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AUTOMATIC DETECTION OF SLEEP-WAKING STATES USING KOHONEN NEURAL NETWORKS.

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ABSTRACT

The present work describes the development and preliminary tests of a method for sleep-waking electrographic signal analysis and pattern recognition using self-organizing Kohonen's Artificial Neural Network (KNN) topology.

INTRODUCTION

In recent years, neural networks (NNs) have been proposed as useful tools for tackling analytical and classification problems in an increasingly high number of biological areas. (anesthesiology, EEG classification and wave-form detection, regional blood flow estimation, diagnosis, see, e.g. Bankman et al, 1992; de Azevedo, 1993; Garcia, 1992; Mamelak et al, 1991; Wu and Slater, 1993). The general advantages of NNs for biological signal processing include high tolerance in dealing with noisy, multimodal, incomplete and/or contradictory data, while extracting and recognizing patterns and intrinsic characters from complex interactive processes such as the biological ones. By far, the most promising biological field for NNs is neurobiology, particularly in processing brain generated electrical signals (Bankman, 1992; Klöppel, 1994a,b; Mamelak et al, 1991; Roberts and Tarassenko, 1992; Schaltenbrand et al, 1993). In fact, the benefits of such an interaction are not confined to biology. The development of NNs methods for complex, "real world", data (like electroencephalographic ones) are supposed to bring improvements to NNs performances with other kind of data (Klöppel, 1994a)

Electrographic sleep signals analysis takes into account a number of interacting phenomena, including electroencephalographic (EEG, electrical oscillations recorded at brain or scalp surface), electromiographic (EMG, electrical oscillations due to muscle activity), electrooculographic (EOG, electrical oscillations due to eyeball movements), and systemic/vegetative data, as arterial pressure, cardio-respiratory activity, metabolism and temperature. Sets and oscillations of all these attributes define a number of sleep-waking stages (or states), and can be used for research and diagnostic purposes for some sleep and mood disorders (Carskadon and Dement, 1988; Reimão, 1990; Timsit-Berthier, 1990).

The present work describes the development and preliminary tests of a method for sleep-waking electrographic signal analysis and pattern recognition

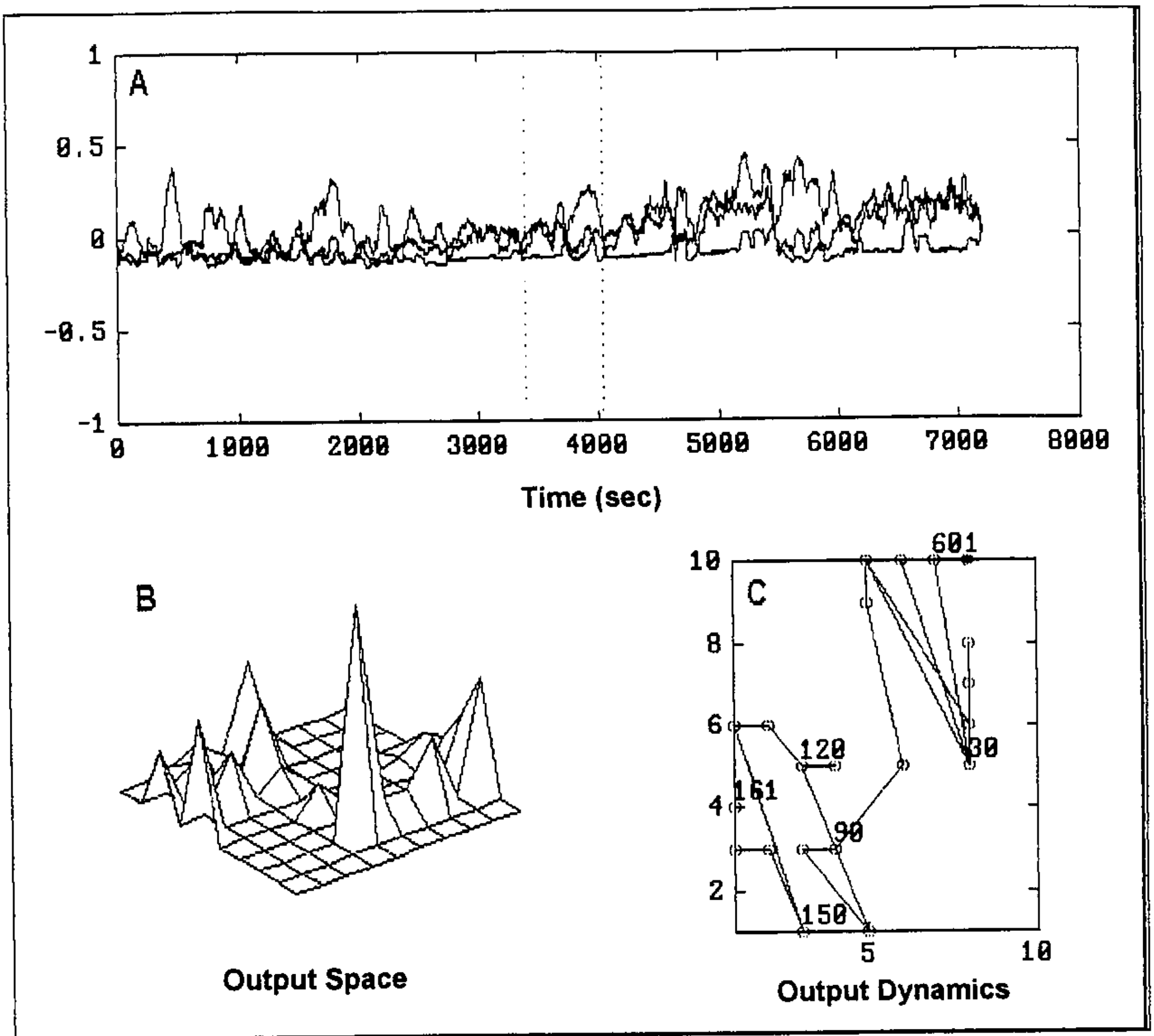

Figure 1 - KNN output space after training with electrographic data from the rat. (See text.)

using Kohonen's Artificial Neural Network (KNN) topology. The use of KNN in this study aims first at the automatic classification of the sleep-waking stages. These procedures are intended to abbreviate and to add accuracy to the laborious and time-consuming routine analysis tasks performed by EEG sleep experts in clinical and research activities. Furthermore, the present work is part of a research effort developed at our labs, designed to study the potential of NN methods for the automatic analysis of biopotentials of clinical relevance.

Most of the recent attempts in using of NNs for the above mentioned purposes employ topologies with supervised learning algorithms (Klöppel, 1994a,b; Mamelak et al, 1991; Schaltenbrand et al, 1993). Such an approach can bring about a number of problems in EEG analysis, including the existence of criteria disagreements among experts and different classifying rules for different abnormal sleep patterns. Roberts and Tarassenko (1992) have recently proposed the use of unsupervised learning algorithms to overcome these problems. Unfortunately, however these authors have employed Kalman filtering to extract the coefficients of the auto-regressive (AR) model of the signal, as input parameters to the KNN. Such parameters, however, are not familiar to the EEG or sleep expert. The use of frequency and amplitude components of the signals is more common in routine analysis, and could be more promptly realized by clinicians/researchers in sleep analysis. We employed here these more familiar signal features to examine their suitability for NN discriminative tasks.

METHODOLOGY

The method developed here is based on the analysis of the dynamics of parameters extracted from the bioelectrical potentials (EEG, EMG, EOG) related to the sleep-waking states in laboratory albino rats, chronically implanted with recording electrodes placed at frontal and occipital cortical surfaces (for EEG), neck muscles (for EMG) and periorbital bones (for EOG). These signals were continuously recorded from these unrestrained rats for as long as 8 hours, during the light phase of the day, so to record samples from most of the sleep-waking continuum.

The signals were first conditioned by a conventional polygraph (amplified and filtered – 2nd order Butterworth low-pass linear phase filter, 30 Hz cut-off frequency, and 0.3 sec time constant), digitized using a 12 bit analog to digital converter, sampled at 64 Hz and stored on an IBM compatible microcomputer hard disk for off-line processing. A software was specifically developed to control the calibration, acquisition and storage processes as well as the analytical procedures (Coimbra, 1994). The electrographic records were partitioned in 4-second epochs (time frames). From the raw data of each epoch 11 numerical parameters were extracted: powers of 4 EEG frequency bands (0.5-30.0, 0.5-4.0, 6.5-9.0, and 12.0-30.0 Hz) and centroid frequency of each channel, and the EMG integral. The time series corresponding to the sequence of values for each parameter was normalized and a 12th parameter was calculated as a linear combination of the other 11, so to form 12 element vectors with norm 1. These formed the input vectors for a self-organizing KNN array (10x10) of processing elements fully interconnected.

Training was performed through the standard Kohonen algorithm (Kohonen, 1984), with a set composed of the 2 first hours of the record. First the connection weights were setup random values. Afterwards, each input vector was randomly picked up from the 1800 vectors pool and fed into the KNN for the updating of the connections weights; this training procedure being repeatedly carried out. After the training phase some "patches" of variable durations were chosen from the records to evaluate the network behavior.

RESULTS & DISCUSSION

Figure 1.A depicts moving averages of only 3 of the 12 parameters measured along an 8-hour record: the EMG module integral, and the powers of 0.5-4.0 and 6.5-9.0 Hz of the frontal EEG. These, and the other 9 parameters, occurring at the time interval defined between the vertical dotted lines, were used in this example as input to the trained KNN, so to produce a 2-dimensional matrix (figure 1.B) illustrating the clusters (regions) of the output space of the KNN activated in that interval. Each of the mesh vertexes represents a processing unit, and the amplitude of each peak represents the unit activation frequency, at the period analyzed. Figure 1.C illustrates the output for the same recording period in a dynamic way indicating the sequence of transitions among the different clusters of output units. In both output space and sequence representations, at least three different clusters can be readily discriminated and temporally followed. These clusters closely correspond to the visually diagnosed states of waking, slow-wave sleep, and paradoxical sleep. These results indicate the suitability and sensibility of the KNN topology, the unsupervised algorithm and the parameters used for

training and classification tasks in discriminating among different sleep-waking states.

It is worth noting that the unsupervised nature of the training algorithm frees the method from any *a priori* (and thus possibly biased) information on these complex parameters sets, so it can also detect transitional and/or unusual association patterns. Handling these data in the sense of analyzing the KNN's feature map, one can also search for feature combinations associated to output events of this kind. Used in this way, such an approach can be employed not only as an automated state detector, but also as a tool for neurological and neurophysiological investigation, supporting the exploration and identification of novel dynamic characteristics of the sleep-waking cycle, and of other behavioral/physiological states where electrographic examination holds.

Additional experiments, using the present methodology, are being carried at our labs, assessing the behavior and suitability of different parameter sets for sleep-waking stage detection and in analysis of pharmacologically-induced changes in ongoing EEG. At present, however, it is reasonable to believe that further developments of self-organizing NN approaches would represent major improvements to the diagnosis and investigation in biological aspects of clinical relevance.

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