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A Continuous Evaluation of the Awake Sleep State using Fuzzy Reasoning

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***Abstract*—Sleep staging is one of the most important tasks on the context of sleep studies. From more than 40 years the gold standard to the characterization of patient's sleep is the use of the rules proposed by Rechtschaffen and Kales (R&K). However this method has the limitation of the unnatural assignment of discrete stages instead of doing it in a continuous manner. As part of a more general framework, this paper reports an automatic method for the characterization of the R&K's awake sleep stage through the use of fuzzy reasoning. A continuous evolution of the wakefulness state of the patient during the night is provided as output.**

I. Introduction

SLEEP studies involve the recording of several biomedical signals of the patient during the night. Resulting recording is called polisomnogram (PSG), which is analyzed afterwards by the physicians in order to the diagnosis of sleep disorders. The main problem is that offline analysis of the PSG is a time consuming task and entails too much effort.

Characterization of the state of the patient during sleep is normally accomplished by the segmentation of the PSG into classifiable intervals called epochs. An epoch is an arbitrary measure of time normally established in 30 seconds. Then each epoch is assigned a label based on the trend of the signals contained in the epoch. This method, which was proposed by Rechtschaffen and Kales (R&K) [1] became the gold standard to the scoring of the sleep. R&K method is based on the monitoring the state of 3 signals: brain activity by Electroencephalography (EEG), muscle tone by Electromyography (EMG) and eye movements by Electooculography (EOG), and proposes 6 different stages: W (or AWAKE), S1,S2,S3,S4 and Rapid Eye Movement (REM) stage. Wakefulness is represented by W. In this phase it is common the presence of high muscle tone and eye movements and the predominance of high frequencies in the EEG. As the patient falls asleep eye movements and muscle tone become more relaxed, from drowsy sleep (S1 and S2) to deep sleep (S3 and S4). Also high frequencies move out to slow waves in the EEG as sleep becomes deeper. Although S1 and S2 are clearly discernible within each other by the presence of K-complex and sleep spindles in S2, recent standards point out about the joint of S3 and S4 [2] into an isolated one representing deep sleep (DEEP). Finally REM stage is characterized by the presence of rapid eye movements in the EOG, low muscle tone and mixed frequencies in the EGG.

Automatic sleep scoring should help to reduce the time needed by the physician to construct the hypnogram. Attempts to develop automatic sleep scoring are almost as old as the R&K rules. A review of the literature on these realizations can be found in [3]. However, limitations on the R&K method were also reported [4]. One of the main limitations is the unnatural assignment of discrete stages in each epoch instead of a continuous marker of the sleep state. In this line recent work can be found in A. Flexer et al. [5] who developed a probabilistic sleep stager (wakefulness, deep sleep and REM) based on a single EEG signal, or the work of M. H. Asyali et al. [6] who determined a continuous marker for sleep depth through sum of absolute power in alpha and beta bands of EEG.

Our approximation proposes an alternative solution using the paradigm of fuzzy logic to obtain some kind of hypogram in which instead of the discrete epoch-based R&K stages, a continuous evolution of the degree of membership for each one might be observed. The general architecture is organized in several subsystems. Each one is the responsible for the analysis regarding to a particular sleep stage.

This is an ongoing work. In the context of this general framework, this paper presents the functionality regarding to the characterization of the awake stage (W). Organization of the document is structured as follows: firstly, a brief description of the general architecture is presented. After that, further description on the design of the W subsystem is given. Subsequently validation results of this module are reported and, finally, contextualization of the results and future work is discussed.

II. System Architecture

The general architecture is structured in 2 layers (Fig. 1): a first layer of parameters extraction in which features over the biological signals of the PSG are obtained, and a second one, in which a reasoning process is performed over the parameters previously obtained. This second layer is in turn organized into several modules belonging to each subsystem. A degree of membership over a different sleep stage, i.e. μ_W,

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μ_{s1}, μ_{s2}, μ_{DEEP} and μ_{REM} is calculated, respectively, by each one. This process is made in a second-by-second granularity, thus a continuous output rather than an epoch-based one is obtained. After that some kind of post-processing could be necessary in order to assign the final stage to the corresponding instant of time under analysis. The later will not be considered in this paper as this only makes sense when several subsystems' outputs are involved. Operations concerning the W subsystem on the two layer architecture are subsequently described.

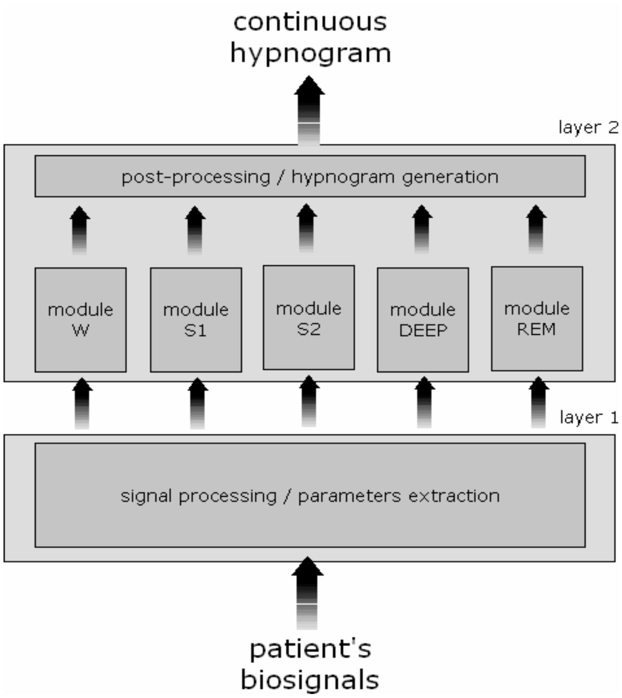

Fig. 1. Architecture of the general system

III. EVALUATION OF W-STAGE

Following it is detailed the operation of the subsystem responsible for the evaluation of the W stage. The method proposed works with EEG both C2/A2 and C4/A1 central derivations, submental EMG and EOG signals from left (EOGL) and right (EOGR) eye electrodes. EEG and EMG signals are sampled at 125 Hz whereas EOG is sampled at 50 Hz.

A. Parameter extraction

In the first layer the analysis of the 5 signals takes place. Each signal is analyzed separately and different parameters are extracted for each type of signal.

In the case of the EOG we are interested in the localization of eye movements. To perform this, a new signal A_{EOG} is constructed representing the amplitude of each EOG signal (left and right). The new resulting signal can be shown in Fig. 2. It can be shown that in the presence of eye movements, the amplitude of this signal increases in respect to a relaxed EOG.

To construct A_{EOG}, a moving window of 3 seconds is used. This window is shifted second-by-second throughout both EOGL and EOGR, measuring the amplitude of the signals into the window. Thereby a value for the amplitude of the EOG is obtained for each second. As we have two different amplitude measures –for EOGL and EOGR-, for the final amplitude estimation average of the two values of each window is calculated.

In the case of EMG, to distinguish between presence and absence of muscle tone, a similar amplitude-based analysis is performed as well. Using a window of 3 seconds and moving it throughout EMG, a new A_{EMG} signal is obtained in which each sample is calculated as the mean of the absolute value of the EMG samples included in the window (Fig. 3). Values of A_{EMG} are taken as the measures of the EMG amplitude in each second. The main reason to do it differently in respect to the EOG is the better behavior in the presence of noise in the EMG signal.

Finally, in the case of EEG (Fig. 4), the processing of this signal is performed in the frequency domain rather than in the amplitude domain. As mentioned in the introduction, the different sleep stages are characterized by the different proportion of frequencies present in the EEG. Thus the analysis is accomplished based on the most representative frequency bands: alpha (α), beta (β), theta (θ) and delta (δ). Respective ranges of frequencies for these waves are 8-12 Hz, 13-30 Hz, 4-7 Hz and 0.5-3 Hz.

Similarly to the EMG, another 3-second window is used for each second of the EEG signal. Within each window we quantify the energy of the signal for each frequency band by means of a band-pass filter in the corresponding range. Then the Energy Spectral Density (ESD) is calculated integrating the Fourier Transform for the spectra resulting from the application of the band-pass filter. Therefore we obtain 4 measures of ESD: E_α, E_β, E_θ and E_δ, one for each kind of wave. By means of these 4 values, the parameters A, B and C are calculated according to (1). In (1) *i* denotes the current instant of time (the window associated with the *ith* second):

$$
\begin{aligned}
A(i) &= (E_\alpha(i) + E_\beta(i)) / (E_\theta(i) + E_\delta(i)) \\
B(i) &= (E_\alpha(i) + E_\beta(i)) / E_\theta(i) \\
C(i) &= (E_\alpha(i) + E_\beta(i) + E_\theta(i)) / E_\delta(i)
\end{aligned}
\tag{1}
$$

The aim of the parameters A, B and C is to represent relations between the different ranges of frequencies in the EEG. Higher values of these parameters are expected in W than in other stages. The reason is the predominance of high frequencies (α, β) during wakefulness.

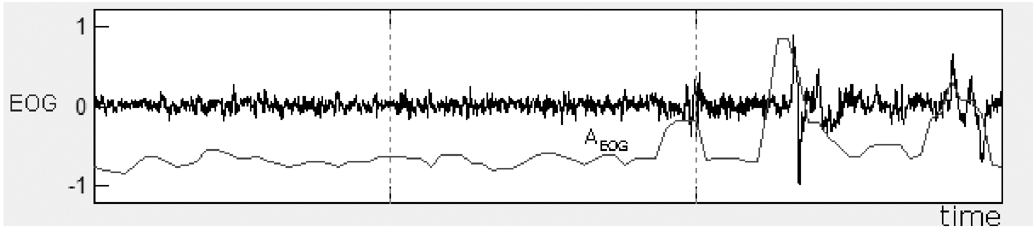

Fig. 2. Displayed are 3-epochs of 30 seconds of the EOG signal with amplitude normalized in [-1, 1]. Signal A_{EOG} is superimposed.

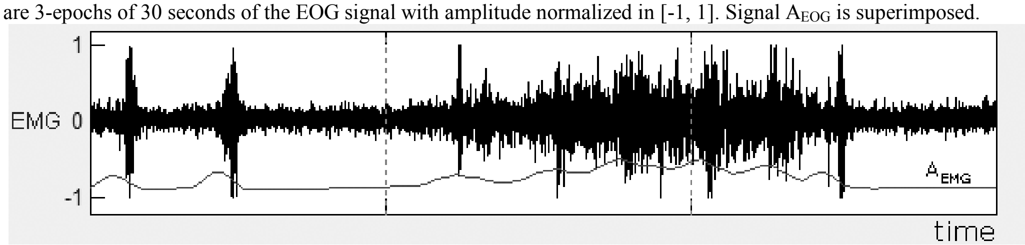

Fig. 3. Displayed are 3-epochs of 30 seconds of the EMG signal with amplitude normalized in [-1, 1]. Signal A_{EMG} is superimposed.

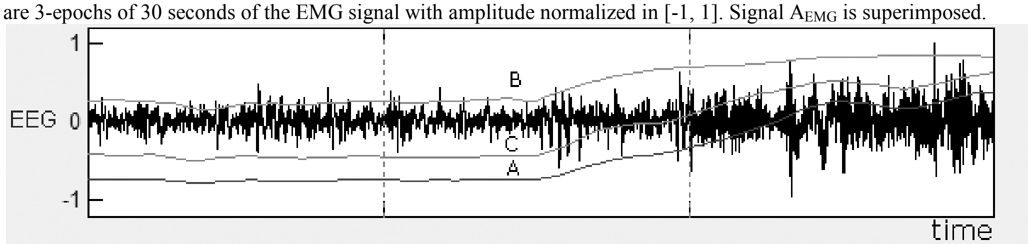

Fig. 4. Displayed are 3-epochs of 30 seconds of the EEG signal with amplitude normalized in [-1, 1]. Signals resulting from the calculation of parameters A, B, and C are superimposed.

Similarly to the case of EOG, as we have two derivations of EEG –C2/A2,C4/A1-, we take as the final values for parameters A, B and C, the respective average of the two derivations.

As the output for the parameter extraction phase, we thus obtain, for each second *i* of the recording, a set of 5 parameters ($A_{EOG}(i)$, $A_{EMG}(i)$, A(i), B(i) and C(i)) which will feed the fuzzy reasoning module placed in the second layer.

B. Fuzzy Reasoning Module

The reasoning module for the W subsystem is implemented in the form of a Fuzzy Inference System (FIS) of type Mamdani [9]. The input vector to this module is composed of the 5 previous parameters obtained in the first layer. Knowledge is formed by a particular set of fuzzy rules in order to distinguish the W stage. Output of the module consists of a value μ_W in the real interval [0, 1], which represents the degree of membership for the current instant of time under analysis, to the concept of sleep wakefulness.

For the partition of the input variables, trapezoidal fuzzy sets were used. For the A_{EOG} 3 fuzzy sets (low, medium and high) were used. Similarly 3 fuzzy sets (relaxed, medium and tense) were established for the parameter $A_{EMG.}$ In the case of the EEG, each of the parameters A, B and C results in a variable partitioned again in 3 sets named low, medium and high. Output variables were also partitioned by defining 3 fuzzy sets uniformly distributed along the interval [0, 1]. All the fuzzy sets are partially superimposed in order to explode major generalization capabilities.

For the configuration of the FIS the minimum was chosen as the T-norm operator for the conjunction and for the implication. The maximum was chosen as the operator for the disjunction operator and for the aggregation process. For the defuzzification, the center-of-gravity method was used.

Once all the seconds of the recording are analyzed, a continuous evolution of the degree of membership for W sleep stage is obtained. This output can be observed in Fig. 5, in which the value of μ_W is represented second-by-second for a whole PSG recording.

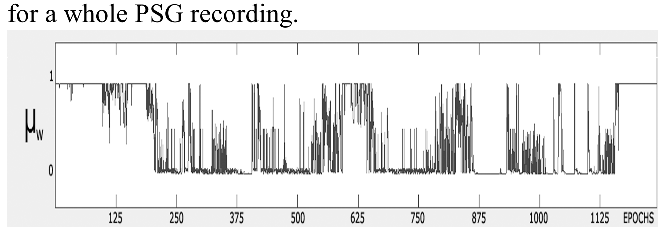

Fig. 5. Evolution for the estimation of stage W throughout the whole recording.

IV. RESULTS

Results for the validation of the evaluation of W stage are reported here. In order to develop and validate the proposed subsystem, a set of PSG recordings from real patients were used. Recordings come from the Sleep Heart Health Study (SHHS). This database, granted by the Case Western Reserve University, contains more than 2000 PSG recordings available to be used as a resource for studies related with sleep. Details about the design of SHHS study can be found in [7]. Each recording comes with an annotation file where sleep stages were marked by expert scorers. Scoring rules follow the American Academy of Sleep Medicine rules, which are based on the R&K method for the scoring of sleep stages. Further detailed explanation is presented in [8]. A total of 6 patients from the SHHS database were randomly chosen for the evaluation of the subsystem. In total the 6 recordings contain 3550 minutes of sleep. Annotations made by expert polysomnographic scorers are taken as reference for the validation process.

As the experts follow the R&K procedure, their annotations are made in an epoch-based scale of 30 seconds. Due to this fact (for comparison purposes), an average of the second-by-second output of the system within each epoch is used as the resulting degree of membership for each epoch. In order to perform this validation, from the average obtained for each epoch, a threshold of 0.5 is applied to the resulting degree of membership μ_W. Those values of $\mu_W > 0.5$ are thus considered to belong to the AWAKE category, whereas those with $\mu_W \leq 0.5$ are considered as SLEEPED (regardless of the depth). In Fig.6 the comparison between expert's evaluation for the awake stage and the system's output after applying the threshold can be found.

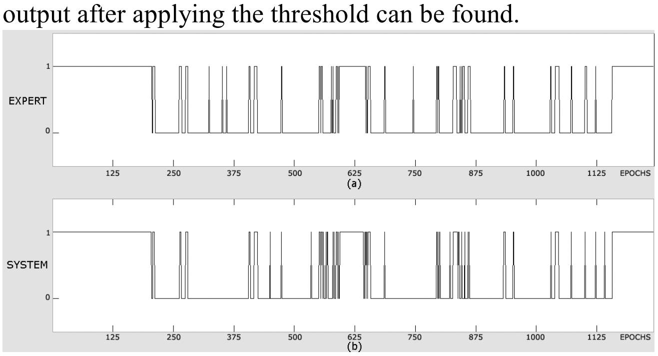

Fig. 6. Comparison between expert's (a) and system's (b) criteria once over the output of the system the threshold was applied.

Table I presents the validation results for each of the 6 patients. Results are provided in form of accuracy, i.e. the proportion of correctly classified epochs, sensitivity and specificity.

TABLE I
VALIDATION RESULTS BETWEEN EXPERT AND SYSTEM

Recording	Accuracy	Sensitivity	Specificity
1	0.954	0.996	0.919
2	0.958	0.930	0.974
3	0.910	0.977	0.879
4	0.980	0.917	0.997
5	0.984	0.932	0.999
6	0.951	0.975	0.937
Average	0.956	0.955	0.951

V. DISCUSSION

In this paper the subsystem for the evaluation of the awake sleep state is presented. This subsystem is situated in the context of a more general architecture which was outlined as well. The main objective of the general approach is to overcome the limitations of the R&K method. Specifically those associated with the discrete way of characterizing the sleep through the assignment of labels in each epoch, which is not natural. State transition on physiological systems involves processes of change in a continuous manner rather than in a discrete evolution.

Validation results on the W subsystem were presented as a fully developed part on the general framework. Future work will emphasize on the development of the remainder subsystems. For example, more parameters apart from A, B and C will be necessary to distinguish among the rest of the sleep stages. As example, for the correct characterization of S2, the detection of sleep spindles and K-complex is necessary.

Concerning to the functionality of the module presented here, the continuous output provided for stage W can be also interpreted as a continuous marker for sleep depth. As the analysis is based on displacing windows, if more one second resolution is required for the output, no more is necessary than increasing the sampling in the analysis.

The main advantage of the proposed method is to provide a natural evolution of the awake sleep state of the patient in a continuous way. Additionally absolute certainty on judgments in diagnostics rarely happens. In this manner, the using of fuzzy logic allows us to mimic physicians' reasoning processes more likely. Expert's knowledge is easily implemented by means of the use of fuzzy rules.

More information and background experience from the authors on the application of fuzzy reasoning and the analysis of sleep studies can be found in [10-11].

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