International Journal of Information, Control and Computer Sciences
ISSN: 2517-9942
Vol:1, No:3, 2007

Alertness States Classification By SOM and LVQ Neural Networks

K. Ben Khalifa, M.H. Bédoui, M. Dogui and F. Alexandre

Abstract—Several studies have been carried out, using various techniques, including neural networks, to discriminate vigilance states in humans from electroencephalographic (EEG) signals, but we are still far from results satisfactorily useable results. The work presented in this paper aims at improving this status with regards to 2 aspects. Firstly, we introduce an original procedure made of the association of two neural networks, a self organizing map (SOM) and a learning vector quantization (LVQ), that allows to automatically detect artefacted states and to separate the different levels of vigilance which is a major breakthrough in the field of vigilance. Lastly and more importantly, our study has been oriented toward real-worked situation and the resulting model can be easily implemented as a wearable device. It benefits from restricted computational and memory requirements and data access is very limited in time. Furthermore, some ongoing works demonstrate that this work should shortly results in the design and conception of a non invasive electronic wearable device.

Keywords—Electroencephalogram interpretation, artificial neural networks, vigilance states, hardware implementation

I. Introduction

Spontaneous electrical brain activities, partly represented by electroencephalographical (EEG) signals, are dynamic, stochastic, non-linear and non-stationary. The EEG recordings depend on the location of the electrodes, their impedance and the state of vigilance. The awakening-sleep transition is characterized by abrupt changes in frequencies, amplitudes and topographic distributions of the EEG signal. These changes vary substantially from one healthy subject to another.

The aim of the study is to obtain an algorithm of vigilance detection from a minimal number of EEG electrodes, easy to implement on programmable devices, to be used in ambulatory and real everyday life conditions, including artefacts.

This study was divided into two stages. The first stage consisted in drawing the cartography of the states of the awakening-sleep transition by using the topological properties of self-organizing maps (SOM). This connectionist unsupervised approach will be summarized in this paper and is more precisely described in [1]. The second stage of our study is the main topic of the present paper. From the unsupervised classification obtained above, a connectionist supervised classification algorithm, the learning vector quantization (LVQ), is used for two different tasks. Firstly, the artefacted states are detected and removed. Secondly, the states deprived of artefacts are then classified in order to decide for the state of vigilance.

Manuscript received November 30, 2004. This work was supported in part by the Medical Imaging and Technology group of the Biophysics Laboratory in the College of Medical Studies at Monastir, the CORTEX Project at the LORIA Laboratory and the STIC program at INRIA.

K. Ben Khalifa , M.H. Bedoui and M.Dogui are with the Biophysics Laboratory in the College of Medical Studies at Monastir. 5000 Monastir, Tunisia (e-mail: Khaled.Benkhalifa@issatso.rnu.tn).

F. Alexandre, is with the CORTEX Project at the LORIA Laboratory, Nancy, France (e-mail: Frederic.alexandre@loria.fr).

II. Materials and Methods

A. Subjects

This study was concerned with a control group of five healthy male medical students, aged 18 to 23. The recruitment was made by direct contact and voluntary membership. Each subject had three 24-hour recordings fortnightly with an interval of 15 days. For each recording, the subject fills in a questionnaire clarifying his sleeping hours, his night and possibly his diurnal awakening. He hourly estimates his level of vigilance during the periods of awakening according to a visual analogical scale ranging from 0 (sleepy) to 10 (wide awakening).

B. Recordings

The equipment in use is an ambulatory long-duration recording system with 8 channels, OXFORD MEDILOG 9000 model. The analogical recording is made on a magnetic tape. The analogical recordings are digitized and visualized by a second reading system.

Each recording contains two EOG channels, an EMG channel of the chin and five EEG channels. For the EOG, the active electrodes are placed at the level of the external canthus (on the right and on the left) with the reference at the level of the contralateral mastoid. The EMG is recorded by a bipolar diversion connected to two 2 cm distant electrodes placed on the cowlick and the chin. The EEG is recorded by bipolar diversions (F3-F4; C3-P3; C3-01; C4-P4 and P4-O2).

The sampling frequency of all the registered signals is 128 Hz. Four noisy recordings are eliminated. A 24-hour recording, for every subject, is selected (five 24 hour recordings are used in our application).

C. Qualification of the states of vigilance by the expert

Questionnaires filled by the subjects and recorded signals are exploited by an expert in EEG and polysomnography interpretation, to label the different vigilance levels. His analysis on the zones of awakening-drowsiness transition

enabled to distinguish five levels of vigilance: wide awakening (**Wa**), calm awakening with wide open eyes (**Cawoe**), calm awakening with closed eyes (**Cace**), drowsiness (**Drow**) and stage 1 of the sleep (**Stg1**).

To take into account artefacted parts and to ensure the continuity of the visual analysis, the expert had to define three other states: artefacted calm awakening with wide open eyes (**Art-Cawo**e), artefacted calm awakening with closed eyes (**Art-Cace**) and artefacts due to movements (**Mv**).

The visual analysis relies on all the recorded signals and especially the EEG which is one of the most sensitive indicators in the changes that occur in the wide awakening-drowsiness cycle [1].

D. Pre-processing

In our approach, we wish to lay emphasis on a realistic design, including hardware implementation as discussed below. In order to allow for a portable, easy-to-wear system, we have tried to find a compromise between as few electrodes as possible and acceptable performances, which is an important drawback with regard to existing approaches. More precisely, we have opted for only a right parieto-occipital EEG derivation (P4-O2). The choice of the derivation P4-O2 helps to avoid the ocular frontal derivation artefacts and allows to get an alpha activity of a posterior topology, a characteristic of the calm awakening with closed eyes.

The spectral pre-processing applied on this derivation (P4-O2) consists of a Short Term Fast Fourier transformation STFFT with 4-second portions and a 512-point Hamming window ponderation type. For this purpose, 23 bands of 1 Hz, normalized from 1 to 23Hz, are used :

$$PPS_i = \frac{PS(i \ \ to \ \ (i+1)Hz)}{PST} \times 100 \quad , i \ from \ \ 1 \ \ to \ \ 23 \ Hz$$

PSS_i = Percentage of the power spectrum of the corresponding i band.

PST = Total power Spectrum.

PS_i = Power Spectrum of the corresponding i band.

After this treatment and the choice of a signal band coding, connectionist treatments are applied, as described below.

III. Connectionist approach

In this work, two kinds of connectionist model have been used for the separation and the classification of the vigilance states:

- The automatic extraction of categories has been performed using a self-organizing models with unsupervised training.
- From the categories extracted above, discrimination of artefacted states and classification of non-artefacted states can be obtained by LVQ with supervised training.

A. Self-organizing map: SOM

The SOM principle models the mechanism of the spatial self-organization of perceptions operated by the cortex in the form of a topographic classification process (Figure 1). According to this process, the input data, that can be represented in the general case in the form of vectors with N dimensions, are converted into classes which self-organize according to a two-dimensional structure of neurons on which neighborhood relations are preset. The process of SOM topographic classification thus combines a stage of classification with one of data projection. In this connectionist model, two layers of neurons are used: the first encodes the inputs and the second computes the outputs (classes). The two layers are entirely connected. The SOM training algorithm model is detailed in [2,3]. It is competitive and unsupervised. For each input example, it includes mainly two stages:

- Propagation of activity and selection of the most activated (winning) neuron.
- Updating the winning neuron's profile and those of the neurons belonging to its neighborhood.

These stages of neuronal selection and specialisation are the basis for self-organization in the map. In our study, we have exploited the capacity of the SOM to separate, in an unsupervised way, states already quantified by the expert to better analyze the distribution of these states on the output space and the associations which can emerge between them.
The maps were initialized, taught and evaluated using the routines in the SOM_PAK program package [4].

B. Learning Vector Quantization: LVQ

The unsupervised Kohonen maps constitute an effective tool for the pre-processing toward the separation of the input vectors and their redistribution in various classes. Indeed, the SOM enables us to have an idea about the statistical distribution of the input vectors on the output layer. After training, a neuron in this layer can be activated by input vectors corresponding to various classes, which is a problem in decision making and neuron labelling process. To overcome this limitation, a second training phase -supervised this time- is applied. This phase allows a readjustment of the distribution probability and of the labels attributed to neurons in the output map, in such a way that only one class is attributed to each neuron.

The supervised-training algorithm suggested by Kohonen is known as the Learning Vector Quantization (LVQ) [2]. The architecture of the LVQ is similar to that of the Kohonen map, without lateral connections on the neurons of the second layer (Figure 1). With its various alternatives, this algorithm improves the separation in classes from the solution suggested by the unsupervised training. For a given input, the method consists in bringing closer the most activated neuron if it is in the right class (supervised training), and to push it back in the opposite case. The other neurons (i.e. losers) remain unchanged. Each neuron thus becomes class-representative.
The maps were initialized, taught and evaluated using the routines in the LVQ_PAK program package [5].

IV. Results and discussions

The results presented below and related to the application of the neuronal tools on portions of EEG signal recorded in the various subjects, are described and analyzed in order to

obtain the best approach to quantify the various states of vigilance.

A. Analysis of transition zones by Kohonen maps

Hata!

For each subject, we have built and trained a SOM with an output layer corresponding to a matrix of 5x5 neurons.

After the unsupervised training phase, an analysis of the map's spatial distribution was carried out. The study was related to the SOM ability to produce a pertinent distribution of the predefined vigilance levels on the output neurons. In case a neuron is activated by only one state, it is said to be specific to this state. If several states take part in the same neuron activation, they are presented by decreasing order of frequency and the analysis is done according to the occurrence, in the same neuron, of pairs and even triplets of states which are generally close states on a scale of vigilance states.

B. Automatic classification by Learning Vector Quantization

Taking into account the results summarized above and detailed in [5], we propose to add a supervised stage to remove the ambiguous cases, when two (or more) different states activate the same neuron. This should thus improve the specificity of each neuron. At this stage, supervision is brought by the expert, who associates a unique vigilance state to each neuron.

For that aim, we used a Learning Vector Quantization network because of its supervised competitive nature. This approach was applied in two different contexts: on the one hand within the framework of the detection of the artefacted states and, on the other hand, within the framework of the classification of two states of vigilance: Awakening and Sleep (deprived of artefacts).

1) Recognition of the artefacts

The network architecture includes 23 units in the input layer which represent the 23 spectral bands, and 25 units in the output layer. Concerning the supervised corpus, for each subject, we gathered on the one hand, the three artefacted states (Art-Cace, Art-Cawoe and Mv) and, on the other hand, all the other states that are not artefacted (Wa, Cace, Cawoe, Drow, Stg1). Thus, we have only 2 groups of vigilance states: artefacted states (Art-State) and non-artefacted states (NArt-state). To evaluate the LVQ performances in each subject we used two normalized and balanced corpora, one for the training and the other for the test.

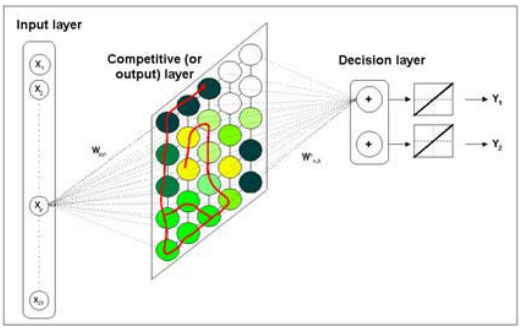

Figure 1: From left to right, the first two layers represent the general architecture of the Self Organizing Map (SOM): Xi(i=1....23) input corresponds to the percentage of the power spectrum of I band (PSSi). $W_{p,n}$(p=1.....23, n=1....25) weights from input to competitive layer. The other two layers indicate the principle of Learning Vector Quantization (LVQ)

TABLE 2
LVQ INTRA AND INTER SUBJECT PERFORMANCES FOR SUBJECTS 1, 2, 3 AND 4 (TASK: AWAKENING AND SLEEP NON-ARTEFACTED STATES RECOGNITION)

		Training corpus	Test corpus			
		LSR* (%)	TSR** for subject1 (%)	TSR** for subject2 (%)	TSR** for subject3 (%)	TSR** for subject4 (%)
Subject1	Awakening	96.43	100	62.03	3.45	29.17
	Sleep	91.84	100	80.95	100	100
	Total	94.29	100	70.42	56.25	63.83
Subject2	Awakening	91.14	96.43	42.31	13.79	12.5
	Sleep	90.48	83.67	95.65	91.43	100
	Total	90.85	90.48	76.39	56.25	55.32
Subject3	Awakening	100	37.5	34.18		64.58
	Sleep	94.29	87.1	74.6		78.26
	Total	96.88	65.45	52.11		71.28
Subject4	Awakening	60	100	57.69	91.67	
	Sleep	62.07	71.43	71.74	84.78	
	Total	60.94	86.67	66.67	88.3	

* : LSR : Learning Success Rate
**: TSR : Test Success Rate

After this treatment, only non artefacted data will be processed for classification. Accordingly, only the rates for that case are interesting here. With that restriction, we obtain rates close to or over 70 %, which is acceptable for further processing even if, as mentioned below, supplementary efforts have to be done in that difficult domain of artefact elimination.

2) Classification of the sleep and awakening states

We are interested here in the automatic classification by the LVQ of non-artefacted states related to sleep and awakening. This time, for each subject, a training and a test corpus were built gathering the two states (Cace and Cawoe), as well as the two states (Drow, Stg1). We thus had only 2 states of vigilance: Awakening and Sleep. It should be noted that in this approach the artefacts (Art-Cawoe, Art-Cace and Mv) are not taken into account. The network architecture includes 23 units on the input layer, which represent the 23 spectral bands, and 25 units on the output layer (cf. discussion above on that point) which characterize the two states (sleep and awakening).

The global performance is first computed for all subjects. One LVQ network is learned with the training corpora of the five subjects and is globally tested with all the test corpora. This experiment yields a total success rate on the test corpus of 76.73% with a recognition rate of the Sleep-Wakening states of 72.28% and 81.19% respectively (see table 1).

Concerning intra and inter-subject evaluation, four identical LVQ networks are learned, each one with the training corpus of one subject (the training corpus of subject 5 was not used because it did not have enough sleep states). As reported in Table 2, each network is tested four times, each time with the test corpus of one subject.

Intra-subject performance can be observed for subjects 1 and 2 and yields excellent recognition rates of the sleep and awakening states in the test corpus which reach respectively 100% and 76.39% (Table 2). It was not possible to compute this performance for subjects 3 and 4, because not enough non-artefacted states were available.

Generally speaking, good inter-subject performances are more difficult to obtain, particularly when too few subjects are considered, as it is the case here. That is the reason why, it is important to underline here that there is a very great correspondence between the states of vigilance in subjects 1 and 2 and subjects 3 and 4. Indeed, for the training parameters of subject 1, the success rate on the test corpus of subject 2 is 70.42%. This rates is 90.48% if the training parameters of subject 2 are applied on the test corpus of subject 1.

The success rate on subject 4 test corpus is 71.28% if the training parameters of subject 3 are used. Finally, it is noticed that if the training parameters of subject 4 are applied to the test corpus of subjects 1, 2 and 3, we obtain good recognition rates of 86.67, 66.67 and 88.30% respectively.

It should be noted that when the network is mistaken, the classification error is made most of the time on the wakening state: the network recognizes it as a vector of the Sleep state (table 3). This can be explained by the absence of artefacts at the level of the sleep state, which makes their visual recognition and their labelling easier by the expert.

V. Conclusion

Connectionist methods with supervised and unsupervised training were used to discriminate the EEG signals characterizing the vigilance states. These models enabled us to attain a level of performance comparable with that of the more recent works in the field [7]. Beyond this performance, we have opted of an artificial neuronal model with a minimal architecture (23 neurons in input layer and 4 neurons on the output layer). Firstly, this architecture minimizes the complexity and allows implementation onto material devices [8] towards real time hypovigilance detection in ambulatory conditions. Secondly, it demonstrates that information, pertinent enough to characterize vigilance states, can be extracted from EEG signal recorded from a single electrode. It should also be noted that the intervention of the expert was fundamental in our approach. Indeed, an expertise made it possible to differentiate 5 non-artefacted vigilance states and 3 artefacted ones.

References

[1] Billiard M. Le sommeil normal et pathologique: troubles du sommeil et de l'éveil. Masson (Ed), 1994. PARIS

[2] Kohonen, T. Self-Organization Maps. (3rd edition 2001). Springer, Berlin.

[3] Bougrain, L. and Alexandre, F. Unsupervised Connectionist Algorithms for Clustering an environmental data set : a comparison. Neurocomputing. 1999. vol 1-3. n° 28. pp.177-189.

[4] Kohonen T., Hynninen J., Kangas J., and Laaksonen J.. SOM_PAK: The Self-Organizing Map Program Package. Technical Report A31, Helsinki University of Technology, Laboratory of Computer and Information Science, FIN-02150 Espoo, Finland, 1996.

[5] Kohonen T., Hynninen J., Kangas J., and Laaksonen J. and Torkkola K. LVQ_PAK: The Learning Vector Quantization Program Package. Technical Report A30, Helsinki University of Technology, Laboratory of Computer and Information Science, FIN-02150 Espoo, Finland, 1996.

[6] K. Ben Khalifa, M.H. Bédoui, L. Bougrain, R. Raychev, M. Dogui, F. Alexandre, Analyse et classification des états de vigilance par réseaux de neurones. Rapport de recherche à l'INRIA. RR-4714. Janvier 2003.

[7] A. Vuckovic, V. Radivojevic, ACN Chen, D. Popovic, Automatic recognition of alertness and drowsiness from EEG by an artificial neural network, Medical Engineering & Physics 24 (5): pages 349-360, 2002.

[8] K. Ben Khalifa, B. Girau, M.H. Bedoui, R. Raychev, F. Alexandre. Implantation basse-consommation de cartes auto-organisatrices pour la détection de l'hypovigilance. RFIA, Toulouse janvier 2004

Table 1
LVQ global performances for all subjects (Task: Awakening and Sleep Non-Artefacted states recognition)

	Training corpus		Test corpus	
	Awakening	Sleep	Awakening	Sleep
Success rate (%)	95.36	88.17	81.19	72.28
Total success rate (%)	92.01		76.73	