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Towards a Wireless Smart Polysomnograph Using Symbolic Fusion

Adrien UGON[a,1], Brigitte SEROUSSI[b,c], Carole PHILIPPE[d], Jean-Gabriel GANASCIA[a], Patrick GARDA[a], Karima SEDKI[b], Jacques BOUAUD[b,e], and Andrea PINNA[b]

[a] *Sorbonne Universités, UPMC Univ Paris 06, UMR 7606, LIP6, Paris, France*
[b] *Sorbonne Universités, UPMC Univ Paris 06, INSERM, Sorbonne Paris Cité, Université Paris 13, LIMICS, UMR_S 1142, Paris, France*
[c] *AP-HP, Hôpital Tenon, Département de Santé Publique, Paris, France*
[d] *AP-HP, Hôpital Pitié-Salpêtrière, Unité Pathologies du sommeil, Paris, France*
[e] *AP-HP, DRCD, Paris, France*

Abstract. Polysomnography is the gold standard test for sleep disorders among which the Sleep Apnea Syndrome (SAS) is considered a public health issue because of the increase of the cardio- and cerebro-vascular risk it is associated with. However, the reliability of this test is questioned since sleep scoring is a time-consuming task performed by medical experts with a high inter- and intra-scorers variability, and because data are collected from 15 sensors distributed over a patient's body surface area, using a wired connection which may be a source of artefacts for the patient's sleep. We have used symbolic fusion to support the automated diagnosis of SAS on the basis of the international guidelines of the AASM for the scoring of sleep events. On a sample of 70 patients, and for the Apnea-Hypopnea Index, symbolic fusion performed at the level of sleep experts (97.1% of agreement). The next step is to confirm these preliminary results and move forward to a smart wireless polysomnograph.

Keywords. Sleep Apnea Syndromes, Polysomnography, Wireless Technology, Artificial Intelligence, Symbolic Fusion

Introduction

Sleep Apnea Syndrome (SAS) is a disorder characterized by repeated respiratory disturbances occurring during sleep. Estimations of SAS prevalence range from 3 to 7% [1]. The early diagnosis of SAS is a public health problem since numerous studies have identified that the disease is associated with increased cardio- and cerebro-vascular morbidities [2,3]. Besides, markedly impaired quality of life [4], increased risk of road traffic [5], and work accidents [6] are also acknowledged consequences of SAS.

Polysomnography is the gold standard diagnostic test for sleep disorders among which SAS. It consists in recording different physiological signals during a whole night. Resulting curves (Figure 1.a) are analysed by sleep experts who assess sleep cycles, highlight abnormal events, and relate them to each other by cause and effect relationships. Some curves are used to stage sleep, others to detect apneas, the last ones are used to

[1] Corresponding Author.

recognize physiological events that occur as consequences of apneas (desaturations, legs movements). The device used to record physiological signals is a polysomnograph. It comprises a central box to which commonly more than 15 sensors are connected by wired connections (Figure 1.b). Data are then stored and processed on a standard computer.

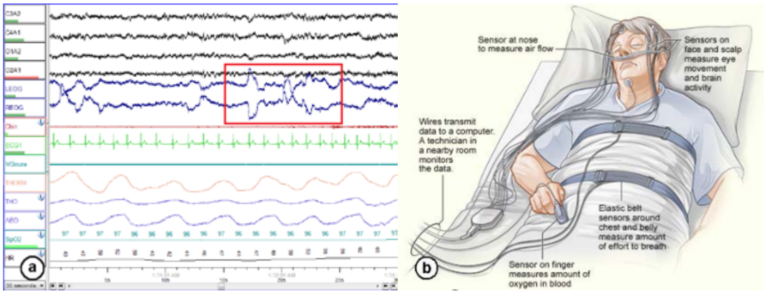

Figure 1. A polysomnograph generates curves (a) from sensor-collected data (b).

The numerous cables used are a source of artifacts for the patient's sleep, which may have an impact on the reliability of the diagnosis. Moreover, sleep scoring is currently performed by sleep experts. This is a tedious and time-consuming task. The inter and intra scorers variability is a real issue, although partially solved by the publication of international guidelines [7]. However, it is still acknowledged that scoring practices need to be improved [8].

We propose two ways to improve the reliability of polysomnography. First, using wireless sensors should help to provide the patient a sleep environment similar to his/her usual sleeping conditions. Second, automatically processing data from sensors with appropriate methods should guarantee the reproducibility of the scoring. Most of marketed digital sleep devices include automatic scoring functionalities, but they are not fully satisfying and sleep physicians do not use them. Research work is being conducted to automate the scoring [9]. Most of this work uses signal-processing methods to extract patterns that are then injected into automatic classification algorithms to recognize abnormal events or sleep stages. However, these methods are not efficient in diagnosing SAS because they are not able to take into account the semantic representations experts use to identify the relationships between the abnormal event and all related events. Unlike purely numerical methods, symbolic fusion is a method used in artificial intelligence that has proven its efficiency to process low level data (raw data coming from heterogeneous sources) and reach a high level, through the management of a semantically-tagged information. This relies on formally represented knowledge and reasoning processes through different abstraction levels [10].

In this paper, we describe the first steps of a project that aims at developing a wireless smart polysomnograph through the use of remote sensors able to record physiological parameters, and the application of symbolic fusion to support the diagnosis of SAS.

1. Methods

We used the set of widely accepted recommendations defined by the American Academy of Sleep Medicine (AASM) for the scoring of sleep and of associated events on polysomnographic curves [11]. Most of the events are defined by the presence of concomitant or lightly delayed observations on the curves. Scored events are used to generate several indexes used for diagnosis. Among them, the Apnea-Hypopnea Index (AHI), defined as the average number of apneas and hypopneas per hour of sleep, is used to assess the existence and severity of a SAS.

Information fusion is defined by Henrik Boström et al. as "the study of efficient methods for automatically or semi-automatically transforming information from different sources and different points in time into a representation that provides effective support for human or automated decision making" [12]. Symbolic fusion uses a formal representation of concepts and fusion strategies. Symbolic concepts are intelligible for experts, which allows to understand how decisions are taken, and helps improve the system by adding or correcting rules.

Figure 2 displays an example of the application of symbolic fusion to stage rapid eye movement (REM) sleep stage. Raw input data come from six different sensors, three electroencephalograms (EEG) for brain activity, two electrooculograms (EOG) for eyes movements and one electromyogram (EMG) for muscle tone. Three layers – data, feature, and decision – are crossed to process these signals and decide whether the treated portion of signal meets the criteria of REM sleep stage. In the "feature" layer, parameters are introduced to reflect the criteria defined in the guidelines.

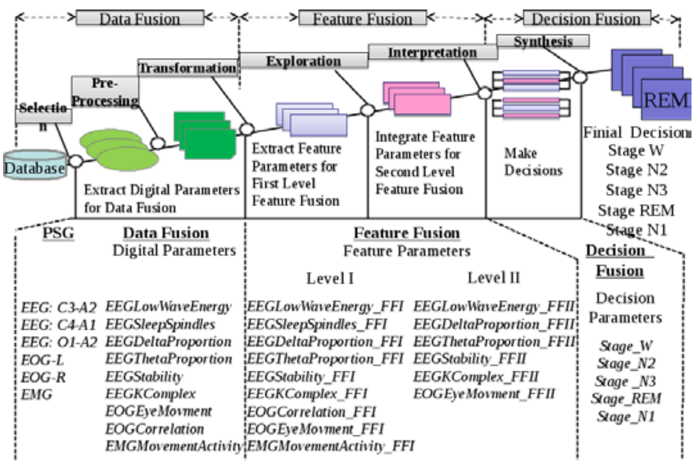

Figure 2. Flowchart of data through the different layers of symbolic fusion to stage REM sleep stage.

Symbolic fusion is implemented by a distributed processing architecture where several abstraction layers are built one above the other, from the sensor to the central unit, to satisfy a low power consumption of autonomous wireless sensors and the correct execution of the expected task (polysomnography recording). Low layers treatments can be processed directly on sensors; upper layers treatments are then processed on a remote computer. We first decomposed sleep into stages, then extract respiratory events for each of these stages. Both steps involve different sub-tasks to recognize and extract relevant patterns and events.

2. Results

We present preliminary results of the use of symbolic fusion to automate SAS diagnosis. Data were collected from 70 patients of the Tenon Hospital (AP-HP), in Paris, France. The sample was composed of 24 men and 46 women, aged 55 ± 12.5 years, with a BMI of 29.9 ± 6.0 kg/m². Data were recorded using the Embla system®; scoring was performed with the Somnologica Software™ (Resmed).

Results produced by symbolic fusion have been compared with those provided by an expert scorer. Figure 3 displays the results for the AHI with data given by the expert, resp. the symbolic fusion, presented on the x-axis, resp. the y-axis. The different ranges of disease severity are represented by colored rectangles. The result is "perfect" when the expert and the symbolic fusion agree, i.e. the point is located on the median axis. It is satisfying when it is located within the same rectangle. It is acceptable when the AHI is overvalued (located above the rectangle), but unsatisfactory when the point is located below the rectangle. Indeed, when the AHI is above a given threshold, a treatment is required. The adaptation of the treatment depends on other parameters and should be decided by a physician. The analysis of the data provided two cases in this later situation. The two points are surrounded by a red circle. The performance of the symbolic fusion was measured by an agreement ratio of 97.1% (68/70).

Figure 3. Comparison of results provided by the expert and the symbolic fusion process.

3. Discussion

Symbolic fusion gave satisfying results to support the automatic scoring of polysomnographic data except in two cases in a sample of 70 patients. In the first case (red square), the event lasted exactly 10 seconds, which was the threshold for an event to be considered. In the other case, the acquired signal was very noisy, which seems to have disrupted the automatic analysis.

Very few works completely automatize the support for SAS diagnosis. Most of them focus on only one step, for example on staging sleep or on recognizing sleep events like apneas or arousals. Diego Álvarez Estévez has proposed in his PhD thesis a method based on fuzzy inference reasoning [13]. Although fuzzy inference reasoning and symbolic fusion provide similar advantages, fuzzy inference reasoning can be used in several consecutive abstraction levels. It is also capable of representing and processing imprecision. Results can be expressed in a human-like understandable way through the use of linguistic terms, which facilitates the explanation of results. However, the reasoning process remains numeric to estimate the degree of membership of a point to a fuzzy set, while symbolic fusion focuses on the use of semantically formalized concepts, and on the application of guideline-based explicit rules.

In future work, we'll consider adding new rules to evaluate new indices for the analysis of sleep disorders in order to improve symbolic fusion in case of noisy sources, and also to consider the clinical context of patients (to support the interpretation of the indexes computed by the events scored on polysomnographic curves, e.g. the AHI). The other dimension of improvement would be to go for a smart wireless polysomnograph implemented using Field Programmable Gate Array (FPGA) circuit.

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