A Neuro-Fuzzy Based Approach for Resting-state Detection Using A Consumer-grade EEG

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***Abstract*—This work aims to introduce a methodology for resting-state brain activities detection by a consumer-grade EEG. From one hand, an adaptive noise reduction methodology based on non-linear Principal Component Analysis Neural Network is adopted. On the other hand, a Neuro-Fuzzy model (i.e., Fuzzy Relational Neural Network) is considered for brain activities detection since a combination of neural networks and fuzzy technology enhances the performance of control, decision-making and data analysis systems. Experiments are made on a corpus containing the activation strength of the fourteen electrodes of an EEG headset for eye state detection. We proved that by using the noised signals, the proposed methodology permits to obtain a high rate of classification accuracy.**

***Index Terms*—Neuro-Fuzzy Models, Non-Linear Principal Component Analysis, Brain-Computer Interface, Signal Denoising, Signal Detection**

I. Introduction

Electroencephalography (EEG) is the most studied non-invasive Brain Computer Interface (BCI) that permits a direct communication between a brain and an external device [1]. In Computer Science and Bioengineering, BCI is mainly used for supporting people with handicap as in the cases of acquisition and interpretation of EEG/Neural data can control the moves of a wheelchair, or replay some vocal synthesis, or also control a Home Automation System [2]. Nowadays, users can control EEG rythm changes through meditation, can do image classification based on EEG response to visual pulse, or can monitor their focus level. Recent investigations have been devoted to neural interface in gaming [3], for tracking emotions [4] and for military scenarios [5]. In [6] a self-adaptive autonomous online learning through a general type-2 fuzzy system for the motor imagery (MI) is introduced. The model is based on a decoding of a BCI and navigation of a bipedal humanoid robot in a real experiment, using electroencephalography (EEG) brain recordings. Moreover in [7] a generalized EEG-based Neural Fuzzy system to predict driver's drowsiness was proposed. In particular, the authors introduced a generalized EEG-based Self-organizing Neural Fuzzy system to monitor and predict the driver's drowsy state with the occipital area. In [8], the authors investigate how the eye state (open or closed) can be predicted by EEG. They tested 42 different Machine Learning algorithms on their performance to predict the eye state after training with a labelled corpus. The best-performing classifier, KStar, produced a classification error rate of only 2.7% which is a 94% relative reduction over the majority vote of 44.9% classification error. In this paper we introduce a classification methodology for EEG signals recorded by a commercial Emotiv Epoc headset [1]. The approach is based on an adaptive noise reduction methodology and a Neuro-Fuzzy model for detection. As in [8] we collected a corpus containing the activation strength of the fourteen electrodes of the EEG headset for eye state detection. The experimental results highlight that the methodology permits to obtain a high rate of accuracy in classification. The paper is organized as follows. In Section II, some concepts about the EEG headset are introduced. In Section III, we describe the noise reduction technique, in Section IV the Fuzzy Relational Neural Network model and, in Section V some experimental results are discussed. Finally, conclusions and future remarks are outlined in Section VI.

II. Emotiv Epoc+

Nowadays, Human–Computer Interaction (HCI) devices are used for interfacing with computers for different purposes as data entry, control or communication. An EEG has direct correlations with user intentions, thereby enabling in a simple way a direct Brain-Computer Interface (BCI) communication [9]. The Emotiv EPOC+ is a personal EEG device that allows for detecting emotions and face expressions and can be used for contextual brain research and BCI applications. The device permits to acquire high-quality raw EEG data captured by electrodes and the communication take place via bluetooth 4.0. The Emotiv EPOC+ has 14 channel where every single channel read the potential difference below the skin. The location of the electrodes is shown in the Figure 1. Emotiv EPOC+ is a consumer-grade EEG device and it is ease of use for simple tasks as data entry, control or communication.

III. Adaptive Noise Reduction

In digital signal processing, one of the main pre-processing steps is the Noise Reduction (NR). NR can improve the quality of the signals and the performance in successive steps as in the pattern classification. Most of the approaches known in

[1] http://www.emotiv.com

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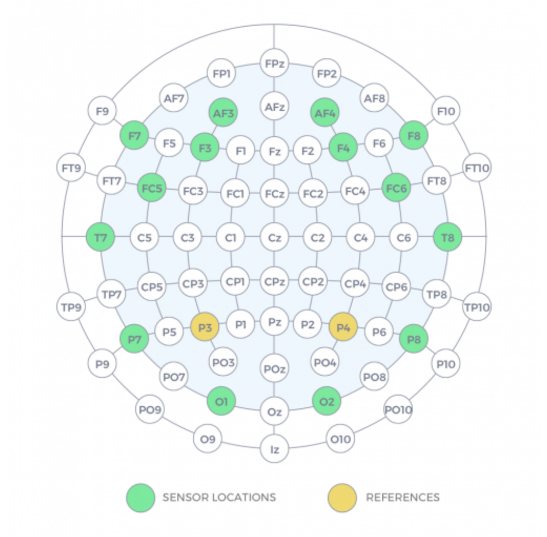


Fig. 1. *Emotiv EPOC+* channels location.

literature are based on filtering (e.g., Wiener, Kalman filter), that perform appropriately when the spectral properties of the noise free signals and the noise are known. Improvements can be obtained adopting an adaptive filtering. In this case, by using a learning methodology, the noise reduction can be obtained directly on the signals without any information on the behaviour and the spectral properties of the signals. In this work, the noise reduction is obtained by an adaptive approach based on a Neural Network (NN). In particular we adopt a single layer feedforward NN based an Hebbian type learning rule for accomplishing a non-linear Principal Component Analysis (PCA) [10], [11] . Noise reduction is obtained after a compression and decompression (reconstruction) of the raw data. The adaptive approach is based on the robust generalization of the variance maximisation in classical PCA, where the objective function $f(t)$ is assumed to be a valid cost function, such as $\ln\cosh(t)$. The general algorithm is described in Figure 1. In particular, the input pattern is obtained collecting q samples $\mathbf{x}_n = [x(n), x(n+1), \ldots, x(n+(q-1))]$ of the source noise signal $x(n) = [x(1), \ldots, x(K)]$ with $n = 1, \ldots, K$ and $q < K$. The weight matrix $\mathbf{W}$ is adopted for the compression and decompression of the signal.

Algorithm 1 Adaptive Noise Reduction

1: Initialize: number of output neurons N, compression/decompression matrix $\mathbf{W} = [\mathbf{w}_1, \ldots, \mathbf{w}_N]$ with small random values with Gaussian distribution, early stopping threshold ϵ, learning rate μ (default $= 0.0001$) and α parameter (default $= 1$).
Reset pattern counter $k = 1$.

2: Input the $m-th$ pattern

$$\mathbf{x}_m = [x(m), x(m+1), \ldots, x(m+(M-1))]$$

where M is the number of input components .

3: Calculate the output for each neuron $y_i = \mathbf{w}_i^T \mathbf{x}_m$. $\forall i = 1, ..., M$

4: Apply learning rule

$$\mathbf{w}_i(k+1) = \mathbf{w}_i(k) + \mu_k g(y_i(k)) \mathbf{e}_i(k)$$

$$\mathbf{e}_i(k) = \mathbf{x}_i - \sum_{j=1}^{I(i)} y_j(k) \mathbf{w}_j(k)$$

where in the hierarchical case we have $I(i) = i$. In the symmetric case $I(i) = N$, the error vector $\mathbf{e}_i(k)$ becomes the same $\mathbf{e}_i$ for all the neurons.

5: UNTIL the number of pattern is not empty GO TO 2

6: Convergence test:
IF $C_T = \frac{1}{2} \sum_{i=1}^{N} \sum_{j=1}^{N} (w_{ij} - w_{ij}^{old})^2 < \epsilon$
THEN GO TO 8

7: $k = k + 1$; GO TO 2.

8: END

IV. Fuzzy Relational Neural Network

Neuro-Fuzzy systems integrates both Neural Networks and Fuzzy Logic principles, capturing the benefits of both in a single framework. In general, its inference system corresponds to a set of fuzzy IF–THEN rules that have learning capability in classification and approximate nonlinear functions [12]. In this work we adopt the Fuzzy Relational NN (FRNN) model for its classification properties [13]. FRNN is a neuro-fuzzy model based on fuzzy relational connections and in Figure 2 the overall architecture is shown. In FRNN a fuzzy system is designed by Fuzzy Relations (R_{rj}^i). It is composed by 3 different hidden layers containing the fuzzification (i.e. fuzzy sets A_r^i) and defuzzification phases. Considering n inputs which are discretized into m_i input levels by the fuzzifier and k outputs which are obtained by the defuzzification of M discretized levels and by using different t-norms and t-conorms, the output of the model is [13]

$$f_k(\mathbf{x}) = \frac{\sum_{j=1}^{M} \overline{y}_k^j \left[\mathbf{T}_{i=1}^{n} \left[\mathbf{S}_{r=1}^{m_i} (\mu_{A_r^i}(x_i) \mathbf{t} \mu_{R_{rj}^i}) \mathbf{s} \theta_{R^j}^i \right] \right]}{\sum_{j=1}^{M} \left[\mathbf{T}_{i=1}^{n} \left[\mathbf{S}_{r=1}^{m_i} (\mu_{A_r^i}(x_i) \mathbf{t} \mu_{R_{rj}^i}) \mathbf{s} \theta_{R^j}^i \right] \right]} \quad (1)$$

where $f : U \subset \mathcal{R}^n \to \mathcal{R}$, $\mathbf{x} = (x_1, x_2, \ldots, x_n) \in U$, s is the number of fuzzy rules, n the number of relation matrices, m_i is the number of input membership functions of the i-th relation, $\mu_{A_r^i}$ is the membership function on the input space, $\overline{y}_k^j$ is the apex on the output space and $\mu_{R_{rj}^i}$ is the weight from the r-th input to j-th output of the j-th relation matrix [13]. For tuning the weights, as described in [13], the learning algorithm is based on both Back-Propagation (BP) and Pseudoinverse matrix strategies.

V. Experimental Results

In this Section we present some experimental results for classifying closed and opened eyes. A tester was in a silent room and unconscious of experiment begin time and he had to switch between two main eyes states: closed and opened eyes. Closed eye state has been considered when eyes was completely closed and opened in all other ways. The eye state

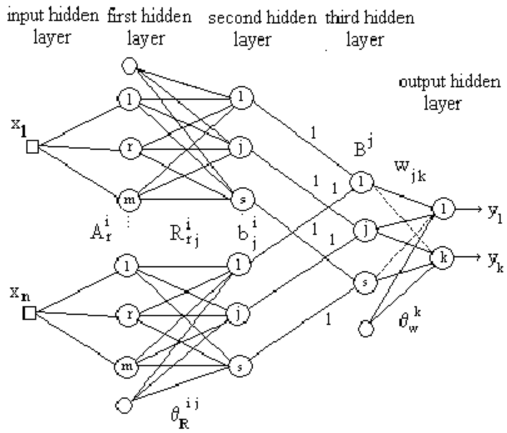


Fig. 2. Fuzzy Relational Neural Network architecture.

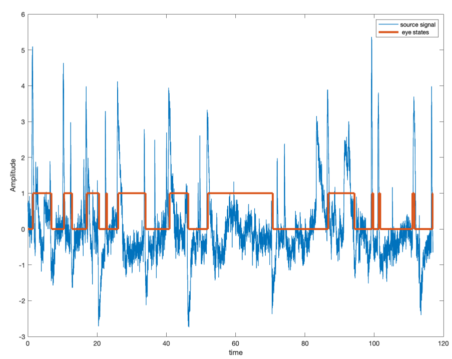
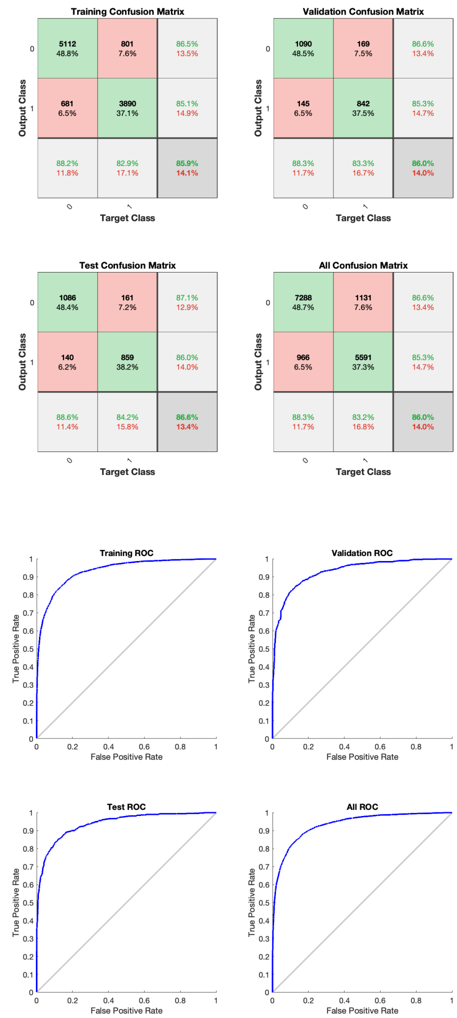


Fig. 3. AF3 EEG signal with eye state labelling.

was manually annotated by analyzing a video recordings the tester activities. Data are obtained by considering a sampling rate of 128 Hz for 117 seconds. The bandwidth is 0.16–43Hz with digital notch filters at 50 Hz and 60 Hz. Data are collected labeling the eye state (0 eye open and 1 eye closed) of the 14 values of the electrodes (channels: AF3, F7, F3, FC5, T7, P7, O1, O2, P8, T8, FC6, F4, F8, AF4) for each temporal sample, in according with the recorded video. In Figure 3 we plot the AF3 EEG signal with the corresponding eye state labeling (0 or 1). Data are pre-processed eliminating some samples with high variance [2].

The FRNN model has been applied by using two Gaussian membership functions for each channel and Lukasiewicz t and s-norms for AND and OR connectives, respectively. A cross-validation mechanism, in which training (75%), validation (15%), and test sets (15%), is used. In Figure 4 we summarize the results considering both confusion matrices and ROCs curves. We note that the percentage of perfect classification for all the data sets is around 86%. Successively, we apply for each channel the adaptive noise reduction approach described

[2]Code and data can be downloaded from the Web Page of the Computational Intelligence & Smart System Lab - http://cisslab.uniparthenope.it



a)

b)

Fig. 4. Data without noise reduction: a) Confusion matrices; b) ROC curves.

in Algorithm 1. An example of noise reduction for the AF4 channel is plotted in Figure 5. In the latter case, applying FRNN, we obtain the confusion matrices and ROCs curves of Figure 6. In this case we observe that the percentage of perfect classification is around 99.6% for all the data sets.

VI. CONCLUSIONS

In this work we introduced a methodology for resting-state brain activities detection by a consumer-grade EEG. The methodology is based on both adaptive noise reduction and Neuro-Fuzzy models. Experiments made on a corpus containing the activation strength of the fourteen electrodes of an EEG headset for eye state detection proved that the proposed methodology permits to obtain an high rate of classification accuracy. We also stress that for this kind of signals the adopted adaptive noise reduction methodology can drastically improve the detection performance. In the next future, the authors concentrate on the use of the methodology

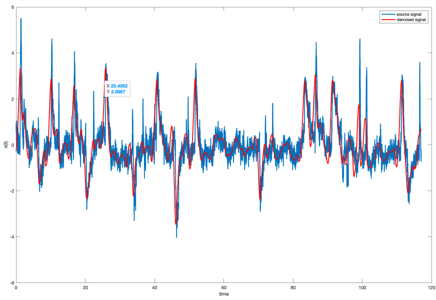


Fig. 5. Example of noise reduction on EEG signal (AF4 channel).

for different applications as hardware control and medical decision support (e.g., dyslexia).

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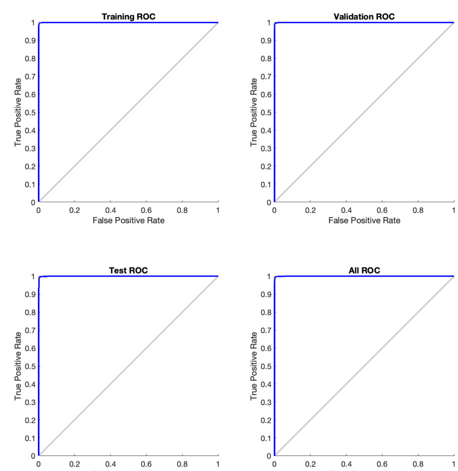
a)



b)

Fig. 6. Data with noise reduction: a) Confusion matrices; b) ROC curves.