Computer-Assisted Diagnosis of the Sleep Apnea-Hypopnea Syndrome: An Overview of Different Approaches *

Diego Alvarez-Estevez, Member, IEEE, and Vicente Moret-Bonillo, Senior Member, IEEE

Abstract—Automatic diagnosis of the Sleep Apnea-Hypopnea Syndrome (SAHS) has become an important area of research due to the growing interest in the field of sleep medicine, and the costs associated to its manual diagnosis. The increment and heterogeneity of the different techniques, however, makes somewhat difficult to adequately follow recent developments. In this paper an overview within the area of computer-assisted diagnosis of SAHS has been performed. This overview of the different methods is presented together with a critical discussion of the current state-of-the-art.

I. INTRODUCTION

The Sleep Apnea-Hypopnea Syndrome (SAHS) is characterized by the repeated occurrence of involuntary episodes of total or partial reduction in patient’s respiration during the night [1]. Several studies estimate that the prevalence of SAHS is between the 3% and the 7% of the adult population [2,3]. The standard diagnostic procedure to determine the presence of SAHS requires of a polysomnographic test to be done during the night. This test is normally carried out in the sleep units of the medical centers, and it involves the recording of several physiological signals during the night, both respiratory and neurophysiological. The resulting recording, namely polysomnographic recording or PSG, is then visually analyzed offline by the medical specialists. Given the complexity of the scoring process, the analysis of the PSG represents a big cost both in time and in effort for the clinician. This high cost associated to the manual visual review of the PSG can eventually degenerate in a loss in the quality of the analysis due to the accumulated tiredness throughout the revision and because of the complexity of the task itself. From the point of view of hospital’s administration, the increasing importance of the sleep medicine during the last years has also contributed to an increasing demand in the diagnosis of SAHS and its associated treatment. As a consequence, the number of PSG prescriptions has also increased. With this precedent, the interest grows toward the development of automatic systems to aid the physician in the diagnosis of SAHS. As a consequence, research in the development of computer methods for the analysis of sleep, and specifically for the diagnosis of SAHS, is today an important open area of interest. The increasing number of research publications, and the lack of comprehensive reviews at this respect, demands for an integrative effort to be done. This has motivated the authors of this paper to perform an overview, trying to group together the most relevant research efforts in this respect, and to make them available as a single resource to serve the scientific community.

II. METHODS

This paper is aimed at covering approaches in the field of SAHS which are supported by automatic computer-based processes helping the diagnosis. The previous includes as well mathematical models and/or algorithm descriptions that can be eventually implemented into a computer program. In order to keep the review attainable the focus will be constrained to methods involving analysis of the respiratory function in tune with the current standard clinical procedures. At this respect the last version of the AASM manual for scoring of sleep and associated events is considered as reference (see [4], section VIII, “Respiratory Rules”). The former rules out, for example, approaches relying on the use of questionnaires, clinical prediction models, and/or the analysis non-standard signals for the diagnosis of SAHS such as the ECG or the EEG. Analysis of the relevant bibliography has been derived in part from our own experience and research in the field, plus literature search which has been carried out using different well-known search engines including ScienceDirect, IEEE explorer, PubMed and Google Scholar. Search terms included combinations of the words “apnoea”, “apnoea”, “intelligent”, “OSAS”, “OSAHS”, “OSA”, “SAHS”, “monitoring”, “diagnosis”, “automatic”, “computer”, and “analysis”. Only peer-reviewed literature in English was included in the study. In general, for all the methods analyzed within this review, discussion is based exclusively on the data published in the corresponding works.

The approaches analyzed in this paper are organized into several categories as described below. For each category the related works are introduced following a descriptive approach.

III. SCREENING APPROACHES FOR SAHS ESTIMATION

Computer analysis of the oxygen saturation has been widely used as screening method because of its simplicity and its lower associated cost with respect to the full PSG. In this regard the most widely used approaches relied mostly on the application of different cut-offs over the computed number of oxygen saturation dips (oxygen desaturations) per hour of time, i.e. so-called Oxygen Desaturation Index (ODI). Other applications based on the cumulative time spent below certain saturation value can be found [5]. Actually a problem with these approaches has to do with the absence of a consensus to establish the appropriate thresholds.
that in mind, Daniels et al. [6] describe the system CADOSA which combines analysis of the overnight oximetry, with evidence from patient’s history, a physical examination, and a questionnaire to assess sleep propensity. Fuzzy set theory has been used to account for variability in the definitions and subjectivity of the interpretations. In this work, knowledge representation and description of the inference process is illustrated to represent patients’ symptoms and to infer a differential diagnosis with particular emphasis on the detection of Obstructive Sleep Apnea (OSA), Central Sleep Apnea (CSA), periodic limb movement syndrome, and upper airway resistance.

On the other hand, Hornero et al. [7] studied the utility of approximate entropy (ApEn) over the oxygen saturation signal for the diagnosis of SAHS. The study concluded that patients with OSA showed a significant increase in the ApEn values.

Following the previous hypotheses, subsequent works investigated the use of different machine learning classifiers to help in the classification. For example, in Victor-Marcos et al. [8], classifiers based on quadratic (QDA) and linear (LDA) discriminants, k-Nearest Neighbor (kNN) and logistic regression were tried with different combinations of features including spectral and nonlinear features (ApEn, CTM, LZ). In this study the classifier based on LDA with spectral features provided the best performance.

Another relevant work in this context is the one by Alvarez et al. [9] in which a total of 16 features are included in the study and selected by means of a step-forward logistic regression process. The set of features included statistics from both time and frequency domains, conventional spectral characteristics from the power density function, and nonlinear features. Second and fourth-order statistical moments in the time domain, the relative power in the 0.014-0.033 Hz frequency band, and LZ were automatically selected as the best features.

The use of Artificial Neural Networks (ANNs) can be found in Victor-Marcos et al. [10, 11], in which Multilayer Perceptron (MLP) and Radial Basis Networks (RBF) are used in order to classify the patients as OSAHS or non-OSAHS using non-linear analysis of the oxygen saturation signal.

The previous screening approximations used the oxygen saturation signal as its main source to extract the relevant information. However besides oxygen saturation, many approaches based on single signal monitoring are used with a similar philosophy for SAHS prediction purposes. In this respect, techniques based on analysis of single channel airflow recordings constitute another widely extended approximation. Two recent studies can be found in Gutierrez-Tobal et al. [12, 13]. In the first one, spectral analysis of the airflow recordings is performed and spectral features in the 0.024-0.056 Hz band are combined into a linear regression model. In the second work, Respiratory Rate Variability (RRV) is measured throughout the signal and spectral and nonlinear features (LZ, ApEn, CTM) are extracted using both raw and RRV airflow signal. Forward stepwise logistic regression is then used for feature selection and subjects’ classification. The highest accuracy was obtained for the model using features extracted from the combination of the raw airflow and RRV signals with 3 out of the 42 features. Only spectral features were included within this set.

Table I summarizes the analyzed approaches and includes some validation data. Column 2 determines the reference SAHS AHI cut-off value. The third column indicates the validation method as follows: “S” stands for “Singleton” that means validation results are obtained from a single dataset of patients; “TR/TS” stands for “Training/Testing” and applies to the cases in which the methods have been developed and parameterized using a training set, whereas validation results have been obtained using an independent testing set. When several testing sets are used this is indicated as “TS1”, “TS2”, and so on. When available, the actual number of patients involved on each of the different sets is indicated in parenthesis; finally, “CV” means validation results have been obtained by using a cross-validation process. Performance is compared using the well-known measures of sensitivity and specificity.

<table>
<thead>
<tr>
<th>Reference</th>
<th>AHI cutoff</th>
<th>Validation method</th>
<th>Performance (Sens. / Spec.)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Daniels et al. [6]</td>
<td>---</td>
<td>S (21)</td>
<td>100 / 66.0</td>
</tr>
<tr>
<td>Hornero et al. [7]</td>
<td>10</td>
<td>TR (73) / TS (113)</td>
<td>82.1 / 87.0</td>
</tr>
<tr>
<td>Victor-Marcos et al. [8]</td>
<td>10</td>
<td>TR (73) / TS (113)</td>
<td>79.1 / 97.8</td>
</tr>
<tr>
<td>Alvarez et al. [9]</td>
<td>10</td>
<td>CV (148)</td>
<td>92.0 / 85.4</td>
</tr>
<tr>
<td>Victor-Marcos et al. [10]</td>
<td>10</td>
<td>TR (73) / TSI (30) / TS2 (83)</td>
<td>89.4 / 81.4</td>
</tr>
<tr>
<td>Gutierrez-Tobal et al. [12]</td>
<td>30</td>
<td>TR (59) / TS (89)</td>
<td>76.7 / 93.2</td>
</tr>
<tr>
<td>Gutierrez-Tobal et al. [13]</td>
<td>10</td>
<td>CV (148)</td>
<td>88.0 / 70.8</td>
</tr>
</tbody>
</table>

IV. DETECTION OF APNEIC EVENTS

This category includes those approaches seeking for the individual localization of the apneic event in the patient’s biosignals.

A. Analysis of single-channel respiratory activity

A simple strategy to detect and quantify the duration of the apneic event can be performed based on the detection of desaturation and/or resaturation patterns in the oxygen saturation signal. The fundamental hypothesis is that the reduction in the respiratory flow caused by each apneic event induces a drop in the arterial blood oxygen concentration levels. Similarly, for a resaturation, the assumption is that after the apneic event causing a respiratory insufficiency, an episode of compensatory hyperventilation must follow inducing a fast increase in the oxygen saturation levels. Burgos et al. [14] propose a feature extraction process performed on minute-by-minute time step followed by a classification stage. Several classifiers are tested on the extracted features, being the best method a meta-classifier bootstrap aggregating (Bagging) based on alternating decision trees (ADTree). Besides, the resulting method is afterwards implemented into a mobile PDA.
device connected via GPRS to the hospital allowing the physician to perform remote patient follow-up.

Apart from oxygen saturation, other detection approaches based on single channel analysis can also be found. Macey et al. [15] employed as reference the abdominal breathing signal and focused on the detection of central events in infants. In this work an expert system is designed which relied on the use of ANNs to perform the detection task.

Varady et al. [16] propose an algorithm for the online detection of apnea and hypopnea events. Their method is based on the analysis of Respiratory Inductance Plethysmography (RIP) derivations. Instantaneous respiration amplitude and interval signals were derived from the respiratory signals and several feed forward neural architectures were investigated.

The proposal of Nakano et al. is based on the spectral analysis of different airflow derivations [17]. The developed algorithm, based on detection of flow-power dips, was firstly developed using a set of patients in which airflow was measured with a thermal sensor. The resulting method was then evaluated against a conventional time amplitude detection-based algorithm, and the detection of oxygen saturation falls (ODI). A second group of patients, in which airflow was recorded through nasal-prong pressure transducer and a thermocouple, was used to assess generalization capabilities of the algorithm over alternative derivations. Event-by-event validation against visually scored events showed similar behavior for the thermal and for the thermocouple channels, however sensitivity when using these derivations was lower when compared with the nasal pressure sensor. These results support the known difference in sensitivity between thermal-based and nasal pressure sensors.

Modeling the diagnostic process but from a particular knowledge engineering perspective is the objective of another specific group of methods. Inference in these systems is performed by a process of chaining through rules recursively in which activation depends on the particular case presented at the input [18]. Specifically fuzzy inference systems have demonstrated to be suited to model human behavior in domains where data and interpretation processes have a component of imprecision. Medical diagnosis, and SAHS in particular, are good examples of such domains [19]. As an example, in the work of Shin et al. [20], online detection of apneic events is performed using a rule-based system. The objective is to develop a feedback variable to be used for automated control of therapy. For that purpose a Fuzzy Inference System (FIS) is developed using three input variables, and analysis is carried out on a breath-by-breath basis from respiratory airflow measurements.

Nazeran et al. [21] have developed also a FIS which operates over the airflow variable. The system is designed to differentiate between apnea and hypopnea events. Parameters of normalized area and standard deviation are used.

B. Analysis of multi-channel respiratory activity

In this case, detection of apneic events in the respiratory signals follows a multi-channel approach and, according to the standards, it involves the analysis of at least one derivation from each of the following signals: airflow, oxygen saturation and thoraco-abdominal respiratory movements.

According to this, the work of Taha et al. can be firstly mentioned [22]. In this work the analysis starts with the detection of desaturation events in the oxyhemoglobin saturation signal, and then the sum of RIP is analyzed to detect periods of no breathing. The resulting detected periods are subsequently classified as apneas or hypopneas according to the corresponding baseline breathing reduction. Apneas were further classified into central, mixed or obstructive based on the presence of abdominal or rib cage breathing efforts.

The idea of combining oxygen saturation with other respiration signals has been used in subsequent works. For example, the use of the capability of time delayed neural networks (TDNN) to deal with prediction and classification tasks in contexts involving the temporal variable was the main idea of Tian and Liu [23]. In their work, features from the airflow and from the oxygen saturation signals are fed to a TDNN on a second-by-second basis to classify the signal into periods of normal respiration, apnea or hypopnea.

More recently, Houdt et al. [24] published a work in which an algorithm was developed based on breath-to-breath analysis of the respiratory recordings (nasal airway pressure, thoracic and abdominal movements). For that purpose respiratory signals were divided into half waves using period amplitude analysis and characterized in terms of duration, amplitude and slope. Apneic events were then detected by dynamical computation of the normal respiratory values and comparing the corresponding respiratory values for each cycle. Further classification of the events into obstructive, central and mixed was also carried out based on amplitude analysis of the thoracic and abdominal movements.

On the other hand, the goal of the study of Al-Angari and Sahakian [25] was to evaluate the classification of whole-night normal and apneic epochs using extracted features from the phase and magnitude of the respiratory effort signals (thoracic and abdominal), compared and combined with some other features from ECG and oxygen saturation signals. SVM classifiers with linear and polynomial kernels were used. The results of their experiment showed that the best performance was achieved when features of the three signals are used.

Intelligent-based modeling of the respiratory signals (airflow, oxygen saturation, and thoraco-abdominal movements) in a multi-channel setting has been proposed by Alvarez-Estvez et al. [26]. In their work signal processing methods are firstly used to extract features over each channel. By using temporal constraint rules the individual features are then grouped together in form of reasoning units. The resulting reasoning units are finally evaluated by means of a FIS to characterize them either as apnea, hypopnea or normal breathing with different degrees of membership.

Table II shows a comparative overview of the analyzed approaches. Structure is similar to Table I with the difference that validation refers to events detection instead of patients classification.
TABLE II. VALIDATION OF DETECTION APPROACHES. A = APNEA; H = HYPOPNEA

<table>
<thead>
<tr>
<th>Reference</th>
<th>Validation method</th>
<th>Performance (Sens. / Spec.)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Burgos et al. [14]</td>
<td>TR (2465) / TS (1498)</td>
<td>92.3 / 93.5</td>
</tr>
<tr>
<td>Macey et al. [15]</td>
<td>TR (619) / TS1 (2833) / TS2 (32222)</td>
<td>94.1 / 60.9 (TS1) 96.1 / 59.2 (TS2)</td>
</tr>
<tr>
<td>Varady et al. [16]</td>
<td>TR / TS (8000)</td>
<td>98.4 / 94.0 (N) 78.7 / 91.0 (H) 97.0 / 88.7 (A)</td>
</tr>
<tr>
<td>Nakano et al. [17]</td>
<td>TR / TS1 (2744) / TS2 (2420)</td>
<td>77 / 91 (TS1) 89 / 86 (TS2)</td>
</tr>
<tr>
<td>Shin et al. [20]</td>
<td>S</td>
<td>---</td>
</tr>
<tr>
<td>Nazarean et al. [21]</td>
<td>S (808)</td>
<td>83 / ---</td>
</tr>
<tr>
<td>Taha et al. [22]</td>
<td>S (1863)</td>
<td>93.1 / ---</td>
</tr>
<tr>
<td>Tian et al. [23]</td>
<td>TR / TS (1151)</td>
<td>90.7 / --- (A) 80.8 / --- (H)</td>
</tr>
<tr>
<td>Houdt et al. [24]</td>
<td>TR / TS (803 scorer1, 833 scorer2)</td>
<td>89.2 / --- (scorer1) 88.9 / --- (scorer2)</td>
</tr>
<tr>
<td>Al-Angari et al. [25]</td>
<td>S (22908)</td>
<td>69.9 / 91.4</td>
</tr>
<tr>
<td>Alvarez-Estevoy et al. [26]</td>
<td>S (4866)</td>
<td>87 / 89</td>
</tr>
</tbody>
</table>

V. CLASSIFICATION OF THE APNEIC EVENT TYPE

The main goal of the classification task is to characterize the detected apneic event according to the nature of its origin—obstructive, central, or mixed.

In this context, Fontenla-Romero et al. [27] developed a system in which the detection of apnea events is performed from the airflow signal, and once detected, a wavelet processing is applied to the corresponding intervals of thoracic effort signal. A Bayesian ANN is finally in charge of classifying the interval as central, obstructive or mixed. In this work, the airflow signal is examined together with the thoracic effort signal. A Bayesian ANN is finally in charge of classifying the interval as central, obstructive or mixed. At this respect the authors concluded that when features from the thoracic channel are used, better performance can be obtained in the classification.

In the study of Morgenstein et al. [28] two different methods are presented in order to differentiate between obstructive and central hypopneas. A first technique is proposed using a Pes sensor (an invasive method) in which features are extracted and used to train different machine learning classifiers based on discriminant analysis, SVMs and Adaboost. A second method was implemented to assess the validity of a non-invasive approach using an airflow tracing recorded with nasal cannula. Similarly several features were extracted and a diagonal quadratic discriminant was fed with four features. Accuracy of the classification was found lower with the second non-invasive approach.

Table III shows some validation data for the two previous approaches. Comparison is done here in terms of mean classification accuracy because sensitivity and specificity measures cannot be extracted from the work of Fontenla-Romero et al. [27].

VI. COMPREHENSIVE DIAGNOSTIC SYSTEMS

The term comprehensive diagnostic systems is here applied to those systems that comprise—as a minimum—the classification of sleep stages and the analysis of the respiratory activity. These approaches are aimed at constituting global solutions in form of clinical decision supporting systems in the context of SAHS.

Within this group, we may start by mentioning PSG-EXPERT [29], in which PSG data are extracted through a series of processing tasks and are inserted into a database organized according to the following categories: clinical history, hypnogram data, sleep parameters, spectral data, EEG time related activity and non EEG activity. The system carries out the diagnosis through a reasoning mechanism over the extracted data which supports the handling of imprecise information using a model of certainty factors [30]. It also includes a validation module which allows testing of concrete patient’s cases by comparing the results of the analysis with those of the medical experts.

Following with the symbolic perspective, Ugon et al. [31] present an approach that relies on the fusion of complex symbolic objects connected to each other following a set of simple predefined rules. The approach of Ugon et al. incorporates a module that handles sleep scoring following a signal processing approach, which extracts features from the neurophysiological signals, and uses binary decision trees to end up with the final labeling of the sleep epochs.

A different approach is that followed in the system TASAS [32] that implements a general framework for the design of expert systems with special emphasis on the handling of temporal knowledge. The core of TASAS relies in the Causal Constraint Temporal Networks (CTCN) representational model which allows handling of temporal information between symbolic items, modeling them either as points or as intervals, and implements effective mechanisms to manage causality [33]. Under the modeling framework provided by TASAS, expert knowledge can be implemented describing temporal patterns that are used to detect physiological evidences of apneic events in the PSG.

The system SAMOA makes use of both artificial intelligence and classical signal analysis techniques for the development of an integrated product which, in addition, is able to provide explanation of its results [34, 35]. The architecture of SAMOA includes four different modules: (i) the polysomnographic prescription module, (ii) the module for the characterization of the respiratory activity, (iii) the module for the construction of the hypnogram, and (iv) the diagnostic module. While the system SAMOA solves many of the problems of its predecessors, still a common drawback on this system is the use of fixed protocols and thresholds while automatically analyzing the raw signals from the PSG.

In an endeavor to solve the previous drawbacks, the MIASOFT system has been recently developed [36]. This system contributes supporting its analysis capabilities under
two fundamental pillars: (i) a comprehensive approach, in which neurophysiological activity is used as a context for the interpretation of the detected respiratory events, and (ii) the implementation of mechanisms to handle data imprecision which mimic human’s reasoning procedures under the principles of generalization and approximation. Neurophysiological analysis in MIASOF comprises characterization of cerebral activity, eye movements, and muscle tone. This neurophysiological information is fed to a module in charge of obtaining patient’s hypnogram [38]. MIASOF system, besides, is provided with mechanisms for the analysis of the sleep microstructure and to deal with the detection of transient events including micro-arousals [39, 40], sleep spindles and K-complexes. Respiratory analysis is structured into three submodules for the identification of apneic intervals, characterization of the SaO2 signal and the analysis of the respiratory effort [37]. The whole analysis in this system is concurrently assisted by additional modules providing functionality for artifact detection, temporal information correlation, and inference with special emphasis in the support of uncertainty and imprecision in the decision process.

Table IV shows a comparative overview of the analyzed comprehensive approaches reporting validation data. Validation results refer to event detection/classification but for the works of Cabrero-Canosa et al. [34-35] that refer to patient diagnosis.

<table>
<thead>
<tr>
<th>Reference</th>
<th>Validation method</th>
<th>Performance (Sens. / Spec.)</th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>Fernández-Leal et al. [32]</td>
<td>S (10 patients, 1243 events)</td>
<td>91.3 / 93.6 (OA)</td>
<td>100 / 95.7 (CA)</td>
</tr>
<tr>
<td></td>
<td></td>
<td>83.7 / 99.8 (MA)</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>91.1 / 98.3 (OH)</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>100 / 98.7 (CH)</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>60.0 / 99.9 (MH)</td>
<td></td>
</tr>
<tr>
<td>Cabrero-Canosa et al. [34-35]</td>
<td>S (13 patients, 1270 events)</td>
<td>87.5 / 100 (patient)</td>
<td></td>
</tr>
<tr>
<td>Alvarez-Estvez et al. [36], Moret-Bonillo et al. [37]</td>
<td>S (26 patients, 8705 events)</td>
<td>89.2 / 89.0 (A)</td>
<td>89.0 / 89.2 (H)</td>
</tr>
<tr>
<td></td>
<td></td>
<td>83.8 / 87.3 (OA)</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>78.3 / 83.8 (CA)</td>
<td></td>
</tr>
</tbody>
</table>

VII. DISCUSSION

The growing interest in the field of sleep medicine, together with the recent advances in computer analysis methods, have contributed to a blooming in the number of developments in the field in the last years. The heterogeneity of the different techniques and the increment of the scientific production, makes somewhat difficult to follow the trace of the recent developments in the area. This situation motivates an overview to be performed whose objective is to serve as a reference for the reader interested in the development of computerized methods for the diagnosis of SAHS. The analysis has effectively shown how the referred context yet constitutes a field with a certain maturity –despite the relatively youth of the sleep science, where the number of approximations has significantly increased, especially in the last years. Even if the scope of the overview has centered on automatic methods that operate over the mostly extended signals used in the clinical routine, the resulting number of approaches is noticeable. In this respect, two concurrent trends may be differentiated. On one hand, a first trend is focused toward reducing the required montage, translating the complex full monitoring carried out in the attended hospital environment, to a more lightweight setting which can be ultimately performed in unattended conditions, even at the patient’s home. On the other hand, and especially motivated by the recent advances in the field of signal processing and artificial intelligence, new analyzing algorithms are breaking through with the purpose of automating the analysis of the resulting data.

Certainly, and although somehow related, these two trends can be considered separately. While reducing the number of signals to be monitored has several advantages, including reduction of costs, more comfort for the patient, or reduction of waiting lists (more recordings can be scheduled in parallel without being constrained by the number of beds in the hospital), still manual scoring of the resulting data, is complex and time-consuming.

Such a situation evidences the need to standardize the validation process in order to achieve meaningful comparisons among the different methods. A standardization process like this would encourage the use of open and consensus databases for which standard tests would be designed, probably organized into different tasks. Each task would fulfill specific necessities demanded from the clinical practice, and for each one, the proper validation process to assess its degree of accomplishment would also be standardized. Besides allowing objective method comparison, such a procedure would set concrete objectives and guide the development of automatic methods, filling the gap between engineering research and clinical necessities.

VIII. CONCLUSION

Several methods have been analyzed which focus on different subtasks of the diagnostic process, from the screening and early diagnosis to full comprehensive systems. Current efforts in the design of these systems are focusing toward the design of robust algorithms which can be used to accurately interpret data registered in ambulatory conditions. This should contribute to unlock the bottleneck of the centralized in-hospital diagnosis and reduce the costs associated to the test. Development of full comprehensive approaches to handle the analysis of the full PSG is also desirable to help the clinician with the time-consuming scoring task. These approaches may also contribute to reveal new data and patterns of relevance to improve the diagnosis task.

REFERENCES

2012.


