Exploring the Feasibility of Sleep Quality Evaluation with a Reduced Parameter Set

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***Abstract*—Sleep covers approximately one-third of life, providing the necessary recovery to fundamental body functions. Sleep deprivation and poor sleep quality cause several side effects in everyday life; among others, the efficiency of the immune system progressively decreases, enhancing the arise of pathologies. Therefore, the evaluation of sleep quality is crucial for providing information about personal health status. However, a uniform and robust method for the assessment of sleep quality is still missing. In this preliminary study, Obstructive Sleep Apneas (OSAs), sleep macro pattern and sleep micro pattern are identified and then combined to provide a comprehensive sleep evaluation. For this purpose, a subset of physiological variables (HR, HRV, SpO_2, body movements) is derived from Polysomnography (PSG) and exploited for the development of rule-based algorithms. This reduced parameter set is selected considering further implementations on wearable off-the-shelf commercial devices.**

***Index Terms*—Sleep, Sleep Quality, Obstructive Sleep Apnea, Hypopnea, Obstructive Sleep Apnea Syndrome, Sleep Macro Pattern, Sleep Micro Pattern, IOT, Smartwatch, ECG, SpO2**

I. Introduction

Sleep is characterized by sequences of behavioral states related to Autonomous Nervous System (ANS) functions. It is a complex physiological process linked to each individual and covers approximately one-third of the lifespan. The circulatory, respiratory, musculoskeletal and central nervous systems, are restored during sleep. Sleep also plays a crucial role in the consolidation of memories, learning, physical development, emotion regulation, and quality of life. A sustained deprivation of sleep or poor sleep quality decreases the efficiency of the immune system and increases the risk of cardiovascular pathologies, hypertension, obesity, metabolic deregulation, diabetes, but also daytime drowsiness [1], [2]. Daytime drowsiness is a widespread problem that leads to a variety of issues. It reduces focus on everyday activities, playing a particularly crucial role in people involved in driving (e.g., professional truck drivers, public transport drivers, etc.) [2].

A sleep disorder that significantly affects sleep quality is Obstructive Sleep Apnea Syndrome (OSAS). As reported by the American Academy of Sleep Medicine (AASM), Obstructive Sleep Apnea (OSA) can be considered both obstructive sleep hypopnea and obstructive sleep apneas, defined as a 10s reduction of airflow of 30% or 90%, respectively. The level of OSAS is evaluated with the Apnea-Hypopnea Index (AHI), which is the average number of apneas per hour. The OSAS associated with a subject can be classified as follows [3]:

- Healthy, if AHI < 5;
- Mild, if $5 \leq$ AHI < 15;
- Moderate, if $15 \leq$ AHI < 30;
- Severe, if AHI ≥ 30.

Sleep quality can be further evaluated by the analysis of the sleep pattern itself. Starting from a macroscopic point of view and considering a normal young adult, sleep is composed of two behavioral states: Rapid Eye Movement (REM), which constitutes approximately 20% of Total Sleep Time (TST), and Non-Rapid Eye Movement (NREM) sleep. NREM sleep is moreover subdivided into light sleep (stage 1 or NREM 1), intermediate sleep (stage 1 or NREM 2), and deep sleep (stage 3-4 or NREM 3-4). REM and NREM sleep alternate cyclically across sleep, constituting at least 3 cycles of approximately 90 to 110 minutes. The typical human sleep cycle is shown in Figure 1 and described below:

- sleep begins with stage 1, which usually persists for 1 to 7 minutes from sleep onset;
- stage 2 follows the brief episode of stage 1 and continues for 10 to 25 minutes;
- stage 3 occurs, lasting only a few minutes in the first cycle;
- stage 3 is transitional to stage 4, which lasts 20 to 40 minutes in the first cycle;
- first sleep cycle ends with REM sleep, which takes 1 to 5 minutes.

NREM and REM sleep continue to alternate through the night: in physiological conditions, REM sleep usually becomes longer across the night, while deep sleep (NREM 3-4) decreases. Therefore, by knowing the physiological sleep macro-pattern, good quality sleep can be defined, for instance, as 7 to 8 hours of TST, with different percentages of NREM 1 (2-5%), NREM 2 (45–55%), NREM 3-4 (5–15%) and REM (20–25%) sleep [4]. In addition, many other features for sleep quality estimation can be extracted from sleep macro-structural analysis [2].

However, an effective sleep quality estimation requires going deeper into the micro-structural analysis of sleep [1], [5].

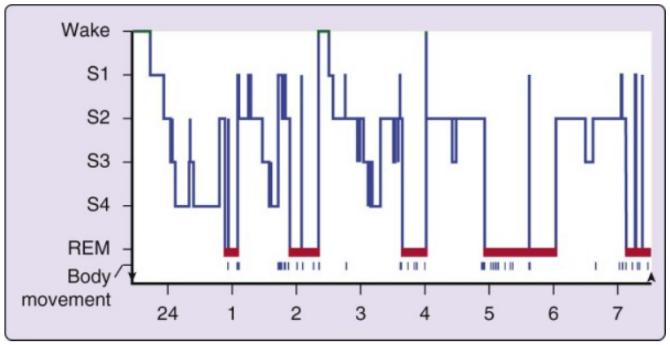

Fig. 1. The progression of sleep stages across a single night in a normal young adult volunteer [4].

Within this context, NREM sleep displays a distinctive pattern known as the cycling alternating pattern (CAP), which consists of two stages:

- Phase A, characterized by a lighter level of sleep;
- Phase B, where the sleep stage returns to its typical behavior.

CAP sleep alternates with nonCAP (NCAP) sleep. CAPrate, which represents the proportion of CAP in relation to NREM sleep, serves as an indicator of sleep quality: a higher CAPrate suggests poorer sleep quality. CAP is an EEG-related event, but there is a correlation between CAP and autonomic arousal. Thus, it is possible to estimate the arousability, considered as a CAP-related variable [6]. An arousal is an activation of the vigilance level, also known as micro awakening, that causes an increase in HR typically during NREM sleep [8].

The aim of this work is to combine the analysis of OSAS, which is the most common sleep-related breathing disorder, with the analysis of sleep macro and micro-pattern, in order to provide a feasible and robust evaluation of sleep quality. The detection of OSAs and different sleep patterns will be implemented by the proposed rule-based algorithms.

II. STATE OF THE ART

Sleep is analyzed with objective and subjective methods. Subjective methods require the subjects to answer questions or estimate their sleep parameters. A widely used subjective method is the creation of a sleep diary, where the subject writes his estimation of TST, Sleep Onset Latency (SOL), satisfaction with the night spent, and other sleep parameters. The gold standard of subjective sleep quality estimation is the Pittsburgh Sleep Quality Inventory (PSQI). PSQI has 24 questions, 19 of them are self-reported, and the other 5 are answered by someone who has slept with the subject [9]. The most employed objective methods for sleep evaluation are Polysomnography (PSG) and actigraphy, often used in combination with sleep questionnaires. PSG is the gold standard for monitoring sleep by means of the detection of various biomedical signals. PSG comprises electroencephalogram (EEG), photoplethysmograph (PPG), electrocardiogram (ECG), electrooculogram (EOG), electromyogram (EMG), nasal cannula and thoracic and abdominal bands to measure brain activity, blood saturation, heart rate (HR), eye movement, muscle activity, breathing and respiration rate (RR), respectively. The signals acquired by PSG are analyzed by the sleep expert medical doctor, who provides the classification and distribution of sleep stages throughout the night, named hypnogram, and identifies eventual sleep disorders, including sleep apneas. However, the PSG itself can affect sleep quality, because subjects are disturbed by an unfamiliar laboratory environment; moreover, it is time-consuming and expensive, requiring professional equipment and a specialized medical doctor [10]. Another medical instrument employed in sleep analysis is actigraphy, which detects limb movement through sensors worn on the wrist, leg and waist. Actigraphy is usually exploited for long-period circadian rhythm monitoring. This procedure is less intrusive and cheaper than PSG, but also less accurate, measuring fewer parameters with less accurate instrumentation [11]. Thus, there is an urgent need to develop a reliable, non-intrusive, time and money-saving method for a simplified sleep analysis.

Nowadays, consumer wearable devices offer an innovative solution for a simplified sleep analysis based on cardio-respiratory and accelerometer parameters [12]. Apple Watch and Fitbit smartwatch are the most popular examples of wrist wearable health devices employed even in sleep monitoring [13]. Specifically, a recent study showed that Apple Watch Series 6, exploited accelerometer, ECG, gyroscope and PPG sensors, providing high sensitivity (99.1%) in detecting sleep time, and adequate specificity (75.8%) in detecting wakefulness, compared to the clinically validated Philips Actiwatch Spectrum Pro [14]. Similarly, another work proved that Fitbit smartwatch, exploiting accelerometer, ECG, gyroscope, PPG and temperature sensors, showed higher sensitivity (95-96%) and specificity (58-69%) values in detecting sleep time compared to values of regular wrist actigraphy [15]. An additional example of a novel consumer device for sleep monitoring is OURA ring: worn on the finger, it provides comfortable and continuous PPG measurement. Oura ring was tested with 60 subjects compared with ECG to measure HR and Heart Rate Variability (HRV) during sleep, showing a very high correlation (r2 = 0.972 and 0.943, respectively). Due to the extremely reliable PPG signals, Oura ring is now employed in sleep tracking, achieving 79% agreement with PSG for 4-stage sleep classification (wake, light, deep, and REM sleep) [16].

Sleep monitoring should not just be limited to the quantification and classification of sleep macropattern, but should also be extended to the analysis of sleep micropatterns and pathologies. For instance, multiple devices have been developed for recognizing OSAs without needing the entire PSG setup [17]. Some of them are electronic devices equipped with sensors such as a naso-cannula for measuring breath, a wristband for detecting HR, a thermistor, and a sensor placed on a finger for detecting PPG, but there is a wide variety of

sensors and signals for this purpose. In the considered devices, there is also a smart mattress, with a balancing tube based on ballistocardiography (BCG) that is able to detect movement related to the breathing process [18]. The SD-101 is a sheet-like medical device that has to be spread between the mattress and a sheet. It has multipoint sensors that measure respiratory movement detecting gravitational alterations in the body [19]. It has a low specificity and a low accuracy for OSAs detection, which can be improved by measuring also SpO_2 [20] The WatchPAT200 is a bracelet with an LCD screen that can be equipped with other sensors; it detects SpO_2, HR, actigraphy, noise, and position, thus measuring movement, snoring, sleep stage, and AHI [21]. The Sleep&Go is a device that measures SpO_2; moreover, it detects airflow with a thermistor and rib-cage and abdominal movement with inductive bands [22]. NOX T3 is a home sleep monitoring system that records respiratory effort, PPG, airflow, oximetry and snoring sounds. It has 2 bands for recording thoracic and abdominal respiratory effort. It is also possible to plug two bipolar channels (ECG, EMG or EEG) [23]. The Sonomat is a device similar to the SD-101. It contains a series of vibration and sound sensors able to recognize movements, breathing, and heart sound [24]. SleepView is a 2 channel wrist device, similar to a watch but with the addition of a naso-cannula and a finger probe for oximetry. It records oral and nasal airflow, snoring, SpO_2, and HR. Moreover, it allows downloading data and processing them with SleepView software [25]. Alice PDx collects simultaneously airflow (nasal pressure cannula and oral thermistor), effort (chest and abdominal movement with two respiratory plethysmography belts), pulse oximetry with a finger probe, and sleep (wrist actigraphy) [26]. Sleep Design is a device with a microphone that extracts snoring from environment noise [27]. Apnia is a seven-channel device that records the respiratory flow, SpO_2 and HR (by pulse oximetry), an abdominal effort by inductive plethysmography, corporal position, and snoring sounds [28]. AHI, Sensitivity and Specificity of these devices are briefly reported in Table I.

In this study, PSG was exploited for the sleep evaluation of the participants provided by the doctor. PSG is a medical device that measures physiological variables with high reliability; therefore, the development of the algorithms was based on data extracted from PSG. Particularly, inspired by sleep monitoring of consumer devices, only HR, HRV, SpO_2 and body movements were considered: HR and HRV were obtained from ECG, body movements were taken from the accelerometer sensor located on the leg and SpO_2 was detected by PPG sensor placed on the finger. This reduced parameter set was selected with the aim of implementing the proposed algorithms in a wearable off-the-shelf commercial device (i.e., smartwatch). Analyzing HR, HRV and accelerometer data, OSAs, sleep macro and micro patter were identified. Then, a sleep quality evaluation was provided.

TABLE I
SLEEP-DISORDERED BREATHING HOME DETECTION DEVICES

Device	Article	AHI	Sensitivity	Specificity
SD-101	[19], [20]	5	95	60
		15	88	86
Watch PAT200	[21]	5	96	43
		10	90	69
		15	92	77
Sleep&Go	[22]	5	92	67
		15	95	56
NOX T3	[23]	5	100	70
		15	92	85
SonoMat	[24]	5	94	77
		15	88	91
		30	100	96
SleepView	[25]	5	80	95
		15	87	85
		30	95	93
Micromovement Sensitive Mattress	[18]	5	95	100
		15	90	97
		30	90	95
Alice PDx T3	[26]	5	69	87
		15	87	66
Sleep Design	[27]	26	71	93
Apnia	[28]	5	88	73
		15	70	94
		30	100	93

III. METHODS

For this preliminary study, a subset of 5 healthy adult volunteers (3 male, 2 female) with a mean age of 49.2 years was considered. A complete PSG test was carried out for each subject for an entire night. ECG, accelerometer and SpO_2 data were extrapolating data from *.edf* PSGs files. HR and HRV were calculated from ECG, as reported by Guagnano et al. [29]. The considered physiological variables were analyzed in post-processing. The development and validation of the algorithms were carried out with Matlab.

A. OSAS

The proposed algorithm exploits HRV and SpO_2 for identifying sleep apnea and calculating AHI. As defined by the American Academy Sleep Medicine (AASM), apneas are a cessation of airflow for at least 10s, usually accompanied by a SpO_2 reduction of at least 3% [30]. Interestingly, HRV during an apnea, has a particular pattern. There is a relaxation stage, where the activity of the parasympathetic system is higher than the sympathetic one. In this stage, the HRV grows in time until HRV stabilization. The stabilization is interrupted by autonomic arousal, a stage where the activity of the sympathetic system is higher than the parasympathetic one. Here HRV decreases over time. The idea behind this algorithm is a recognition of the HRV pattern, accompanied by a SpO_2 desaturation of at least 3% [29]. A schematic representation of the proposed algorithm can be found in Figure 2. Finally, the AHI is calculated by dividing the number of found apneas by TST, evaluated in section III-B.

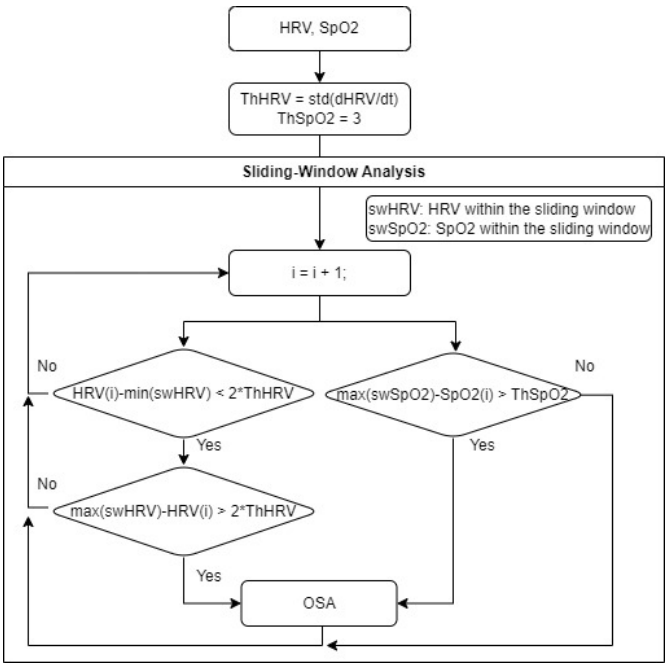

Fig. 2. A schematic representation of the algorithm for the detection of OSA

B. SleepScoring

Firstly, the awake-sleep transition was analyzed. Actigraphy, exploiting an accelerometer, is often used as a tool for recognizing sleep onset. However, the accelerometer by itself can recognize motionless wakefulness as a sleep stage or miss the sleep onset for tremors or movement caused by external conditions [31]. Therefore, in this study sleep onset was detected by combining both the decrease of HR, typical of wake-sleep transition, and the decrease of body movements through accelerometer signal.

Then, sleep macro pattern recognition based on HR, HRV and accelerometer measures was performed considering typical behavior in different sleep stages [32], [33], [34]:

- in NREM sleep, HR is expected to be lower compared to wakefulness and REM sleep;
- in REM sleep, HR increases similarly to wakefulness, but the body is motionless;
- deep sleep (NREM 3-4) is characterized by less body movements than light sleep.

Finally, sleep micro pattern was identified. A variable called arousability was calculated, as the percentage of arousals in NREM sleep.

IV. Results

A. OSAS

The previously described algorithm for OSA detection has been developed and has been tested with PSG data at our disposal. The algorithm was executed on the above-mentioned set of measures, having the effective number of apneas scored by sleep expert medical doctor as a comparison term. Evaluation is based on the following results and shown in Table II:

- a True Positive (TP) is an OSA scored by both the algorithm and the medical doctor;
- a False Positive (FP) is an OSA scored by the algorithm and not scored by the medical doctor;
- a False Negative (FN) is an OSA not scored by the algorithm but scored by the medical doctor.

From TP, FP and FN sensitivity, specificity, and positive predictive value (PPV) were obtained. They are defined as:

$$sensitivity = TP/(TP + FN) \quad (1)$$

$$PPV = TP/(TP + FP) \quad (2)$$

The goal of this algorithm is not to obtain a substitution to the medical scoring, but to screen healthy, mild, moderate and severe OSAS using a little set of measures acquirable with a commercial off-shelf smartwatch. Moreover, the algorithm requires less than 1 minute to process a night scoring instead of hours needed by a sleep expert medical doctor. In addition, this methodology is cheaper than the gold standard PSG exam. Table II shows that healthy and affected subjects are always recognized. The most difficult part is distinguishing mild (AHI between 5 and 14) and moderate (AHI between 15 and 30) subjects, this was failed with subject 5, but they were never confused with healthy or severe subjects.

B. Sleep Scoring

The output of the algorithm for sleep analysis provided various parameters for the estimation of sleep quality. Firstly, TST found with the algorithm was compared to the PSG analysis of medical doctor, as reported in Table III. Good, medium and low-quality sleep were classified for TST > 7 hours, $5 \leq$ TST ≤ 7 and TST < 5, respectively. A precise correspondence was seen for records 1, 2, and 5, while for both records 3 and 4 the algorithm overestimated TST. Considering that sleep onset was accurate for almost all the records, as reported in Table III, this result demonstrated that further improvements must be implemented for awake time.

Then, sleep was classified into its macro-pattern, which comprises (NREM 1-2), deep (NREM 3-4) and REM stages. However, particular attention was given to the identification of sleep micro-pattern, defined by the alternance of phase A and phase B in NREM sleep. Phase A is characterized by a very high presence of arousals, which deeply affected sleep quality. Therefore, the percentage of phase A in NREM sleep, named arousability, was evaluated as a parameter for sleep quality assessment. Table III shows the comparison between arousability evaluated in NREM sleep scored by medical doctor and by the algorithm. Good, medium and low-quality sleep was classified for arousability > 0.025, $0.015 \leq$ arousability ≤ 0.025 and arousability < 0.025, respectively. A precise correspondence was seen in record 1, 3, 4, and 5, while in record 2 algorithm overestimated the

TABLE II
SECOND SCORING AND ALGORITHM COMPARED

Rec.	apneas from scoring	apneas from algorithm	AHI from scoring	AHI from algorithm	TST	Severity scoring	Severity algorithm	TP	FP	FN	Sensitivity	PPV
1	0	5	0	1	06:07:04	Healthy	Healthy	0	5	0	100%	0%
2	61	30	10	5	06:21:03	Mild	Mild	29	1	32	48%	97%
3	136	151	19	21	07:05:32	Moderate	Moderate	91	58	44	67%	61%
4	0	6	0	1	04:29:03	Healthy	Healthy	0	1	0	100%	0%
5	107	77	15	11	06:57:30	Moderate	Mild	63	13	44	59%	83%

TABLE III
SLEEP QUALITY EVALUATION

Rec.	Doctor TST	Algorithm TST	Doctor Sleep Onset	Algorithm Sleep Onset	Doctor Arousability	Algorithm Arousability
1	medium	medium	22:37:20	22:25:27	good	good
2	medium	medium	23:47:11	23:57:04	good	medium
3	medium	good	22:45:24	22:42:09	low	low
4	low	medium	0:40:18	0:18:24	low	low
5	medium	medium	0:33:37	0:30:35	low	low

number of arousals.

V. CONCLUSION

In this study, rule-based algorithms for sleep quality evaluation were successfully developed. Particularly, HR, HRV, SpO_2 and body movements were chosen as inputs, considering the possibility of the implementation on a commercial off-shelf smartwatch. The algorithms were developed on physiological variables extracted from PSG, which is the gold standard for sleep monitoring. The level of OSAS, TST and arousability were successfully calculated and combined for evaluating a primary screen of sleep quality. However, due to the limited size of the dataset, further validations of the algorithm will be performed.

In a clinical context, sleep quality is monitored with PSG, considering ECG, EOG, EMG, EEG, and a lot of other parameters, measured with high-quality instruments and evaluated by an expert. Undoubtedly, results acquired from medical exams have very high accuracy, but the procedure is invasive and time-consuming. Therefore, portable devices represent a more comfortable and less expensive way to obtain preliminary information about sleep.

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