EVALUATION OF PSD COMPONENTS AND AAR PARAMETERS AS INPUT FEATURES FOR A SVM CLASSIFIER APPLIED TO A ROBOTIC WHEELCHAIR

André Ferreira, Teodiano Freire Bastos-Filho, Mário Sarcinelli-Filho
Department of Electrical Engineering, Federal University of Espirito Santo, Vitória, Brazil

José Luis Martín Sánchez, Juan Carlos García García, Manuel Mazo Quintas
Department of Electronics, University of Alcala (UAH), Alcalá de Henares, Spain

Keywords: Adaptive autoregressive parameters, Power spectral density components, Support-vector machines, Brain-computer interfaces, Robotic wheelchair.

Abstract: Two distinct signal features suitable to be used as input to a Support-Vector Machine (SVM) classifier in an application involving hands motor imagery and the correspondent EEG signal are evaluated in this paper. Such features are the Power Spectral Density (PSD) components and the Adaptive Autoregressive (AAR) parameters. Different classification times (CT) and time intervals are evaluated, for the AAR-based and the PSD-based features, respectively. The best result (an accuracy of 97.1%) is obtained when using PSD components, while the AAR parameters generated an accuracy of 94.3%. The results also demonstrate that it is possible to use only two EEG channels (bipolar configuration around C_3 and C_4), discarding the bipolar configuration around C_z. The algorithms were tested with a proprietary EEG data set involving 4 individuals and with a data set provided by the University of Graz (Austria) as well. The resulting classification system is now being implemented in a Brain-Computer Interface (BCI) used to guide a robotic wheelchair.

1 INTRODUCTION

A Brain-Computer Interface (BCI) is a system that includes a way of acquiring the signals generated by the brain activity, a method/algorithm for decoding such signals and a subsystem that associates the decoded pattern to a behavior or action (Sajda et al., 2008). The BCI and its inherent challenges, involving areas such as signal processing, machine learning and neurosciences, have been the focus of several important research groups. The results of this new technology could be applied to improve the quality of life of many people affected by neuromotor disfunctions caused by diseases, like amyotrophic lateral sclerosis (ALS), or injuries, like spinal cord injury.

A basic structure of a BCI, according to the previous definition, is presented in Figure 1. This paper is related to the phases of *feature extraction* and *feature translation* or *classification*, both indicated in the figure. The objective here is to evaluate Power Spectral Density (PSD) components and Adaptive Autoregressive parameters as inputs for a Support-Vector Machine (SVM) classifier. The SVM is supposed to be able to distinguish two mental tasks related to hands motor imagery, based on these two features extracted from the EEG signal. Two data sets (a proprietary one acquired in the University of Alcala and one provided by the University of Graz) are used to evaluate the implemented algorithms. Configurations of three EEG channels (bipolar around C_3, C_z and C_4) and two EEG channels (bipolar around C_3 and C_4) are tested.

The preliminaries and the results of such evaluation are hereinafter presented as follows: Section 2 contextualizes this work, introducing some previous works involving a robotic wheelchair commanded by a BCI; the methodology used to reach the objective is explained in Section 3, where the feature extraction and the classifier are described in details. The results obtained with the two data sets aforementioned and some comments are presented in Section 4, which is followed by Section 5, where the main conclusions of this work are highlighted.

Ferreira A., Freire Bastos-Filho T., Sarcinelli-Filho M., Luis Martín Sánchez J., Carlos García García J. and Mazo Quintas M. (2009).
EVALUATION OF PSD COMPONENTS AND AAR PARAMETERS AS INPUT FEATURES FOR A SVM CLASSIFIER APPLIED TO A ROBOTIC WHEELCHAIR.
In *Proceedings of the International Conference on Biomedical Electronics and Devices*, pages 7-12
DOI: 10.5220/0001379100070012
Copyright © SciTePress

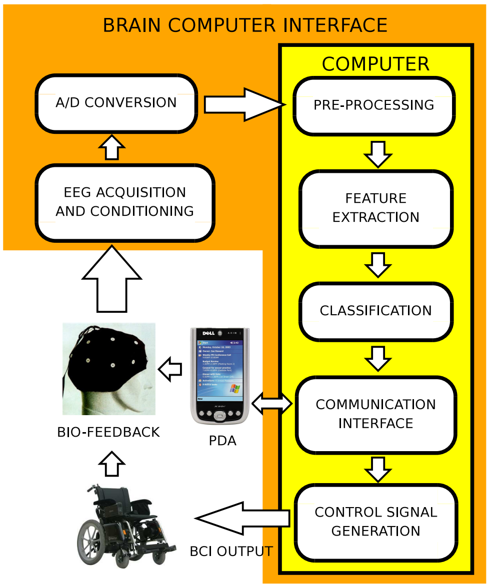

Figure 1: Brain-Computer Interface available at UFES.

2 BACKGROUND

A robotic wheelchair commanded through a BCI is being developed at the Federal University of Espirito Santo, Brazil. The users of such BCI can select movements to be executed by the wheelchair from a set of options presented in the screen of a PDA connected to the BCI, as illustrated in Figure 1.

A drawback of this approach is the need of eye-closing to generate the desired pattern, in this case an ERS (Pons, 2008). An user who is not able to close the eyes for a while to select an option of movement, for example, will not get any profit using the current version of the BCI implemented in the wheelchair. In order to overcome such problem, other EEG information should be used.

In such a context, hands motor imagery is being tested here, in connection to a SVM-based classifier, to check the possibility of using this approach to implement a BCI to be used to command the robotic wheelchair aforementioned. The idea underlying this study is to use imaginary hand movements, instead of eye-closing, to generate recognizable EEG patterns.

3 METHOD

The focus of this paper is to evaluate the use of PSD components and AAR parameters, associated to EEG signals acquired in the region of the motor cortex of the human brain, as inputs of a classifier based on a SVM. The system is supposed to classify two different mental tasks related to hands motor imagery, aiming at allowing to implement a BCI to be used to command a robotic wheelchair (Pons, 2008). In order to perform such evaluation, the following methodology was carried out:

1. evaluate two different approaches: PSD-SVM and AAR/RLS[1]-SVM, according to the sketch of Figure 2;
2. evaluate different channel configurations: $[C_3\ C_z\ C_4]$ and $[C_3\ C_4]$[2];
3. PSD approach: evaluate for different time intervals (3-5s, 4-6s, 5-7s, 6-8s and 7-9s);
4. AAR/RLS approach: evaluate for different Classification Times (CT) (Schlögl et al., 1997). The CTs used are 3s, 4s, 5s, 6s, 7s and 8s;
5. evaluate the algorithms using the proprietary UAH dataset and search for the best configuration (feature extractor and SVM classifier);
6. apply such configuration to the Graz dataset and evaluate the results.

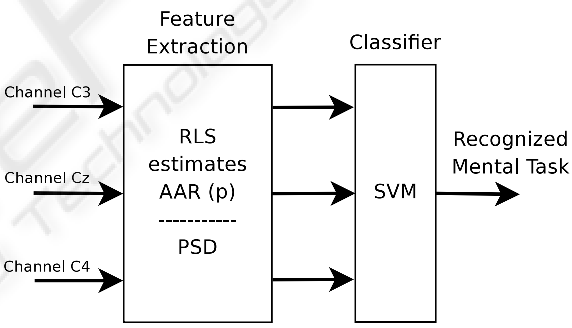

Figure 2: A representation of the systems being evaluated.

3.1 Graz Dataset

The Graz dataset was provided by the Department of Medical Informatics, University of Graz (Austria), during the BCI Competition 2003. It is named *Data set III* and is related to motor imagery. In this paper, 140 trials of this dataset, and the respective labels, were used, 70 related to left hand motor imagery and 70 related to right hand motor imagery. Each trial lasts 9 seconds, with a sampling rate of 128 Hz, resulting in 1152 samples/channel/trial. The data was obtained using a bipolar configuration around the positions C_3, C_z and C_4, according to the 10-20 International System, as presented in Figure 3. In the same

[1] Recursive Least Squares

[2] Actually, the channels are bipolar, with electrodes placed around these positions, as shown in Figure 3

figure (on the right side), an illustration of the protocol used during the experimental phase is presented. After the 2 initial seconds, a beep sounds and a cross is presented in the center of the screen, calling the subject's attention to the beginning of the experiment. One second later ($t = 3$ s), an arrow pointing left or right is presented to the operator, suggesting which mental task should be accomplished, and lasts for 6 seconds (until $t = 9$ s). The data was filtered, keeping the spectrum ranging from 0.5 Hz to 30 Hz, and visual feedback was used (more details can be found in (Schlögl, 2003)).

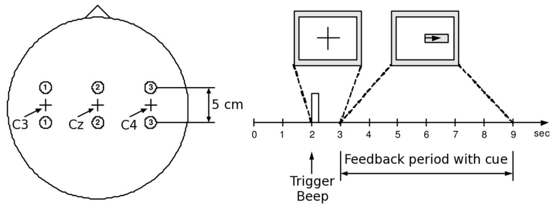

Figure 3: Electrodes Placement and the experimental protocol associated to the Graz dataset.

3.2 UAH Dataset

Experiments similar to those described in Section 3.1 were accomplished at the University of Alcala (UAH), Spain. The mental tasks are the same of the Graz dataset, also related to hands motor imagery. The dataset was recorded from 4 normal subjects in different sessions. Each session corresponds to 60 trials (half to each one of the two mental tasks considered) and each trial was 9 s long, resulting in 9 minutes/session. Three subjects participated in 3 sessions and one subject participates in 4 sessions, thus resulting in 780 trials. The bio-signal amplifier *g.BSamp* and the subsystem *g.16sys* compound the *g.tec* system used to record the EEG data, the software being implemented in Matlab. The data was also filtered to keep only the spectrum from 0.5 Hz and 30 Hz, but the volunteer had no visual feedback.

3.3 Feature Extraction: PSD

Due to the fact that EEG rhythms have been defined mainly in the frequency domain, the Power Spectrum Density (PSD) analysis of the signal is the non-parametric technique used for feature extraction. Other reasons that motivate this choice are the computational efficiency involved, the direct relation between PSD and power, power components can be interpreted in terms of cerebral rhythms and the estimations (via FFT) of spectral components are not biased as those estimated via AR models, as described in (Mouriño, 2003).

The PSD is estimated here via he Welch's Method, computed over sections of 1 s, averaging spectral estimates of 3 segments of 0.5 s each (64 samples, sampling rate of 128 Hz) with 50% of overlap between segments. The maximum size of each segment is important in order to consider the stationary behavior of the EEG signal (Mouriño, 2003; McEwen and Anderson, 1975). A weighting *Hanning* window is applied to the signal due to its considerable attenuation in the side-lobes. The spectral components extracted from the signal and used as features spans from 8 Hz to 30 Hz, with a frequency resolution of 2 Hz. Thus, 12 components are generated, in connection to each channel. This feature extraction procedure is illustrated in Figure 4.

3.4 Feature Extraction: AAR/RLS

The other technique used for feature extraction is based on Adaptive Autoregressive parameters (AAR), estimated via Recursive Least Squares (RLS) algorithm, as described in (Schlögl et al., 1997; Haykin, 2001). This procedure is performed according to

$$E_t = Y_t - \mathbf{a}_{t-1}^T \mathbf{Y}_{t-1} \quad (1)$$

$$\mathbf{r}_t = (1 - UC)^{-1} \mathbf{A}_{t-1} \mathbf{Y}_{t-1} \quad (2)$$

$$\mathbf{k}_t = \mathbf{r}_t / (\mathbf{Y}_{t-1}^T \mathbf{r}_t + 1) \quad (3)$$

$$\mathbf{a}_t = \mathbf{a}_{t-1} + \mathbf{k}_t E_t \quad (4)$$

$$\mathbf{A}_t = (1 - UC)^{-1} \mathbf{A}_{t-1} - \mathbf{k}_t \mathbf{r}_t^T, \quad (5)$$

where

$$\mathbf{a}_t = [a_{1,t} \dots a_{p,t}]^T \quad (6)$$

$$\mathbf{Y}_{t-1} = [Y_{t-1} \dots Y_{t-p}]^T. \quad (7)$$

The initial values adopted were $\mathbf{A}_0 = I$, $\mathbf{a}_0 = \mathbf{0}$ and $UC = 0.007$, and the model order was chosen as $p = 6$. Although the RLS algorithm has a higher computational complexity in comparison with the Least Mean Squares (LMS), it has some advantages: the faster convergence, the higher accuracy of the estimate and the fact that no matrix inversion is necessary. Figure 5 shows the temporal evolution of six AAR parameters. In this case, the channel C_3 of the first trial included in the Graz dataset was considered.

3.5 Classifier: SVM

Although the concept of Support-Vector Machines (SVM) was introduced in COLT-92 (Fifth Annual Workshop on Computational Learning Theory) (Boser et al., 1992), its evaluation in BCIs is quite recent.

Briefly speaking, the main idea of a SVM is to find an optimal separating hyperplane for a given feature set. Given a training set of instance-label pairs

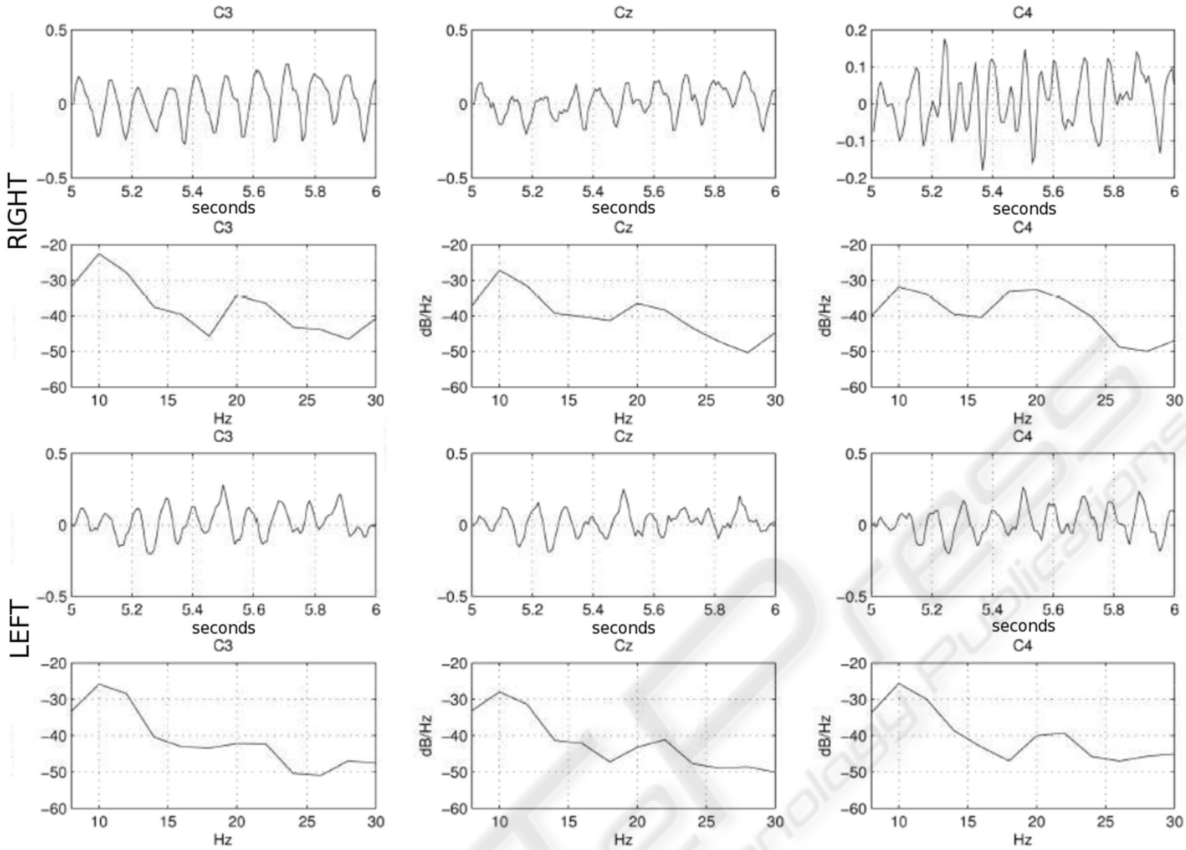

Figure 4: Example of feature extraction using PSD components. Signals related to C_3, C_z and C_4 (bipolar) during hands motor imagery. PSD is presented from 8 up to 30 Hz in dB/Hz.

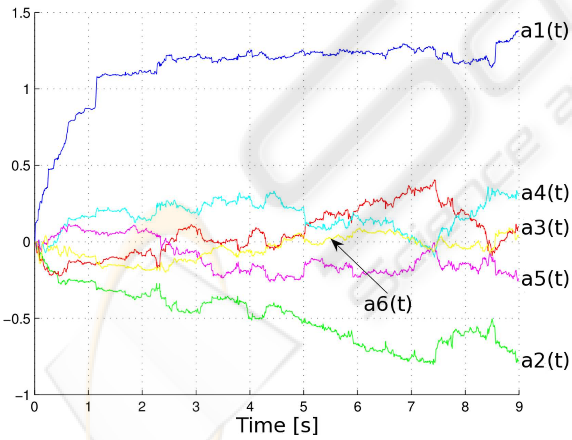

Figure 5: Temporal evolution of six AAR parameters.

$(\mathbf{x}_i, y_i), i = 1, \ldots, l$, where $\mathbf{x}_i \in R^n$ and $y \in \{1, -1\}^l$, the SVM requires the solution of the optimization problem

$$\min_{\mathbf{w},b,\xi} \frac{1}{2}\mathbf{w}^T\mathbf{w} + C\sum_{i=1}^{l}\xi_i, \tag{8}$$

subject to

$$y_i(\mathbf{w}^T\phi(\mathbf{x}_i) + b) \geq 1 - \xi_i \tag{9}$$

$$\xi_i \geq 0. \tag{10}$$

Training vectors $\mathbf{x}_i$ are mapped into a higher dimensional space (maybe infinite) by the function ϕ. The SVM finds a linear separating hyperplane with the maximal margin in this higher dimensional space. $C > 0$ is the penalty parameter of the error term. The function $K(\mathbf{x}_i, \mathbf{x}_j) \equiv \phi(\mathbf{x}_i)^T\phi(\mathbf{x}_j)$ is called *kernel*. The kernel function used in this paper is a Radial Basis Function (RBF) defined as

$$K(\mathbf{x}_i, \mathbf{x}_j) = exp(-\gamma\|\mathbf{x}_i - \mathbf{x}_j)\|^2), \gamma > 0. \tag{11}$$

The choice of a SVM-based classifier and a RBF kernel function relies on previous works that considered this configuration (Shoker et al., 2005; Guler and Ubeyli, 2007; Khachab et al., 2007). Furthermore, a SVM classifier has improved the accuracy in 13% when compared to LDA (Linear Discriminant Analysis) and 16.3% when compared to NN (Neural Networks), using the same features (Nicolaou et al., 2008).

Table 1: PSD + SVM (UAH dataset).

	2 channels (C_3 C_4)					3 channels (C_3 C_z C_4)				
Subject	3-5s	4-6s	5-7s	6-8s	7-9s	3-5s	4-6s	5-7s	6-8s	7-9s
S_{01}	71.1	71.1	73.3	73.3	66.7	73.3	**80.0**	66.7	75.6	64.4
S_{02}	68.7	**80.0**	73.3	73.3	71.1	75.6	75.6	73.3	73.3	66.7
S_{03}	68.3	**76.7**	66.7	66.7	66.7	68.3	70.0	66.7	65.0	70.0
S_{04}	75.6	**91.1**	82.2	84.4	84.4	73.3	86.7	82.2	84.4	75.6

Table 2: AAR/RLS + SVM (UAH dataset).

	2 channels (C_3 C_4)						3 channels (C_3 C_z C_4)					
Subject	3s	4s	5s	6s	7s	8s	3s	4s	5s	6s	7s	8s
S_{01}	66.7	**73.3**	66.7	68.9	62.2	**73.3**	66.7	**73.3**	64.4	66.7	71.1	66.7
S_{02}	66.7	68.9	66.7	**80.0**	57.8	57.8	68.9	68.9	64.4	73.3	64.4	64.4
S_{03}	60.0	66.7	**73.3**	61.7	66.7	**73.3**	58.3	61.7	68.3	66.7	65.0	70.0
S_{04}	66.7	71.1	**86.7**	82.2	75.6	73.3	66.7	73.3	**86.7**	77.8	71.1	75.5

Table 3: PSD + SVM (Graz dataset).

	2 channels (C_3 C_4)					3 channels (C_3 C_z C_4)				
Subject	3-5s	4-6s	5-7s	6-8s	7-9s	3-5s	4-6s	5-7s	6-8s	7-9s
S_{Graz}	88.6	**97.1**	85.7	74.3	77.1	85.7	94.3	85.7	80.0	71.4

Table 4: AAR/RLS + SVM (Graz dataset).

	2 channels (C_3 C_4)						3 channels (C_3 C_z C_4)					
Subject	3s	4s	5s	6s	7s	8s	3s	4s	5s	6s	7s	8s
S_{Graz}	65.7	74.3	**91.4**	**91.4**	82.9	80.0	74.3	68.6	**91.4**	**91.4**	80.0	80.0

The scripts developed during this work are based on the library *libsvm* (Chang and Lin, 2001).

4 RESULTS

Taking into account the data distribution, 75% of each dataset was used for training and validation, while the other 25% were used for test. After evaluating two different techniques for feature extraction (based on PSD components and AAR parameters), the results are presented in the following four tables. The first one (Table 1) shows the classification accuracy obtained for each subject of the UAH dataset, when PSD+SVM is used. The gray cells represents the best classification accuracy found for each subject. The higher values are related to the central period of the experiment (4-6s) and, except by the subject S_{01}, these values are obtained with only two channels.

Table 2 contains the results for the other explored configuration (AAR/RLS+SVM). Four subjects of the UAH dataset are evaluated using different CTs and channel configuration. Once more, the gray cells represents the best classification values for each subject during the test. Equal values are all highlighted (gray cells) to show in which situations they can appear. As in PSD case, the higher classification rates are related to the middle of the experiment (Table 1 and Table 2 (4-6s)). The best results can also be reached with only 2 channels, taking into account that all the high values obtained with 3 channels appear on the left side of the Table 2 (2 channels).

Thus, the best results with the UAH dataset can be found using PSD+SVM, 2 channels (C_3 C_4) and in the middle of the experiment. A summary of the results is presented in Table 5.

Table 5: Best Results (UAH dataset).

Subject	Accuracy	Configuration
S_{01}	80.0	PSD+SVM,C_3 C_z C_4,4-6s
S_{02}	80.0	PSD+SVM,C_3 C_4,4-6s
S_{03}	76.7	PSD+SVM,C_3 C_4,4-6s
S_{04}	91.1	PSD+SVM,C_3 C_4,4-6s

As the next step of the proposed methodology, this configuration was applied to the Graz dataset, in order to evaluate it. The results obtained for this configuration and the other are shown in Tables 3 e 4.

5 CONCLUSIONS

This paper evaluates the use of two set of features (PSD components and AAR/RLS parameters of an EEG signal) as inputs for a SVM classifier, in order to distinguish between two mental tasks related to hands motor imagery.

The approach based on PSD (Welch's Method) components and a SVM (RBF kernel) generated the best results. The highest classification rates are related to the middle of the experiment, usually between seconds 4 and 6. It can be explained taking into account that the subject needs some time to setup him/herself (the cue, an arrow, is presented to the subject at instant $t = 3\ s$) to the end of the trial (the trial finishes at $t = 9\ s$).

The best results can be accomplished using only 2 channels, four electrodes placed around positions $[C_3\ C_4]$ of the 10-20 International System.

After evaluating the system with the UAH dataset, the algorithms were applied to the Graz dataset and the best classification rate (accuracy) was 97.1% (99.4% to mental task 1 and 93.5% to mental task 2).

The replacement of the method currently used to select a symbol in a PDA, which requires a brief eye-closing, by another based on motor imagery, such as the one here discussed, is the next step of our research. In other words, the idea is that motor imagery of a hand (the one with higher accuracy) it is enough to the user without eyes control to select desired symbols in the PDA that will be translated into commands to the robotic wheelchair or into some communication outputs, also available in this system.

ACKNOWLEDGEMENTS

The authors thank CAPES, a foundation of the Brazilian Ministry of Education (Project 150/07), and FACITEC/PMV, a fund of the Vitoria City Hall to support scientific and technological development (Process 061/2007), for their financial support to this research.

REFERENCES

Boser, B. E., Guyon, I. M., and Vapnik, V. N. (1992). A training algorithm for optimal margin classifiers. In *COLT'92: Proceedings of the Fifth Annual Workshop on Computational Learning Theory*, pages 144–152, New York, USA.

Chang, C.-C. and Lin, C.-J. (2001). *LIBSVM: a library for support vector machines*. Software available at `http://www.csie.ntu.edu.tw/~cjlin/libsvm`.

Guler, I. and Ubeyli, E. (2007). Multiclass support vector machines for EEG-signals classification. 11(2):117–126.

Haykin, S. (2001). *Adaptive Filter Theory (4th Edition)*. Prentice Hall.

Khachab, M., Kaakour, S., and Mokbel, C. (2007). Brain imaging and support vector machines for brain computer interface. In *Proc. 4th IEEE International Symposium on Biomedical Imaging: From Nano to Macro ISBI 2007*, pages 1032–1035.

McEwen, J. A. and Anderson, G. B. (1975). Modeling the stationarity and gaussianity of spontaneous electroencephalographic activity. (5):361–369.

Mouriño, J. (2003). EEG-*based Analysis for the Design of Adaptive Brain Interfaces*. PhD thesis, Universitat Politècnica de Catalunya, Barcelona, Spain.

Nicolaou, N., Georgeou, J., and Polycarpou, M. (2008). Autoregressive features for a thought-to-speech converter. In *Proceedings of the International Conference on Biomedical Electronics and Devices - BIODEVICES 2008*, pages 11–16, Funchal, Portugal.

Pons, J. L. (2008). *Wearable Robots: Biomechatronic Exoskeletons (1st Edition)*. Wiley, Madrid, Spain.

Sajda, P., Muller, K.-R., and Shenoy, K. (2008). Brain-computer interfaces [from the guest editors]. *Signal Processing Magazine, IEEE*, 25(1):16–17.

Schlögl, A. (2003). Data set: BCI-experiment. `http://ida.first.fraunhofer.de/projects/bci/competition\_ii`.

Schlögl, A., Neuper, C., and Pfurtscheller, G. (1997). Subject specific EEG patterns during motor imaginary [sic.: for imaginary read imagery]. In Neuper, C., editor, *Proc. 19th Annual International Conference of the IEEE Engineering in Medicine and Biology society*, volume 4, pages 1530–1532.

Shoker, L., Sanei, S., and Sumich, A. (2005). Distinguishing between left and right finger movement from EEG using svm. In Sanei, S., editor, *Proc. 27th Annual International Conference of the Engineering in Medicine and Biology Society IEEE-EMBS 2005*, pages 5420–5423.