Supervised neuronal approaches for EEG signal classification: experimental studies

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SUPERVISED NEURONAL APPROACHES FOR EEG SIGNAL CLASSIFICATION: EXPERIMENTAL STUDIES

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ABSTRACT
Using artificial neural networks for Electroencephalogram (EEG) signal interpretation is a very challenging tasks for several reasons. The first class of reasons refers to the nature of data. Such signals are complex and difficult to process. The second class of reasons refers to the nature of underlying knowledge. Expertise is manifold and difficult to formalize and to be made compatible with a numerical processing. In previous studies we have deeply described that expertise and explained, from theoretical and bibliographical studies, why artificial neural networks could be interesting candidates to perform such a signal interpretation. In this paper, we report recent experiments that we have made on real EEG data in a classification framework. These results are interesting with regard to the state of the art. They also indicate that further work must be done on expertise integration in our neuronal platform.

KEY WORDS
Neural networks, self-organizing maps, multi-layer perceptrons, electroencephalographic signal interpretation, medical application

1. Introduction

Human body can deliver a huge quantity of information, through the recording, analysis and interpretation of physiological signals, among which electroencephalographic (EEG) signals are of particular interest here. Such signals generally deliver in an indirect way information about physiological functions, which are related to brain functioning in the case of EEG. Possible applications using such signals are very numerous. They are for example integrated in the design of new technological devices with embedded intelligence and allow for Brain-Computer-Interfaces in the case of EEG processing. There is also an important demand, in the medical domain, for automatic signal interpretation systems. This is particularly caused by the fact that, today, recordings of physiological signals are interpreted by human experts, which are very busy and qualified people. Moreover, signal reading and diagnosis is a very time consuming process.

For that reason, we have studied, in previous studies [1], human expertise related to EEG signal interpretation in the medical domain and we have proposed that artificial neural networks could be interesting candidates to go towards more automatic signal processing. In these studies, we have mainly described the dynamic, stochastic, non-linear and non-stationary nature of EEG signals and the complex structure of the corresponding human knowledge. We summarize this aspect in Section 2. We have also reviewed a series of publications assessing that, among techniques of soft computing, artificial networks were promising tools for such tasks. In this paper, we report recent works that we have carried out to measure the rough performances of neural networks on EEG signals. Using Self-Organizing Maps for alertness categorization and Multi-Layer Perceptrons for sleep stages classification are reported respectively in Sections 3 and 4. The interpretation of the results that we have obtained are encouraging and it also gives hints on the domains to explore now, as discussed in Section 5.

2. Physiological signal interpretation

The analysis of vigilance states and sleep in the medical domain rely on the analysis of electrooculogram (EOG), electromyogram (EMG) and electroencephalogram (EEG), the latter being certainly the most complex signal to interpret, but also the signal in which most information can be retrieved [2]. Such signals are recorded here with a sampling frequency of 256Hz and often during hours, days and night in the case of sleep pathology study. This represents a huge amount of data and human expertise must be used at that level to select a reasonable quantity of information to process. Concerning EEG interpretation, apart from graphical elements that will be discussed later, human analysis rely on the spectral distribution of

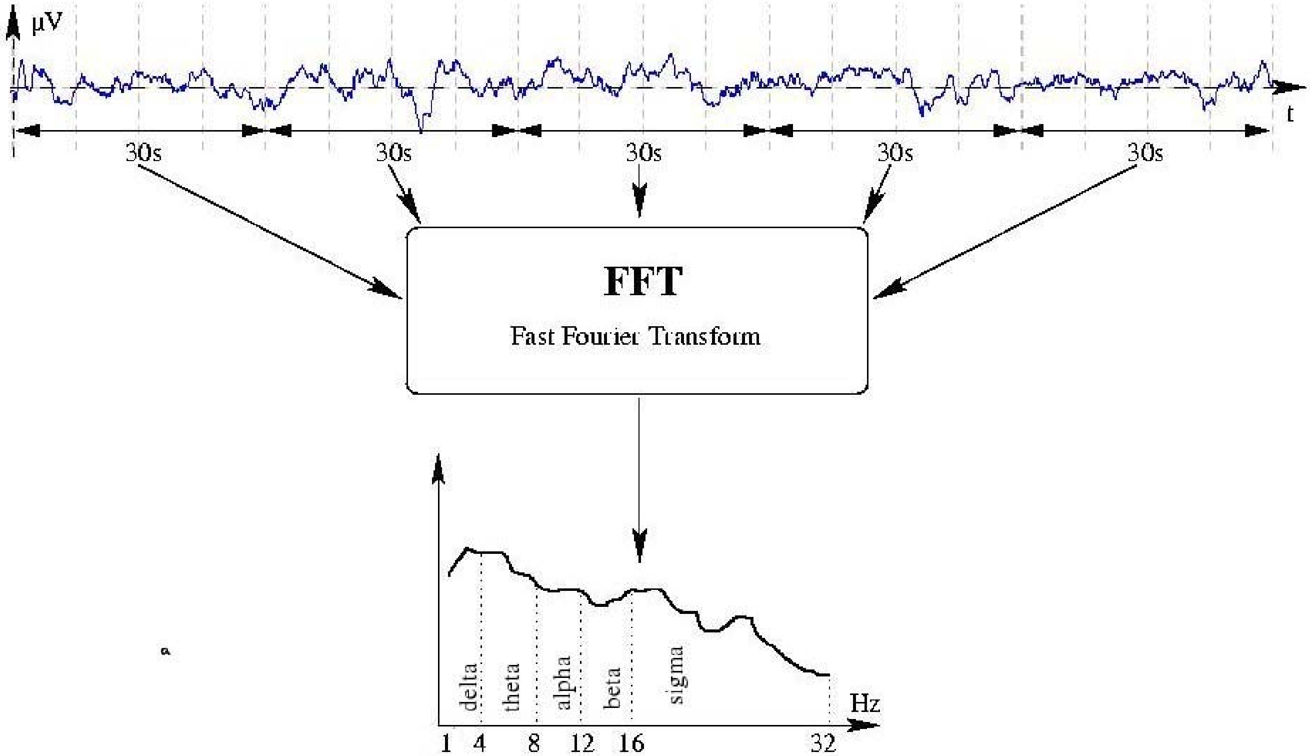

Figure 1: each 30s of physiological signal is transformed into 5 values (sleep bands) through a spectral transformation used as inputs in neural networks.

the signal. That is the reason why the first pre-processing is a Fourier Transform, representing the signal in a set of frequency bands. Figure 1 above gives a representation of a recording of a derivation of EEG, together with its spectral transformation. Human expertise has also led to choose 23 bands of frequency, regularly displayed from 1 to 23 Hz in the case of vigilance state detection. In the case of sleep stages analysis, we have chosen, through discussions with medical experts, to concentrate on typical waves (alpha, theta, delta, sigma, beta waves) [3], related to stages of sleep as reported in Table 1, which gives only five inputs to the neural network.

Indicator	Definition	State
Alpha wave	Frequency of 8 to 12 Hz	Awake
Theta wave	Frequency of 4 to 8 Hz	Stage 1, 2 and REM
Delta wave	Frequency of 0.5 to 4 Hz	Stage 3 and 4
K complex	Transient slow waves	Stage 2
Spindles	Frequency of 12 to 14 Hz	Stage 2
Vertex sharp wave	Pointed waves with great amplitude	Stage 1
Sawtooth	Saw tooth pattern	REM

Table 1. EEG indicators and related stages of sleep, including Rapid Eye Movements (REM)

Building and labelling corpus of data of high quality is critical in the domain of neural networks that learn from examples. In the domain considered here, this task is difficult because artefacts are very frequent and among all because the task of labelling data for supervised learning or validating categories obtained by unsupervised learning are very time consuming for human experts: labelling a night of sleep can last several hours. As a consequence and as will be discussed later, it revealed very difficult to perform multi-user learning.

Finally, we have also discussed with our experts in the medical domain to identify tasks of interest to be explored, both in the domain of machine learning and in the clinical domain. From that discussion, we have selected categorization of vigilance states and classification of stages of sleep and report in the forthcoming sections experiments that we have carried out on these topics.

3. Alertness and drowsiness categorisation and classification using Self-Organizing-Maps (SOM)

The first study consists of vigilance state detection. From a medical point of view, the goal is to better understand the categories of vigilance states from alertness to drowsiness. From a more applicative point of view, we have also proposed ways to simplify the underlying processing in order to be able to embed it onto a FPGA programmable device [4] to use such a system in real life conditions, for example to avoid drowsiness in drivers. From a machine learning point of view, the goal here was to study how to exploit Self-Organizing Maps (SOM) [5], after the categorization process. Two principles have been explored. First, the evolution of vigilance has been characterized, with the help of a medical expert, as a trajectory onto the topological map [6]. Second, a supervised learning phase using the Learning Vector Quantization (LVQ) algorithm [7] has been added so as to obtain a separation in two classes (alertness/drowsiness) for the applicative context of assistance to drivers evoked above. Here, we only report the classification results obtained in the supervised phase.

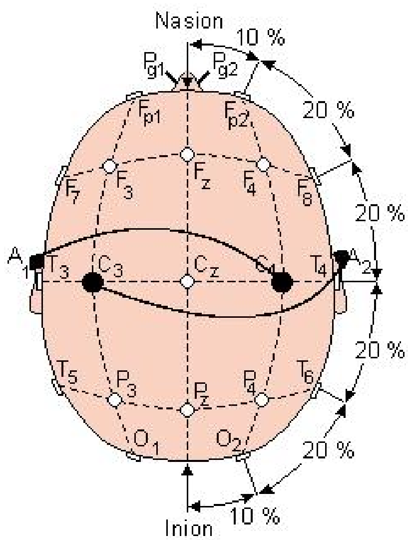

Figure 2: Standard electrodes placements : C3-A2 and C4-A1 for sleep stages classification and P4-02 for vigilance state detection.

In the context of a light, easy to wear system, we have only used EEG signal from one derivation, namely the P4-O2 derivation (cf [6] for a justification), as can be seen in figure 2 that presents the standard electrodes placement references.

Four subjects have been recorded during 24 hours and each 4 seconds of signal have been sent in the spectral domain with a Fourier transform. Such a short duration has been chosen because drowsiness detection must generally be performed quickly. As explained above, the Fourier transform is displayed here in 23 frequency channels that will lead to 23 inputs for the SOM.

A 5x5 map has been chosen for the competitive layer and, after learning, an analysis of the map with a medical expert has led to distinguish five levels of vigilance, namely wide awekening, calm awakening with open eyes, calm awakening with closed eyes and stage 1 of sleep (other stages of sleep were not investigated further here but will be studied in the next section). This process of non-supervised learning is more fully described in [8].

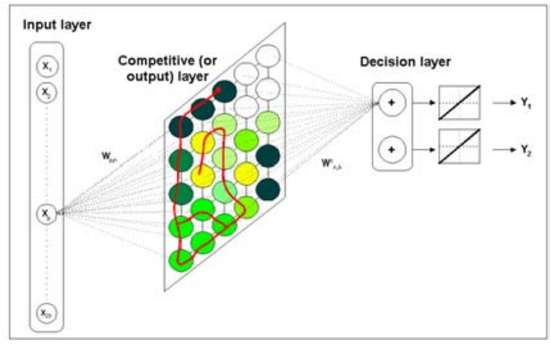

Figure 3: The SOM network (two layers on the left side) or LVQ (three layers) network

From this labelling, a supervised learning phase has been studied in order to discriminate two levels of vigilance, corresponding to alertness (gathering the former three levels above) and drowsiness (gathering the latter two levels). The corresponding network is described in Figure 3. The architecture of a LVQ network corresponds to that of a SOM, without lateral connections in the competitive map.

A decision layer (including here two neurons for the two classes to discriminate) is added to gather the neurons that have been labelled with the same label in the competitive layer. The LVQ supervised learning phase [9] consists in improving the position of the neurons in the input space, obtained by the competitive process during the non-supervised learning, with the help of the supervised corpus built by the expert.

Table 2 reports the classification results obtained with the four recorded subjects in intra- and inter-subjects conditions. In the table, some results are missing because some corpus are not big enough to give meaningful results.

If intra-subject performances are very good, inter-subject results remain very difficult to use from one subject to the other. We have also measured a global performance in another study, learning with the training corpus of all subjects and testing with the test corpus of all subjects and obtained a global 76.7% performance rate, which is much more satisfactory.

4. Stages of sleep classification using Multi-Layer-Perceptrons (MLP)

The second study is about stages of sleep classification. We have indicated in Table 1 the global relationship between domain of frequency of waves and stage of sleep but the exact matching is known as difficult to learn in the medical domain. For example, differentiating stage 3 and 4 is only a matter of distribution of delta waves along

time, on which human experts agree with a 95% confidence rate [10].
As we are not interested here in the topological relation between stages, we have chosen another neural network with supervised learning, known as one of the most efficient [11], the multi-layer perceptron.
We have recorded data during one night on two derivations (C3-A2 and C4-A1, cf figure 2) in a healthy patient and have selected over 1000 examples for learning, distributed in the 5 stages of sleep and the awake. The classical architecture of the multi-layer perceptron is represented in figure 4.

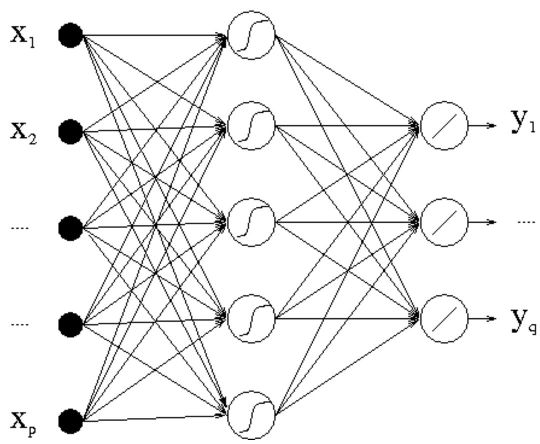

Figure 4: Architecture of a multi-layer perceptron with p inputs, one hidden layer and q outputs.

We have explained above that, in the case of stages of sleep analysis, five neurons representing five frequency bands related to cerebral waves have been selected to encode data.
Six neurons for the five stages of sleep and the awake are set in the output layer. After an experimental study [12], the hidden layer has been chosen composed of six neurons.
The corresponding best global performance is 76% recognition rate, obtained after a cross-validation process on ten randomly selected data sets. It is interesting to see in Table 3 that this average recognition rate corresponds in fact to an excellent recognition of four stages and a very bad performance on two stages, Stage 1 and Stage 3.

as →	**Awake**	**S1**	**S2**	**S3**	**S4**	**REM**	**Success**
Awake	**59**	0	0	0	5	3	**88%**
S1	11	**0**	17	0	2	24	0%
S2	3	1	**291**	0	21	31	**84%**
S3	0	0	39	**3**	52	13	3%
S4	1	0	9	2	**278**	2	**95%**
REM	7	0	16	0	6	**204**	**88%**

Table 3: Confusion matrix for sleep stages discrimination

We have explained above that it was very difficult, even for human experts, to discriminate stages 3 and 4. Similarly, stages 1, 2 and REM (Rapid Eye Movements) are very similar from a frequency distribution point of view. Moreover, stage 1 and stage 3 have a smaller number of examples than stage 2 and stage 4 which also contributes to some misclassifications.

4. Conclusion

The first goal of this paper was to assess the possibility to use Artificial Neural Networks to process, categorize and classify EEG data.
The preliminary results reported here are very encouraging in that direction. Tests reported here aimed at exploring a wide range of properties including several supervised neural networks (LVQ and MLP), several tasks (analysis of sleep and alertness) and several tests (mono- and multi-users).
The performances that we have obtained can be satisfactorily compared to the state of the art with other processing techniques, both in the case of alertness studies [13] and in the case of sleep analysis [14, 15, 16].
If these results confirm that Artificial Neural Networks are interesting tools for that kind of analysis, they also underline several weaknesses or problems on which to concentrate our efforts.
The first problem (which is not specific to neural networks but common to all techniques that learn from data) is the need to have large and well labelled corpus of data, which is a very difficult task. This is particularly important for multi-user systems.
The second problem is that of temporal processing. At the moment, our systems propose a classification on small windows of time (some seconds). Working with human experts clearly indicates that they sometimes decide not on the basis of only one window of time but on a more global analysis at different scales of time. We are consequently presently thinking of using a temporal architecture integrating these neural networks only as elements of decision.
The third problem is related to the statistical analysis made by neural networks. If human experts also rely mainly on the spectral distribution of the signal, they also sometimes use specific indicators (called graphical elements) or specific patterns in the signal to desambiguate some analysis. For example, this clearly appears in the case of sleep stages discrimination which, as reported above, is not always possible only on the basis of spectral analysis. For that reason, we are also exploring the possibility to integrate such hints with neural analysis.
While these observations give us new ways of research to explore, the results that we have reported here validate the principle of using neural networks for EEG signal interpretation and encourage us to continue interactions with medical experts to integrate more knowledge in the approach.

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		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	

Table 2: Intra- and inter-subjects performances (LSR*: Learning Success Rate; TSR**: Test Success Rate) with a LVQ network, in a alertness/drowsiness discrimination task. Some data are missing because not numerous enough to be statistically valid (cf. text for details)