Visual Knowledge-Based Metaphors to Support the Analysis of Polysomnographic Recordings

Abraham Otero[1], Paulo Félix[2], and Carlos Zamarrón[3]

[1] Department of Information and Communications Systems Engineering, University San Pablo CEU, 28668 Madrid, Spain
abraham@dec.usc.es
[2] Department of Electronics and Computer Science, University of Santiago de Compostela, 15782 Santiago de Compostela, Spain
paulo@dec.usc.es
[3] Division of Respiratory Medicine, University Hospital Complex of Santiago de Compostela, 15752 Santiago de Compostela, Spain
carlos.zamarron.sanz@sergas.es

Summary. This paper presents algorithms that provide support in the task of reviewing the physiological parameters recorded during a polysomnography, the gold standard test for the diagnosis of Sleep Apnea-Hypopnea Syndrome (SAHS). This support is obtained through the generation of visual metaphors which help identify events (apneas, hypopneas and desaturations) that occur over the span of the recording and are relevant to the diagnosis of SAHS.

The definition of these events is not completely standardized and it is not unusual that different physicians use different criteria when identifying them. To tackle this problem our algorithms start with a linguistic description of the events to be identified. This description is obtained directly from the clinical staff and is projected onto a set of algorithms of a structural nature that support the generation of the visual metaphors. To represent and manipulate the imprecision and vagueness characteristic of medical knowledge we rely on the fuzzy set theory.

The metaphors proposed herein have been implemented in a tool aimed at supporting the diagnosis of SAHS. The tool provides wizards that permit the morphological criteria that define the apneas, hypopneas and desaturations to be customized by the physician and the visual metaphors automatically reflect the new criteria.

1 Introduction

Sleep Apnea-Hypopnea Syndrome (SAHS) is a common sleep-breathing disorder characterized by recurrent episodes of the upper airway narrowing or collapsing during sleep. An obstruction is caused by the soft palate and/or base of the tongue collapsing against the pharyngeal walls. When the obstructions are complete they are called apneas; when they are partial, hypopneas. It is estimated that SAHS affects 4% of the adult male population and 2% of the adult female population [15], having an especially high prevalence in adult males with obesity problems, and it is recognized as an important public health issue [12].

Apneas and hypopneas are accompanied by hypoxemia, with a drop in SpO2, surges in blood pressure and brief arousal from sleep. Arousals do not necessarily

J.M. Corchado et al. (Eds.): IWPACBB 2008, ASC 49, pp. 10–20, 2009.
springerlink.com

take the patient to a conscious state, but they make him/her leave the deeper sleep stages – i.e., stages where sleep has more refreshing effects – and make him/her spend a higher fraction of nightly rest in stages closer to vigil. As a result, the patient's sleep architecture is fragmented and its refreshing effects are diminished. Thus, patients often suffer diurnal somnolence and cognitive deficits that increase the risk of working and driving accidents [3]. They may also suffer from depression, anxiety, excessive irritability and several sexual dysfunctions.

Overnight polysomnography is currently considered the diagnostic gold-standard for SAHS. It is performed in a hospital Sleep Unit and consists of the registration of a wide range of physiological parameters while the patient is asleep: respiratory airflow (RA), blood oxyhemoglobin saturation (SpO2), respiratory effort, electroencephalography (EEG), electrooculography (EOG), electromyography (EMG), electrocardiography (ECG), etc. The diagnosis of SAHS is a tedious undertaking that requires visual inspection, usually with the assistance of a computer, of the long signal recordings obtained during the polysomnography.

Our goal is to develop a set of visual metaphors to provide support in the task of inspecting a polysomnographic recording. To this end, the metaphors try to highlight the most relevant events in the diagnosis of SAHS: apneas, hypopneas and desaturations. One of the challenges of this task is the lack of a universally accepted definition of such events: different physicians may identify them using different criteria. This had led us to start with the linguistic definition of the events that the physician feels more comfortable with, and to adapt the visual metaphors accordingly.

Section 2 describes the representation we will use for time and it summarizes some basic fuzzy concepts on which our algorithms are based. Sections 3 and 4 present the algorithms which provide support for the generation of the visual metaphors aimed at simplifying the identification of apneas and hypopneas, and desaturations, respectively. These algorithms are of a structural nature and they take advantage of the fuzzy set theory to model and represent medical knowledge close to human intuition. A desktop tool that implements the aforementioned techniques is presented in section 5. Finally, the results obtained are discussed and a series of conclusions are given in sections 6 and 7, respectively.

2 Prior Definitions

We consider time as being projected onto a one-dimensional discrete axis $\tau = \{t_0, t_1, ..., t_i, ...\}$ such that for every $i \in \mathbb{N}$, $t_{i+1} - t_i = \Delta t$, where Δt is a constant. Δt is the minimum step of the temporal axis. Thus given an i belonging to the set of natural numbers $\mathbb{N}$, t_i represents a *precise* instant.

Given as discourse universe the set of real numbers $\mathbb{R}$, a **fuzzy number** A is a normal and convex fuzzy subset of $\mathbb{R}$ [5]. A fuzzy set A with membership function μ_A is *normal* if and only if $\exists\ v \in \mathbb{R}$, $\mu_A(v) = 1$. A is said to be *convex* if and only if $\forall v, v', v'' \in \mathbb{R}$, $v' \in [v, v'']$, $\mu_A(v') \geq \min\ \mu_A(v), \mu_A(v'')\}$.

Normality and convexity properties are satisfied by representing π_A, for example, by means of a trapezoidal representation. In this way, $A = (\alpha, \beta, \gamma, \delta)$,

$\alpha \leq \beta \leq \gamma \leq \delta$, where $[\beta, \gamma]$ represents the core, $core(A) = \{v \in \mathbb{R} |\ \pi_A(v) = 1\}$, and $]\alpha, \delta[$ represents the support, $supp(A) = \{v \in \mathbb{R} | \pi_A(v) > 0\}$ (see Fig. 1). We have opted for this representation for possibility distributions on the basis of its computational efficiency and the intuitiveness of its semantics for medical users.

We obtain a fuzzy number A from a flexible constraint given by a possibility distribution π_A, which defines a mapping from $\mathbb{R}$, to the real interval $[0, 1]$. A fuzzy constraint can be induced from a piece of information such as emph"x has a high value", and given a precise number $v \in \mathbb{R}$, $\pi_{A=high}(v) \in [0, 1]$ represents the possibility of x being precisely v. By means of π_A we define a fuzzy subset A of $\mathbb{R}$, which contains the possible values of A, being A a disjoint subset.

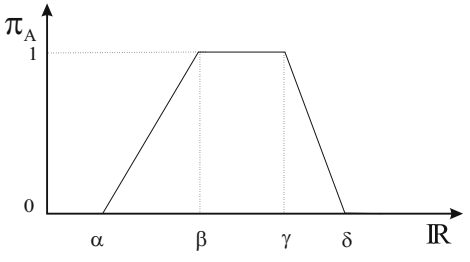

Fig. 1. Trapezoidal possibility distribution

3 Providing Support for the Identification of Apneas and Hypopneas

In the bibliography there is no absolute consensus on the criteria to be fulfilled by an episode of apnea [13]. The criteria which is probably most widely accepted in Europe is a reduction in the volume of air inhaled to at least 10% of the basal value sustained for at least 10 seconds. However, some authors defend that the reduction in the airflow must be to at least 5% [6], while the American Academy of Sleep Medicine (AASM) requires a total cessation [9]. The latter criteria leaves the problem of noise: it is not uncommon that even when there is no airflow the RA signal presents a non null value because of the presence of noise.

Hypopneas are associated with a reduction in RA to at least 50% of the basal value. For some physicians this event is enough to label the hypoventilation as an episode hypopnea, while others require the hypoventilation to provoke an arousal and/or a drop in SpO2. Under certain conditions, the AASM also labels reductions in RA of just 70% of the basal value as hypopneas.

The algorithms we have developed do not commit to any criteria. Our goal is to project the event's linguistic description with which the physician feels more comfortable onto a computational representation. Then this representation will be used to create a visual metaphor to assist in the task of identifying those fragments of the RA in which there has been a reduction of flow compatible with the description. This visual metaphor will take the form of a semitransparent grid drawn over the RA.

3.1 The Algorithm

We start by filtering the RA signal with a third-order Butterworth bandpass filter with cut-off frequencies of 0.20 Hz (one breath every 5 seconds) and 0.45 Hz (one breath every 2.2 seconds). On average, during the night the patient breathes every three seconds. In order to obtain a null-phase filter, after filtering in the forward direction, the filtered sequence is then reversed and run back through the filter; the filtered signal is the reverse of the output from the second filtering operation.

The RA signal presents continuous oscillations corresponding to inhalations and exhalations of the patient (see Fig 2). Its instantaneous value is not relevant to the study of SAHS; its envelope is what really reflects the air that is being inhaled or exhaled. Thus we start by obtaining a signal, which we shall call V, whose value at every instant attempts to reflect the amount of air that is being inhaled or exhaled. To this end we search for the maximum and minimum of RA within a mobile window of 1.5 seconds (the approximate length of an inhalation or exhalation), and calculate the difference between the two values. This difference will be the value of V during the 1.5 seconds window. The value of this signal is directly proportional to the instantaneous amount of air being inhaled or exhaled.

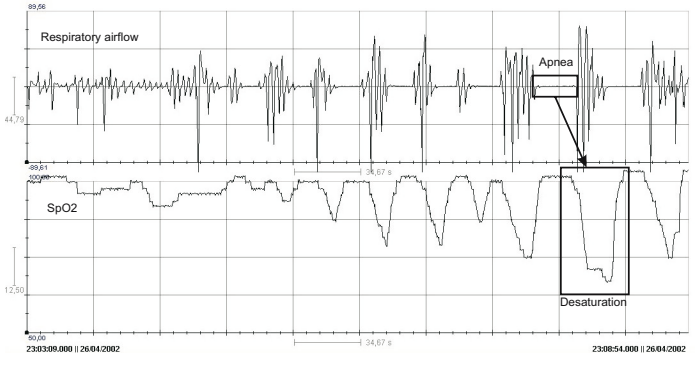

Fig. 2. Fragment of a polysomnogram with several apneas and the corresponding desaturations. The association between one of the apneas and its desaturation is shown.

The calculation of the basal value is challenging: both the different sleep stages and the patient postural changes during the night affect the amplitude of RA. Therefore, it is not acceptable to calculate a basal value considering the whole recording, or its first few minutes. The use of a mobile window does not provide good results either. In the basal value calculation only normal breathing should be considered, while those intervals containing hypoventilations should be ignored. If not, the calculated value will be less than the one corresponding with normal breathing.

To overcome this problem for each sample $RA[t_i]$ we take a two minute window centered on it, in order to calculate the basal value. For each sample of the

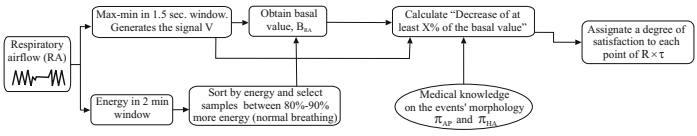

Fig. 3. Block diagram of the algorithm which supports the visual metaphor for highlighting apneas and hypopneas

previous window we calculate the instantaneous energy of RA using a 3 seconds window centered over the sample itself. Then the energy values obtained are sorted from lowest to highest. The time instants corresponding to the samples whose energy falls between 80% and 90% higher energy are selected. Finally the basal value for each sample, $B_{RA}[t_i]$, is estimated as the average value of the samples of V corresponding with the selected time instants (see Fig. 3).

By ignoring those samples corresponding with energy values under 80% we are trying to discard the apneas and hypopneas in the basal value calculation. Given that in the intervals where these hypoventilations have occurred there is a reduction in the amplitude of the signal RA, the energy of the signal in such intervals is expected to be low. By ignoring those samples with energy values above 90% we are trying to discard possible artifacts that the signal may contain.

Fuzzy logic has proven its capabilities to represent and manipulate the vagueness characteristic of medical knowledge [2]. We shall take advantage of this formalism to represent the linguistic descriptions of apneas and hypopneas. More specifically, we shall represent the percentages of reduction from the basal value that the physician wants to use for the identification of these events by means of the trapezoidal possibility distributions D_{AP}, for apneas, and D_{HA}, for hypopneas. For example, if a physician defines apnea as a "*decrease to at least approximately 10% from the basal value*", the percentage of reduction "*decrease to at least approximately 10%*" can be represented by the trapezoidal possibility distribution $D_{AP} = (0, 0, 0.1, 0.15)$. Thus "*decrease to at least approximately 10% of its basal value*" can be obtained as: $D_{AP} \otimes B_{RA}[t_i]$, where $\otimes$ represents the fuzzy product of the fuzzy value D_{AP} by the basal value of RA in t_i, $B_{RA}[t_i]$ [5].

The RA signal presents continuous oscillations which are approximately symmetrical around the x-axis. Given a point $(y, t_i) \in \mathbb{R} \times \tau$, the possibility of the patient experiencing an apnea if y is the maximum or the minimum value of the RA oscillation which contains t_i will be given by:

$$\pi_{AP}(y, t_i) = \mu_{D_{AP} \otimes B_{RA}[t_i]}(|y|) \tag{1}$$

where $|y|$ is the absolute value of y. This expression allows us to obtain the degree of compatibility of each point of $\mathbb{R} \times \tau$ with the linguistic expression represented by D_{AP}, i.e., with a reduction in airflow compatible with an apnea (see Fig. 3). To obtain the degree of compatibility of a point of $\mathbb{R} \times \tau$ with the criteria used for a reduction in airflow compatible with hypopnea we use a similar expression:

$$\pi_{HA}(y, t_i) = \mu_{D_{HA} \otimes B_{RA}[t_i]}(|y|) \tag{2}$$

where D_{HP} represents the percentage of a reduction in RA compatible with hypopnea: D_{HP} = "*decrease to at least approximately 50%*".

3.2 The Visual Metaphor

Our goal is to build a desktop application which provides support for the reviewing of polysomnograms. This tool must plot the polysomnogram signals; each of them is represented in a rectangular area of the screen which we shall call channel. When the channel represents RA, the 0 magnitude value will be placed in the middle of the channel, so that the screen pixels of the upper half of the channel correspond to positive values and the pixels in the bottom half correspond to negative values.

There is a one to one correspondence with each pixel of the channel and a point of $\mathbb{R} \times \tau$. Therefore, using equations 1 and 2 we can calculate the degree of compatibility of each pixel of the RA channel with the apnea and hypopnea criteria. A graphical representation appropriate for this information can be a color code that represents the compatibility of each pixel with each of the two criteria. In our tool the color red has been associated with the total compatibility of the apnea criteria and yellow with the null compatibility. To obtain colors corresponding to intermediate levels of compatibility the red color is degraded to yellow using a linear gradient, and a mapping between colors and compatibilities is generated. The total compatibility for the hypopnea criteria has been associated with yellow, and this color is degraded to green, when compatibility for this criteria becomes null, using a linear gradient. Our tool makes a semitransparent drawing of this information over the RA channel. To this end we have taken advantage of the capabilities of the Java2D graphics library.

The information about the compatibility with the apnea and hypopnea criteria can be represented in two different copies of the RA signal. However, no matter which definition is used, the region where the apnea criteria presents non null compatibility will always be located inside the region of maximum compatibility with the hypopnea criteria. Thus we have chosen to superimpose both representations. A gray line is drawn where the compatibility of the apnea criteria becomes null, so the physician can easily identify this point.

Fig. 4 shows a fragment of a polysomnogram where the RA signal is displayed using the grid described herein. Approximately in the middle of the fragment, the amplitude of the RA oscillations changes. Note how at the beginning both the regions corresponding with apneas and with hypopneas are wider, and they tighten towards the end, adapting themselves to the new basal value of RA.

4 Providing Support for the Identification of Desaturations

There is no absolute consensus on the criteria to be fulfilled by a relevant drop in SpO2, although this time the differences are more subtle: the criteria usually requires a fall in SpO2, relative to the basal value of the signal, of 3%, 4% or

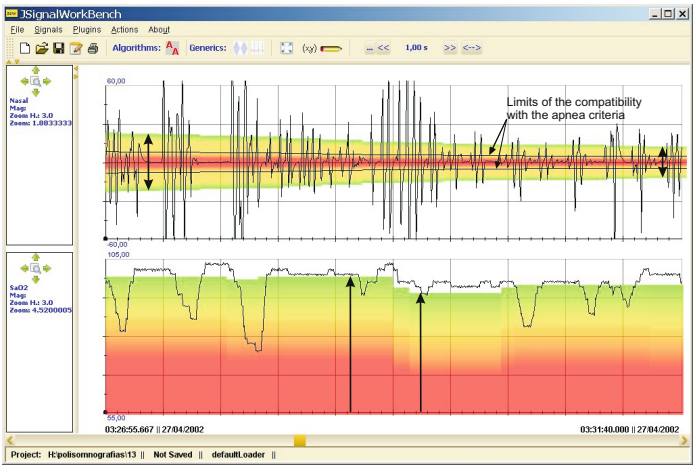

Fig. 4. Tool which implements the algorithms and permits the modification of the morphological criteria that define the relevant events in the SAHS study

5%. Again, our algorithms do not commit to any criteria but seek to capture that one with which the physician feels more comfortable.

4.1 The Algorithm

SpO2 basal value can also vary throughout the night. Long periods of hypoventilation may produce a decrease in the basal value, which can recover if the patient breathes normally for a sufficient amount of time. For the calculation of the SpO2 basal value our algorithms use a mobile window of 10 minutes centered over each sample of the signal. The values of SpO2 in this window are sorted from highest to lowest, and the basal value for the sample SpO2$[t_i]$, $B_S[t_i]$, is obtained as the average of the values of the 10% samples with higher value inside the window.

The artifacts that occur over the SpO2 always produce null values. By considering only the 10% samples with higher value we are ignoring the episodes of desaturation -whose samples will fall within the 90% smaller values-, and the possible artifacts.

Given a point $(y, t_i) \in \mathbb{R}^+ \times \tau$ -SpO2 is always positive-, the possibility of the patient experimenting a desaturation in t_i if SpO2$[t_i] = y$ will be given by:

$$\pi_{Des}(y, t_i) = \min\{\mu_C(B_S[t_i] - y)\} \tag{3}$$

where C is a trapezoidal possibility distribution that represents the value of a drop in SpO2 compatible with a desaturation. For example, if the linguistic criteria that the physician prefers is "*fall of more than approximately 4%*" then C can be represented by $(3, 4, 100, 100)\%$.

4.2 The Visual Metaphor

Eq 3 can be used to calculate the degree of compatibility of each screen pixel of the SpO2 channel, which corresponds to a point in $\mathbb{R}^+ \times \tau$, with the criteria chosen by the physician. This compatibility will be represented, again, by a color code where red represents the maximum compatibility and green, the minimum. A linear gradient is used to obtain a set of intermediate colors between red and green corresponding with compatibilities between 1 and 0.

Although it is not a standardized polysomnographic criteria, the team of pneumologists which works with us prefer to use $C = (3, 20, 100, 100)\%$, whose linguistic meaning is "*drop in SpO2 of moderately high severity*". With this criteria our visual metaphors will assign a low possibility value to small drops in SpO2 compatible with a desaturation, but they still will be highlighted. Drops of high severity (drops of more than 20 %) are assigned the total compatibility. Thus, the metaphor provides visual feedback not only on the number and position of the desaturations, but also on their severity.

In Fig. 4 we can see how the patient's SpO2 basal value presents a decrease approximately in the middle of the recording, probably as consequence of the decrease in amplitude of the oscillations of RA. Note how the grid also falls in the middle of the recording, adapting itself to the new SpO2 basal value.

5 Experimental Results

All algorithms presented in this paper, as well as the visual metaphors they support, have been implemented in a desktop tool (see Fig. 4). This tool is capable of loading polysomnographic recordings that are stored in MIT-BIH format. The parameters of the algorithms that represent the different morphological criteria that apneas, hypopneas and desaturations must fulfill can be customized by means of visual wizards (see Fig. 5), and the effects of the customization are immediately reflected on the visual metaphors.

The tool has been tested by physicians belonging to the Division of Respiratory Medicine of the University Hospital Complex of Santiago de Compostela. They have found that the visual metaphors that we have developed provide an

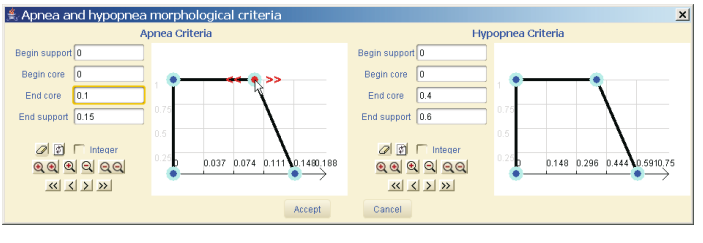

Fig. 5. Wizard which allows the customization of the morphological criteria that define apneas and hypopneas. The trapezoidal possibility distributions can be modified with the mouse or by typing the values in the text fields.

effective support in the identification of episodes of apneas, hypopneas and desaturations. They also consider the metaphors useful in the task of estimating the duration of the events and their severity (percentage of reduction of RA or magnitude of the drop in SpO2). Thus, the physicians are optimistic regarding the potential of the techniques presented in this paper as a support for the diagnosis of SAHS.

A video of the tool showing a polysomnographic recording with the visual metaphors proposed here can be found in [10] . We recommend that the reader watch that video, since it is more effective at demonstrating the visual metaphors we have developed than printed media.

6 Discussion

In the bibliography there are several works which propose a diagnostic test to determine automatically whether or not a patient suffers from SAHS [11]. These test usually take one or several of the physiological parameters recorded during a polysomnography as input. There also are works which propose techniques to identify each episode of apnea and hypopnea individually [1, 4, 7, 8, 14], as well as several commercial solutions with similar capabilities. From this data it can be calculated the apnea-hypopnea index (AHI), which is defined as the number of apneas and hypopneas that the patient suffers per hour of sleep. Based on this index there are medical criteria for associating different levels of severity to the patient's condition.

While these tools provide a significant support for the physician, it is still too early to consider eliminating physicians' intervention in the diagnosis of SAHS. On the one hand, the medical community has been reluctant, probably with good judgment, to trust the results given by automated analysis tools without a contrast. On the other hand, these tools are not able to generate all the information that a physician takes into consideration when diagnosing a patient.

The severity of the condition of two patients who have the same AHI can vary substantially if the average duration of apneas and hypopneas, the average percentage reduction of respiratory airflow during them and the severity of the desaturations are significantly different. When the physician inspects a polysomnographic recording he/she performs a characterization of the various pathological events suffered by the patient. This characterization plays a major role in the final diagnosis. Usually, the tools that perform an automated analysis of the recordings do not provide any of this information, and when they do it is incomplete and unreliable. Thus, at present polysomnographic recordings are always inspected visually by a physician before a diagnosis is issued and a therapy is suggested. Therein lies our interest in providing tools which simplify the reviewing process by helping to identify events relevant in the SAHS diagnosis.

The visual metaphors that we have created also help in the task of characterizing apneas, hypopneas and desaturations. In the first two events, the grid we have developed serves as an aid to measure the duration of the events, as it helps

to identify their beginning and their end. It also helps measure the percentage of reduction from the basal level, as it delimits the regions of the screen which correspond to reductions in RA compatible with apneas and with reductions compatible with hypopneas.

In the case of the SpO2 grid, it helps in measuring the duration of the desaturation, and provides visual feedback on the severity of the drop. The team of physicians which tested the tool decided to use the criteria "*drop in SpO2 of moderately high severity*"to describe the desaturations, instead of a standard one. This reflects their interest in having tools which assist them not only in identifying the events, but also in characterizing them.

7 Conclusions

We have presented a set of structural algorithms whose purpose is to provide support in the reviewing of polysomnographic recordings. The algorithms try to facilitate the identification of apneas, hypopneas and desaturations by generating visual metaphors that help locate these events over the span of a recording. To this end we project a linguistic description of the morphology of these events onto a computational representation. The fuzzy set theory has provided invaluable support in this task. The computational representation is used to calculate the compatibility of each screen pixel of the channel where the signals RA and SpO2 are displayed with the events' linguistic description. This information is represented by a semitransparent grid where different colors represent different levels of compatibility with the criteria.

Our proposal has been implemented in a desktop tool which allows the clinical staff to edit the morphological criteria of the events to be highlighted. Thus, the tool provides support for the use of customized criteria in the analysis of polysomnographic recordings. This solves the problem of the lack of a universal agreement on these criteria in the bibliography, by allowing each physician to use the criteria he/she feels more comfortable with.

For future work, we intend to create new metaphors to identify other events that are recorded during a polysomnography and which, despite having a lower relative importance than the events covered in this paper, are also considered by physicians in the diagnosis of SAHS. Among these events are muscular activity recorded in the electromyography, pauses in respiratory effort and snoring.

Acknowledgments

The authors wish to acknowledge the support by the Spanish Ministry of Education and Science (MEC), the European Regional Development Fund of the European Commission (FEDER) and University San Pablo CEU through grants TIN2006-15460-C04-02 and USP 04/07, respectively.

References

1. Al-Ani, T., Hamam, Y., Fodil, R., Lofaso, F., Isabey, D.: Using hidden Markov models for sleep disordered breathing identification. Simulation modelling 12, 117–128 (2004)
2. Barro, S., Marín, R., Palacios, F., Ruíz, R.: Fuzzy logic in a patient supervision systems. Artificial Intelligence in Medicine 21, 193–199 (2001)
3. Beebe, D.W., Gozal, D.: Obstructive sleep apnea and the prefrontal cortex: towards a comprehensive model linking nocturnal upper airway obstruction to daytime cognitive and behavioral deficits. Journal of Sleep Research 11(1), 1–16 (2002)
4. Cabrero-Canosa, M., Castro-Pereiro, M., Graña Ramos, M., Hernández-Pereira, E., Moret-Bonillo, V., Martin-Egaña, M., Verea, H.: An intelligent system for the detection and interpretation of sleep apneas. Expert Systems with Applications 24, 335–349 (2003)
5. Kaufmann, A., Gupta, M.M.: Introduction to Fuzzy Arithmetic. Van Nostrand Reinhold Company Inc. (1984)
6. Köves, P.: Obstructive Sleep Apnea Syndrome. Springer, Heidelberg (1999)
7. Morsy, A.A., Al-Ashmouny, K.M.: Sleep apnea detection using an adaptive fuzzy logic based screening system. In: 27th IEEE EMB Conference, pp. 6124–6127 (2005)
8. Nazeran, H., Almas, A., Behbehani, K., Lucas, E.: A fuzzy inference system for detection of obstructive sleep apnea. In: 23th IEEE EMB Conference, pp. 1645–1648 (2001)
9. American Academy of Sleep Medicine Task Force. Sleep-related breathing disorders in adults: recommendations for syndrome definition and measurement techniques in clinical research. Sleep 22, 667–689 (1999)
10. Otero, A.: Visual knowledge-based metaphors to support the analysis of polysomnographic recordings, Video (2008), `http://biolab.uspceu.com/sahs`
11. Penzel, T., McNames, J., de Chazal, R., Raymond, B., Murray, A., Moody, G.: Systematic comparison of different algorithms for apnea detection based on electrocardiogram recordings. Med. Biol. Eng. Comput 40, 402–407 (2002)
12. Phillipson, E.A.: Sleep apnea. A major public health problem. N. Engl. J. Med. 328, 1271–1273 (1993)
13. Ulukavak, T., Kokturk, O., Ozkan, S.: Apnea-Hypopnea Indexes Calculated Using Different Hypopnea Definitions and Their Relation to Major Symptoms. Sleep and Breathing 8(3), 141–146 (2004)
14. Varaday, P., Micsik, T., Benedeck, S., Benyo, Z.: A nobel method for the detection of apnea and hypopnea events in respiration signals. IEEE Transactions on Biomedical Engineering 49, 936–942 (2002)
15. Young, T., Palta, M., Dempsey, J., Skatrud, J., Weber, S., Badr, S.: The occurrence of sleep-disordered breathing among middle-aged adults. Med. Biol. Eng. Comput. 328(17), 1230–1235 (1993)