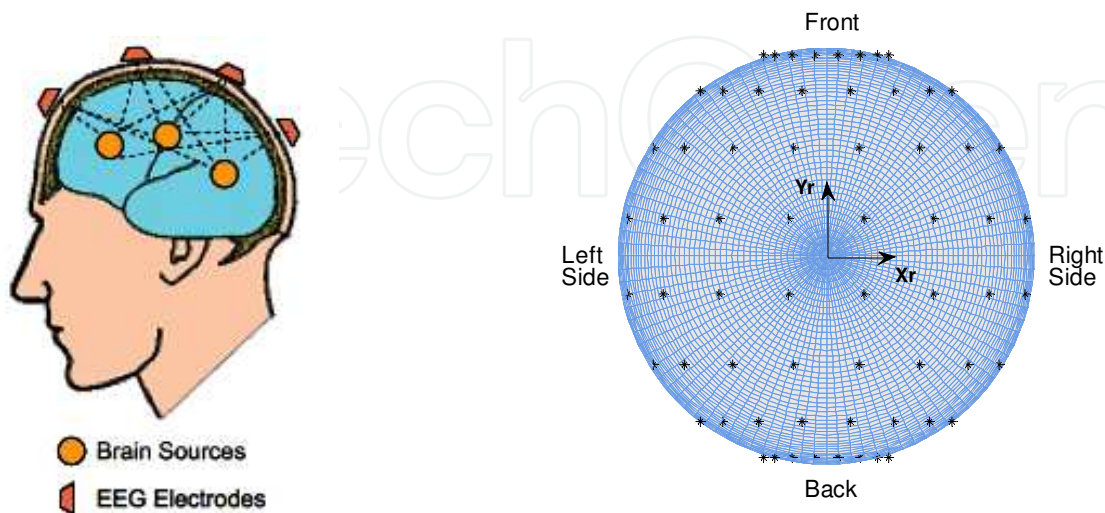
$$y(t) = w_m^T x(t) \tag{2}$$

Fig. 1. The realistic head shape (left) is approximated by three concentric spherical shells; the referece coordinate frame has its origin at the centre of the spheres (right)

The choice o the beamformer weights w_m is based on the statistics of the signal vector $x(t)$ received at the electrodes. Basically, the objective is to optimize the beamformer response with respect to a prescribed criterion, so that the output $y(t)$ contains minimal contribution from noise and interference. There are a number of criteria for choosing the optimum weights. The method described above represents a linear transformation where the transformation matrix is designed according to the solution of a constrained optimization problem (the early work is attributed to Capon, 1969). The basic idea is the following: assuming that the desired signal and its direction are both unknown, one way of ensuring good signal estimation is to minimize the output signal variance. To ensure that the desired signal is passed with a specific gain, a constraint may be used so that the response of the beamformer to the desired signal is:

$$w_m L_m(r) = I \tag{3}$$

where L_m is the lead field matrix of a unit source at target location r and I is the unit matrix. Minimization of contributions to the output due to interference is accomplished by choosing the weights to minimize the variance of the filter output:

$$Var\{y\} = tr\{w_m^T R_x w_m\} \tag{4}$$

Here, $tr\{\ \}$ is the trace of the sub-matrix of the bracketed expression and R_x is the covariance matrix of the EEG signals. In practice, the covariance matrix R_x will be estimated from the EEG signals during a given time window. Therefore, the filter is derived by minimizing the output variance subject to the constraint defined in (3). This constraint ensures that the desired signal is passed with unit gain. Finally, the optimal solution can be

derived by constrained minimization using Lagrange multipliers (Van Veen, *et al.*, 1997) and it can be expressed as:

$$w_m^{opt} = R_x^{-1}L_m(L_m^TR_x^{-1}L_m)^{-1} \tag{5}$$

The response of the beamformer is often called the linearly constrained minimum variance (LCMV) beamformer. The LCMV provides not only an estimate of the source activity, but also its orientation, reason why is classified as vector beamforming. The differences and similarities among beamformers based on this criterion for choosing the optimum weights are discussed in Huang *et al.* (2004). It is also shown that the output power *P* of the beamformer, for a specific brain region at location *r*, can be computed by the following equation:

$$Var\{y\} = tr\left\{\left[L_m^TR_x^{-1}L_m\right]^{-1}\right\} \tag{6}$$

This is known as the Neural Activity Index (NAI) and it can be calculated for over the whole head at each grid point (Van Veen *et al.*, 1997).

3.2.1 Two dipole simulation

The performance of the beamformer algorithm in determining the magnitude and direction of the source is evaluated in a specific scenario. First, two uncorrelated sources are defined based on sinusoidal waveforms with amplitudes 0.1 and frequencies 10 Hz and 15 Hz. The dipole moments are oriented along the z-axis and they are located at the following coordinates: $d_1:(x,y,z)=(-4,4,1)$ cm and $d_2:(x,y,z)=(4,-4,1)$ cm. The radii of the three concentric hemispheres are 8.7, 9.2 and 10 cm. The corresponding conductivity values are 0.33, 0.0165 and $0.33\,S\cdot m^{-1}$. The scalp electrodes are distributed on a regular grid of 64-electrodes covering the entire hemisphere. Second, white noise is added into the EEG representing the effect of external sources not generated by brain activity, but by some disturbance. The noise power was defined in such a way that the maximum signal-to-noise ratio (SNR) among the electrodes never exceeds 10. It is assumed that the EEG recording system operates with a 1kHz sampling rate.

Fig. 2 shows the original and the estimated waveforms, giving an idea of the achieved accuracy provided by the LCMV algorithm. It must be emphasised that the reconstruction is performed considering that the location of one dipole is known, while the other represents an unknown interference source (single-source beamformer). The method is able to reconstruct the original signal and suppress the interfering source activity, though both estimates are noisy. The considerable noise gain can be reduced by subspace projection: the measurement space is separated into a signal and noise space by applying an eigenspace decomposition of the covariance matrix R_x. The dimensionality is reduced to the subspace defined by the eigenvectors whose eigenvalues are significantly bigger than zero. This eigenspace-based LCMV is able to strongly suppress the interfering source, as well as to provide a low noise gain (Fig. 3). However, the condition (3) is not preserved affecting slightly the amplitude of the output signal. In the simulations, the mean square error (MSE) is used to quantify the difference between the estimated source moments (beamformer output) and the reference signals.
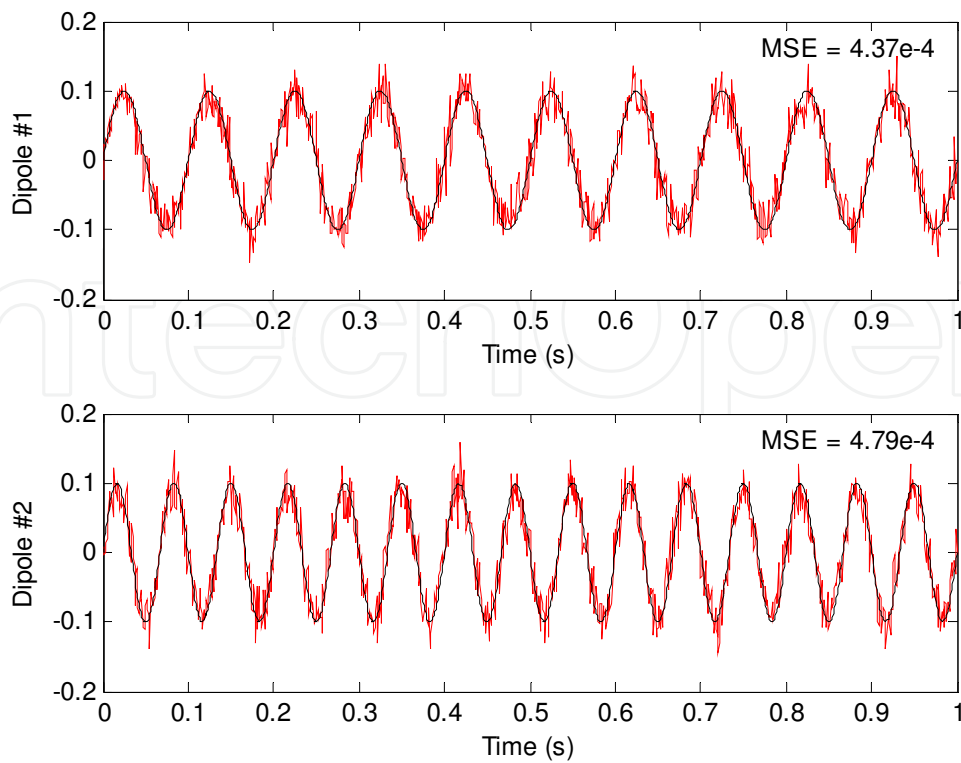
Fig. 2. The original and estimated source waveforms represented together for dipole 1 (top) and dipole 2 (bottom) using the LCMV beamformer
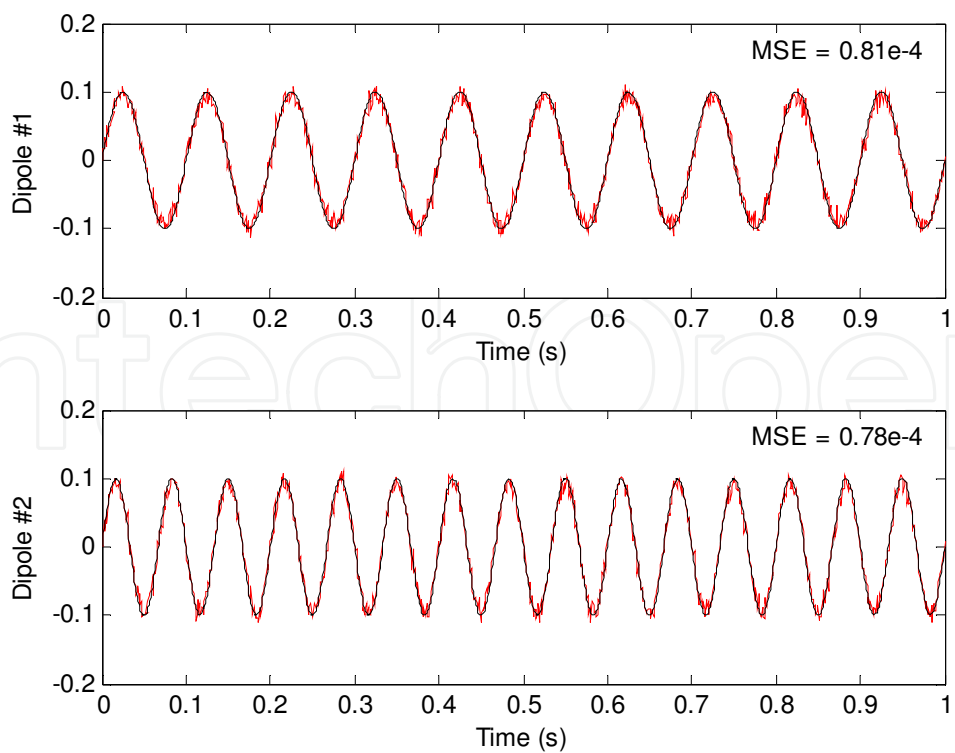

Fig. 3. The original and estimated source waveforms represented together for dipole 1 (top) and dipole 2 (bottom) using the eigenspace-based LCMV beamformer

3.2.2 Performance limitations

The distance and correlation among sources are two factors that may lead to degradation in the beamforming algorithm. Van Veen *et al.* (1997) pointed out these limitations by calculating the neural activity index in brain areas over a certain time interval. On the one hand, sources that are close to each other tend to merge. On the other hand, when the sources are correlated it is difficult to detect distinct source locations. A number of techniques have attempted to address the problem of correlated sources, such as a dual beamformer (Herdman *et al.*, 2003) or using only half of the sensor array (Popescu *et al.*, 2008). The idea of a multiple-source beamforming is to account for the activity from possibly correlated brain regions: the calculation contains not only the leadfield matrix of the source at the target location, but also those of possible sources whose interference is to be minimized. For example, this allows for source separation of highly correlated bilateral activity in the two hemispheres that commonly occurs during motor imagery tasks (a common control paradigm in BCI). Anyway, localising potentially correlated sources remains an open problem and it is not addressed along this chapter. Instead, the sources are assumed uncorrelated and relatively distant. Fig. 4 shows the contour plot of the global neural activity measured in a horizontal cross section for two uncorrelated dipoles, as defined in the previous subsection.
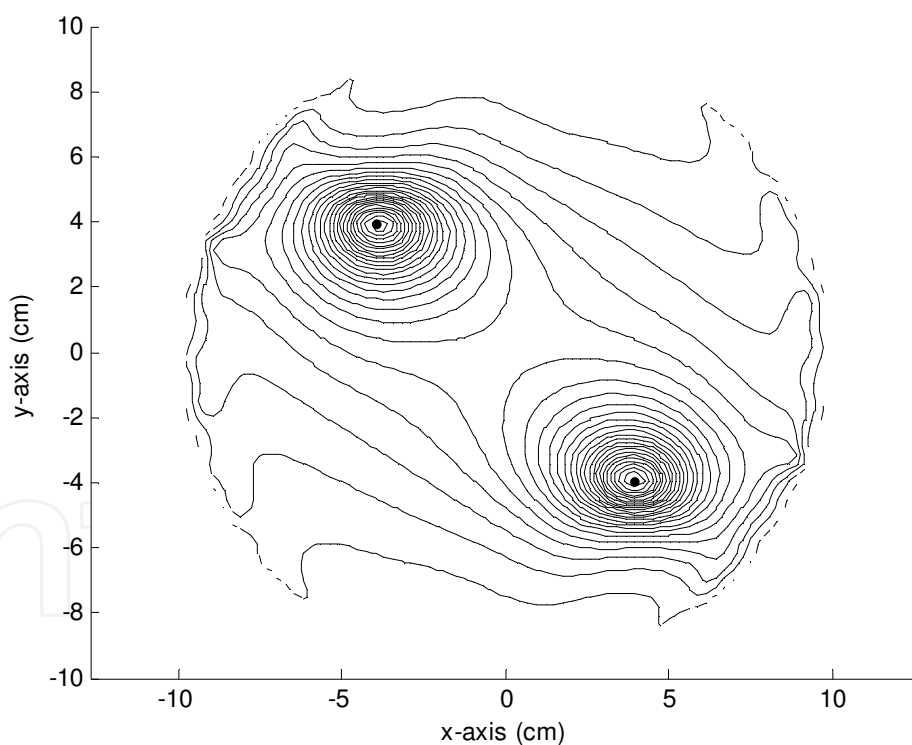

Fig. 4. Contour plot of the neural activity index in a horizontal cross section 1 cm above the centre of the sphere where the two dipoles are localized

3.3 Number and localization of the electrodes

One of the questions about applying beamforming techniques to BCIs is the choice of the number and localization of the electrodes. Here, the goal is to understand how the

performance of the LCMV beamformer is influenced by these two factors, for example: (1) to what extend the number of electrodes can be reduced and (2) what is the optimal distribution of the electrodes on the scalp. In line with this, the MSE between reference and estimated waveforms is evaluated for different number of electrodes and distributions. The electrodes form a grid of points covering a variable percentage of the total hemisphere surface area (see Fig. 5). In this study, the electrodes are located, symmetrically, around a specific point in the scalp considering two different situations: a first in which this point has coordinates $(x,y)=(0,0)$ and a second in which the point has coordinates $(x,y)=(-5,0)$ cm (exactly where the dipole vector points). The parameters associated with the head and dipole models remain unchanged, but the dipole locations: $d_1:(x,y,z)=(-5,0,1)$ cm and $d_2:(x,y,z)=(5,0,1)$ cm. The additive noise power is assumed to be the same throughout the simulations.
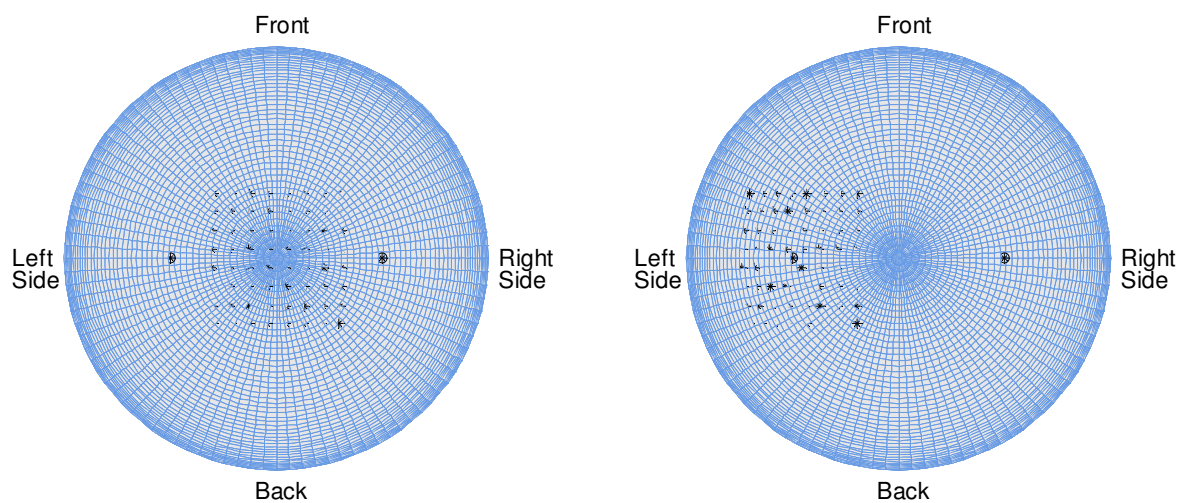

Fig. 5. Top view of the hemisphere with the locations of two dipoles and 64-electrodes (with a normalized area of 0.062); the electrodes are located, symmetrically, around a point with coordinates $(x,y)=(0,0)$ cm (left) and a point with coordinates $(x,y)=(-5,0)$ cm (right)

Fig. 6 shows the achieved results for dipole 1 in terms of MSE as function of the normalized area. The two graphics were obtained by superimposing the curves for $N=\{4,9,16,32,64\}$ electrodes. The first observation is the quite modest performance with only 4 electrodes. However, for $N=9$, the second arrangement (closer to the target dipole) is able to achieve improved results, especially by increasing the surface area. When the number of electrodes increases, the curves give a good indication of the required area and number of electrodes from which no improvements are achieved. At the same time, the second distribution leads to only a slightly better performance than the first one, observable at higher areas.

In conclusion, when fewer electrodes are more suitable (*e.g.*, BCI applications), an optimal local distribution seems to be essential to reduce the number of electrodes, while maintaining an acceptable performance from the viewpoint of source reconstruction. However, the extrapolation of these results for other scenarios is more difficult since they are the direct consequence of the selected dipoles, as well as the time course of the signal-to-noise ratio.
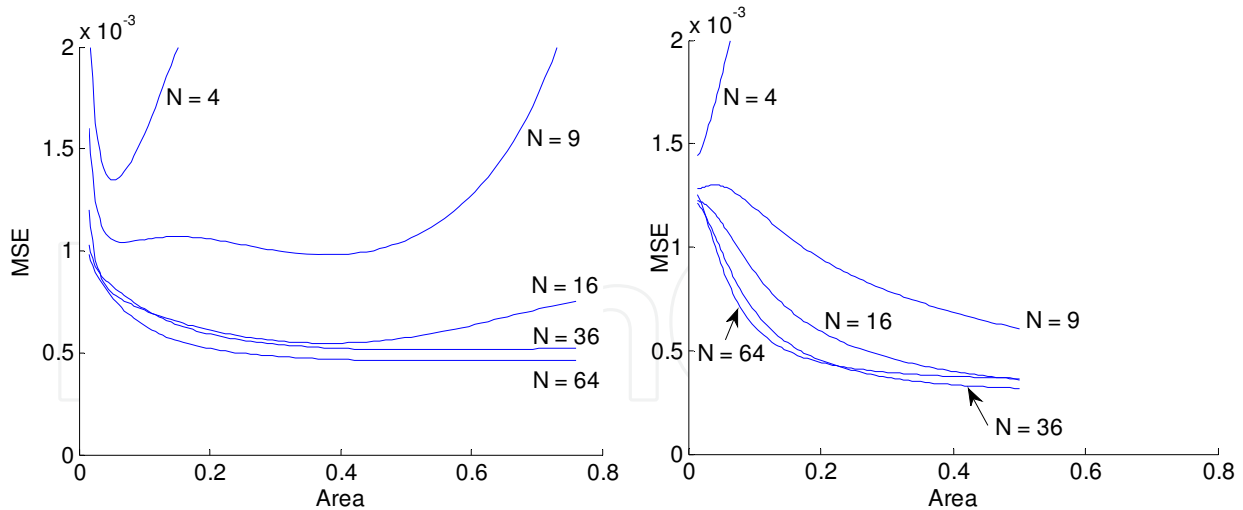
Fig. 6. Mean-square error for dipole 1 as function of the normalized area using N electrodes

3.4 Sensitivity analysis to errors in the forward model

In this subsection, we will discuss the sensitivity of the reconstruction system to uncertainties in the mathematical model. More precisely, we intend to study how the uncertainties in the parameters of the forward model can affect the performance of the beamformer. The forward model is derived as function of the dipole location, electrodes positions and head geometry. Here, the attention is devoted to parameters related with the localization of the electrodes and the *a priori* estimation of the source location. The objective is to execute the model repeatedly for a combination of parameter values with some probability distribution. In the first case, the error in the location of each electrode is represented by the radius R_c of a circumference centred at the original electrodes' locations. Every electrode moves the same distance from the original position, but with a random direction. In Fig. 7, the MSE as function of radius are plotted for the two dipoles.
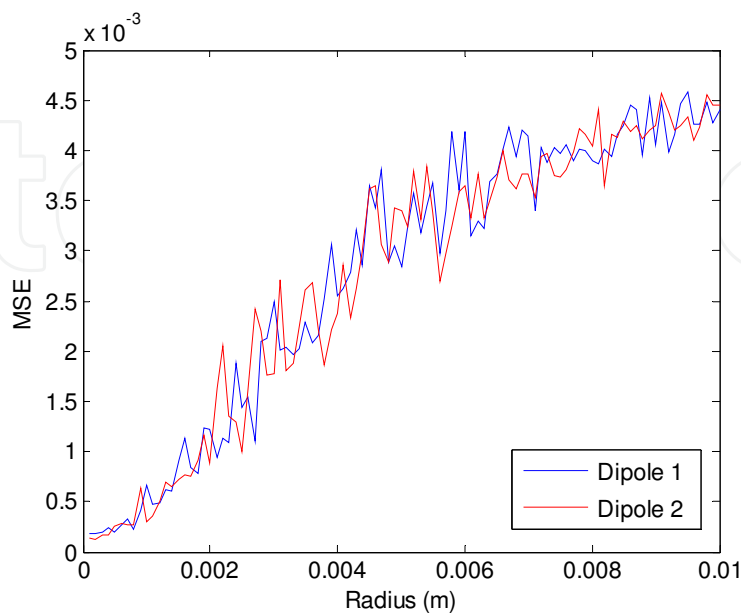

Fig. 7. Mean-square error for the two dipoles as function of radius R_c

In this simulation, the dipole locations are $d_1 : (x,y,z) = (-5,0,1)$ cm and $d_2 : (x,y,z) = (5,0,1)$ cm, while the simulated EEG is generated using 36 measurement electrodes distributed over the whole head. Then, the LCMV beamformer algorithm estimates the sources based on a leadfield matrix that incorporates the random errors. As expected, the MSE tends to increase with the radius, but with random fluctuations. A small increase in R_c does not necessarily signify a degradation of the system's performance due to the random orientation applied in each electrode. In some way, this procedure represents well a real scenario involving the placement of electrodes in the scalp. A similar analysis is performed when small deviations between the real and the estimated dipole's locations occur. Fig. 9 shows the MSE degradation when the location of dipole 1 is not correctly estimated in the directions defined by the x-, y- and z-axis in the reference coordinate frame.
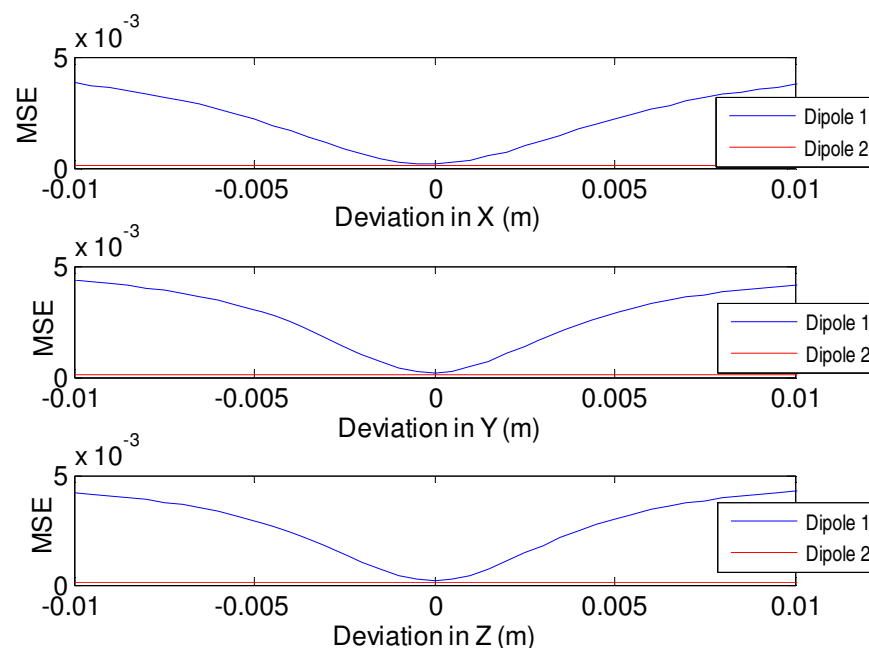

Fig. 8. Mean-square error for the two dipoles as function of deviation in the dipole 1

3.5 Adaptive algorithm

The simulations performed so far use the complete dataset to calculate the filter weights and then to estimate the time course of the target source. However, in a practical situation the EEG signals are not known and a nonstationary (time-varying) environment can be anticipated. To evaluate the performance of the spatial filter as a function of the amount of available data the following procedure is employed: first, in the static mode, the beamformer weights are computed once using a given segment of data and they are applied to new data without further update. The beamformer algorithm uses estimates of the covariance matrix based on the available EEG data. Further, this matrix needs to be inverted and, in certain circumstances, it can be close to singular. Theoretically, the number of observations must greater than number of sensors to avoid singularities. Fig. 9 shows the influence of the number of observations on the MSE of the dipole 1 with 36 sensors. Independently of the SNR, a number of 400 independent observations should be used to estimate the covariance matrix (dashed line).
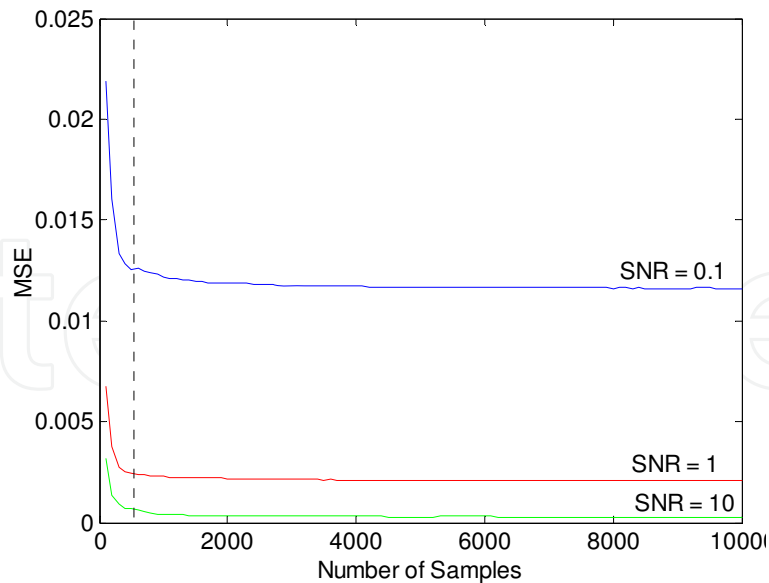
Fig. 9. Mean-square error for dipole 1 as function of the number of samples used to estimate the covariance matrix when varying the noise power

Second, an adaptive algorithm is continually updating the weight vector to meet the new requirements imposed by the varying conditions. This need to update the weight vector without *a priori* information leads to the expedient of obtaining estimates of the covariance matrix in a finite observation interval and then using these estimates to obtain the optimum weight vector. This is a block-adaptive approach where statistics are estimated from successive temporal windows. In the present simulation, the source waveform is a damped sinusoid and the EEG acquisition uses a sampling rate of 512 Hz with 36-electrodes. Fig. 10 allows the comparison between the static and block-adaptive approaches.
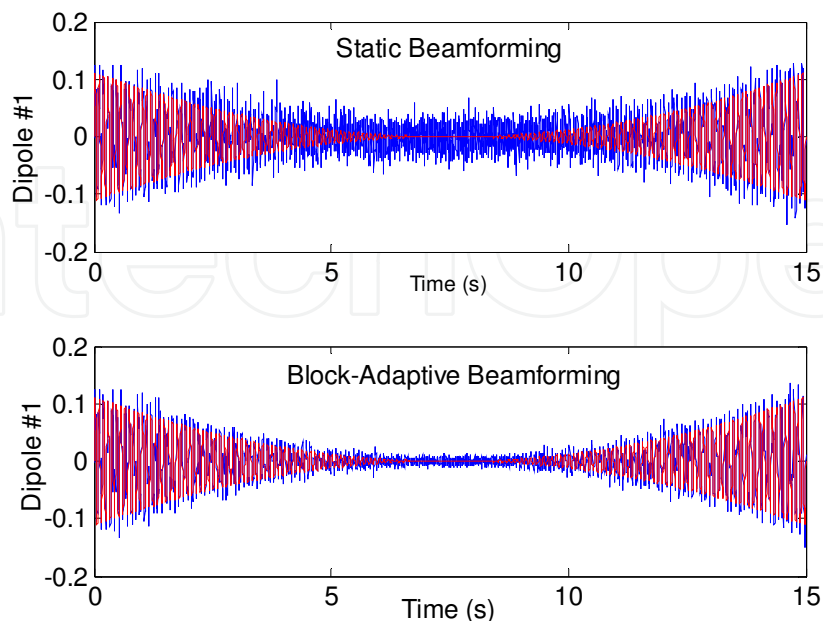

Fig. 10. The original and estimated source waveforms represented together for dipole 1 using static beamforming (top) and block-adaptive beamforming (bottom)

In block-adaptive beamforming the optimal weights are recomputed from time windows of 1 second. As can be observed, the adaptive approach outperforms the static approach when the amplitude of the source waveform reduces significantly. This suggests its potential utility to deal with dynamic changes in the source brain activity.

4. EEG-based biometry

Like the BCIs discussed in the previous sections, the EEG based biometry provides an alternative communication channel between the human brain and the external world. There is very little research work published using brain signals as biometric tools to identify individuals (Poulos et al., 1999; Paranjape, et al., 2001; Palaniappan & Mandic, 2007). Nevertheless, in these studies it was suggested that the brain-wave pattern of every individual is unique and, therefore, the EEG can be used for building personal identification or authentication systems. The identification attempts to establish the identity of a given person out of a closed list of persons (one from many), while the authentication aims to confirm or deny the identity claimed by a person (one to one matching), Marcel & Millan, 2007. The identified person is exposed to a stimulus (usually visual or auditory) for a certain time and the EEG signals coming from a number of electrodes spatially distributed over the subject's scalp are collected and input to the biometry system. The EEG signals induced by mental or perception tasks related with visual stimuli are known as Visually Evoked Potentials (VEP).

The raw EEG signals are too noisy and variable to be analyzed directly. Therefore, the EEG signals need to go through a sequence of processing steps: i) Data acquisition, storage and format transforming; ii) Filtering (removal of interferences from other unwanted sources, as for example physiological artifacts or baseline electrical trends); iii) Feature extraction and classification; iv) Feedback generation and visualization.

The identification/authentication systems built so far differ basically in filtering and classification components (Palaniappan & Mandic, 2007; Marcel & Millán, 2007). However, our initial study (Ferreira et al., 2010) has shown that the discrimination process is slightly dependent on the specific filter and classifier. Critical issues related with building an efficient EEG based biometry system are briefly discussed below.

Biometry as a modeling problem. The EEG recordings are unique for each person and the problem of EEG-based biometry can be interpreted as a modelling problem, *i.e.*, design a feature model that belongs to a certain person and design a personal classifier with a respective owner. The trained identification model has to identify the subject from a data base of personal profiles and the authentication system has to confirm or not that the subject being evaluated is who he claims to be.

Stimulus. Study on the type and the duration of the evoked potentials (visual or auditory) that would enhance the identification/authentication capacity. Preliminary tests have demonstrated that the type of the stimulus (for example mental task, motor task, image presentation or a combination of them) is crucial for reliable extraction of personal characteristics. It seems that some mental tasks are more appropriate than others. At the same time, experiments with combination of stimuli appear to be more advantageous for the personal uniqueness of the EEG patterns.

Post-processing. Ongoing research suggests that post-processing techniques on the classifier output as instant error correction and averaging would improve the identification/ authentication capacity.

Real-time biometry. Optimization of the evoked potential duration (EPD) in order to implement the paradigm in an on-line scheme. Current study has shown that both two short or too long EPD worsen the biometrical system (Ferreira *et al.*, 2010). The compromise can be learned by cross validation during the classifier training.

This section is organized as follows: Subsection 4.1 presents the experimental setup for the present study. In subsections 4.2 to 4.5 the main modules of the EEG biometry system are discussed, namely the feature extraction, the classification and the post-processing procedure. Finally, in subsection 4.6 the effect of the EPD is analyzed.

4.1 Experimental setup

VEP signals were extracted from thirteen female subjects (20-28 years old). All participants had normal or corrected to normal vision and no history of neurological or psychiatric illness. Neutral, fearful and disgusting faces of 16 different individuals (8 males and 8 females) were selected, giving a total of 48 different facial stimuli. Images of 16 different house fronts to be superimposed on each of the faces were selected from various internet sources. This resulted in a total of 384 grey-scaled composite images (9.5 cm wide by 14 cm high) of transparently superimposed face and house with equivalent discriminability.

Participants were seated in a dimly lit room, where a computer screen was placed at a viewing distance of approximately 80 cm coupled to a PC equipped with software for the EEG recording. The images were divided into two experimental blocks. In the first, the participants were required to attend to the houses (ignoring the faces) and in the other they were required to attend to the faces (ignoring the houses). The participant's task was to determine, on each trial, if the current house or face (depending on the experimental block) is the same as the one presented on the previous trial. Stimuli were presented in sequence, for 300ms each and were preceded by a fixation cross displayed for 500 ms. The inter-trial interval was 2000 ms.

EEG signals were recorded from 20 electrodes (Fp1, Fp2, F3, F4, C3, C4, P3, P4, O1, O2; F7, F8, T3, T4; P7, P8, Fz, Cz, Pz, Oz) according to the 10/20 International system (see Fig. 11). EOG (Electrooculogram - eye movemen) signals were also recorded from electrodes placed just above the left supraorbital ridge (vertical EOG) and on the left outer canthus (horizontal EOG). VEP were calculated off-line averaging segments of 400 points of digitized EEG (12 bit A/D converter, sampling rate 250 Hz). These segments covered 1600ms comprising a pre-stimulus interval of 148 ms (37 samples) and post-stimulus onset interval of 1452 ms. Before processing, EEG was visually inspected and those segments with excessive EOG artifacts were manually eliminated. Only trials with correct responses were included in the data set. The experimental setup was designed by Santos *et al.* (2008) for their study on subject attention and perception using VEP signals.

4.2 Feature extraction

The neuro-engineering theoretical and application studies related with the EEG signals are based on the knowledge that the EEG signals are composed of waves inside the 0-60 Hz frequency band and that different brain activities can be identified based on the recorded oscillations. For example, signals within the delta band (below 4 Hz) correspond to a deep sleep, theta band (4-8 Hz) signals are typical for dreamlike state, alpha frequencies (8-13 Hz) correspond to relaxed state with closed eyes, beta band (13-30 Hz) are related with waking

activity and gamma frequencies (30-50 Hz) are characteristics for mental activities as perception and problem solving. The relationship between the EEG and the brain functions is well documented in Niedermayer and Lopes da Silva (1999).
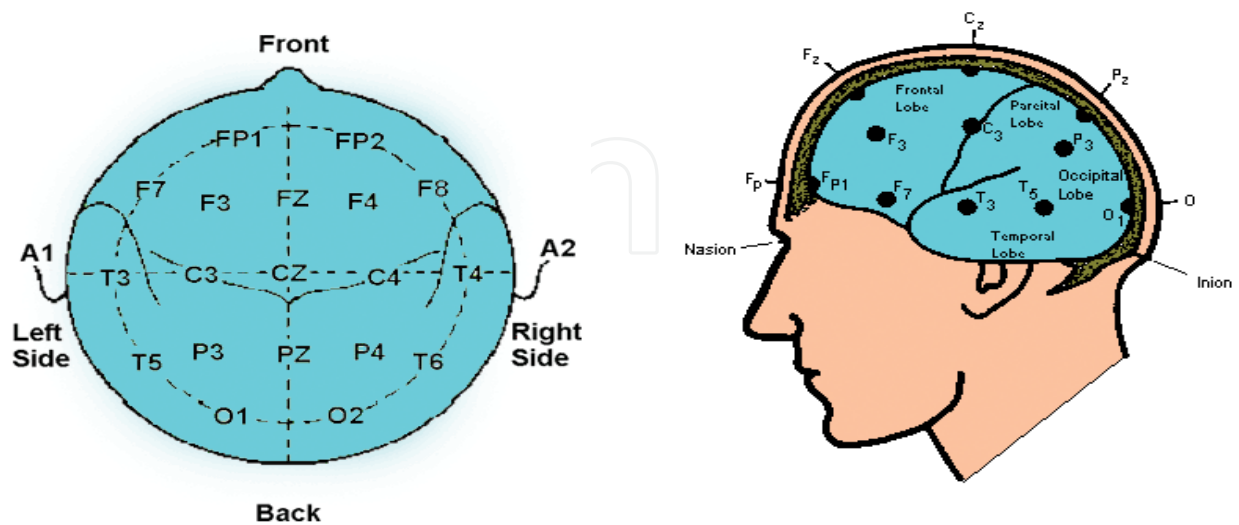

Fig. 11. Spatial location of the EEG electrodes over the frontal, central and parietal areas

For the present study the gamma-band spectral power of the VEP signals was computed by the Welch's periodogram method. The temporal segments, over which one value of the spectral power matrix is computed, correspond to one trial (around 1600 ms), *i.e.*, the samples collected during one image presentation. The normalized gamma-band spectral power for each channel was computed. It is a ratio of the spectral power of each channel and the total gamma-band spectral power of all channels. The level of perception and memory access among individuals are different and this reflects in significant difference between the gamma-band spectral power ratios of the subjects which is the key for the VEP based individuals identification.

4.3 Classifiers

Two strategies of training multiple binary classifiers for classification of the VEP spectral power ratios were implemented, Tan (2006): i) Support Vector Machine - One Against Other (SVM_OAO) and ii) Support Vector Machine - One Against All (SVM_OAA). Each strategy creates a set of binary classifiers that are afterwards combined to output the final labeling. Linear or nonlinear functions are comparatively tested as the SVM feature space mapping functions. Radial Basis Function (RBF) is selected for the nonlinear SVM case. The SVM-OAO creates P(P-1)/ 2 binary classifiers where P is the number of the persons identified. The classification principle is the max-wins voting strategy, in which every classifier assigns the instance to one of the two classes, the class with most votes determines the instance classification. The SVM-OAA creates P binary classifiers with the classification principle - the winner-takes-all and the binary classifier with the highest output function assigns the class.

Two training scenarios were considered:

- **Scenario 1**: The classifier is trained with data set coming from one experimental block (subject has to attend to the faces ignoring houses) and tested with data from the other experimental block (subject has to attend to the houses and ignore the faces).

- • **Scenario 2**: The classifier is trained with data coming from both experimental blocks and tested with unseen data from the same blocks.

4.4 Principal component analysis (PCA)

A possible way to increase the signal to noise ratio is to accompany the feature extraction step with the principal component analysis (PCA). For the case considered, the PCA was designed first to extract only principal components of the normalized gamma-band spectral power (the feature space) that accumulates 95% of the signal energy (this is equivalent to feature space reduction). Then, it follows a step to reconstruct the feature space with the same dimensionality. The performance of both SVM classifiers was evaluated with or without PCA processing in the framework of the two scenarios. The results, summarized in Table 1 and Table 2, suggest that while the PCA is aimed at capturing the main EEG patterns, the individual specificity is lost and the classification accuracy is worsen. A possible interpretation is that the energy in the 30-50 Hz band of the original data set is already attenuated due to an embedded filtering process of the EEG acquisition apparatus. The PCA processing additionally reduces the VEP power spectral density and, therefore, all classifiers studied exhibit worse generalization performance (Table 1).

4.5 Post processing (PP) procedure

Both classifiers perform a static (memoryless) classification that does not consider explicitly the temporal nature of the VEP signals. Time accounting classifiers, as for example Recurrent Neural Networks (NNs), Time Lag NNs or Reservoir Computing, have the disadvantage to require complex training procedures that not always converge.

In order to keep low complexity of the biometrical system, we propose here an empirical way to introduce memory into the classifiers. During a post processing (PP) procedure, a moving window of a sequence of n past classifier outputs (personal labels) is isolated and following a predefined strategy the labels are corrected. For example, during the first PP step a window of the last three labels is defined (n=3) and, in case the first and the last labels are the same but different from the central one, this label is corrected to be equal to the others. The window dimension of the second PP step is increased with one (n=4). If the first and the last elements have the same label, but the two central elements are different from each other and from the lateral elements they are corrected. It was observed that increasing the dimensionality of the moving window (third PP step with n=5; fourth PP step with n=6; fifth PP step with n=7) the overall performance of both classifiers improved. The strategy of each next step is to increase the number of central elements and to correct them in case they are different from the equal lateral elements of the moving (with one sample) window. After the fifth PP step the performance started to decrease, therefore five PP steps were subsequently implemented in the EEG-based biometry system (see Table 1 and Table 2 below). In Fig. 12 an example of classifier response for 5 classes with a sequence of 10 samples per class is depicted. Though the classifier recognizes in general the different persons correctly some of the responses are incorrect and the aim of the PP procedure is to correct these wrong guesses. The incorrect responses of the classifier decrease after each subsequent PP step.

4.6 Evoked potential duration

The effect of the Evoked Potential Duration (EPD) was particularly studied since it defines the viability of the biometry system. If the identified person has to be exposed too long time

With PCA		Classifier	1st PP step	2nd PP step	3rd PP step	4th PP step	5th PP step
SVM_ OAO (One Against One)	Linear (Scenario 1)	65,94	63,10	60,01	59,71	59,79	59,61
	Linear (Scenario 2)	56,42	51,58	48,05	47,12	46,25	45,57
	Nonlinear (Scenario 1)	44,53	37,26	31,24	27,95	26,19	24,07
	Nonlinear (Scenario 2)	**36,43**	**28,00**	**22,08**	**19,01**	**17,41**	**14,49**
SVM_ OAA (One Against All)	Linear (Scenario 1)	58,65	54,24	50,64	49,88	49,34	48,60
	Linear (Scenario 2)	59,79	56,55	54,42	53,42	52,36	51,24
	Nonlinear (Scenario 1)	43,78	36,76	31,12	28,03	24,93	23,33
	Nonlinear (Scenario 2)	**35,99**	**27,60**	**21,24**	**18,67**	**16,44**	**15,17**

Table 1. Average classification error with PCA feature selection

Without PCA		Classifier	1st PP step	2nd PP step	3rd PP step	4th PP step	5th PP step
SVM_ OAO (One Against One)	Linear (Scenario 1)	38,21	35,36	33,43	31,89	31,63	30,37
	Linear (Scenario 2)	29,98	24,88	23,19	23,55	22,77	21,54
	Nonlinear (Scenario 1)	26,42	20,31	17,42	16,87	15,97	14,95
	Nonlinear (Scenario 2)	**15,67**	**10,16**	**8,32**	**6,95**	**5,54**	**5,10**
SVM_ OAA (One Against All)	Linear (Scenario 1)	30,57	25,02	23,56	22,58	21,27	20,26
	Linear (Scenario 2)	26,84	21,17	17,87	16,45	14,52	13,71
	Nonlinear (Scenario 1)	26,99	21,54	18,32	16,70	15,16	14,49
	Nonlinear (Scenario 2)	**17,43**	**12,05**	**9,78**	**8,49**	**6,96**	**6,62**

Table 2. Average classification error without PCA feature selection

to a stimulus in order to be identified, it would make the system not quite practical and difficult to realize in real time. Therefore, the length of the ERP time series required for person identification needs to be reasonably short. The results of this study are summarized in Fig. 13 to Fig. 15 where the average classification error (ACE) is depicted as a function of the training segment length (Nº of trails). This analysis was done for the two studied SVM classifiers: SVM_OAO (Fig. 13), SVM_OAA (Fig. 14) and confirmed also for the k-Nearest
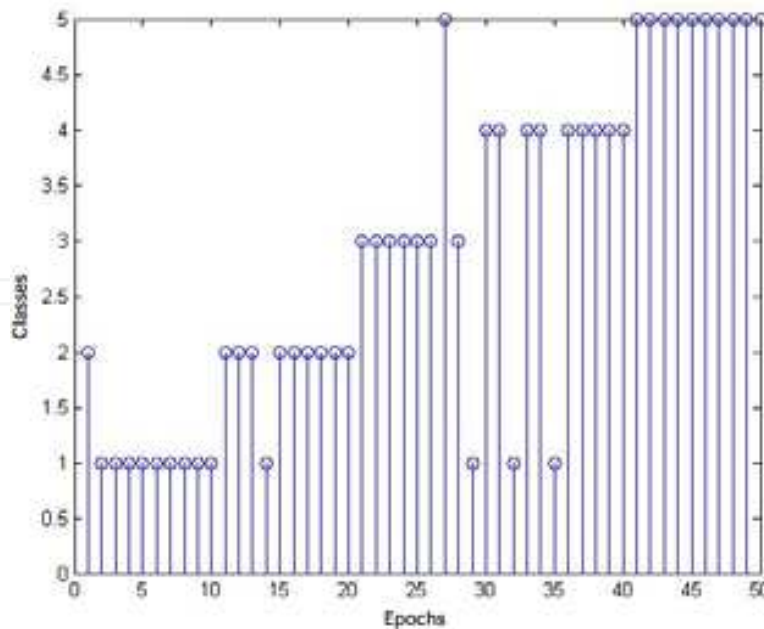
Fig. 12. Example of classifier response for 5 classes with a sequence of 10 samples per class

Neighbor (k-NN) basic classifier (Fig. 15) with k=3 and k=5. Note that for all classifiers there is a number of trails for which the ACE is minimized and longer time exposure does not suggest better person's discrimination. These results are averaged over the total number of identified subjects (13 persons) and an interval of 25-30 trials is determined as the optimal duration. Each trial corresponds to 400 samples with duration of about 1.5 s. Subsequently, 40-45 s is going to be the expected times for stimulus expose before the classifier identify one person with the highest probability to make a correct guess. Though the conclusions go beyond of what can be analytically proved, the intuition behind is that too long time exposure to visual stimuli leads to accommodation and tiredness, thus the personal specificity encoded in the ERPs is vanishing and the classifier error increases.
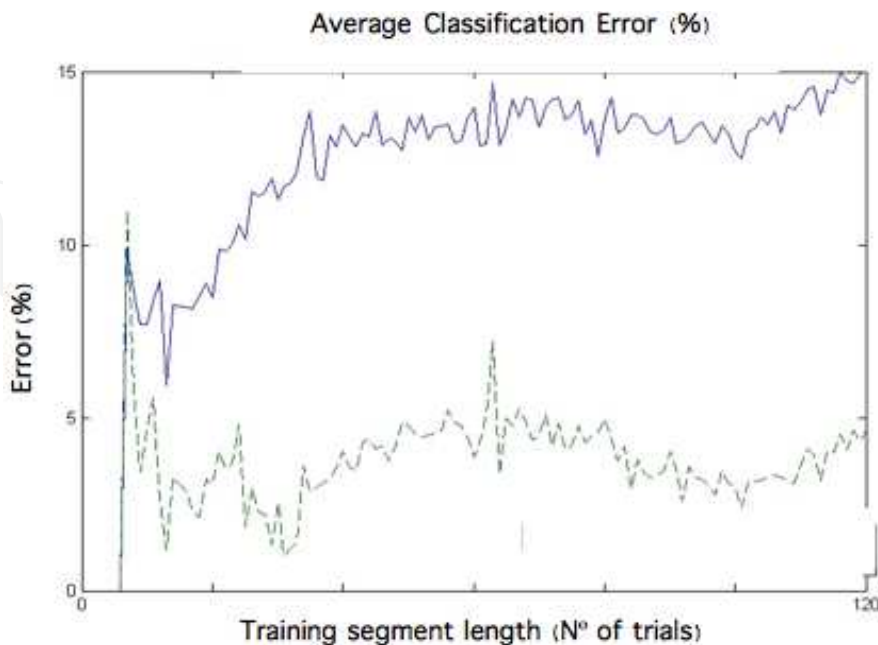

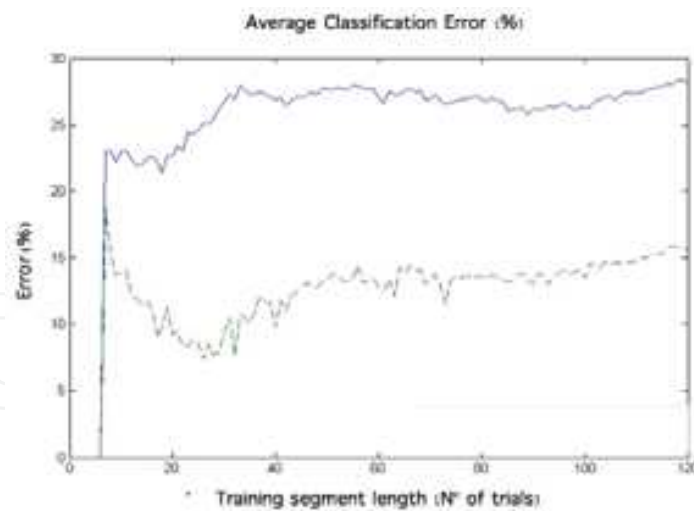Fig. 13. SVM_OAO: ACE without PP (bold line) & after the 5th PP step (dashed line)

Fig. 14. SVM_OAA: ACE without PP (bold line) & after the 5th PP step (dashed line)
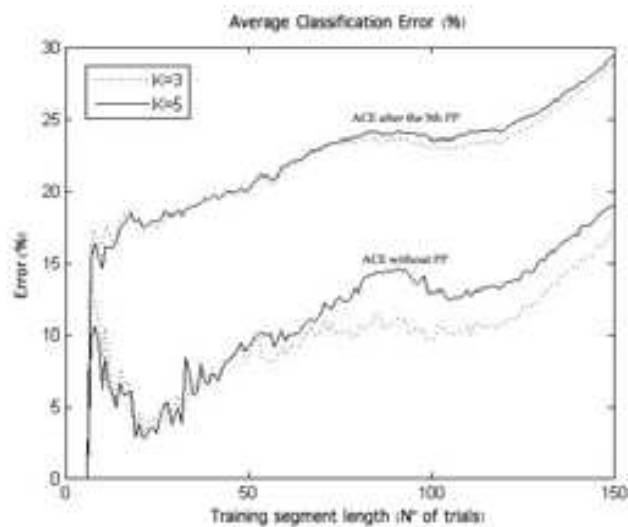

Fig. 15. k-NN: ACE without PP (bold (K=5) and dashed (K=3) lines below) & after the 5th PP step (bold (K=5) and dashed (K=3) lines above)

5. Conclusion

This chapter described recent efforts towards the development of EEG-based brain computer interfaces for control and biometry. In the first part, the chapter focuses upon an introduction of the principles underlying the use of beamforming to reconstruct the brain activity. Completely different problems in developing BCI systems and in their applications arise when moving from electrode-based domain to source-based scale. The goal of this source-based approach is to obtain knowledge about our brain activity and to answer fundamental questions about interacting regions. Beamforming techniques for source-based estimation are being proposed and recent research efforts demonstrate potential as a new direction in BCI design.

In this line of though, the first study was dedicated to source signal estimation based on vectorised beamformers and to the optimization of certain parameters that have influence in the system's performance. For example, the problem of the localization and number of

measurement electrodes was addressed, as well as how modelling errors in the constraint matrix or imprecise dipole locations can result in signal attenuation. LCMV beamforming does not require the *a priori* knowledge about the number of active sources. Instead, it provides an adaptive filter in which the degrees of freedom are used so that the activity from the target location is accepted, while being as insensitive as possible to activity from other brain regions.

The insights gained with this study can be relevant when optimizing the design and implementation of a practical source-based BCI. However, there are a number of open issues to be investigated in the near future. For example, defining a real-time model paradigm in an EEG-fMRI environment provides, in theory, new perspectives to achieve innovative designs. At the same time, the inverse solution is constructed from the forward or lead-field matrix which makes the system greatly underdetermined considering that the solution space consists typically of thousands of source locations. Regularisation and smoothing methods need to be applied to create a unique solution. Finally, on-line and off-line experiments are essential to full access the advantages and limitations of beamforming in BCI applications when compared with other alternative approaches.

The present study also confirmed the feasibility of the EEG-based person identification. Although the results are only for 13 person subject pool, it does provide evidence of stability and uniqueness in the EEG shapes across persons. However, the classification accuracy of the EEG biometry currently cannot compete with the conventional biometrics (such as fingerprint, iris or palm recognition systems) and in general the EEG person identification modality can be seen just as a supplement ("a second opinion").

Nevertheless, our long term goal is to use the principles of EEG-based biometry to detect abnormal scenarios, *i.e.*, scenarios where a person is not acting as it would normally do in similar circumstances. Cognitive functions, such as attention, learning, visual and audio perception and memory, are critical for many human activities (for example driving) and they trigger numerous brain activities. Assuming that those brain activities follow a pattern for each person in normal circumstances (reference pattern), they are likely to change when the person is stressed, fatigued (physically, visually or mentally), or under the influence of several substances (alcohol, stimulants, drugs, etc.) (deviation pattern). In this context, the EEG-based biometry would be particularly effective in health care applications, where it could be used not only to verify a patient's identity in medical records, prior to drug administration or other medical procedures but also to detect early in advance abnormal physiological or mental states of the patient.

In all, we expect several potential applications to emerge in the future. Control of the classified access into restricted areas security systems, illnesses or health disorder identification in medicine, gaining more understanding of the cognitive human brain processes in neuroscience are among the most appealing.

6. Acknowledgments

7. References

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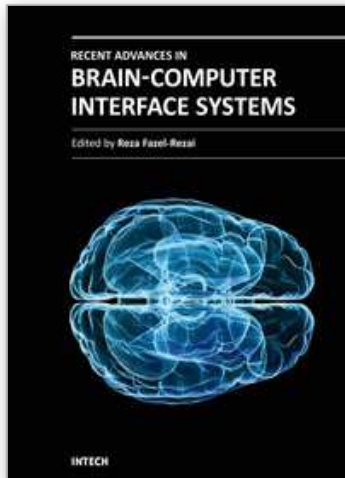
Recent Advances in Brain-Computer Interface Systems

Edited by Prof. Reza Fazel

Brain Computer Interface (BCI) technology provides a direct electronic interface and can convey messages and commands directly from the human brain to a computer. BCI technology involves monitoring conscious brain electrical activity via electroencephalogram (EEG) signals and detecting characteristics of EEG patterns via digital signal processing algorithms that the user generates to communicate. It has the potential to enable the physically disabled to perform many activities, thus improving their quality of life and productivity, allowing them more independence and reducing social costs. The challenge with BCI, however, is to extract the relevant patterns from the EEG signals produced by the brain each second. Recently, there has been a great progress in the development of novel paradigms for EEG signal recording, advanced methods for processing them, new applications for BCI systems and complete software and hardware packages used for BCI applications. In this book a few recent advances in these areas are discussed.

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