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Review of neural network applications in sleep research

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Abstract

To find a better automated sleep-wake staging system for human analyses of numerous polygraphic records is an interesting challenge in sleep research. Over the last few decades, many automated systems have been developed but none are universally applicable. Improvements in computer technology coupled with artificial neural networks based systems (connectionist models) are responsible for new data processing approaches. Despite extensive use of connectionist models in biological data processing, in the past, the field of sleep research appeared to have neglected this approach. Only a few sleep-wake staging systems based on neural network technology have been developed. This paper reviews the current use of artificial neural networks in sleep research. Following a brief presentation of neural network technology, each of the existing system is described and attention drawn to the heterogeneity of the different processing approaches in sleep research. The high performances observed with systems based on neural networks highlight the need to integrate these tools into the field of sleep research. © 1998 Elsevier Science B.V. All rights reserved.

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1. Introduction

Despite numerous studies dedicated to the sleep process (Hasan, 1985; Ruigt et al., 1989; Borbely and Achermann, 1992), its real function remains unknown. The establishment of an hypnogram from electrophysiological records (electroencephalogram 'EEG', electrooculogram 'EOG', electromyogram 'EMG',...) is a highly time-consuming part of sleep experiments and highly subjective. Over several decades, thanks to the development of microcomputer technologies, automated systems to build hypnograms have emerged, either based on classical algorithms (Gaillard and Tissot, 1973; Lim and Winters, 1980; Itowi et al., 1990; Witting et al., 1996), or artificial intelligence methods (Kumar, 1977; Ray et al., 1986). Neural networks (or connectionist models) are a new form of artificial intelligence techniques recently introduced to biological data processing (Gevins and Morgan, 1988; Kemsley et al., 1991; Leuthausser, 1991; Miller et al., 1992; Micheli-Tzanakou, 1995).

This article presents an overview of neural network technology and describes several neural network-based systems developed during the last decade to discriminate sleep-wake stages.

2. Artificial neural network technology

Artificial neural networks are computational tools composed of a large number of highly interconnected elementary processors (also named 'cells' or 'neurons'). Information is stored in each processor as intensities (also named 'weights') of its connections. The basic idea of connectionism is that global coherent behaviour can emerge from such organization. Though a wide variety of artificial neural network models exist, each can be completely defined by three characteristics:

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2.1. The transfer function of each cell

Each cell sums up the weighted inputs it receives from other cells and generates an output value (also referred to as the state of the cell) using a transfer function. This transfer function is usually a sigmoid or a binary function with the output value generally evolving between two limits (-1 and $+1$ or 0 and $+1$ for example).

2.2. The topology of the network

This characteristic relates to the network organization. Data are generally presented to the network through a set of input cells. After a processing phase, the result is available through a set of cells referred to as output cells. These cells interact with the external world but other cells with no direct interaction with the external world can exist (they are referred to as hidden cells). Each connection is characterized by its intensity (weight) and by the direction of propagation of the information.

An individual network is characterised by the numbers of cells and the connections between the cells.

The most employed model is the multilayer perceptron wherein cells are set in successive layers. The input layer is separated from the output layer by one (or more) hidden layer(s). Each layer is generally fully connected to its adjacent layer, information being processed from the input layer to the output layer.

2.3. The learning rule

To process data properly, the intensity of each connection is adjusted during a training phase which orients the global behaviour of the network toward the one expected by the operator. The learning rules applied during the training phase can be divided into two main classes; supervised and unsupervised learning rules. The unsupervised learning procedures strive to catch regularities in the input data. The supervised learning procedures require external intervention (performed by a 'teacher') to guide the training phase. The principle of supervised learning is to provide the network with a set of reference 'patterns' with which adequate weights are computed.

With the multilayer perceptron, the most frequently employed learning rule is the back propagation algorithm described by Rumelhart et al. (1986). This algorithm is based on the presentation by a teacher, to the network, of vectors (an input vector and the expected output vector). Information from the input layer is thus propagated down through the network to the output layer. After propagation, the quadratic error computed from the observed and expected outputs is used to modify the value of each weight in the network. When the learning phase is ended, the network is supposed to associate any input vector with an appropriate output vector.

Further details concerning artificial neural network computation can be found in Rumelhart et al. (1986), Hertz et al. (1991), Leuthausser (1991), Freeman and Skapura (1992).

3. Description of the neural network-based systems

The different systems are presented in chronological order and are referred to by the first author's name. The subject is specified in parentheses.

3.1. Principe's system (human sleep analysis)

Principe and Tome (1989) have developed a neural network-based system for discriminating sleep-wake stages in humans. The objective was to classify each 1 min epoch into one of the four following stages: awake, sleep stage 1/5, sleep stage 2 and sleep stage 3/4. Three EEG, one EOG and one EMG channels were used to detect amounts of alpha, beta, sigma, delta, rapid eye movements and EMG levels (six parameters used in this study). Each parameter was codified in four different levels (on 2 bits) according to its proportional appearance (0 for absence or short presence and 3 for the higher presence) during the minute period under consideration.

The input vector presented to the neural network was a 24-component vector: the duplicated 6 parameters $\times$ 2 bits. Three multilayer perceptrons were studied: a simple perceptron, a 1-hidden layer (3 cells) perceptron and a 2-hidden layer (5 and 3 cells) perceptron. Each output layer was composed of 4 cells and each network was fully connected. The learning rule was the classical backpropagation algorithm (Rumelhart et al. 1986).

Agreement between the output of classifiers and the expert visual analysis computed on records of five healthy subjects was similar and ranged from 78.8 to 96.9% (preference was given to the simple perceptron). In a second paper (Principe et al., 1993), using a second independent expert scorer, a 85.2% agreement rate was obtained between the output of simple perceptron classifier and the human consensus analysis..

3.2. Mamelak's system (cat sleep analysis)

The connectionist model which have been used by Mamelak et al. (1991) was dedicated to cat sleep stage analysis. Its aim was to discriminate four stages: wake, slow wave sleep (SWS), desynchronized sleep (D), and transition from SWS to D states. Each epoch was 15 s long. Classifier was a simple perceptron. The bioelectrical information was composed of delta wave activity, sigma wave activity, nuchal muscle activity, bilateral EOG and bilateral ponto-geniculo-occipital (PGO) waves.

The input pattern was made up by converting each of the numbers of wave band counts into its binary equivalent (5 units representing delta, spindle, PGO and movement counts; 7 units for EMG amplitude). The 32-input cells of the network were fully connected to the 3-output cells. The learning rule used to train the network was the one presented by Rumelhart et al. (1986).

Reliability of this system was evaluated on six records from healthy and treated animals (with Carbachol or Eltoprazine) and by two independent expert scorers. High correlations between human and neural network assignments were observed (93.8% for healthy animal records and 92.7% for treated animal records).

3.3. Pfurtscheller's system (baby sleep analysis)

Sleep classification in babies was the objective of the neural network-based system designed by Pfurtscheller et al. (1992). Each epoch was 30 s long. Six classes were defined: movements, awake, REM (Rapid Eye Movements) sleep and sleep stages 1, 2 and 3/4; in addition, technical artifacts could be identified. Input data presented to the network were the fifteen values obtained from respiratory variabilities, from nasal and thoracal signals, EEG (1–4 Hz power of C_z-A_1 derivation), EOG, heartrate and heartrate variability, Hjorth parameters (3 for each derivation) from EEG 1 (C_z-A_1) and EEG 2 (O_z-A_1) (these parameters are detailed in Hjorth (1970)), actograms of left and right hands and EMG level.

Two types of neural networks were tested: a multilayer perceptron (15 – or 2×15 – input cells, 10-hidden cells and 6-output cells) and a Kohonen model (Kohonen, 1990) combined with a linear vector quantizer (LVQ). The classical backpropagation algorithm (Rumelhart et al. 1986) was used to train the multilayer classifier. The LVQ classifier was initialized with reference vectors.

Tested on four baby records and using different configurations (multilayer perceptrons with 8 or 15 input cells, 4 to 7 output classes for the LVQ classifier), outputs of the two classifiers were in agreement (ranging from 64 to 80%) when compared with the outputs of two expert raters. In a second paper (Kubat et al. 1994), the performance of the Kohonen LVQ classifier was detailed class by class.

3.4. Roberts' system (human sleep analysis)

Roberts' system (Roberts and Tarassenko, 1992) was dedicated to human sleep analysis. Six sleep classes were defined: wakefulness, REM sleep and sleep stages 1, 2, 3 and 4. The parameters extracted from one digitized (sampling rate: 128 Hz) EEG derivation (C_4-A_1) were the ten first coefficients of the Kalman filter. Each input vector was a set of ten coefficients composed of the averaged 128-consecutive sets of coefficients representing a 1-s period.

The neural network was a Kohonen model (Kohonen, 1990) the aim of which was to converge to an ordered output. An average of thirty-one second vectors processed by the connectionist classifier produced a half-minute resolution hypnogram. The EMG signal was used to refine Kohonen model discrimination between light sleep and REM sleep states.

In a second paper (Roberts and Tarassenko, 1995), an application to disturbed sleep records was presented and the ability of their system to detect micro-events (arousal) was studied.

3.5. Schaltenbrand's system (human sleep analysis)

The system developed by Schaltenbrand et al. (1993) was dedicated to human sleep analysis. Seven classes were defined: movements, awake, REM sleep and sleep stages 1, 2, 3 and 4. The different signals (2 EEG, 1 EOG and 1 EMG channels) were segmented into 2 s intervals. Each 30 s epoch was characterized by 17 parameters (which are the 17 components of the input vector) obtained by averaging 15 consecutive estimates. These estimates were: EEG relative power in the different bands – delta (0–4 Hz), theta (4–8 Hz), Alpha (8–13 Hz), Beta1 (13–22 Hz), Beta2 (22–35 Hz); total power of the EEG (0–35 Hz); ratio of powers delta/theta; ratio of powers alpha/theta; mean frequency and dispersion of EEG spectral density; EOG relative power in the band (0–4 Hz); total power of EOG spectral density; mean frequency and dispersion of EOG spectral density; total power of EMG spectral density; mean frequency and dispersion of EMG spectral density.

The neural network model used was a multilayer perceptron trained with the classical backpropagation algorithm (Rumelhart et al., 1986). The input layer (17 cells) was fully connected to the hidden layer (10 cells) which was fully connected to the output layer (6 cells).

Using 11 all-night recordings, agreement between neural network results and the consensus of ten human experts reached 80.6%. In a second study (Schaltenbrand et al., 1996), the performance of the multilayer perceptron was tested on 20 healthy subject records and on 40 patient records (20 depressive patients and 20 insomniac patients treated with a benzodiazepine). Agreement between one visual scorer and the connectionist classification was 84.5% for healthy subject records, 81.5% for depressive and 81.0% for insomniac patient records.

3.6. Grözinger's system (human sleep analysis)

Grözinger et al. (1995) have developed neural networks for detecting REM sleep periods in human sleep using a single EEG channel. The EEG was segmented into 20 s epochs. The digitized signal was filtered into six frequency bands (0.5–3.5, 3.5–7.5, 7.5–15, 15–35, 35–45 and 0.5–45 Hz) by Fourier transformation, deletion of the corresponding coefficients and retransformation. The Root Mean Square value of each retransformed signal was computed. The input vector was composed of the six values previously computed.

The topology of the connectionist classifier elaborated by this group was an input layer (6 cells), a hidden layer (4 cells) and one output cell. The network was fully connected including connections between input and output cells and was trained with the classical backpropagation algorithm (Rumelhart et al., 1986).

This system was able to discriminate REM from NREM (Non Rapid Eye Movement) sleep periods with 89% accuracy (the evaluation was performed using two expert analysis of 13 healthy volunteer recordings). In a second paper (Grözinger and Röschke, 1996), reliability of this system was tested on eleven depressive patient recordings (five without medication and six treated with amitriptyline). When the network was compared with the two human experts, the percentage of misclassified periods ranged from 7 to 11.1% for NREM sleep and from 34.4 to 59.6% for REM periods.

3.7. Robert's system (rat sleep analysis)

The system elaborated by Robert et al. (1996) was devoted to the discrimination of three states of vigilance (wake, NREM and REM sleep) in the rat from a single EEG channel. After analog filtering (bandwidth: 3.18–25 Hz), the EEG signal was digitized and for each 8 s epoch, the following five parameters were computed:

- the standard deviation of the sampled EEG;
- the third order moment of the EEG amplitude histogram (Skewness);
- the fourth order moment of the EEG amplitude histogram (Kurtosis);
- the number of relative minima and maxima detected in the digitized EEG and
- the number of zero-crossings detected in the EEG signal.

Data from these five parameters were presented to the network.

Two multilayer perceptrons were tested. First was an input layer (5 cells) fully connected to a hidden layer (2 cells), fully connected to an output layer (3 cells). In the second one, five parameters of the epoch under interest were added to the five parameters of each adjacent epoch and presented to an input layer (15 cells) fully connected to a hidden layer (5 cells), and connected to an output layer (3 cells). The backpropagation algorithm described by Rumelhart et al. (1986) was performed to train each network.

Using six 24-h recordings, agreement between the output of each classifier and the consensus of two human experts was above 94%. Preference was given to the network that integrated contextual information (the second model described). A post-processing procedure was proposed to enhance REM sleep discrimination.

4. Discussion

The different neural network-based systems introduced in this review are, to our knowledge, the first connectionist applications dedicated to sleep scoring.

The features extracted from the bioelectrical signals to establish hypnograms varied from one group to another. For example, the feature extraction carried out by Schaltenbrand et al. (1993) was based on the frequency domain of various bioelectrical signals (see Section 3.5 – Schaltenbrand's system) while the data preprocessing performed by Roberts and Tarassenko (1992) relied on analysis in the time domain of a single EEG channel (see Section 3.4 – Roberts' system). This diversity is also observed in non connectionist sleep staging system reviews (Hasan, 1985; Ruigt et al., 1989). Feature extraction is an important stage in development of any sleep-wake staging system and is an interesting 'delicate' subject of investigation. We shall assume that the feature extraction procedure used by each group was optimal and focus our attention on the neural network processing.

Rigorous comparisons between all the systems introduced in this paper can hardly be carried out since the studies reported differed in recording conditions, data preprocessing and validation procedures. However, many similarities can be noticed.

Indeed, the connectionist systems tested in the majority of the works described in this review were multilayer neural networks. This approach is characteristic of the great majority of models (in comparison with other connectionist models) used in the field of biological data processing (Kemsley et al., 1991; Leuthausser, 1991; Miller et al., 1992; Micheli-Tzanakou, 1995). Another important similarity is the difficulty encountered by Schaltenbrand et al. (1993) and Pfurtscheller et al. (1992) in discriminating sleep stages 3 from sleep stage 4 in human. Since one notices that Principe and Tome (1989) grouped sleep stages 3 and 4 into a single class and Grözinger et al. (1995) recognized only one non-REM sleep class, this point would seem critical in the development of future human sleep-staging systems.

The reliability of the various systems described varied from one to another. The fully automated system aimed at building human hypnograms presented by Roberts and Tarassenko (1992) seemed highly attractive but detailed results were not available. According to the authors, the systems developed by Pfurtscheller et al. (1992) aimed at discriminating sleep-wake stages in babies was highly sensitive to training set selection and in the quality of the physiological information processed (Kubat et al., 1994). This sensitivity induced high but heterogeneous performances. Taking into account the fact that the maturation process of the brain, during the first year of life is highly present and strongly influenced sleep scoring, the first results are full of promise. The systems elaborated by Principe and Tome (1989), Mamelak et al. (1991), Schaltenbrand et al. (1993), Grözinger et al. (1995) and Robert et al. (1996) can be considered as reliable tools, since their validation was carried out on several subject records using several human scorer experts, more than 85% of correct recognition was obtained.

Improvements provided by connectionist classifiers in comparison with other systems can be assessed when comparing neural network-based system performances with those of other classification methods. Principe et al. (1993) were convinced that the performances of the expert system was more robust than their connectionist classifier but believed that their neural network system attained the best compromise between simplicity and performance accuracy. Schaltenbrand et al. (1993) compared their connectionist system with conventional classifiers (Bayesian and k-nearest neighbour) and also gave preference to their neural network system for its robustness. Upon analysis of data which were not part of the training set, Grözinger et al. (1994) found superiority in their neural network classifier over a classical non parametric discriminant analysis. The comparison between their connectionist and several conventional (Bayesian, Euclidean and linear) classifiers led Robert et al. (1997) to choose their connectionist classifier for its higher global accuracy and also for its accuracy to discriminate REM sleep state. Preprocessed data are characterized by a certain degree of variability due to the biological phenomena generating the recorded signals (EEG, EMG,...). The ability of neural networks to correctly process such noisy or new data (meaning that these data are not used during the training phase) is one of the major properties associated with connectionist processing (Hertz et al., 1991; Freeman and Skapura, 1992). This is the main advantage of neural networks over conventional classifiers (Grözinger et al., 1994; Robert et al., 1997).

Another good property of neural networks is their fault tolerance which is of importance in sleep research experimentation where undesirable events (disruption in the electric device for example) can partially impede the recording phase and blur the data to be processed. Robustness of neural network processing makes this tool most attractive when elaborating a sleep-wake staging system.

The investigation of Pfurtscheller et al. (1992) was the only one of seven studies introduced in this review in which two types of connectionist classifiers (multilayer perceptron and Kohonen model) were compared. The performances were similar but a slight preference was given to Kohonen model due to its rapidity of computation. While the multilayer perceptron was the most commonly employed model, other connectionist systems (such as Kohonen or Hopfield model for example) must not be neglected.

Most of the systems presented here needed a supervised training phase and worked on a subject-to-subject basis (Principe and Tome, 1989; Mamelak et al., 1991; Pfurtscheller et al., 1992; Robert et al., 1996), meaning that a particular set of weights must be computed to analyse each subject record. The ability to construct a neural network-based classifier with a limited number of examples leads to a sensitive reduction in operator time when establishing hypnograms. Nevertheless, intervention of a human operator was still necessary.

Another point of interest is the behaviour of a connectionist classifier when it processes limited extracts of data from patient records. While no impairment of the artificial neural network classifier was observed by Mamelak et al. (1991), Grözinger et al. (1995) and Schaltenbrand et al. (1996) reported the need to alter their system. Although the systems developed by Roberts and Tarassenko (1992), Grözinger et al. (1995) and Robert et al. (1996) mainly relied on a single EEG channel to establish an hypnogram, these systems are limited in that they can not be used in protocols which induce dissociation between EEG patterns and the behaviour of the subject. Nevertheless, initial applications of these systems should give interesting information about their behaviour under experimental conditions.

Moreover, most of the sleep-wake stage classifiers developed were aimed at processing data recorded from subjects with an abnormal sleep pattern. In such a context, the validity of hypotheses established from standard data (data coming from normal subjects) to build rule-based or statistical classifiers is uncertain and reconsideration of these hypotheses is often required. Connectionist classifiers are assumption-free about data distribution and this property confers on these tools an attractive advantage in the field of sleep research when choosing a method of data classification.

Because of the particularities of each system, detailed comparisons between connectionist and non connectionist systems are not easily performed. Nevertheless, the various neural network-based systems reviewed were as efficient as non connectionist systems developed by other groups (Gaillard and Tissot, 1973; Smith et al., 1978; Ray et al., 1986; Itowi et al., 1990; Witting et al., 1996). Furthermore, performances of connectionist classifiers were often similar to those of experts (Mamelak et al., 1991; Robert et al., 1996; Schaltenbrand et al., 1996).

Most of the non connectionist systems previously developed in sleep research were well controlled (Itowi et al., 1990; Witting et al., 1996), in that the function of each component of the method used can be easily detailed and justified. Conversely, the connectionist approach is singularized by the fact that one can hardly explain and justify the mechanism which generates a particular set of weights. Neural networks are generally regarded as black boxes. This characteristic is sometimes considered a drawback and put forward to restrain their utilization as a clinical diagnosis support, but results obtained with the connectionist systems (Kemsley et al., 1991; Miller et al., 1992; Itchhaporia et al., 1996) justify their use.

In conclusion, the qualities of artificial neural networks make them highly suitable tools for sleep-wake stage analysis. Promising first results reviewed in this paper and further development of neural network technology should lead to an interesting and fruitful future for this association.

Objectivity was the principal guideline employed in this review.

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