Expert-system classification of sleep/waking states in infants

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Abstract—*This work is part of a project to develop an expert system for automated classification of the sleep/waking states in human infants; i.e. active or rapid-eye-movement sleep (REM), quiet or non-REM sleep (NREM), including its four stages, indeterminate sleep (IS) and wakefulness (WA). A model to identify these states, introducing an objective formalisation in terms of the state variables characterising the recorded patterns, is presented. The following digitally recorded physiological events are taken into account to classify the sleep/waking states: predominant background activity and the existence of sleep spindles in the electro-encephalogram; existence of rapid eye movements in the electro-oculogram; and chin muscle tone in the electromyogram. Methods to detect several of these parameters are described. An expert system based on artificial ganglionar lattices is used to classify the sleep/waking states, on an off-line minute-by-minute basis. Algorithms to detect patterns automatically and an expert system to recognise sleep/waking states are introduced, and several adjustments and tests using various real patients are carried out. Results show an overall performance of 96.4% agreement with the expert on validation data without artefacts, and 84.9% agreement on validation data with artefacts. Moreover, results show a significant improvement in the classification agreement due to the application of the expert system, and a discussion is carried out to justify the difficulties of matching the expert's criteria for the interpretation of characterising patterns.*

Keywords—*Sleep/waking states, Expert system, Sleep/waking classification, Fuzzy sets, Ganglionar lattices*

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1 Introduction

COMMON KNOWLEDGE allows a naïve distinction between a person being awake or asleep. However, sleep is not a unique state. In healthy subjects, two distinct sleep states exist that occur naturally and recur periodically in a predictable manner. Through the ages, these states have been found to serve different purposes in human physiology (RECHTSCHAFFEN and KALES, 1968; CARSKADON and DEMENT, 1989; GUILLEMINAULT, 1998).

Sleep/waking states are classified as wakefulness (WA); active or rapid eye movement sleep (REM), and quiet or non-REM sleep (NREM), as shown in Table 1. In turn, NREM is subdivided into four distinct stages. These states and stages are defined by the concordance of overtly expressed behavioural criteria and electronically recorded electrophysiological parameters, using a 1 min time frame. In the electroencephalogram (EEG), the background predominance of alpha (8–12 Hz), theta (3–7 Hz), and/or slow or fast delta (0.2–3.0 Hz) activity, and the presence or absence of sigma (12–14 Hz) spindles are measured. Other signals are also obtained, such as the presence or absence of rapid eye movement (REM) in the electro-oculogram (EOG), and presence or absence of chin muscle tone in the electromyogram (EMG) (RECHTSCHAFFEN and KALES, 1968; CARSKADON and DEMENT, 1989; GUILLEMINAULT, 1998). All signals are obtained simultaneously through long-term polysomnographic recordings.

The states included in Table 1 can be called 'well-defined' sleep/waking states. However, during early human central nervous system development, the sleep patterns expressed both in physiological signals and behaviour are not yet fully characterised, as in adults. For instance, there are no characteristic alpha waves in the waking EEG activity during closed-eye resting, and, besides, several sleep episodes lasting at least 1 min do not fit into any of the sleep/waking states described in

Table 1 Coarse characterisation of sleep/waking states based on signal patterns found in EEG, EOG and EMG activities. EEG during WA usually has many artefacts

State	WA	NREM	REM
1: EEG: predominant background activity:	fast waves	delta waves, sleep spindles	theta waves
2: EOG:	eye movements	absence of REMs	REMs
3: EMG activity:	tonicity	unspecified	no tonicity

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adults. This indicates that either a long transition between states occurs, or that a less robust coalescence among variables exists within a given state, thus introducing indeterminate sleep (IS) (ANDERS *et al.*, 1971; CURZI-DASCALOVA *et al.*, 1988; CURZI-DASCALOVA and MIRMIRAN, 1996; CURZI-DASCALOVA and CHALLAMEL, 0000). This pseudo-state is present whenever a combination of patterns does not fulfil the conditions of any other state, for at least 1 min. The presence of IS is normal in healthy infants; it diminishes with age (CURZI-DASCALOVA *et al.*, 1988) and increases in pathological conditions (PEIRANO *et al.*, 1989; 1990).

Infants younger than four months are not included in this study: although the sleep spindles appear in normal infants at about six weeks of post-term age, other elements required to classify the NREM stages are not well established until that age (FAGIOLI *et al.*, 1995; PEIRANO *et al.*, 1989; 1990; 1993; BES *et al.*, 1994).

Visual evaluation of long-term polysomnographic recordings requires well-trained personnel and is extremely time-consuming; thus it is an expensive procedure. Furthermore, after an intense and highly focused concentration period, it could become less accurate. To facilitate the classification of these states, it is convenient to have an expert system (ES) capable of identifying the sleep/waking states, based on invariant and objective criteria. Furthermore, the automated procedure noticeably decreases the global cost of such a task. The need for an automated system for analysis and classification of sleep states has been recognised by different authors (COLLURA *et al.*, 1993; HARPER *et al.*, 1987; PARK *et al.*, 1990; SMITH, 1986; BESSET, 1998; TAFTI, 1998). Different approaches have been attempted. BANKMAN *et al.* (1992) presented a procedure considering only cardio-respiratory signals. Experimental automated sleep analysis systems in rats were described in RONCAGLIOLO and VIVALDI (1991) and VIVALDI *et al.* (1984). In a different approach, JANSEN and DAWANT (1989) introduced the use of an ES to analyse EEG signals based on numerical routines and symbolic information. It describes a detailed application in a few cases (feasibility study), suggesting a rather complex solution.

2 Methodological basis

The classification of sleep states is divided into two stages:

(*a*) detecting specific patterns in the EEG, EOG and EMG signals of digital polysomnographic recordings

(*b*) identifying the corresponding sleep/waking state using the temporal concordance of these basic patterns and other criteria, lasting at least a minute.

2.1 *Patterns to recognise sleep/waking states*

The raw data are taken from digital polysomnographic recordings obtained in normal infants during their naturally occurring naps, under spontaneous (non-induced) sleep/waking cycles, usually spanning about 3–4 h. These recordings were performed at the Sleep Laboratory of the Instituto de Nutrición y Tecnología de Alimentos (INTA) of Universidad de Chile. The data are stored in magnetic or laser media by multiplexing digitised signals of EEG, EOG and EMG and other activities at 250 samples s^{-1}. The patterns for sleep/waking state classification are searched in a moving window spanning 1 min of data.

The data acquisition operation is complex. Usually the infant sleeps on his/her mother's lap. The monitored signals have low power and cannot be isolated from physiological and ambient noise. Body movements of the infant and the mother add to the signal noise. Artefacts including movement signals and any other interfering signals such as EEG presence in the EOG channel, are present in the polysomnographic recording.

Not all data available in recordings obtained from infants at INTA are useful: a significant number of these had to be discarded or only partially used, either because the recording was faulty, the scales to apply to the data were missing, or the expert classification was incomplete. A case typical of this last point was that, in some recordings, the EEG predominant background activity was characterised either as theta or delta, but not as slow delta. The useful data were divided to have tuning, testing and validation data sets.

2.1.1 *Preprocessing:* The EEG and EOG channels are smoothed by a 15 Hz lowpass filter to simulate the needle recording limitations on the polygraph, which correspond to the information available to the human expert during visual evaluation. The significant frequency band in the EMG is 30–50 Hz; therefore a 10th-order Yulewalk 100 Hz lowpass filter is used to reduce noise.

2.1.2 *EEG detection of background activity and sleep spindles:* The EEG provides a considerably noisy signal that is analysed to find the predominant background activity and to detect sleep spindles. Each of these steps is described here in a more detailed way. The EEG recording comprises five bipolar derivations (FP1-C3, C3-O1, FP2-C4, C4-O2 and C3-C4). According to expert knowledge, the posterior derivations (C-O) are preferred for background activity, and the anterior derivations (FP-C) are preferred for sleep-spindle detection.

The predominant background activity refers to the predominant frequency present in the EEG spectrum. For the purpose of this study, the frequency ranges of interest are the slow delta and the theta bands. Several signal analysis techniques were tested to model the expert classification criteria. A zero-crossing detection strategy gave the best results to detect slow-delta predominance, and a fast Fourier transform (FFT) was better to detect theta predominance in each successive temporal window. The size of the temporal window is one page (corresponding to the expert analysis on paper register) and lasts 30 s or 20 s, depending on the register protocol.

A slow delta wave is defined by frequencies up to 2 Hz and, in addition, a peak-to-peak amplitude of at least 75 μV. The baseline is obtained as the average of all samples in the page. Consecutive zero-crossings define the period and thus the wave frequency. Slow delta wave predominance was initially established whenever it existed in at least 20% of the page. However, to enhance the agreement with the expert classification, experimental results later raised the threshold to 38% of slow delta wave presence to establish predominance. Body movements can cause false slow delta waves in the EEG channels, particularly in WA. To avoid these, the power of the body movement in the strongest channel of the two available in the polysomnographic recording is monitored simultaneously, and slow delta wave detection is suspended if the body movement power surpasses a given threshold, empirically determined.

Theta waves lie in the frequency range of 3–7 Hz. To detect these, a relative power index is calculated from the fast fourier transform (FFT) of the EEG signal, to obtain the amount of power within the window of 3–7 Hz with respect to the total power. After the computation of this index for the whole recording, two thresholds were determined: one to detect the presence of theta activity, depending on relative power amplitudes, and another to assert theta wave predominance within a page, which depends on time. The 'presence' threshold is expressed as a percentage between the highest and lowest

physiological relative theta power index obtained, and was set at 38% in this work. The 'predominance' of theta waves was established whenever the 'presence' would surpass a threshold of 30% in a page.

A sleep spindle is a sequence of fast (sigma) EEG waves lasting more than 0.5 s and with a magnitude above 10 μV. In normal adults, sigma activity lies within the range 12–14 Hz. However, in infants, a range of 10–15 Hz is considered adequate (LOUIS *et al.*, 1992). The sleep spindles are usually mounted on other slower waves with larger amplitudes in the EEG, which make inadequate the previous signal-analysis methods. The procedure to determine the presence of sleep spindles is decomposed into the following steps:

(i) To verify whether there is a 10–15 Hz wave, the instantaneous slope of the signal is monitored. The slope is determined by obtaining a straight line adjusted by the least square error method using five consecutive samples. A sign change in this slope identifies a peak. The current period is given by the time elapsed between three consecutive sign changes in the slope (i.e. two consecutive peaks of the same sign).

(ii) sigma wave sequence has peak-to-peak magnitudes higher than 10 μV and shows at least limited symmetry, given by a rise to decay time ratio within 0.2–5.0.

(iii) A sleep spindle occurs whenever a sigma wave sequence lasts at least 0.5 s.

2.1.3 *Detection of REMs in the EOG:* The EOG is a single-channel signal that shows the small potential difference between the front and the back of the eye (the cornea is positive with respect to the retina). As the eye moves, the position of the cornea and the retina change relative to the fixed position of the electrodes, and the corresponding change in potential is registered. Thus the EOG activity is inspected to detect REM patterns, which are isolated pulses in the EOG, occurring within a duration range and exceeding thresholds of amplitude and power, as specified in the following criteria:

(*a*) The baseline is obtained using the same technique in this EOG channel as for the slow-delta waves in the EEG. Two consecutive zero-crossings determine the pulse duration, and the pulse amplitude is given by the maximum difference between samples in this interval and the baseline.

(*b*) An REM pulse candidate is acceptable if it lies between 0.06 and 0.5 s.

(*c*) REM signals are not periodic, but interfering periodic signals from other sources can show in the EOG and must be identified and eliminated. To eliminate trains of pulses, two parameters that consider the amplitude and the energy of the signal are defined. The duration and amplitude of five consecutive REM pulse candidates are held in a moving window. As the pulses are defined by the zero-crossings, consecutive pulses have alternate signs. In each analysis, the three pulses of the same sign are considered, i.e. pulses 1 (left), 3 (centre) and 5 (right). The REM pulse candidate is pulse 3 in the array.

(*d*) The amplitude parameter is calculated as

$$REM - Pa = 2^{*}AMP_c/(Ka + AMP_l + AMP_r)$$

where AMP_c is the amplitude of the central lobe (REM candidate), Ka is a non-zero constant to avoid divisions by zero, AMP_l is the amplitude of the lobe to the left, and AMP_r is the amplitude of the lobe to the right of the central lobe (with the same sign). Thus an REM signal will have a high *REM-Pa* value.

(*e*) The energy contained in the signal window is considered in the energy parameter

$$REM - Pe = (RMS_l + RMS_c + RMS_r)/(Ke + RMS_l + RMS_r)$$

$REM - Pe$ combines the RMS value of the central window containing the REM candidate (RMS_c) and the RMS values of equal-width windows to the left and right side of it. Windows of 1 s duration are considered.

(*f*) After the computation of *REM-Pa*, *REM-Pe* and their product ($REM - Pa^{*}REM - Pe$) is complete for the whole recording, a second run is performed to determine physiological maximum and minimum values of the product.

(*g*) Thus, any REM candidate is eliminated whenever the product ($REM - Pa^{*}REM - Pe$) does not surpass a fixed threshold. In this work, the threshold was set to 50%, including pages with saturations, which optimised the agreement with the expert.

(*h*) False REM pulses can appear on the EOG recording owing to EEG activity or to artefacts seen as saturations on the EEG. The EEG electrode output closest to the EOG electrode is analysed, in a 1 s window corresponding to an REM candidate (peak value), and further REM candidates are eliminated if

- over 40% of EEG samples are saturations
- or the RMS of the EEG surpasses a specified threshold (set to 40% in this work, including pages with saturations).

2.1.4 *Detection of chin muscle tone in the EMG:* The EMG algorithm detects differences in the tonic chin EMG activity measuring the mean square value of the signal. The log function is used to compress the dynamic range of the samples. The window considered for the computation is relatively small, i.e. 128 samples (about 0.5 s). The algorithm to detect EMG activity is as follows:

(i) A baseline is determined by computing $BL = \exp((1/N)\sum \log(x_i))$, where x_i are the samples of the EMG signal, and N is the number of samples within the window.

(ii) The logarithm of the mean square value (LMSV) is calculated as

$$LMSV = \log(\sum(x_i - BL)^2)100/N$$

(iii) After the computation of $LMSV$ is complete for the whole recording, a second run is performed to determine the maximum $LMSV_M$ and minimum $LMSV_m$ values.

(iv) The threshold to validate muscle tone presence is set as a percentage of the difference $LMSV_M - LMSV_m$, such that it optimises the agreement with the expert. In this work, the percentage was fixed at 30%.

2.2 *Further criteria for classifying sleep/waking states*

The time frame for an 'observation window' is given by the usual procedure established by experts, i.e. making a visual assessment of each page of recording, which is typically 0.5 min long. However, the minimum time frame to establish a sleep/waking state is given by a window defined as 1 min long, equivalent to two consecutive observation windows or two pages. This is another significant consideration for adequate classifier performance, as some of the patterns appear only sporadically. For example, REMs or sleep spindles can be left out of a shorter window, but included in a window with a 1 min span. Therefore the use of shorter periods of time for classification would cause an incremental loss of temporal

concordance of patterns that define a certain state, thus introducing a higher incidence of IS.

The outputs of the pattern-acquisition algorithm section of the sleep/waking state classification system are presented as the amount of time where each characteristic activity was present in each window. The algorithms determine a value in the [0.0, 1.0] interval for each of five patterns: slow-delta waves, theta waves, sleep spindles, REM and muscle tone. Thresholds to define which signals correspond to the sought activity patterns are adjusted by training the detection system.

For the purpose of classifying states, the values corresponding to sleep spindle and REM detection are modified, taking their episodic nature into account. Usually, more than a single episode occurs in a time window when they appear. However, one such event suffices to establish a state, as follows:

(*a*) The occurrence of a single sleep spindle in a 5 min time frame is enough to assert its presence (GUILLEMINAULT and SOUQUET, 1979).

(*b*) A single REM episode asserts REM presence for an REM state classification purpose (CROWELL *et al.*, 1997). In the normalised scale used, zero means absent, and 1 means 100% (total assurance) presence. Hence, the REM time presence value is modified for the pattern acquisition output using the following equation, which shows a huge increase as a function of REM presence:

$$REMs' = 1 - \exp(-a^* REMs)$$

where $REMs'$ is the modified REMs value and a is a correction factor obtained during the training phase.

2.3 *Model for sleep/waking states*

A model of the different sleep/waking states and stages is presented here, focusing on the characteristics to differentiate these and therefore help in their identification. This model further describes the possible time sequences among the sleep/waking states and stages. For the purpose of this research, NREM stages 3 and 4 have been unified, as shown in Table 2. Indeed, NREM stages 3 and 4 are usually pooled together and classified as 'slow-wave' sleep within NREM sleep.

The model is conceived as a state variable automaton consisting of the above mentioned states and the allowed transitions, as shown in Fig. 1. An infant will always be in one of the described states, including IS. As time progresses, he or she can stay in the same state, i.e. a transition to the same state, or change to any other allowed. To avoid an overcrowded representation of sleep/waking states, the transitions to the same state have been purposely left out of the diagram. Besides, as IS is a pseudo-state, it does not belong in the model.

In an infant's sleep physiology, an IS episode can appear in any transition between two states, or between two episodes of the same state (CURZI-DASCALOVA and MIRMIRAN, 1996). State transitions occur naturally, or are endogenously determined (JOUVET, 1994). Note that NREM 1 can also be considered as a transition; in fact, several researchers consider the onset of a sleep episode only from the beginning of the first NREM 2 stage appearance. However, it is not classified as IS, because it is a relevant stage to describe both physiological and pathological events occurring just at the onset of a sleep episode (or at the waking–sleep transition).

The duration of WA is paramount to establish the transitions as described. After a sustained WA period, the sleep will normally progress as stated in the model, i.e. NREM 1 is a natural step stage when a completely awake infant is falling asleep. However, if the WA is a short agitation episode in the middle of sleep, other transitions can occur. In fact, in the latter case, it is possible to observe a transition directly from WA to REM.

Physiological sleep–waking transitions are age-dependent. In infants up to 2–3 months of age, direct transitions from WA to IS clearly predominate (we do not show them in Fig. 1, because our main focus is on infants from four months onward). Later on, they reach the adult pattern of progressing first from WA to NREM through NREM 1, and then to the other NREM stages. Nevertheless, in some cases, they can proceed directly from WA to NREM 2. During a sleep episode, transitions between NREM and REM normally occur either from NREM 2 or NREM 3 + 4; in contrast, the transition from REM to NREM-3 + 4 is forbidden (GUILLEMINAULT and SOUQUET, 1979).

ble 2 Criteria concordance for sleep/waking state classification in infants, according to expert classification

State/stage	WA	NREM 1	NREM 2	NREM 3 + 4	REM
EEG: slow delta	absent	absent	absent	present	X
EEG: theta	X	present	X	absent	present
Sleep spindles	absent	absent	present‡	X	absent
REM	present	absent	absent	absent	present
MT	present	X	X	X	absent
Other	artefacts*	from WA†		from NREM 2**	

X = Irrelevant

*Artefacts: fast waves (fast theta or sub-alpha: 6–8 Hz) and artefacts (caused mainly by movements, crying, fighting, being fed etc.) are present in WA

†From WA: NREM 1 is defined as necessary transition from WA to other, deeper stages of NREM. Exceptions can occur, with short WA episodes emerging in an extended sleep period, where state can step directly to other sleep states

‡Sleep spindles must be present for onset of NREM 2 stage, but can be absent up to maximum of 5 min (GUILLEMINAULT and SOUQUET, 1979), within ongoing stage. Thus already established NREM 2 stage will remain NREM 2 if all other criteria are met but there are no sleep spindles within a few minutes

**As sleep deepens, NREM 3 + 4 state follows NREM 2 stage

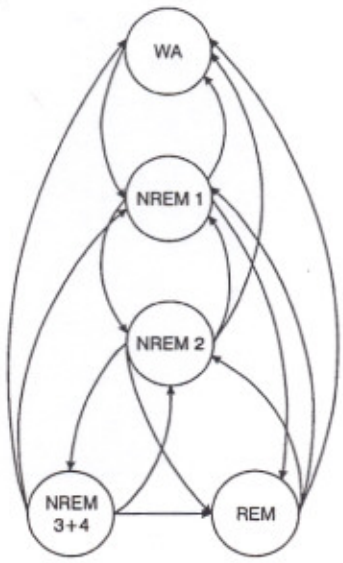

Fig. 1 *Model of sleep/waking states, showing transition trajectories. IS and transitions within a state have been intentionally left out for clarity*

2.4 *Expert system*

The inference engine and the knowledge base to simulate the human expert have been constructed using fuzzy ganglionar lattices (GLs) based on analogue variables. The advantages of using GLs are the power of their explanatory capabilities and the possibility to include uncertainty easily, both in the data and in the reasoning process. A characteristic of a GL is that each unit of the lattice is associated with a meaningful concept in the knowledge base. Besides, a GL knowledge base is not a list of rules and provides a powerful tool to avoid inconsistencies.

In general, a GL is a hierarchical network, formed by functional units quite similar to a 'sigma-pi' type of neural network (NN) (DURBIN and RUMELHART, 1989). In a GL, each unit of the network depends on a number of antecedents, or inputs, which are combined in the form of weighted sums of products of any number of the antecedents. The output is defined by a linear activation function, without a threshold.

During the initial stages of development of the GLs as a model for human-expert reasoning, the defined structure only considered pairs of inputs to generate an output, in the form

$$z = a_1 x_1 + a_2 x_2 + (1 - a_1 - a_2) x_1 x_2$$

This expression has the property to be equal to zero when $x_1 = x_2 = 0$, and equal to one when $x_1 = x_2 = 1$, i.e. no constant term is considered, and the sum of the coefficients is equal to one. The output z corresponds to the probabilistic sum if $a_1 = a_2 = 1$, and to the probabilistic product if $a_1 = a_2 = 0$. Normalising the inputs within the range [0, 1] provides an output in the same range. If the inputs are associated through a sum, then the output will be equal to or larger than the largest input. However, if the inputs are associated through a product, then the output will be equal to or smaller than the smallest input. If the coefficients are also in the [0, 1] range, then the expression of z can be set to satisfy a number of different associations, apart from the ones already mentioned, such as weighted sum, arithmetic average etc. In fact, with these associations, it has been possible successfully to model human reasoning with two given inputs. For example, let us assume that 'body size' depends only on the normalised height and weight of a person. The 'size' is a concept of a higher level (more elaborate) than the antecedents of height and weight. For example, we could have an expression relating the inputs to the output of the form:

$$\text{size} = 0.5 \times \text{height} + 0.8 \times \text{weight} - 0.3 \times \text{height} \times \text{weight}$$

Note that, if height = weigh = 0 (1), then the size = 0 (1). If a person has height of 0.9 and weight of 0.3, then, using the association just defined, the person's size is approximately 0.61.

GL units of higher complexity were developed (HOLZMANN *et al.*, 1996), introducing the capability to handle simultaneously more antecedents, which allowed the adequate modelling of higher-level concepts. The case with three antecedents is shown to induce a generalisation of the association formula:

$$z = a_1 x_1 + a_2 x_2 + a_3 x_3 - a_{12} x_1 x_2 - a_{13} x_1 x_3 - a_{23} x_2 x_3 + a_{123} x_1 x_2 x_3$$

where $a_0 = 0$ and $\sum a = 1$.

The main difference between a GL and an NN is that each ganglion (unit) of the lattice is related to a concept that is of a higher level than its inputs. This reasoning structure, which utilises intermediate concepts to reach the conclusion, is widely used in medicine, and the GLs were specifically developed to model reasoning in this field of expertise (HOLZMANN *et al.*, 1988; 1990; 1996; HOLZMANN and AVARIA, 1992; HOLZMANN and SAN MARTÍN, 1997). Human reasoning is based on the evaluation of some elemental antecedents to value intermediate consequents within a degree of uncertainty, progressing to higher-level concepts. The GL, like an expert, allows the simulation of a specialist's reasoning, establishing the current situation of a top-level concept. The developed methodology is also capable of providing explanations that are as precise as possible, according to the given uncertainty of the data. Using fuzzy coefficients, the variability in human reasoning can also be modelled. Finally, the GL methodology helps in finding a procedure to add certainty to the conclusions, providing an adequate prospecting plan (HOLZMANN *et al.*, 1996; HOLZMANN and SAN MARTÍN, 1997).

To create the GLs that characterise each sleep/waking state, the uncertainty in raw data had to be eliminated, i.e. only noise- and artefact-free segments of real recordings were considered for training. The following steps are followed to develop the ES: adequate representation of sleep patterns, states and stages using GLs; computational implementation; training and tuning; and validation.

2.4.1 *Representation in terms of fuzzy sets:* Sleep/waking patterns and states were presented as linguistic concepts, whereas artificial ganglionar lattices operate on fuzzy numbers of trapezoidal form. To achieve a common ground, numbers (real or fuzzy) were also assigned the concepts of interest. For expert-assessed cases, the extreme values of 1.0 and 0.0 were associated with each concept, meaning the possibility of presence or absence, respectively. However, intermediate values can also be found, whose interpretation will depend on the associated concept. The membership value of a sleep state, as defined by the expert, is also translated as an extreme value 1.0 or 0.0, as for the sleeping patterns. As the expert defines one sleep state in each time window, there is one sleep state with the value 1.0, and all other states have the value 0.0, for each window in the training data.

The ES is composed of six GLs, one for each sleep/waking state, i.e. WA, REM, NREM 1, NREM 2, NREM 3 + 4 and IS. The inputs of the GLs are outputs of the specific pattern algorithms described before. Fig. 2 shows diagrams of the GLs involved.

2.4.2 *Training and tuning of the GL:* The ES requires that its coefficients be determined. This is performed by a training method published elsewhere (HOLZMANN *et al.*, 1996) over a representative training database. The training procedure

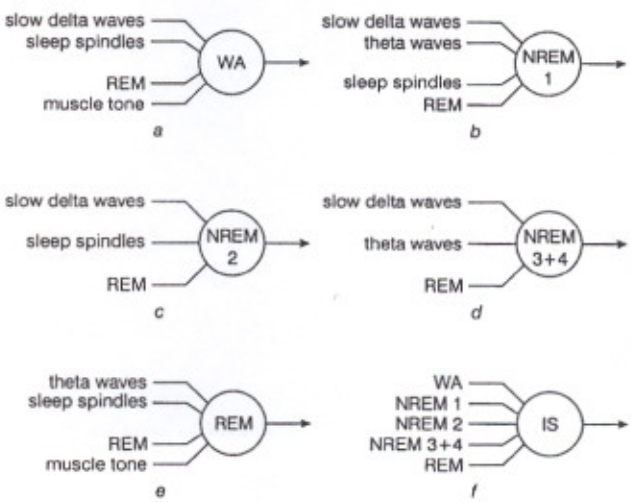

Fig. 2 *Diagram of different GLs that are parts of ES for sleep/waking state classification. Note that inputs of GL representing IS (f) are outputs of all other GLs*

resembles the back-propagation method used in artificial neural networks. The ES is validated using a testing data set different from the training set, by directly comparing the results given by the system with those determined by the expert. The membership values obtained for the different sleep states will be in the [0.0, 1.0] range. A state is determined when one GL has a value close to 1.0, and all other GLs values are close to 0.0. Ill-defined patterns tend to give intermediate values. Each of the training and testing data sets are composed of n-tuples of inputs and outputs, corresponding to an expert's visual evaluation of paper polysomnographic recordings showing wave patterns, and their corresponding state classification. At the beginning of the training phase, the coefficients for each GL are given arbitrary values. Sequentially, the input data of each n-tuple in the training set are applied to the system, giving the output of each GL, and the associated error compared with the n-tuple outputs is calculated. The corresponding error value determines modifications of the GL coefficients, according to the methods explained in HOLZMANN *et al.* (1996), until an error of less than 1% is obtained, or when no further improvement can be made.

3 Results

The results involving direct automated analysis of real polysomnographic recordings came from three different patients. In these cases, the expert sorted out the characterising patterns and also classified the sleep state accordingly, for each page of the recording. This allowed for separate tests of the different parts of the system.

To correct and adjust the detection of the characterising patterns, several partial tests were performed during the development of the system. Section 2.1 describes the detection algorithms that were finally applied. Several pages of the three available recordings were eliminated, owing to inconsistencies: 30 pages out of 220 in record 1 (FH120594); 101 pages out of 610 in record 2 (CV061493); and 20 pages out of 201 in record 3 (CR082995). Hence, a total of 880 pages of data were considered. Even so, there are differences between the criteria detailed in Table 2 (given by the expert) and the assessments given by the same expert for the data that were used, as detailed in Table 3. In some cases, the situation does not involve a contradiction, e.g. sleep spindles must be present for the onset of stage NREM 2, but can be absent for up to 5 min within NREM 2.

Table 4 shows the performance of the pattern-detection algorithms with the training data set (recording 1) in terms of number of pages wrongly classified, and Table 5 shows the same results as a percentage of the total number of cases, for each pattern and sleep state. The two other available recordings were used as testing data. The performance of the detection algorithms on recordings 2 and 3, using the parameters set with recording 1, is shown in Tables 6 and 7, respectively. The corresponding percentages are not shown, but can be easily obtained with the information given.

The sleep/waking state identification ES was tested on the same polysomnographic recording data, dividing these into three sets, namely training, test and validation data. However, for this part of the experiment, the data of the three recordings were mixed, to provide a good set of data for each sleep/waking state, and to ensure that the training set comprised only consistent data, without artefacts. The ES is trained using these data, and automatically checks its performance with the testing data set. If the results are not satisfactory, it goes back and trains again, proceeding back and forth until the desired performance threshold is met on the testing data set. Then, the performance of the ES is independently measured using the validation data set.

Table 8 shows the sleep/waking state classification obtained by the ES using the training data set. Once the ES is completely trained, the outcome of this test should reach 100% correct classification. The errors are a sign of inconsistent data, which

Table 3 Inconsistencies between criteria for sleep/waking state classification in infants given in Table 2, and actual expert classification performed on each page of data of three recordings. Data corresponding to IS were not included. They do not necessarily convey contradictions, e.g. sleep spindles must be present for onset of stage NREM 2, but can be absent for up to 5 min within NREM 2

State/stage	WA	NREM 1	NREM 2	NREM 3 + 4	REM
EEG: slow delta	no inconsistencies found	3 inconsistent (r_2)	7 inconsistent (r_2)	11 inconsistent (r_2:10;r_3:1)	X
EEG: theta	X	10 inconsistent (r_2:6;r_3:4)	X	2 inconsistent (r_2:1;r_3:1)	no inconsistencies found
Sleep spindles	no inconsistencies found	5 inconsistent (r_2)	111 inconsistent (r_1:14;r_2:85;r_3:12)	X	no inconsistencies found
REM	no inconsistencies found	4 inconsistent (r_1:1;r_2:2;r_3:1)	no inconsistencies found	3 inconsistent (r_2:2;r_3:1)	10 inconsistent (r_1:2;r_2:8)
MT	7 inconsistent (r_1)	X	X	X	17 inconsistent (r_2)
Total number of pages	128	102	205	248	132

r_1, r_2, r_3 = recordings, 1, 2 and 3, respectively

Table 4 Errors in detection of sleep patterns from polysomnographic recordings using expert-assessed patterns status as input. Number of total incorrect detections is shown, separated by sleep/waking state, indicating number of false negatives (FN) and false positive (FP) in each case, for training data set (recording 1)

State	Total pages	EEG: slow delta	EEG: theta	sleep spindles	REM	MT
WA	36	0	8 (FP)	0	1 (FN)	8 (FN)
NREM 1	7	1 (FP)	0	0	1 (FN)	0
NREM 2	23	4 (FP)	9 (FN:2;FP:7)	5 (FN)	2 (FP)	5 (FN)
NREM 3 + 4	94	1 (FN)	0	5 (FN:4;FP:1)	9 (FP)	31 (FN:30;FP:1)
REM	16	0	0	0	2 (FN)	0
IS	14	5 (FN:2;FP:3)	3 (FN:2;FP:1)	1 (FN)	3 (FN:1;FP:2)	0
Total	190	11	20	11	18	44

Table 5 Errors in detection of sleep patterns from polysomnographic recordings, using expert-assessed patterns status as input. Percentage of pages in error for each feature detected and state are shown for training data set (absolute values shown in Table 4)

% State	Total pages	EEG: slow delta	EEG: theta	Sleep spindles	REM	MT
WA	18.9	0.0	22.2	0.0	2.8	22.2
NREM 1	3.7	14.3	0.0	0.0	14.3	0.0
NREM 2	12.1	17.4	39.1	21.7	8.7	21.7
NREM 3+4	49.5	1.1	0.0	5.3	9.6	33.0
REM	8.4	0.0	0.0	0.0	12.5	0.0
IS	7.4	35.7	21.4	7.1	21.4	0.0
Total	100.0	5.8	10.5	5.8	9.5	23.2

Table 6 Errors in detection of sleep patterns from polysomnographic recordings, using expert-assessed patterns status as input Number of total incorrect detections is shown, separated by sleep/waking state, indicating number of false negatives (FN) and false positives (FP) in each case for recording 2 (testing data set)

State	Total pages	EEG: slow delta	EEG: theta	Sleep spindles	REM	MT
WA	54	0	7 (FP)	1 (FP)	10 (FN)	1 (FN)
NREM 1	79	3 (FN:1;FP:2)	16 (FN:11;FP:5)	1 (FN)	9 (FP)	3 (FN:2;FP:1)
NREM 2	154	6 (FP)	54 (FN:25;FP:29)	28 (FN:20;FP:8)	6 (FP)	26 (FN)
NREM 3+4	80	7 (FN:2;FP:5)	7 (FP)	12 (FN:4;FP:8)	2 (FN:1;FP:1)	0
REM	105	4 (FP)	2 (FN)	0	38 (FN:37;FP:1)	0
IS	37	8 (FP)	7 (FN:6;FP:1)	5 (FN:2;FP:3)	7 (FN:1;FP:6)	0
Total	509	28	93	47	72	30

Table 7 Errors in detection of sleep patterns from polysomnographic recordings, using expert-assessed patterns status as input. Number of total incorrect detections is shown, separated by sleep/waking state, indicating number of false negatives (FN) and false positive (FP) in each case, for recording 3 (testing data set)

State	Total pages	EEG: slow delta	EEG: theta	Sleep spindles	REM	MT
WA	38	0	15 (FP)	3 (FP)	6 (FN)	0
NREM 1	16	1 (FP)	4 (FN:2;FP:2)	1 (FP)	1 (FN)	2 (FN:1;FP:1)
NREM 2	28	0	5 (FN:3;FP:2)	10 (FN)	0	8 (FN)
NREM 3+4	74	4 (FN:3;FP:1)	2 (FN:1;FP:1)	26 (FN:25;FP:1)	1 (FN)	8 (FN)
REM	11	0	0	0	7 (FN)	0
IS	14	3 (FP)	1 (FN)	2(FP)	6 (FN:5;FP:1)	1 (FP)
Total	181	8	27	42	21	19

is not unexpected, and they set an upper limit for the overall performance capability of the ES. Each Table compares the specialist (medical expert) classification with the ES classification for all possible states, showing the number of pages of agreement on the diagonal and the number of pages confused by the ES elsewhere. The ES showed itself to be sensitive to data with artefacts. Therefore the performance of the system is first shown on the test set where the pages with artefacts were left out (Table 9), and then on the whole testing data set (Table 10). The same separation of data was carried out with the validation set. The validation data are the closest data set to a new recording. The results obtained on the data without artefacts are shown in Table 11, and those using the whole validation set are shown in Table 12.

The performance of the ES as opposed to plainly applying the criteria detailed in Table 2 was also tested. Tables 13–15 show the results of applying Table 2 to the training, test and validation data sets defined for the ES, respectively. Comparing these Tables with Tables 8, 10 and 12, respectively, indicates the contribution of the expert system towards the adequate classification of sleep/waking states.

The performance of the ES, isolated from the characteristic pattern-detection algorithms, was tested separately. Tables 16 and 17 show the results obtained from the ES, applying the pattern data identified by the medical expert in the polysomnographic recordings as inputs to the system, i.e. bypassing the pattern-detection algorithms. The available data were separated into two sets for training and testing. As the raw signals were not used here, more pages of the data available were suitable. Table 16 shows the classification performance obtained with the data used for adjusting the parameters of the expert system (training set). Table 17 shows the same experiment, but applying testing data, and using the same parameters adjusted using the training data.

Table 8 Sleep/waking state classification obtained by ES using training data. Number of pages classified in each state/stage is indicated

ES expert	WA	NREM 1	NREM 2	NREM 3+4	REM	IS	Total, pages	Error, pages	Error, %
WA	70						70	0	0.0
NREM 1		39					39	0	0.0
NREM 2			45				45	0	0.0
NREM 3+4				49			49	0	0.0
REM					38		38	0	0.0
IS		1				3	4	1	25.0
Total	70	40	45	49	38	3	245	1	0.4

Table 9 Sleep/waking state classification obtained by ES using testing data. Number of pages classified in each state/stage is indicated. Data with artefacts are not included

ES expert	WA	NREM 1	NREM 2	NREM 3+4	REM	IS	Total, pages	Error, pages	Error, %
WA	28						28	0	0.0
NREM 1		13					13	0	0.0
NREM 2			33				33	0	0.0
NREM 3+4				47		2	49	2	4.1
REM					12		12	0	0.0
IS						3	3	0	0.0
Total	28	13	33	47	12	5	138	2	1.5

Table 10 Sleep/waking state classification obtained by ES using all testing data, including pages with artefacts. Number of pages classified in each state/stage is indicated

ES expert	WA	NREM 1	NREM 2	NREM 3+4	REM	IS	Total, pages	Error, pages	Error, %
WA	29						29	0	0.0
NREM 1		21					21	0	0.0
NREM 2		1	37	5			43	6	14.0
NREM 3+4				48		2	50	2	4.0
REM		5		1	16		22	6	27.3
IS						3	3	0	0.0
Total	29	27	37	54	16	5	168	14	8.3

Table 11 Sleep/waking state classification obtained by ES using validation data. Number of pages classified in each state/stage is indicated. Data with artefacts are not included

ES expert	WA	NREM 1	NREM 2	NREM 3+4	REM	IS	Total, pages	Error, pages	Error, %
WA	26						26	0	0.0
NREM 1	3	10					13	3	23.1
NREM 2			37			1	38	1	2.6
NREM 3+4				47			47	0	0.0
REM		1			14		15	1	6.7
IS						2	2	0	0.0
Total	29	11	37	47	14	3	141	5	3.6

Table 12 Sleep/waking state classification obtained by ES using all validation data, including pages with artefacts. Number of pages classified in each state/stage is indicated

ES expert	WA	NREM 1	NREM 2	NREM 3+4	REM	IS	Total, pages	Error, pages	Error, %
WA	28						28	0	0.0
NREM 1	4	16					20	4	20.0
NREM 2		1	40	9		7	57	17	29.8
NREM 3+4				50			50	0	0.0
REM		6			16		22	6	27.3
IS						2	2	0	0.0
Total	32	23	40	59	16	9	179	27	15.1

Table 13 Sleep/waking state classification obtained using training data of ES and applying Table 2 instead of ES. Number of pages classified in each state/stage is indicated

ES expert	WA	NREM 1	NREM 2	NREM 3+4	REM	IS	Total, pages	Error, pages	Error, %
WA	70						70	0	0.0
NREM 1		38				1	39	1	2.6
NREM 2			45				45	0	0.0
NREM 3+4				46		3	49	3	6.1
REM					37	1	38	1	2.6
IS		1				3	4	1	25.0
Total	70	39	45	46	37	8	245	6	2.5

Table 14 Sleep/waking state classification obtained using all testing data applied to ES, including pages with artefacts, and applying Table 2 instead of ES. Number of pages classified in each state/stage is indicated

ES expert	WA	NREM 1	NREM 2	NREM 3+4	REM	IS	Total, pages	Error, pages	Error, %
WA	27					2	29	2	6.9
NREM 1	4	8				9	21	13	61.9
NREM 2			34	4		5	43	9	20.9
NREM 3+4				42		8	50	8	16.0
REM	2	8			10	2	22	12	54.6
IS	1					2	3	1	33.3
Total	34	16	34	46	10	28	168	45	26.8

Table 15 Sleep/waking state classification obtained using all validation data applied to ES, including pages with artefacts, and applying Table 2 instead of ES. Number of pages classified in each state/stage is indicated

ES expert	WA	NREM 1	NREM 2	NREM 3+4	REM	IS	Total, pages	Error, pages	Error, %
WA	22					6	28	6	21.4
NREM 1	2	4	5			9	20	16	80.0
NREM 2	2	4	11	7		33	57	46	80.7
NREM 3+4				41		9	50	9	18.0
REM		8			12	2	22	10	45.5
IS	1				1		2	2	100.0
Total	27	16	16	48	13	59	179	89	49.7

Table 16 Sleep state classification using expert-assessed pattern status as input. Numbers of pages correctly and incorrectly classified are shown, contrasting system with specialist, for training data. Coincidences are shown on diagonal

Specialist System	WA	NREM 1	NREM 2	NREM 3+4	REM	IS	Total, pages	Error, pages	Error, %
WA	201	1			2		204	3	1.5
NREM 1		90					90	0	0.0
NREM 2			163		1		164	1	0.6
NREM 3+4				459			459	0	0.0
REM	5	1			110		116	6	5.2
IS					2	108	110	2	1.8
Totals	206	92	163	459	115	108	1143	12	1.1

Table 17 Sleep state classification using expert-assessed patterns status as input. Numbers of pages correctly and incorrectly classified are shown, contrasting system with specialist, for testing data. Coincidences are shown on diagonal

Specialist System	WA	NREM 1	NREM 2	NREM 3+4	REM	IS	Total, pages	Error, pages	Error, %
WA	96				1		97	1	1.0
NREM 1		57					57	0	0.0
NREM 2			78		3		81	3	3.7
NREM 3+4				232			232	0	0.0
REM					60		60	0	0.0
IS						31	31	0	0.0
Totals	96	57	78	232	64	31	558	4	0.7

4 Discussion and conclusions

The development of the model based on state variables to describe the sleep/waking states in infants, as detailed in Section 2.3, is a contribution towards the objective formalisation of these physiological states. It is also helpful in designing an ES for automatic classification.

An ES to classify sleep/waking states in infants has the potential to be a powerful tool in sleep-related research (sleep medicine and chronobiology) (FERBER and KRYGER, 1995). This includes a wide variety of applications, such as the neurofunctional assessment of the central nervous system, nutritional deficits, or those relative to evaluating the risk of presenting sudden infant death syndrome (SIDS), with the added virtue of being a non-invasive approach.

There are various sources of uncertainty for the sleep/waking state identification ES, including noise in the signals, individual variations in acquired signals, uncertainty (inconsistency) in the expert's classification process etc. The uncertainties can be separated into two types, according to the division of tasks stated for the system structure: uncertainty in the pattern-detection algorithms, and uncertainty in the reasoning process for sleep classification.

As mentioned previously, noise and artefacts are important sources of error for pattern-detection algorithms, originating in electromagnetic noise, body movements of the infant and the mother, and interfering physiological signals. The body movements can cause artefacts in different signals, such as false slow delta waves in the EEG channels, particularly in WA. False REM pulses can appear on the EOG recording owing to EEG activity or owing to artefacts seen as saturations on the EEG, and so on. In our experience, several difficulties encountered in the development of the ES were related to the noise and artefacts in the polysomnographic recording. The design of adequate algorithms to identify the characteristic activity patterns, such that they would be robust in the presence of noise and able to identify and discard artefacts, introduced a significant complexity to the problem. No single solution would give the best result in all situations. For example, to characterise predominant background EEG activity, slow-delta predominance was better detected using a zero-crossing strategy, whereas theta-predominance detection was performed better using FFT.

Another source of error is the high variability in the amplitudes of the same signals, which vary from patient to patient and also with time within the same patient record. The visual interpretation made by the specialist for pattern detection takes contextual knowledge 'for filtering' into account, which is not stated as a sleep-stage characteristic. Therefore it is difficult properly to interpret these filters in a formal way.

The detection of specific patterns in the EEG, EOG and EMG signals in polysomnographic recordings for the ES was performed using algorithms developed by the research team (see Sections 2.1 and 2.2). The visual assessment made by the expert was interpreted by using FFT, RMS or other calculations, which are an approximation of his definitions. Although the algorithms are intended for translating the expert's criteria in an accurate way, this is a source of uncertainty.

Several algorithms were developed to detect patterns in the EEG, EMG and EOG signals. The results obtained for recordings 1, 2 and 3 (Tables 4, 6 and 7) indicate that the error rates vary from case to case. The muscular tone-detection algorithm shows a high error rate for recording 1 (Table 4); EEG theta-predominance detection is worst in recording 2 (Table 6), and sleep spindle detection is weakest in recording 3 (Table 7).

However, it is important to evaluate these results based on Table 2, i.e. considering that the error is important only in the cases where the particular pattern is relevant in determining the particular sleep/waking state. For example, muscular tone is irrelevant to classification of any NREM sleep (Table 4). Another example: the overall results obtained with testing data in Table 6 show 93 out of 509 pages wrongly classified, in terms of theta-wave predominance in the EEG (third column in Table 6). However, as the predominance of theta is irrelevant in WA and NREM 2 stage, there are only 32 relevant pages wrongly classified, out of 509, i.e. 6.3%. The training of the characteristic pattern-detection algorithms was focused to optimise their performance for relevant cases.

Based on the characteristic patterns, an ES to recognise sleep/waking states was implemented, performing several adjustments and tests using data from real patients. Results show an overall performance of 96.4% agreement with the expert on validation data without artefacts (Table 11), and 84,9% agreement on validation data with artefacts (Table 12). This last result compares favourably with the almost 50% error obtained if the criteria of Table 2 were plainly applied to the validation data with artefacts (Table 15), which shows the significant enhancement due to the ES. This is corroborated when testing the ES on expert-classified patterns instead of those obtained by the pattern-detection algorithms from real data, where most of the pattern-detection error is eliminated (Tables 16 and 17).

The inconsistency in the experts' classification process, i.e. the uncertainty in the reasoning process, was also explored. Several already classified pages were selected, i.e. where an expert had already established the sleep/waking state of the patient. The same pages were presented again to an expert, establishing that it was an independent judgment, either because it was a different expert, or because there was no memory about the particular record. The expert was asked to classify the page and confronted with the original classification. If the classification was the same as before, then a total agreement was annotated. Otherwise, the expert was asked to qualify his degree of agreement with it, from agreement to total disagreement. The results shown in Table 18 seem to indicate that there is a degree of contradiction in the experts' assessments. However, these results, as well as those discussed before, should not be overstated. The experts' confrontation performed here was based on register pages and does not take into account the minimum 1 min time span to determine a sleep/waking state, nor that a single sleep spindle is enough to assert its presence in a 5 min time frame, as stated in Section 2.2.

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Table 18 Uncertainty in reasoning: expert classification agreement on revisited recording pages

Diagnosis State	Totally agree	Agree	Indifferent	Disagree	Totally disagree	Total pages
WA	55	1		1	3	60
NREM 1	42	7	1		36	86
NREM 2	69				5	74
NREM 3 + 4	222	1			7	230
REM	56				2	58
IS	6	5			10	21

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