Mental Tasks Classification for a Noninvasive BCI Application

Alexandre Ormiga G. Barbosa[1], David Ronald A. Diaz[1], Marley Maria B. R. Vellasco[2], Marco Antonio Meggiolaro[1] and Ricardo Tanscheit[2]

[1] *Department of Mechanical Engineering,*
[2] *Department of Electrical Engineering*
Pontifical Catholic University of Rio de Janeiro - PUC-Rio
aormiga@yahoo.com.br, david251@aluno.puc-rio.br, marley@ele.puc-rio.br, meggi@puc-rio.br, ricardo@ele.puc-rio.br

Abstract. Mapping brain activity patterns in external actions has been studied in recent decades and is the base of a brain-computer interface. This type of interface is extremely useful for people with disabilities, where one can control robotic systems that assist, or even replace, non functional body members. Part of the studies in this area focuses on noninvasive interfaces, in order to broaden the interface usage to a larger number of users without surgical risks. Thus, the purpose of this study is to assess the performance of different pattern recognition methods on the classification of mental activities present in electroencephalograph signals. Three different approaches were evaluated: Multi Layer Perceptron neural networks; an ensemble of adaptive neuro-fuzzy inference systems; and a hierarchical hybrid neuro-fuzzy model.

Keywords: Brain Computer Interface, artificial neural network, neuro-fuzzy, hierarchical network.

1 Introduction

The development of interfaces between humans and machines has been an expanding field in the last decades, including several interfaces using voice, vision, haptics, electromyography (EMG) signals, electroencephalography (EEG) signals, as well as and combinations of these, as communication support [1].

Recent studies [2-3] have shown the possibility of online brainwaves analyses to derive information about the subject's mental state, which can then be mapped onto some external action such as selecting a letter from a virtual keyboard or moving robotics devices. Systems that utilize these brainwaves are called Brain Computer Interface (BCI) [4].

People who have severe motor disabilities, that are partially or totally paralyzed, can use BCI as an alternative communication and control channel that does not depend on the brain's normal output pathway - peripheral nerves and muscles. Hence, BCI enhances these persons' quality of life [5].

BCIs can be noninvasive or invasive. The latter faces substantial technical difficulties and entails significant clinical risks: they require that recording electrodes are implanted in the cortex and are functional for long periods. Most importantly, however, is the risk of infections and other damages to the brain [6]. On the other hand, non-invasive BCIs are based on the EEG analysis associated with various brain function aspects [7], offering, therefore, a more secure and accessible interface.

Pattern classification of brain activity is one of the important aspects in BCI systems [8]. Artificial Neural Networks have already been applied to the classification of brain activities, attaining better performance than traditional methods [9].

In [10], a Probabilistic Neural Network (PNN) [11-12] and a Multi-Layer Perceptron (MLP) neural network [12-13] have been used as classifiers to recognize five different mental activities in noninvasive BCIs. These models presented promising results, but due to the inherent complexity of the problem, more complex models are necessary to achieve more accurate classification rates. As in [10], no user-independence is evaluated in this paper.

Therefore, this paper presents the study of more efficient classifiers in order to increase the hit rate in pattern classification of mental activities. Three different models were developed: a MLP neural network, for comparison purposes, and two hybrid approaches, consisting of an ensemble of ANFIS (Adaptive Neuro-Fuzzy Inference Systems) [14-15] models and a hierarchical neuro-fuzzy classifier.

This paper is organized in four additional sections. Section 2 presents the real database used in this study. Section 3 describes in details the proposed classification models. Section 4 presents the results obtained with all three models and, finally, section 5 discusses the conclusions of this work.

2 Mental Activities Database

The mental activity database was obtained from [10], where an electroencephalograph, composed of ten electrodes placed on the user's scalp (according to International System 10-20 [16]), was implemented (Fig. 1). Usual classification of the main EEG rhythms is based on five frequency ranges [17], called: delta (0 to 4 Hz), theta (4 to 8 Hz), alpha (8 to 13 Hz), beta (13 to 30 Hz), and gamma (higher than 30 Hz). After an independent analysis of each frequency range, better results were obtained in delta band [10]. Therefore, in order to reduce the number of inputs for the neural network and hybrid models, as well as to allow a direct comparison between studies, only delta band was considered in this study. Using the knowledge of the brain activity specialization and electrodes positions (see Fig. 1), it is possible to discard six electrodes readings, reducing the relevant signals to four (C3, C4, P3 and P4) [10].

In order to capture useful information in the time and frequency domain, wavelet transform [18] was used to preprocess the EEG signals. The mean of the wavelet coefficients of the four relevant signals in the delta band were selected as inputs of the neural network and hybrid models.

The database was created by asking the user to carry out 100 trials for each of the five chosen mental activities: motor imagery of the forefinger movement to the right side (RM), motor imagery of the forefinger movement to the left side (LM), 3D rotation of a cube (CR), arithmetic operation of subtraction (AS), and the mental state of relax (MR) [10]. The produced data was divided into 70% for training, 15% for validation, and 15% for testing. Figure 2 presents the histogram analysis of wavelet coefficients averages obtained from the four selected electrodes. As can be noticed from Figure 2, the EEG signals contain outlier values that can be visually detected as the ones located far from the value with samples concentration.

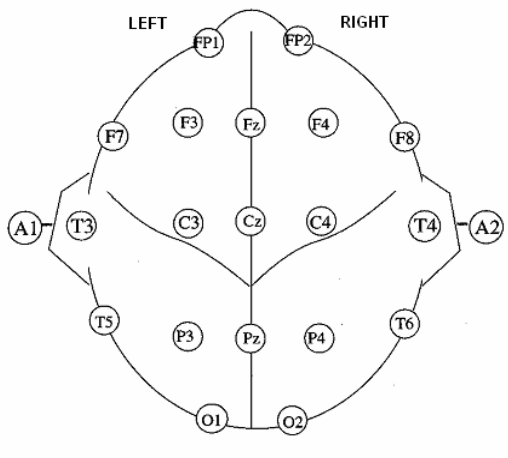

Fig. 1. Electrodes positions from the International System 10-20

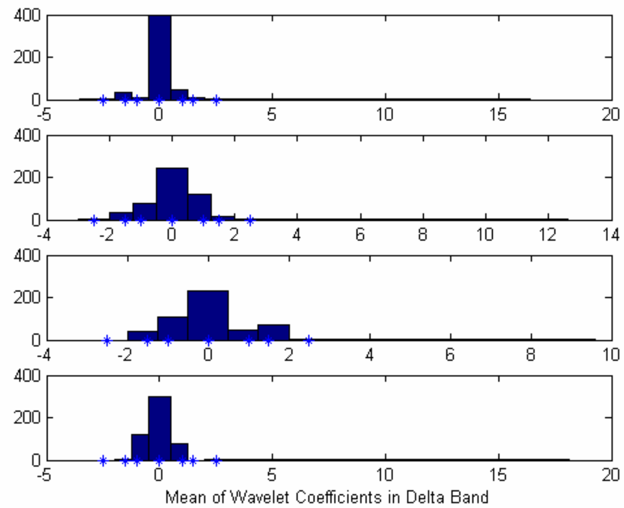

Fig. 2. Histogram of C3, C4, P3 and P4 respectively.

To reduce outliers, two distinct data pre-processing were evaluated. In the first approach (see Fig. 3), outliers were replaced by neutral values (mean of the other values). In the second approach, signal values were also linear normalized, in addition to outliers' replacement (see Fig. 4).

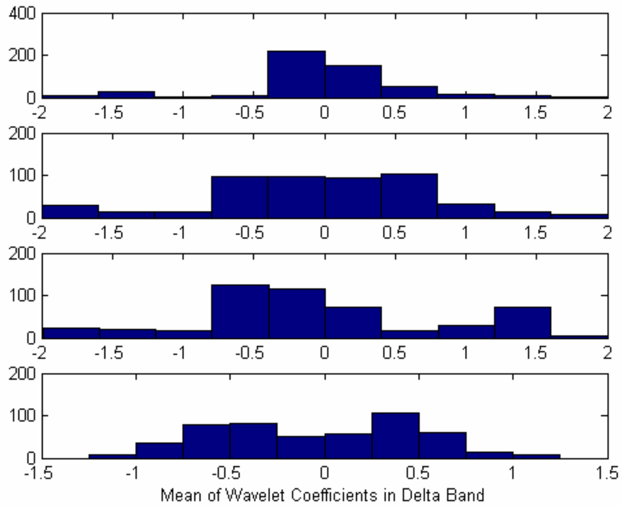

Fig. 3. Histogram with outliers' replacement of C3, C4, P3 and P4 respectively.

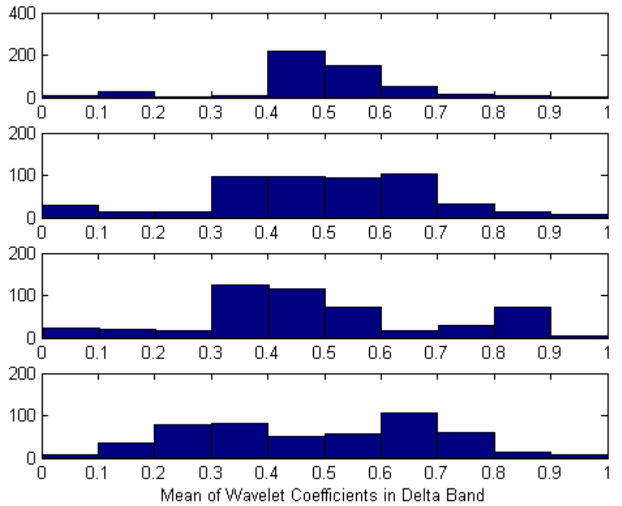

Fig. 4. Histogram with outliers' replacement and normalization of C3, C4, P3 and P4 respectively.

3 Brain Activities Classification Models

3.1 MLP Neural Network

The first proposed classification model is a single MLP Neural Network, which was developed in Matlab® Neural Network Toolbox for comparison reasons. The MLP is composed of four inputs, one hidden layer and five neurons in the output layer, one for each of the five chosen mental activities. The best MLP configuration in terms of number of neurons in the hidden layer and number of training epochs was obtained by evaluating the best performance in the validation set. Different neural networks were trained for maximum 5000 epochs, changing the number of neurons on the hidden layer from 2 to 15 and the learning rate from 0.2 to 0.8. The number of neurons in the hidden layer was chosen as the one that presented the lowest mean between minimum validation errors for all learning rates used. Similarly, the learning rate was chosen to present the lowest validation error for the selected number of neurons on the hidden layer.

This methodology was applied to define the neural network topology for each pre-processing applied to the database, resulting in different topologies. Table 1 presents the obtained topologies for each of the three different configurations.

Table 1. MLP Neural Network parameters.

	Database		
	No Pre-Processing	**Outlier Replacement**	**Outlier Replacement and Normalized**
Neurons on Hidden Layer	10	5	8
Learning Rate	0.72	0.59	0.43
Momentum	0.9	0.9	0.9

3.2 Ensemble of ANFIS Models

Adaptive Neuro-Fuzzy Inference Systems (ANFIS) [14-15] were already proposed as good classifiers to pattern recognition for brain-computer interfaces [19]. The main advantage of this hybrid neuro-fuzzy system is the ability to provide linguistic rules that indicate the relation of the input variables and the output classification variable. Although ANFIS models are of Takagi-Sugeno type [20] (rules' consequents are singletons or a linear combination of the input variables), they are more interpretable than artificial neural networks.

In this study, an ensemble of five ANFIS classifiers is proposed (Fig. 5): each one specialized in one of the five possible mental tasks classification. The final ensemble classification is accomplished by applying the MAX operator among subsystems output value, that is, the final classification of the mental activity is indicated by the ANFIS model with the highest output value.

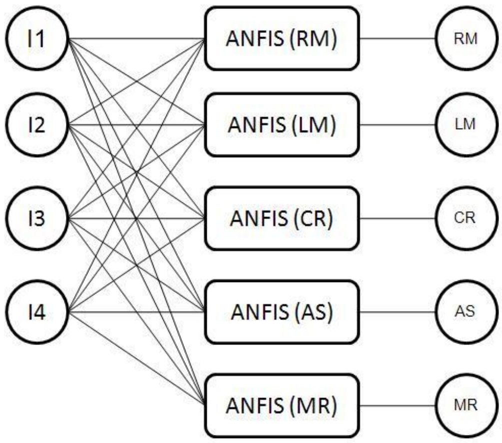

Fig. 5. Classifier model based on an ensemble of ANFIS models.

Each subsystem was trained with backpropagation algorithm in the Matlab® Fuzzy Toolbox, with maximum training epochs specified by the validation set (early stopping process) to avoid overfitting.

Each ANFIS subsystem was trained with two and three fuzzy sets per input signal. The best generalization performance was obtained with two fuzzy sets, resulting in 16 fuzzy rules. Different shapes were also evaluated for the fuzzy sets (triangular and bell function), with the best performance attained with bell shape.

3.3 Hierarchical Hybrid Model

The third classification model was proposed after evaluating the classification performance of the ANFIS ensemble. By analyzing the resulting confusion matrix of the ANFIS ensemble (see results presented in Table 3 for the database with outlier replacement), it is possible to verify that the majority of missed classification is bettween "LM" and "CR" patterns.

Therefore, a hierarchical hybrid structure was modeled (Fig. 6), composed of four ANFIS classifiers, trained to recognize "RM", "LM *or* "CR", "AS" and "MR", and one MLP neural network to identify between "LM" and "CR" patterns when "LM *or* CR" has been pre-classified by its respective ANFIS subsystem.

Table 2. ANFIS classifier confusion matrix.

	RM	LM	CR	AS	MR
RM	9	3	0	3	0
LM	0	7	8	0	0
CR	0	0	15	0	0
AS	0	2	0	13	0
MR	0	0	0	0	15

The same four input signals are applied to all classifiers, and the final system response depends on the ANFIS classifiers. If the ANFIS subsystem trained to identify LM or CR provides the highest output level among all subsystems, the hierarchical hybrid system response is given by the MLP network classification (MAX between LM and CR outputs). Otherwise, the final response is provided by ANFIS with the highest output value.

The methodology described in Section 3.1 used to define the MLP neural network topology was also applied to train the MLP subsystem in the hierarchical hybrid model. The ANFIS topology used in the hierarchical hybrid model is also the same applied in the ANFIS ensemble.

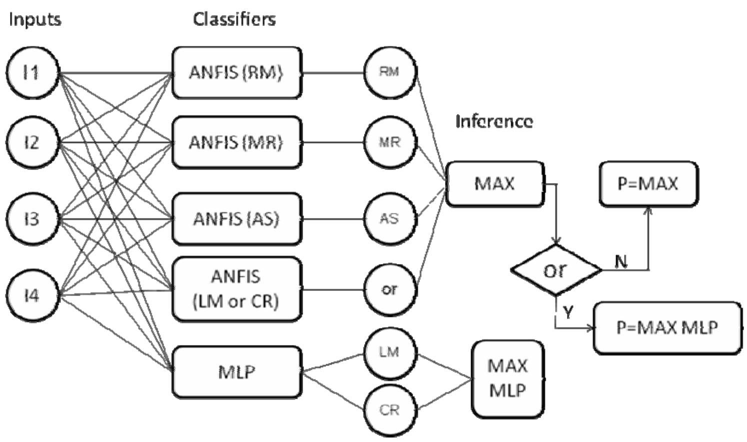

Fig. 6. Hierarchical model.

Table 3 presents the new confusion matrix obtained with the hierarchical hybrid model, using the same dataset provided in Table 2. As can be observed, the discrimination between "LM" and "CR" classes has improved considerably, maintaining the accuracy in the other classes.

Table 3. Confusion matrix of hierarchical model.

	RM	LM	CR	AS	MR
RM	9	1	3	2	0
LM	0	13	2	0	0
CR	0	0	15	0	0
AS	0	0	0	15	0
MR	0	0	0	0	15

4 Results

The three classification models described in the previous sections were evaluated in the testing datasets described in Section 2, that is, the dataset with no pre-processing, dataset with outlier replacement and dataset with normalization and outlier replacement. The classification results of all models are presented in Table 4. The obtained results were also compared with the ones presented in [10], where a PNN and another MLP neural network have been tested with the same database.

As can be observed from Table 4, the best performance was obtained with the outlier replacement pre-processing, for both MLP and ANFIS ensemble. Therefore, the hierarchical hybrid model was only evaluated with this dataset, improving accuracy to almost 90%. By using data pre-processing and the hierarchical structure, better results than the ones presented in [10] were obtained.

Table 4. Classifiers hit rates.

	MLP	ANFIS Ensemble	Hierarchical Hybrid Model	PNN[1]	MLP[1]
No Pre-Processing	83%	72%	X	83%	63%
Outlier Replacement	86%	78%	89%	X	X
Outlier Replacement and Normalization	85%	76%	X	X	X

[1] Results obtained in [10]

5 Conclusions

This paper presented the evaluation of three different classification models for the discrimination of mental activities for a noninvasive BCI (Brain Computer Interface) application.

The models presented in this paper were proposed to improve the classification performance presented in previous work [10], where a Probabilistic Neural Network and a Multi-Layer Perceptron were used as classifiers. By analyzing the difficulty in separating some of the brain activities, a hierarchical hybrid model was proposed, which led to a better overall classification accuracy, as well as better classification per class.

The ANFIS ensemble classifier proposed did not provide good results when compared to a simple MLP neural network. Better results can be obtained if neuro-fuzzy systems specifically developed for classification problems are used in the ensemble formation, such as the Inverted BSP System [21-22]

According to other studies [23-24], alpha and beta bands contain the relevant information for mental activity analyses in a BCI application. So a new database including these bands will be created for future work to test the classification models proposed. Closed-loop feedback learning will be also implemented in order to improve signals quality, making pattern recognition easier. Considering a better scenario, future works should present better results.

References

1. Garcia, G. N. Direct brain-computer communication through scalp recorded EEG signals, Doctor’s thesis, Dept. of Electricity, Ecole Polytechnique Fédérale de Lausanne, 2004.
2. Galán, F., Nuttin, M., Lew, E., Ferrez, P.W., Vanacker, G., Philips, J., and Millán, J. del R. (2008). A Brain-Actuated Wheelchair: Asynchronous and Non-Invasive Brain-Computer Interfaces for Continuous Control of Robots. *Clinical Neurophysiology*, 119:2159–2169.
3. Babiloni, F.; Cincotti, F.; Lazzarini, L.; Millan, J.; Mourino, J.; Varsta, M.; Heikkonen, J.; Bianchi, L.; Marciani, M. G. Linear Classification of Low-Resolution EEG Patterns Produced by Imagined Hand Movements, IEEE Transactions Rehabilitation Engineering, 8(2):186–188, 2000.
4. Millán, José del R. “*Handbook of Brain Theory and Neural Networks”*, Second edition, 2002.
5. Wolpaw, J.R.; McFarland, D. J.; Vaughan, T.M. Brain Computer Interface Research at the Wadsworth Center, IEEE Transactions on Neural Systems and Rehabilitation Engineering, 8:222–226, 2000.
6. Wolpaw, J.R. and McFarland, D.J.; “Control of a Two-dimensional Movement Signal by a Noninvasive Brain-Computer Interface in Humans,” *Proc. Nat’l Academy of Sciences*, vol.101, no. 51, pp. 17,849-17,854, 2004.
7. Millán, J. del R.; Mouriño, J.; Franzé M., Cincotti, F., Varsta, M., Heikkonen, J.; Babiloni, F. A local neural classifier for the recognition of EEG patterns associated to mental tasks, IEEE Trans. on Neural Networks, 11:678–686, 2002.
8. Montri Phothisonothai and Masahiro Nakagawa; EEG-Based Classification of New Imagery Tasks Using Three-Layer Feedforward Neural Network Classifier for Brain–Computer Interface, J. Phys. Soc. Jpn. 75, 2006.

9. M. Phothisonothai and M. Nakagawa, "EEG-Based Classification of Motor Imagery Tasks Using Fractal Dimension and Neural Network for Brain-Computer Interface," IEICE Transactions on Information and Systems, vol.E91-D, no.1, pp.44-53, January 2008.
10. Diaz, D.R.A., "Activation of a Mobile Robot Through a Brain Computer Interface Based on Electroencephalographic Signal Processing", M.Sc. Thesis, Pontifical Catholic University of Rio de Janeiro, 2009.
11. Wasserman, P.D., *Advanced Methods in Neural Computing*, Van Nostrand Reinhold, 1993
12. Haykin, S., *Neural Networks - A Comprehensive Foundation,* Mcmillan College Publishing Co, 1999.
13. Reed, R.D., and Robert J. Mark II, *Neural Smithing – Supervised Learning in Feedforward Artificial Neural Networks*, Bradford Book, The MIT Press, 1999.
14. Jang, J.-S. R., Sun, C.-T., E. Mizutani, Neuro-Fuzzy and Soft Computing: A Computational Approach to Learning and Machine Intelligence, Prentice-Hall, 1997.
15. J.-S. R. Jang, ANFIS: Adaptive-Network-Based Fuzzy Inference Systems, IEEE Trans. On Systems, Man and Cybernetics, Vol. 23, No. 3, pp. 665-685,1993
16. Harner, P. F.; Sannit, T. A review of the International Ten-Twenty system of electrode placement, Grass Instruments Company, 1974.
17. Garcia, G. N.; Hoffmann, U.; Ebrahimi, T.; Vesin. J. M. Direct Brain-Computer Communication through EEG Signals, IEEE EMBS Book Series on Neural Engineering, 2004.
18. Ogden Tood R.,Essential Wavelets for Statistical and Data Analysis, 1997.
19. Rubin D. D. Ben Dayan et al. “An adaptative neuro-fuzzy method (ANFIS) for estimating single-trial movement-related potentials”, 2004.
20. Takagi, T. and Sugeno, S., “Fuzzy Identification of Systems and its Application to Modelling and Control,” IEEE Trans. on Systems, Man and Cybernetics, 15 (1): 116-132, 1985.
21. Gonçalves, L., Vellasco, M., Pacheco, M, Souza, F., Inverted Hierarchical Neuro-Fuzzy BSP System: A Novel Neuro-Fuzzy Model for Pattern Classification and Rule Extraction in Databases, IEEE Trans. on S.M.C., Part C: V. 36, N. 2, pp. 236-248, 2006.
22. Vellasco, M., Pacheco, M., Figueiredo, K. Souza, F., Hierarchical Neuro-Fuzzy Systems - Part I, "Encyclopedia of Artificial Intelligence", J. Rabuñal, J. Dorado & A. Pazos (eds), Information Science Reference 2008.
23. Millán, J. d. R.; Renkens, F.; Mouriño, J.; Gerstner, W. Noninvasive Brain-Actuated Control of a Mobile Robot by Human EEG, IEEE Transactions on Biomedical Engineering, vol. 51, no. 6, pp 1026-33,2004
24. Millán, José del R.; Mouriño, Josep “*Asynchronous BCI and Local Neural Classifiers: An Overview of the Adaptive Brain Interface Project”***.** IEEE Transactions on Neural Systems and Rehabilitation Engineering, Vol. 11, No. 2, pp. 159-161, 2003,