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Unobtrusive Sleep Monitoring Using Cardiac, Breathing and Movements Activities: An Exhaustive Review

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ABSTRACT At least 50% of the world's elderly population, whose range is fast growing, experience disturbed sleep. Sleep studies have become an extensive approach serving as a diagnostic tool for health-care professionals. Currently, the gold standard is polysomnography (PSG) recorded in a sleep laboratory. However, it is obtrusive, requires qualified technicians, and is time and cost expensive. With the introduction of commercial off-the-shelf technologies in the medical field, alternatives to the conventional methods have been conceived to ensure sleep stages and sleep quality detection, which may be now used at home on several nights. Cardio respiratory and physical activities abide the most promising physiological measurements to detect sleep stages without complete PSG. The statistically proven impacts and budgets related to sleep disorders are phenomenal, showing that the field needs more research. This paper aims at providing the reader with a multidimensional research perspective by presenting a review of research literature on developments made in unobtrusive sleep assessment. Additionally, a categorization of current approaches is presented based on methodological considerations, from data acquisition frameworks and physiological measurements, to information processing. Subsequently, limitations and challenges facing current solutions are discussed, and open research areas are highlighted, which we hope would pave the way for future research endeavors addressing the question: how to assess sleep stages and sleep quality less intrusively, and reliably?

INDEX TERMS Actigraphy, body movements, patient monitoring, polysomnography, pressure sensor mattress, cardiac activity, unconstrained sleep monitoring, unobtrusive sleep studies, respiration.

NOMENCLATURE

AASM	American academy of sleep medicine
ADC	analog-to-digital conversion
AR	auto-regressive
AUC	area under curve
BPM	breaths per minute
BR	breathing rate
CPAP	continuous positive airway pressure
CPM	counts per minute
DI	digital integration
ECG	electrocardiogram
EEG	electroencephalogram
EMG	electromyogram
EOG	electroocculogram
HRV	heart rate variability
HF	high frequency
IR	infrared
ICSD-3	third international classification of sleep disorders
LF	low frequency
MA	moving-average
NIR	near infrared
NREM	non rapid eye movement
OSA	nbstructive sleep apnea
OSAS	obstructive sleep apnea syndrome
PIM	proportional integrating mode
PSG	polysomnography

PLM	periodic limb movement
PLMD	periodic limb movement disorder
PLMS	periodic limb movement during sleep
PSD	power spectral density
REM	rapid eye movement
RGB	red-green-blue
RBD	rapid eye movement behavior disorder
R/K	Rechtschaffen and Kales
RLS	restless legs syndrome
RRV	respiratory rate variability
SA	sino-atrial node
SBD	sleep breathing disorders
SBSM	society of Behavioral Sleep Medicine
SD	standard deviation
SDB	sleep disordered breathing
SDNN	standard deviation of N-N intervals
TAT	time above threshold
ToF	time of flight
TST	total sleep time
ZC	zero crossing

I. INTRODUCTION

According to sleep research, the numbers related to sleep disorders propagation worldwide are becoming phenomenal with at least half of people over the age of 65 experience disturbed sleep [1]. This number is expected to fast grow until at least 2050 with a tendency to continue more, leading to a solid increase in sleep disorders around the world with further demanding budgets and care [2]. Researchers have shown the direct socioeconomic impact on the population and the public health [3]–[5].

Prevalence linked numbers being said, sleep disorders are a result of physiological disturbances and an inducing factor to others, making sleep a very important behaviour to explore to maintain a healthy well-being and physiological functions [6], [7].

Although the high spreading and impact of sleep disorders, a considerable reduced people's willingness to resorting to the current medical sleep evaluation is on the rise [8]. The reasons for that reduction are many, including burdensome physiological signal acquisition protocols and clinical conditions that constrain both comfort and sleep quality of the subjects, very high costs for sleep evaluation and long waiting lists before exam [9].

Therefore the need for less constrained sleep studies has given rise to a prominent research line through which researchers have been trying to propose unobtrusive alternative solutions to the conventional methods. These alternatives mainly consist of significantly reducing the large number of sensors attached on the body, and making the signal acquisition process more comfortable by targeting unobtrusively acquired signals such as breathing, cardiac and movement activities instead of obtrusive conventional measures such as *electroencephalogram (EEG)*, *electrooculogram (EOG)* and *electromyogram (EMG)*. With the application of unobtrusive sleep studies, not only comfort, costs and waiting lists are bound to improve, but also 1) this gives the option to measure sleep in ecological conditions i.e., at home, with several nights and 2) being able to reach many more people with sleep tests which gives an impactful step forward in sleep research with the collected Big Data. Several algorithms and hardware have been proposed, implemented, validated, and some of them have succeeded to reach industrial gates, thus they can be classified in two groups: industrial and academic. The concept behind these methods is to monitor a certain physiological behaviours such as physical activity, *heart rate variability (HRV)*, *breathing rate (BR)* or others, and correlate its evolution with sleep stages occurrence as defined by *polysomnography (PSG)*, or with general sleep parameters such as *total sleep time (TST)*, or wake after sleep onset. However, due to the acquisition process induced challenges facing signal quality, either one of the proposed unobtrusive methods has succeeded to join the medico-industrial production who's typical outcome is a validated, widely used, and class-defined medical device [10], [11].

Advancements in the last decade involved in coming up with alternative solutions for an unobtrusive sleep assessment have shown that an interdisciplinary collaborative work is essential. Thus a substantial collaboration abides crucial, combining medicine with engineering to assess medical and technical constraints arising in hardware integration and signal acquisition, as well as in various levels of signal processing and data communication. Previous works have been focusing on developing unobtrusive sensing devices and hardware [12]. Thus, several sensing approaches and sensor types have been conceived and regarded as potential solutions to specific types of parameters or sleep monitoring like posture identification applications [13] and sleep/wake measurement [14]. Although the existing unobtrusive means for sleep evaluation do not provide the sufficient insight for rigorous classification of sleep cycling and sleep stage scoring, yet can give a more general and limited indications on certain important aspects of sleep such as the physical and cardiac activities during sleep.

Accordingly, the need is obvious for more advancement in this field, which requires defining the challenges and opportunities paving this line of research.

A. RELATED WORKS

The growing interests in monitoring sleep quality and the large number of emerging devices and technologies related to unobtrusive data acquisition have inspired researchers for surveying the in-market devices and their technical characteristics. For instance Roomkham *et al.* [16] and Kelly *et al.* [17] have classified, based on the measured biological data, some of the in-market devices and gave a description for each. They concluded that the majority of existing devices have not been validated clinically with respect to a golden standard such as PSG, and hence remain unreliable to some extent. In their paper, the focus was on what these particular branded devices can offer, and what their limitations are. Hence, there were no recommendations, discussions of technical challenges, and review of the potential measures and parameters to use in this line of research, i.e., unobtrusive sleep monitoring. In other words, the existing devices were reviewed, but not the theoretical concepts and applied techniques in the field in general and not limited to some specific devices. Several works have reviewed the unobtrusive devices for general patient monitoring including vital signs and physiological parameters surveillance. No emphasis has been given in particular on sleep monitoring devices or the challenges faced in acquiring signals during sleep [12], [18], [19]. Werth *et al.* have reviewed the existing unobtrusive sleep monitoring techniques that are exclusively used in preterm infants [20]. The techniques have been classified based on the hardware acquisition category and reviewed accordingly. However, due to the physiological differences and specific characteristics and variables to be monitored, what can applied to preterm infant sleep can not be generalized or used for the general population. Hence this survey can serve only for the preterm infant population.

B. OBJECTIVE, CONTRIBUTIONS AND STRUCTURE OF THE PAPER

In previous surveys, only devices existing in the market have been covered. The main objective of this paper is to present a comprehensive review on the advancements made in proposing unobtrusive sleep studies as alternatives to PSG by measuring unobtrusively autonomous physiological functions, i.e., cardiac activity, breathing and body movements activity. Technical considerations and challenges encountered in the acquisition and signal processing steps are discussed while comparing the proposed methods and algorithms.

Our main contributions can be resumed as follows:

- Exploring the physiological changes during sleep and their signification with respect to monitoring sleep quality in a less obtrusive way.
- Surveying the advancements made in unobtrusive studies but including the studies and the hypotheses made in research, i.e., behind the industrial scenes.
- Reviewing and discussing the challenges facing the application of the theoretical concepts, and the potential solutions that could be applied and tested.
- Comparing different approaches of the same methods, showing the impact of specific parameterization on the overall outcome of the system, such as electrodes positioning or the algorithm type used.
- Identifying the most recent needs and opportunities in various lines of research and giving recommendations and remarks for future work.

The structure of the remaining part of the paper can be resumed as follows: section II gives a brief introduction to the important notions and facts related to sleep, sleep disorders and sleep monitoring. The potential biomarkers involved in unobtrusive sleep evaluation are described in section III. Activity and cardiac based unobtrusive sleep monitoring technologies are reviewed and discussed in section IV and V, respectively. Open research areas and a conclusive observation are presented in section VI.

II. AN OVERVIEW OF SLEEP STAGES, DISORDERS AND MONITORING TECHNIQUES

A. SLEEP STAGES

Sleep is a physiological state defined by specific characteristics [21]. Being periodic, naturally-occurring, reversible, recurring and involving suspension or reduction of alertness and muscular activity, it has been a subject of interest and a field that encompasses some controversial theories, even the question 'why humans need to sleep?' has not succeeded yet to obtain a clear consensus from scientists [22].

The sleep architecture is formed by different sleep stages, each characterized by specific physiological changes. There are 4 sleep stages: rapid eye movement (REM) sleep, and three non rapid eye movement (NREM) stages: NREM1, NREM2, and NREM3 reflecting the progression from lighter NREM1 to deep NREM3 sleep. In 1968, Rechtschaffen and Kales (R/K) proposed the "Manual of Standardized Terminology, Techniques and Scoring System for Sleep Stages of Human Subjects" to score sleep stages based on pre-defined range criteria of the physiological parameters measured during sleep [23]. The American academy of sleep medicine (AASM) issued the latest version to date (v.2.5.0) of the manual of sleep scoring and associated events in 2018 that is based on the R/K and researchers' recent findings [15]. The manual is continuously hence upgraded. Moser *et al.* compared the effects of both scoring systems on the derived scoring parameters and the overall scoring outcome [24]. Fig. 1 illustrates a brief description of the physiological changes with respect to each sleep stage, in addition to the transition-specific physiological changes that are noted during transitions between sleep stages. For instance, cardiac, breathing and body movement activities that could be measured unobtrusively are shown separately than the conventional polygraphic *EEG*, *EOG* and *EMG* signals that are the gold standard to score sleep stages to derive the evolution of sleep stages over time, i.e., sleep hypnogram.

B. THE BURDENSOME IMPACT OF SLEEP DISORDERS

There exist seven major categories of sleep disorders, according to the latest and third international classification of sleep disorders (ICSD-3) [25] published by Sateia in 2014. They can be classified as follows: 1) sleep-related breathing disorders, 2) insomnia disorders, 3) circadian rhythm sleep/wake disorders, 4) central disorders of hyper-somnolence, 5) parasomnias, 6) sleep-related movement disorders and 7) other sleep disorders. The physiological dysfunctions standing behind sleep disorders that have been described in the literature are many. Common are neurological factors such as narcolepsy and *periodic limb movement disorder (PLMD)*, or *sleep breathing disorders (SBD)* such as *nbstructive sleep apnea (OSA)*.

The negative physiological impacts of sleep disorders are serious. Accordingly, studies have shown that a one

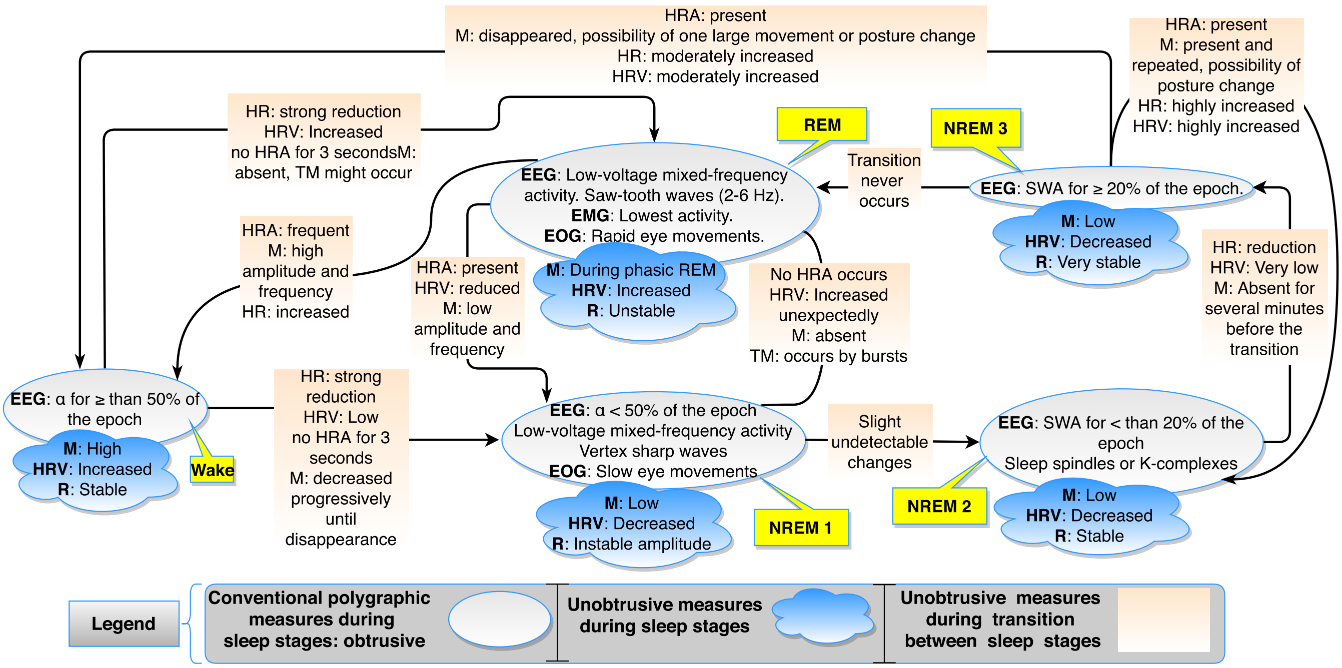

FIGURE 1. **Physiological changes during sleep stages in accordance with the *AASM* [15].** ***α: Alpha activity (8-13 Hz). TM: Twitches movements. M: movement of the body. R: Respiration. HR: Heart rate. HRA: Heart rate acceleration. HRV: Reart Rate Variability. SWA: Slow wave activity (0.5-2 Hz). LVMFA: Low-voltage mixed-frequency activity (2-6 Hz).***

night of sleep deprivation can cause impairment to insulin sensitivity at the same extent as six months of a high-fat diet [26]. Moreover sleep disorders can alter pain tolerance in humans [27], can cause heart dysfunctions such us ischemic heart disease [28], and cause a wide range of health issues such as metabolism impairment and hormonal disturbances leading to severe physiological alterations and bad consequences [29].

Not only sleep disorders are known to induce health issues and have bad physiological consequences [30], [31], but they are a consequence of physiological disturbances underlying behind as well [32]; in other sense, sleep disorders occurrence could be a manifestation, or a symptom displaying autonomous physiological function abnormalities that if not treated, severe health conditions could arise [33]. Beside health related problems, sleep disorders are shown to have potential sociological, professional [34], and economical [35] impacts on the world population. For instance, around 150 Million people are estimated to have sleep disorders. In the united states, 48% report snoring, while more than 40 000 injuries occur annually due to drowsy driving [3]–[5]. Motivated by this major prob, numerous studies were put forward addressing various solutions in order to make the acquisition protocol during sleep studies less obtrusive, including home-based solutions, wearable textiles and electronic gadgets. In the next sub section, we give a brief classification of the devices types based on their relative clinical significance, and based on the world-wide established medical devices classification [36].

C. STATE-OF-THE-ART SLEEP MONITORING TECHNIQUES

In this subsection, we classify in four categories the devices currently used in sleep studies in both research and clinic. Sleep studies are medical examinations performed to evaluate the sleep quality of people based on scoring schemes. The aim of sleep studies is to explore a person's abnormal sleeping state that is a result of some health issues, and a causation of others; then they serve as a diagnostic tool and an identifier for several health problems. Depending on the application, sleep monitoring devices can be divided in four main types ranging from 1 to 4. In general terms they can be described as follows:

- Type 1: trust worthiest among others for sleep diagnosis. Operate in attended sleep tests that take place in clinical places, the most known among them is *PSG* (Fig. 2) [37].
- Type 2: being able to carry out the full spectrum of *PSG* signals in an unattended signal acquisition protocol, type 2 devices provide the advantage of longer term *PSG* recording, which makes them suitable for use an important range of sleep disorders, with less but acceptable rigorousness in the results [38], [39].
- Type 3: unattended, physiological parameters specific, e.g, respiratory monitoring devices such as *continuous positive airway pressure (CPAP)* machines.
- Type 4: unattended, portable non-medical devices delivering highly unobtrusive measurements at the expense of accuracy and reliability, also referred to as electronic gadgets.

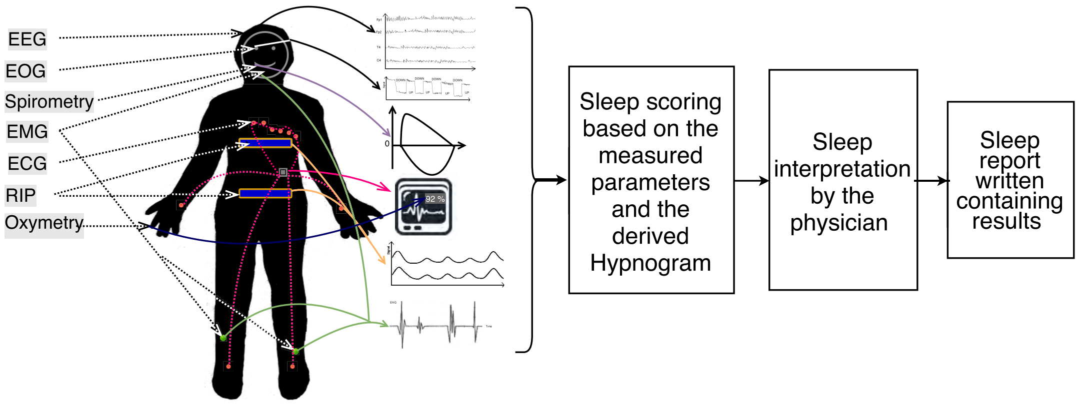

FIGURE 2. Typical acquisition protocol and general workflow in a *PSG* procedure. The minimal number of wires and sensors attached to the patient's body is 22.

Several types of conventional sleep quality assessment methods exist. Each among them is prescribed depending on the person's health status and the aim behind the study. Some are very specific and designed to measure somnolence and specific sleep characteritics, they include multiple sleep latency test [40], Maintenance of wakefulness test [41], and others are are designed to measure sleep quality in general such as home-based portable monitor [42] and the most widespread *PSG* test [37]. In addition, special sleep studies exist with a relatively narrow and focused application. Such tests are only used to deal with specific illnesses; the well known among them are the tests dedicated to analyze *obstructive sleep apnea syndrome (OSAS)* such as *CPAP* or *CPAP* Titration [43], Bi-Level Titration [44], and Split Study for severe *OSAS* cases [45]. Moreover, there are some modifications to the nocturnal *PSG* test [46] such as the expanded *EEG* sleep recording test [47] where a recording of a full montage of *EEG* is required to analyze not only sleep disorders but also the existence of nocturnal seizures, and the nocturnal *PSG* Test with End Tidal CO2 [48].

Being the most accurate and trust worthy among all other means to conduct sleep studies for general sleep disorders, the *PSG* abides the decisive and far-reaching approach in many cases [49]. Fig. 2 illustrates the sensors attached to the body and the general procedure followed in a PSG test. During a *PSG* procedure, the movement of the chest and abdominal wall, blood O2 saturation, brain and heart electrical activities, eyes movement, respiration, limb and chin muscles activities are measured. Data is partitioned in 30 seconds epochs based on the criteria defined by the manual to score sleep stages accordingly [15]. Afterwards, the scoring results are sent to the physician for interpretation. However it remains a complex, high demanding and obtrusive procedure especially for some people having a low requirement or prescription for sleep assessment such as a suspicious diagnosis that need to be ensured or a minor need for sleep assessment for a healthy person and mostly for adult and elderly people that for some reason need to be health-monitored during sleep such as people having unjustified and frequent laziness, increased sleep propensity along day, or abnormal sleeping behaviour.

III. UNOBTRUSIVELY MEASURABLE PHYSIOLOGICAL PATTERNS DURING SLEEP

During sleep monitoring, it is important to take into consideration the normal sleep patterns, or physiological changes that are supposed to occur during each of sleep stages, in order to detect anomalities and irregularities. The brain provides the most useful information about sleep regulation, it's the measurement target of *EEG* recording in *PSG* procedures.

However, brain's electrical activity measurements range in the order of microvolts, making it harder to measure using unobtrusive apparatus, i.e., sensors requiring the least contact with the subject and providing comfort during acquisitions. On the other hand, since the autonomic nervous system is highly influenced by the activity of the central nervous one [50], autonomic physiological functions such as blood pressure, muscular activity, movements, and the electrical activity of the heart are affected and alternated by the central nervous system. In addition, these autonomic functions are displayed in ample variations (millivolts for *electrocardiogram (ECG)*, movements, or breathing) when compared with the microvolts *EEG*'s small amplitude variations, which makes them less sensitive to noise and more suitable for unobtrusive measurements apparatus, that require less stable contact with the body. Hence, unobtrusive sleep monitoring consists of capturing physiological changes that reflect and are correlated with the brain activity, but without interfering with the subject's comfort during sleep. For instance, vagal activity related features have been showing potential results that could lead to a reliable estimation of sleep hypnogram using unobtrusively acquired physiological signals. The diagram depicted in the Fig. 3 shows three categories of sleep monitoring methods that will be addressed in this paper. The target physiological behavior, the acquisition method and hardware, and the obtained physiological parameters are split accordingly. In this section, each of the three activity patterns

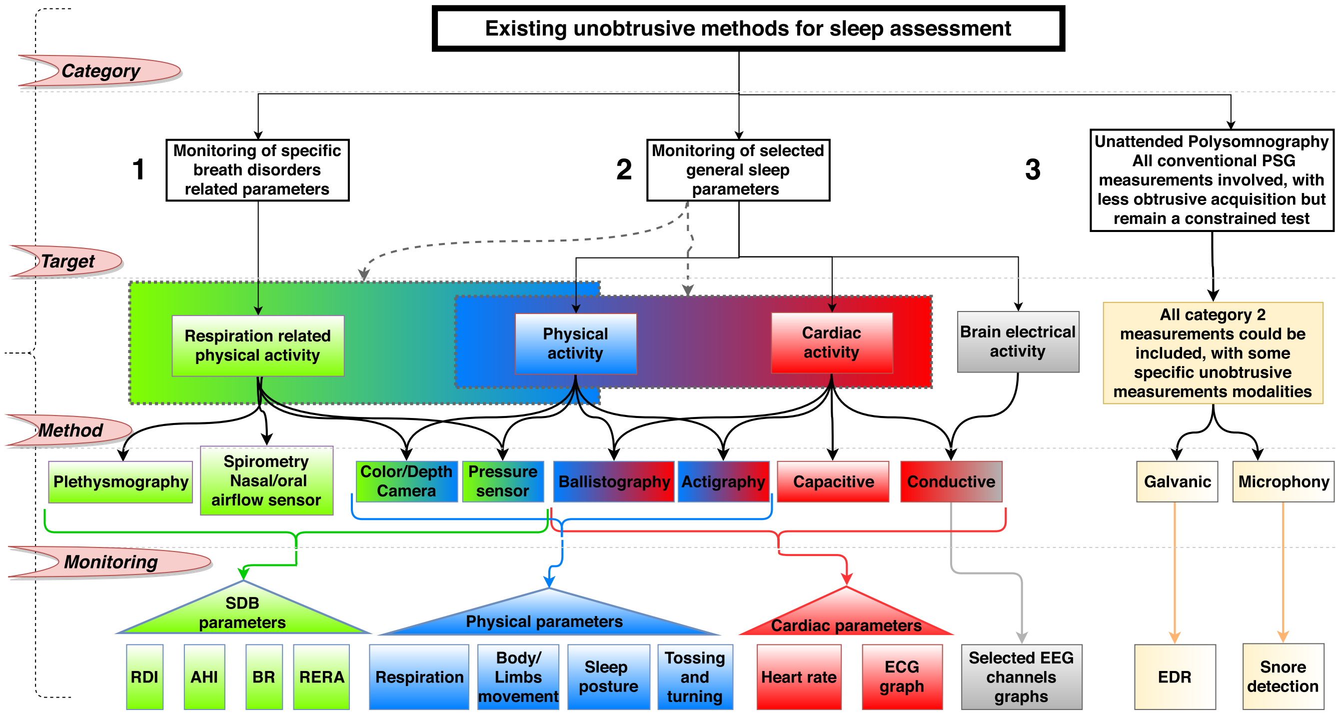

FIGURE 3. Unobtrusive sleep monitoring methods.

is described and discussed in details in what is related to sleep cycles and staging.

A. BREATHING ACTIVITY PATTERNS

Respiratory effort has been used to analyze sleep in humans using several characteristics such as spectral power features variations in respiratory rate, respiratory effort signal regularity and auto-similarity [51]. Patterns of body movement are induced by breathing over time, and they depend on the posture of the body on the mattress [52]. Therefore, it is possible to continuously monitor the respiratory movement to calculate the respiration rate, that is, the number of breaths per minute (BPM) and other characteristics that reflects the regularity, depth, and auto-similarity of the signal. Several aspects make breathing activity a tremendous physiological behaviour to study during sleep: 1) estimating sleep stages: respiratory patterns have been shown to vary during different sleep stages which makes it possible to combine respiration with other parameters to estimate sleep stages and hypnogram, 2) *sleep disordered breathing (SDB)* are one of the most widespread sleep disorders and they could be detected and identified through monitoring breathing, and 3) *BR* is one of the five vital signs that provide measurements of the body's most basic functions, thus an irregular, increased or decreased *BR* may be the symptom of other medical conditions such as fever or other illnesses, which makes it a very interesting behavior to monitor during sleep.

Researchers have shown that *respiratory rate variability (RRV)* analysis during sleep could give potential insights on sleep stages. This latter is mathematically modelled in [53] as following:

$$\mathrm{RRV} = (100 - \frac{H_1}{DC})\%, \tag{1}$$

where H_1 and DC are the amplitude powers of the first and the zero harmonic peaks, respectively. For instance, as defined by (1), *RRV* is proven to have different values at each sleep stage, with the lowest occurring at *NREM*3, followed by *NREM*2, *NREM*1, *REM*, then wake that has a value that is highest than all other sleep stages, including *REM* [53].

During wake, breathing becomes irregular if the eyes are open, and tend to be more regular by closing the eyes, and during *NREM*1. In *NREM* 2 and 3, the breathing becomes regular with few disturbances or some variations in rate. In the *REM* phase, breathing becomes irregular with short breathing breaks.

As for the respiratory amplitude, the volume of inhaled air is more irregular with a smaller tidal volume during *REM* than *NREM* stages [54].

B. BODY MOVEMENT PATTERNS

Body movements occur during sleep in specific periods, patterns, durations and frequencies, indicating the state of the person and giving insights on further physiological changes. The movement information can be analyzed and a variety of parameters can be derived in order to monitor sleep or give a diagnosis of sleep disorders.

In this paper, the term *body's physical condition* during sleep is used to designate the dynamism of the body and limbs in what is related to type, presence or absence of dynamism. Specific behaviors characterize a normal and abnormal body's physical condition during sleep:

- Normal physical conditions during sleep: includes random, periodic and absence of dynamism that occur naturally and are not associated with any disorder, among them:
  – Major body movements: in *PSG*'s terminology, can be defined as body movements and muscle activity that are considered as characteristics of arousals and used to discern wake periods from sleep. For instance, if they can obscure the *EEG* signal for more than 15 seconds and prevent the identification of the current sleep stage, the epoch is classified as a wake state.
  – Minor body movements: are lighter body or limb movements that occur during sleep, and do not induce an identification of the corresponding epoch as a wake state. After deep sleep at *NREM*3, a transition to lighter sleep stages, *NREM*2 then *NREM*1, is accompanied by the occurrence of possible minor body movements.
  – Periodic movements: periodic patterns of minor chest movements are induced by breathing due to the change of the diaphragm's volume during the recurring periodic inspiratory and expiratory phases. An increase, then a pause followed by a decrease of volume are induced by inspiration, inspiratory hold and expiration, respectively.
  – Body paralysis: during *REM* sleep, the body and members undergo a muscular atonia with occurring muscular twitches, also referred to as paralysis, which can be used as one of the biomarkers of the *REM* sleep state in both conventional and unobtrusive means of sleep monitoring.
- Abnormal physical conditions: includes all types of random and periodic movements or absence of movements that are not supposed to occur naturally. These movements are associated with well known disorders and physiological disturbances, among them REM behavior disorder where people act their dreams, which could be potentially dangerous [55]. Another disorder is the *periodic limb movement during sleep (PLMS)* that occur commonly in elder population. Being one of the most widespread among sleep movement disorders, it consists of repetitive movements of the limbs that occur sporadically, more often to occur in the legs i.e., periodic legs movement disorder, than arms i.e., periodic arms movement disorder, they specially involve extension of the big toe accompanied by an occasional slight bend of hip and knee, and dorsiflexion of ankle. They do not prevent the person from sleeping, however they affect sleep quality. They can last between 0.5 to 5 seconds with a period of 20 to 40 seconds that could last between few minutes to an hour. Although they're not supposed to occur naturally, they are not considered as a disorder unless they affect severely sleep and daily life, then they are known as *PLMD*. *REM SBD* has proven to have impacts on body movements patterns and muscle tone [56]. Several other sleep movement disorders exist such as hypnic jerks, bruxism, rhythmic movement disorder and nocturnal leg cramps [57].

C. CARDIAC ACTIVITY PATTERNS

There exists a considerable number of works trying to discuss and assess the relationship between *HRV*, or the physiological cardiac changes, and the evolution of sleep stages [58]–[61]. Authors in [62] and [63] have proven the correlation between *EEG* power spectrum and *HRV*, showing that *HRV*'s normalized high frequency is linked to *EEG*'s power bands, hence sleep stages, and that delta band changes in the *EEG* signal is preceded by a parallel changes in the cardiac vagal activity monitored through *HRV* frequency domain analysis. In fact, the aforementioned electro-cardiac changes are correlated with cycling of sleep stages and could be measured and evaluated through a *HRV* analysis, which can lead to a sleep quality assessment as it will be described in this section. *ECG* is currently being used in *PSG* procedures, and has been used for decades as a partial measure, and a part of the combination of signals needed to be acquired and analyzed. However, for non-diagnosis uses of sleep assessments, i.e., where a general insight on sleep is required, not detailed diagnosis on cardiac activity, *ECG* can be used as a standalone approach along with *HRV* analysis. Currently used conductive *ECG* electrodes requires a direct contact with the body's skin that should remain stable all night, which is a limitation that makes this approach unrealistic for unobtrusive applications that are often held in non-clinical conditions. Moreover, tosses involving posture changes are not allowed during conventional *ECG* acquisitions. Using unobtrusive means of acquiring *ECG* signals can overcome such weakness and take into account tosses that are a part of sleep architecture, and can not be avoided, ignored, or even banned. Moreover, unobtrusive acquisitions allows taking advantage and exploiting body movements, position changes and tosses in a way to consider them as an indicator that helps the sleep assessment not alters it.

1) SLEEP STAGING USING *HRV* ANALYSIS

HRV analysis consists of assessing how much variability a time-duration between consecutive heart-beats can undergo over time [65]. The time interval between two beats is referred to as R-R interval, or sometimes N-N interval where R is the peak of the QRS complex, and N is a normal R peak. Several methods have been employed in the literature to show the strength of correlation between *HRV* and autonomic physiological functions [66], [67]. The first to observe beat-to-beat variability were Hon *et al.* in 1965 [68]. They noticed that N-N intervals were the only parametric variation to occur before a fetal distress. Since then, researchers have been trying to investigate more in assessing *HRV* by proposing hypothesizes to be tested, methods, and algorithms [69].

Different types of *HRV* analysis methods exist. Time and frequency methods have been the most widespread among

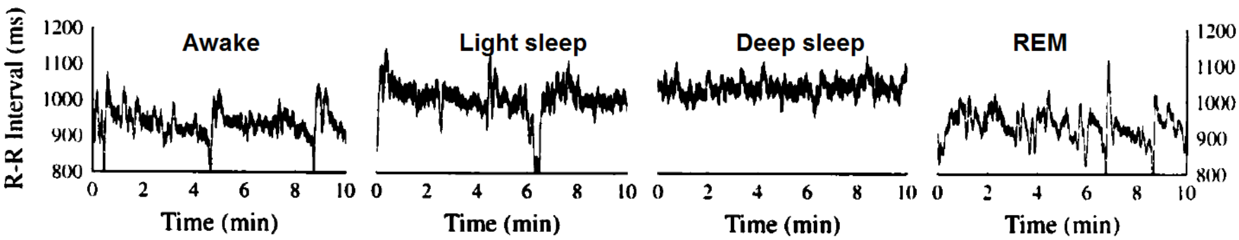

FIGURE 4. ***HRV* changes with sleep stages. R-R intervals [ms] plotted over time [min] during: Awake, Light (Including stages 2 or 3), deep (stages 3), and *REM* sleep [64].**

them, whereas frequency methods have yielded the best results in sleep staging procedures. Several types of noise could be found in unobtrusively acquired *ECG* signals, and should be taken into account. For instance, applications where there is no direct contact between the electrodes and the person's skin, e.g., capacitive coupling, in which we have to acquire *ECG* signals from a subject that is not in a clinical room, a high input impedance for the system is induced due to the body-electrode poor contact interface [70].

In an ECG signal, the waves that will be influenced the most by noise and interferences are the ones having the least amplitudes. The highest amplitude wave in a normal *ECG* pattern is called the R peak. Although these peaks are modified in shape and amplitude during the process of unobtrusive signal acquisitions due to the added noise, but they almost remain detectable and will preserve having the highest amplitude among other waves in a given pattern. That explains the fact that *HRV* computation, or the analysis of R-R peak intervals, will remain feasible even where the acquisition protocol is done using the unobtrusive methods of signal acquisition.

Sleep stages are characterized by a variation of the cardiac activity. Several studies have explored the feasibility of sleep staging by performing an *HRV* analysis e.g., correlating frequency domain parameters with sleep stages [58], [71].

Moreover reasearchers have reviewed the potential application of HRV parameters in clinics by evaluating the clinical validation studies that have been performed to date. For instance, Stein and Pu [71], have presented a detailed review of these methods, as well as Smith *et al.* [72] with respect to several application including sleep. Even though a number of validation has already been performed, a research agenda giving rise to more works and research collaborations with regard to clinical validation is in the horizon.

Table 1 shows the mean and standard deviation of LF and HF, that fall in the range of 0.04-0.15.Hz and 0.15 - 0.40.Hz, respectively [71]. For instance, the wake and *REM* stages are characterized by dominance of $\frac{LF}{HF}$ and $\frac{LF}{Total}$, where total is the area under the entire power spectral curve (usually âLď0.40 Hz) [58]. Hence the frequency domain parameters changes are due to R-R time interval variations in each of the sleep stages, as illustrated in Fig. 4.

TABLE 1. **Mean (Standard deviation) [s^2/Hz] of high frequency (HF) and low frequency (LF) components power measured during sleep stages [58].**

Sleep stage	HF	LF
Wake	0.189(0.15)	1.998(1.47)
*NREM***1**	0.217(0.17)	1.667(1.60)
*NREM***2**	0.359(0.17)	0.984(1.36)
*NREM***3**	0.490(0.19)	0.589(1.21)
REM	0.208(0.17)	1.846(1.47)

IV. ACTIVITY BASED UNOBTRUSIVE SLEEP MONITORING TECHNOLOGIES

Acitivity based sleep monitoring methods have been existing since 1922 [73], among them systems that use slow motion cinematography [74], motion induced ultrasonic interruption [75] and many others. In this paper, only the widespread systems that are still used in modern research and sleep studies are covered and discussed, i.e., actigraphs, cameras and infrared (IR). Previous works have tried to compare between several acquisition methods such as video monitoring and actigraphy [76] and [77].

A. SLEEP ACTIGRAPHY

Sleep actigraphy consists in recording the body's movements during sleep. Depending on the application, the recorded data can be used to predict some insights on the neurobehavioral state, infer sleep or discern wake periods. By counting the number of body movements and assessing their amplitude, sleep parameters could be estimated using actigraphy such as quality, latency, duration, efficiency, and fragmentation, circadian rhythms, sleep and wake periods, and activity levels [78]. The convenience of using actigraphy in sleep studies is being a low-cost unobtrusive method that could be used in both clinics and subject's home. Hence, actigraphy can be used for acquiring sleep related data in situations where *PSG* is logistically impractical, or for long acquisition periods in the patients home.

When the idea of unobtrusive sleep monitoring using actigraphy has came out in the early seventies, researchers have started using telemetric actigraphy, before switching to accelerometer-based systems in 1978, as it is the case in current systems [79]. Before accelerometer-based, the telemetric systems consisted of three main units: transmitter, receiver and the readout unit. The measurement's target was the identification of the presence of activity, and the output mainly consisted of a graph showing the number of activity per minute, i.e., *counts per minute (CPM)*. In a first study of its kind, Foster *et al.* have proposed a wrist worn telemetry-based actigraphic system for measuring sleep quality and biological rhythms [80]. They derived parameters including sleep onset and movement's *CPM* using the actigraphic system in order to calculate the correlation between wrist activity and the subject's wakefulness as derived from the conventional *EEG* system. Interestingly, they obtained promising results in their work [80] that have been able to improve in their update work later [81]. Then Kripke *et al.* have made the transition to a wrist piezoelectric actigraphy, and recorded 9 hours of sleeping for 5 normal subjects using the actigraphic system and a *EEG-EOG-EMG* signals combination. The results obtained have shown a better correlation between actigraphy and the conventional signals combination for *TST*, total sleep period, and mid-sleep awakenings, respectively [79]. Since then, several works have been trying to explore actigraphy's ability in the sleep time parameters estimation [82]–[86]. The *AASM* indicates in it's practice guidelines that actigraphy is reliable in measuring sleep for healthy adults [87]. Moreover, actigraphy has proven to be sufficiently sensitive to be used in more specific applications of sleep studies. For instance, monitoring sleep changes following treatment for insomniac patients has been explored in [88] and [89]. In 2015, the *society of Behavioral Sleep Medicine (SBSM)* has published a guide to actigraphy monitoring to assist clinicians and researchers to use actigraphy, citing more than 150 actigraphy based works, including many on sleep applications [90].

Although their usefulness in specific applications, sleep actigraphy systems have been facing several limitations and concerns on several levels, i.e., not only the system itself, but also how it is validated relatively with the conventional reference systems. As they form the vast majority of systems used in both research and industry, only concerns and challenges facing accelerometer-based sleep actigraphy systems are discussed in this paper.

1) PLACEMENT OF THE SENSOR

most sleep actigraphy systems are watch-like wrist-worn bracelets that contains an accelerometer and a clock to record activity patterns. Also, the vast majority are worn by the non-dominant hand, and this particular placement has proven to be the most practical for sleep applications while providing a relatively good sensitivity to mobility. In few applications, where clinical tests have been conducted to find potential placements for actigraphic sensors, diaphragm and chest have shown respiratory induced movements artifacts, which makes it harder to discern wake states and movements during sleep [85], [91]. In the same context, the trunk has been tested by Enomoto *et al.* to wear an actigraphic sensor and has shown an improved specificity [92]. Moreover, some actigraphy systems are equipped with a light sensor that measures the ambient light intensity values in Lux in order to assess the relationship between the activity level of the subject and the variation of the ambient light [93].

2) N-AXIAL N-SITE MOVEMENTS REPRESENTATION

one of the core properties of an accelerometer is the number of axis it uses to represent movements. Another feature of interest, when using actigraphy in sleep studies, is the number of sites adopted to acquire data i.e., sensors placement or position on the body. The most widespread type is the one-site, particularly, with that site being the wrist. Another widespread sensor placement is the ankle that is mostly recommended and used in pediatric population [94]. Studies have shown that the number of axis and sites used in accelerometer-based sensing affects directly the movement detection ability, and hence, sleep and wake detection. Movements having an orthogonal direction to the axis, or low amplitude movements occuring in other body organs than the wrist, could remain undetected in uni-axial one-site accelerometer actigraphy causing a *TST* overestimation. A tri-axial multisite accelerometer based actigraphy can be used to make the activity detection more robust and accurate [95].

3) SENSITIVITY TO DISCERN WAKEFULENESS

one major concern about sleep actigraphy systems is their sensitivity to discern wakefulness. Many researchers have been giving insights on the robust system's ability in the sleep prediction, which in fact reflects the system's sensitivity to immobility. However, it's the system's sensitivity to mobility that matters in the wakefulness detection and separation from sleep. As a result, the more wakefulness occurs, the more the results can be erroneous leading to a sleep overestimation [96]. Hence, detecting sleep becomes more inaccurate for patients suffering from disturbed sleep, i.e., repeated arousals and reduced *TST* [97].

4) DATA QUANTIFICATION MODALITIES

several movement quantification modes have been proposed and implemented to process acquired data in the existing actigraphy monitors. Researchers have shown that, given the same activity pattern, these quantification modes have led to different quantification of activities [98]. Hence it is proven that these modalities could not be used interchangeably for movement quantification. Most common movement quantification modalities in actigraphy can be described as follows:

- *time above threshold (TAT)*: consists of counting for a time epoch, the amount of time during which the activity level exceeded a custom (age range-specific) predefined threshold, then storing the sum of counts for that epoch in memory. A typical value of threshold could be between 0.1 and 0.2g, where g is the acceleration of gravity. The process is then repeated for the next epoch after the counter is reset to zero [99].

Giving a general idea about the number of movement's occurrence during sleep, *TAT*'s approach suffers from an insensitivity to movement's amplitude. Using only the time during which a movement exists, a small movement period is counted equally as a more intense one. Moreover, *TAT* has been shown insufficient in measuring the muscle force induced acceleration, which could evidently result in an incomplete evaluation of the analyzed activity pattern [100].

- *zero crossing (ZC)*: consists of counting the number of time the activity level crossed the zero level. The zero level, or zero-reference, is a predefined threshold that represents the absence of activity without artifacts. Thus for each epoch of time, the number of zero-level crossings is counted and stored. The counter is reset to zero for the next epoch [101].
  Similar to *TAT*, *ZC* has the limitation of insensibility to movement's amplitude as it cares about the number of activities regardless of their magnitude. In general, and especially during sleeping or resting periods, body movements are known to lay in the lower frequencies components. However *ZC* has been shown to favor high frequency components of the acceleration (activity) signal that are a prominent source of noise, which leads to an inaccurate overall activity index, or inaccurate quantification of movement-induced acceleration [102].
- *digital integration (DI)*: also known as *proportional integrating mode (PIM)*, consists of calculating the *area under curve (AUC)* of the acceleration signal for an epoch of time using numerical integration techniques. A high sampling frequency is used (typically 40 Hz) in the *analog-to-digital conversion (ADC)*. Thus the output count for an epoch is given by calculating the total *AUC* for that epoch, which represents the average level of activity [102]. The advantage of *DI* quantification is taking account of movement's amplitude during the counting process. Hence it literally performs a movement *quantification* technique, by considering the occurrence and intensity of movements during specific epochs.
- *SUMACT*: is a particular type of *PIM* or *DI* quantification that consists of returning data linearly related to the integrated acceleration over a predefined time epoch of 1 minute. *SUMACT* has been used widely in market actigraphy monitors [103].
- *MAXACT*: is a particular type of *SUMACT* that consists of performing multiple proportional integration on n sub-epochs belonging to a time epoch, then selecting the sub-epoch that contains the maximum value. The most widespread version of *MAXACT* are the one having 10 seconds sub-epochs and 1 minute epoch [103].

Furthermore, researchers have compared the utility of using each of the data quantification modalities in sleep studies [103]. More specifically, the effect of changing data quantification modalities on the movement detection has been explored using wrist actigraphy, and then, the effect on the accuracy of sleep detection has also been explored. Results have shown that *TAT* and *ZC* have a high cross-correlation, considerably higher than each's correlation with *DI*. However, *DI* has shown to yield the best results for sleep detection accuracy. The concept of *DI* has been discovered and suggested to yield better results in sleep studies long before its application in sleep studies because of its higher computational cost, when compared to *TAT* and *ZC*.

5) VALIDATION OF ASSESSMENT

in several works, authors trying to validate the actigraphy and its performance to predict sleep-wake periods have been missing a very important notion in what's related to the neurobehavioral state itself. More particularly, these papers have used the agreement rate between the outcomes of actigraphy and electrographic data (*EEG*, *EMG*, and *EOG*) as a criterion for evaluating how successful the performance is. However, this requires taking the assumption that electrographic data provides an alternative of the neurobehavioral state, or is an exact measure of it, which is not the case, even if researchers have agreed that the electrographic measures (used in *PSG*) are the standards to measure the neurobehavioral states, and are more sensitive to body movements. This raises concerns about actigraphic outcomes being judged by *PSG*'s. Thus instead of using agreement rate between *PSG* and actigraphy to evaluate actigraphy's performance in predicting sleep-wake periods, the evidence requires calculating the correct classification rate by taking sleep-wake periods as determined by actigraphy, to the ones calculated by *PSG* but only the ones that are correct, i.e., represents the neurobehavioral state.

6) SCORING ALGORITHMS

in activity level quantification, sleep state scoring is the last processing level after data acquisition, *ADC*, pre-processing and activity counting. It is the step in which a correlation is established between sleep/wake states and the body activity level using a threshold-specific decision function by comparing the number of activity counts in a time segment to the threshold itself. Several scoring algorithms have been proposed in the literature, the most widespread among them being *Sadeh's* [85], and Cole-Kripke's [84]. Inspired by Sadeh's algorithm [85], the general steps for sleep scoring are given in the current sub-section in order to be used when reading all the algorithms mentioned in the Table 2, as they all follow a common general procedure as follows: 60 seconds epochs y-axis data is fed to the algorithm in order to give a sleep/wake classification for each epoch. The scoring procedure is made in three main steps:

- Initialization: parameters are defined and/or set to initial values, including the index of the current epoch, the window length (Number of epochs taken in consideration when counting) and the number of activity counts.
- Counting: the decision function is defined and calculated using statistical parameters of the activity counting such as logarithmic values of standard deviation of the number of counts in a window.

TABLE 2. A comparison of the main contributions to actigraphiy scoring algorithms.

Algorithm / Author name, year	Validation dataset	Computation scheme	Data processing	Decision function	Age range
Levine , 1986 [105]	n=1 and s=7	w=5, and e=60	Compute na over window	$If na < \alpha$, c_i ='sl', 'wk' otherwise, $\alpha =$ sensitivity settings	Young
Dunham, 1991 [106]	n=1 & s=11	w=2 & e=32	Compute na over window	If $\ln na < \alpha$, c_i ='sl', 'wk' otherwise, $\alpha =$ sensitivity settings	Young
Cole-Kripke, 1992 [85]	n=1, s=41, & m=50.2	w=7, e=60, & p=5	for $x = -4, ..., 2$, compute $\frac{na_{i+x}}{100}$	$SI_i = 0.001 \cdot (106 \cdot na_{i-4} + 54 \cdot na_{i-3} + 58 \cdot na_{i-2} + 76 \cdot na_{i-1} + 230 \cdot na_i + 74 \cdot na_{i+1} + 67 \cdot na_{i+2})$. If $SI_i < 1$, c_i ='sl', 'wk' otherwise	Adult 35<age<65
Sadeh, 1994 [86]	n=1, s=36, & m=18.27	w=11 & e=60, p=6=center of w	Compute ma, M, SD, and $Log(na_i)$.	$SI_i = 7.601 - (0.065 \cdot m) - (1.08 \cdot M) - (0.056 \cdot SD) - (0.703 \cdot log(na_i))$. If $SI_i > 0$, c_i ='sl', 'wk' otherwise.	Young 10<age<25
ADAS , 1997 [107]	1) n=2, s=20, & m=30 2) n=3, s=26, & m=46.5	w=3, & e=60	Compute wake threshold of na_i, & wake-interval postarousal threshold z	• $\mathbf{C_1}$: $na_i = 10$ • $\mathbf{C_2}$: $z = 3$, s.t. $na_i \in \{na_{i+z}\}$, $z = 1, .., 3$ epochs of activity. If $\mathbf{C_1}$ or $\mathbf{C_2}$ is true, c_i ='wk', 'sl' otherwise	Adult
Oakley, 1997 [108]	n=1,s=11, & m=45	w=5,e=60, & p=3	for $x = -2, ..., 2$, compute na_{i+x}	$SI_i = \frac{1}{25} \cdot na_{i-2} + \frac{1}{5} \cdot na_{i-1} + 2 \cdot na_i + \frac{1}{5} \cdot na_{i+1} + \frac{1}{25} \cdot na_{i-2}$ If $SI_i < \alpha$, c_i ='sl', 'wk' otherwise, $\alpha =$ sensitivity settings	Adult
Sazonova, 2004 [109]	n=1, s=26, & m=0.66	w=9, e=30, & p=1	for $x = 0, ..., 8$, compute $ma_{i+x} = max(na_{i+x})$	$SI_i = 1.99604 - 0.19450 \cdot ma_0 - 0.09746 \cdot ma_1 - 0.09975 \cdot ma_2 - 0.10194 \cdot ma_3 - 0.08917 \cdot ma_4 - 0.08108 \cdot ma_5 - 0.07494 \cdot ma_6 - 0.07300 \cdot ma_7 - 0.10207 \cdot ma_8$. If $SI_i > 0$, c_i ='sl', 'wk' otherwise	Infant
Crespo , 2010 [110]	n=2, s=104, & m=22.43	w=1, & e=60	Calculation of morphologicaland rank-order filters parameters	Probability model-based data validation filtered to give a decision binary signal where 0 and 1 indicate 'sl' and 'wk', respectively	Young

n: number of actigraphy + PSG recording nights per subject, s: number of subjects, ma: mean age in years old, w: rolling window size in epochs, e: epoch length in seconds, p: position of current epoch in w, na_i: number of activity count for epoch i, m_a: mean(na) over w, M: # of i in w, SD: standard deviation of na, SI: sleep index function, c_i: classification for epoch i, wk : 'wake', sl: 'sleep'

- Scoring: the value of the decision function is compared to a pre-defined threshold in order to score the current epoch by giving it a label, e.g., 'wake' or 'sleep'.

B. SLEEP VIDEO MONITORING

Several types of sensors have been used for video monitoring during sleep studies to monitor different physiological aspects such as posture, body and limb movements, breathing activity and the sleep/wake states [118]. Depending on the application, the targeted measures and the clinical and environmental constraints, red-green-blue (RGB), *IR*, or thermal cameras are used as a standalone or in combination in the data acquisition step [118]–[125].

Although its limited clinical application, sleep video monitoring offers several advantages over other conventional or unobtrusive methods, especially when used for specific applications such as periodic limb detection.

Some of the main advantages of sleep video monitoring over conventional methods can be resumed as follows:

- Unobtrusive, requires no direct contact with the subject, does not induce skin discomfort caused by electrodes, does not limit or constraint movements, and can be adopted outside supervised clinical conditions.
- Apart from tibials, where *EMG* electrodes are applied [15], some legs muscles activity are often missed by *EMG*. This information is preserved in 3D methods of video monitoring [110].
- *EMG* signals are sensitive to tonic muscle contractions leading to an over detection of limb movements in most *PSG* procedures caused by signal deflections over time. Moreover, an alteration of skin-electrodes contact causes signal deflections and false movements annotations, which can affect sleep/wake detection and an overestimation of the *periodic limb movement (PLM)* index (number of *PLM* per hour of sleep time). These problems can be avoided in video monitoring. Next, we will present the two widely used video-based monitoring methods:

1) POSTURE AND MOVEMENT MONITORING

researchers have been trying to develop and validate materials and methods to make video-surveillance a potential solution for posture and movement analysis and quantification during sleep. Image processing based approach is essential to extract the human body from the captured images during video-surveillance. Several approaches have been proposed and implemented such as skin and edge segmentation and skin color detection in order to provide a reliable estimate of sleep/wake states and further sleep parameters and behaviours such as sleep latency, *TST*, sleep efficiency, *PLM* index and awakenings by detecting and tracking human body movement [110], [112], [130], [131]. Moreover, some works have succeeded to reach further levels of sleep analysis by

TABLE 3. A comparison of the main contributions to video-surveillance of body movements during sleep and the involved physiological behaviors.

Author name, year	Sensor type and placement	Aim of the study	Methodology	Validation dataset	Validation method	Results with respect to the aim of the study
Garn *et al.*, 2016 [111]	3D time of flight IR camera mounted above the bed	Contactles body position & motion analysis. Infer *PLMS*	Detect face then body. Changes in the 3D silhouette indicate motion	n=1 & s=17 *PLMS* participants, only s=10 are considered	Sleep motion analysis, video, and *EMG* comparison for limb movements	TP=98%,FN=2% & PPV=98%
Lee *et al.*, 2015 [112]	3D time of flight IR camera mounted above the bed	Contactles body position & motion analysis. Infer sleep and deep sleep times	Posture recognition Distance between previous and current tracked joints positions. Classify sleep state	n=1,s=20 & m=23	Validation of posture changes and movement detection coherence	No validation with a ground truth
Heinrich *et al.*, 2014 [113]	Monochrome light camera + *NIR* sensor	Contactles body position & motion analysis. Infer *PLMS*	Illumination, texture & depth information. Video motion detection features and thresholds. *PLMS* counts	n=1 & s=11	Comparison with a variance plus method	Sensitivity = 68.5, Specificity = 96.5
Cuppens *et al.*, 2010 [114]	IR camera mounted in several positions around the bed	Detecting movement during sleep in epileptic patients	Optical flow algorithm applied to video recordings	11 recordings from 8 patients	Comparison to manual labelled videos	Test set results 0.7931≤ Ppv≤ 1
Lio *et al.*, 2008 [115]	*NIR* camera sensor mounted above the bed	Sleep/wake epoch detection	Estimate activity levels, then motion history image approach to analyze movements patterns [116]	n=1, s=10 & m=22.6	Comparison of video and actigraphy versus *PSG* as groundtruth	Accuracy: Actigraphy: 91.24, Video: 92.13
Frauscher, *et al.*, 2007 [117]	IR camera mounted above bed	Characterization of motor activity in RBD patients.	Classification based on duration, type of movement, and topographical distribution	s=5, parkinson patients with RBD	Comparison and analysis with age- and sex- matched controls.	Motor events type and numbers differed significantly compared to controls P≤ 0.005
Aaronson *et al.*, 1982 [118]	IR camera sensor mounted above the bed	Study relationship of movements to sleep cycle phase and sleep parameters	Measure sleep latency and predict the occurrence of *NREM*	s=4 & m=28.75. 8 hours of day sleep recording	Comparison with polygraphic data (*EEG*, *EMG*, *EOG*, & *ECG*)	4 disagreements every 100 scored movements

n: number of nights per subject, s: number of subjects, m : mean age in years old

providing a relatively acceptable classification of the five sleep stages in question (N1, N2, N3, W and *REM*) [132]. Although the advantages this method can provide, it suffers from weaknesses when used in posture and/or movement detection. For instance, lower limbs are harder to detect in some cases such as sleep-monitoring a female wearing a one-piece sleep dress, or a person covered by a blanket, leading to a posture misclassification and in some cases, movement underestimation due to undetected limbs, especially for skeleton-based video tracking. Moreover, the required vision to detect some joints can be occluded and confusion may occur for some postures classification as well [133]. Researchers have also been trying to identify posture and estimate sleep stages using bed sheets containing textile based pressure sensors [134], [135]. In our previous work, a support vector machine algorithm has been developed and tested to automatically identify posture [136]. Unlike other methods such as camera surveillance, the advantage of such method is the ability of recognizing posture without interfering with the subject's comfort. More particularly, some types of clothes or blankets obstruct the view of cameras and impact the performance, which is not confronted in pressure sensor mattresses. Table 3 shows some of the existing video-surveillance methods that have proven the pertinence of this line of research in analyzing sleep behaviors especially in environments where *PSG* can not be applied.

2) BREATHING ACTIVITY MONITORING

sleep video monitoring has been used to monitor breathing activity and detect specific breathing disorders [137]. For instance, the physiological changes induced by breathing, discussed in section III-A, could be detected via several methods and algorithms. There exist two main approaches in the literature to monitor breathing using video surveillance:

- depth information based monitoring, that consists in dynamically using the skin-*IR* sensor distance via points or patches of interest, in order to have a surrogate measure of the volume change induced by breathing.
- skeleton tracking that consists in detecting joints in the human body and monitoring their periodic displacement in the frequency range of respiration in order to correlate this change with breathing.

TABLE 4. A comparison of the main contributions to video-surveillance of breathing activity during sleep and the involved physiological behaviors.

Author name, year	Sensor type and placement	Aim of the study	Methodology	Validation dataset	Validation method	Results with respect to the aim of the study
Pavlidis *et al.*, 2017 [127]	Thermal *IR* sensor	Calculate *BR* and Infer apnea events	Sensing the breath temperature signal	$s = 9$, 19 thermal clips	Comparison with a respiratory belt transducer	R1=0.891, R2=0.9895, R3=0.9906. (R=Linear correlation coefficient)
Samir *et al.*, 2015 [128]	Kinect v1 (RGB + structured IR) & Kinect v2 (RGB+ToF IR)	Compare kinect 1 & 2 for respiratory motion tracking	Depth measurement over chest region. Deflection detection	s=1	Comparison with respiratory belt signal as ground truth	Absolute quadratic fit error: Kinect v1: 20 mm Kinect v2: 5 mm
Yan *et al.*, 2014 [119]	Kinect v1	Monitor sleep using only depth information. Infer sleep events e.g., hypopnea	Ellipse model fitting of the chest region	s=6, diagnosed with *OSA*	Comparison with a professional sleep monitoring system	$0.94 \leq$ accuracy ≤ 1 for classification of hypopnea and normal breathing
Falie *et al.*, 2010 [129]	3D ToF camera	Sleep stages detection from respiratory motion. Infer sleep apnea events	Divide depth image in 12 zones. Features are distances to zones. For *OSA*, a + and - correlation between chest and abdomen region indicate a normal and *OSA* breathing, respectively	s=1, diagnosed with *OSA*	Comparison with *PSG* recording	Strong correlation coeffitients (≥ 0.8) of distance features with respiratory motion
Fei *et al.*, 2009 [130]	Thermal camera	Monitor sleep apnea	Automatic tracking/localization of the nasal region. Onset of higher energy at lower frequency wavelets to detect apnea events	s=22 (10 with *OSA*, 12 normal control group), m=45, 1 hour recording per patient	Comparison with *PSG* recording	Accuracy: 94.59% Precision: 90.42% Recall: 94.76%

n: number of nights per subject, s: number of subjects, m : mean age in years old

Table 4 shows the main contributions made in the field of breathing activity video monitoring during sleep. It is shown that applications of such approach vary from simple *BR* monitoring to more complex behaviors such as inferring apnea and hypopnea events. Authors in [138] have classified wake, *REM* and *NREM* using respiratory features extracted from plethysmographic data and achieved an accuracy of 80.30% with a cohen's kappa coefficient of $\kappa = 0.65$ approximately. Another approach could be used in unobtrusive monirot-ing of breathing activity that has been merely explored by researchers is by dynamically acquiring the body pressure distribution on the mattress during sleep. We acquired pressure images of the body during sleeping positions at a frame rate of 10 Hz in order to extract breathing activity information from the data. The algorithm developed in [136] has been used to identify sleep posture, and accordingly select a collection of pressure sensors that are believed to be involved in acquiring the volume changes induced by breathing i.e., the chest area. Fig. 5 shows a sample of the obtained signal for dorsal posture.

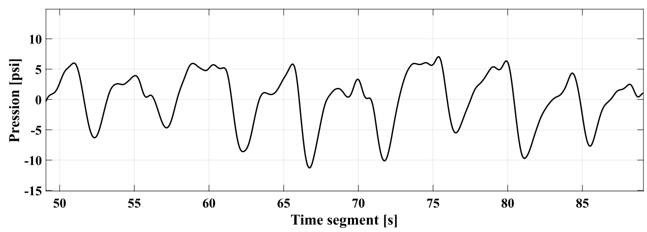

FIGURE 5. Respiratory effort signal derived using a pressure sensor mattress from a subject sleeping in a dorsal position.

V. CARDIAC BASED UNOBTRUSIVE SLEEP MONITORING METHODS

A. HRV ANALYSIS IN SLEEP STUDIES

Researchers have tried to classify sleep stages using several types of *HRV* features such as time and frequency domain, geometric and non linear methods [69], [139]. For instance, wake and *REM* stages have been proven distinguishable using a combination of non-linear features and a global increase of linear *HRV* features [140]. Xiao *et al.* have interestingly obtained an accuracy of 88.67% with a cohen's kappa coefficient of $\kappa = 0.7393$ while trying to classify three group of states, i.e., wake, *REM*, and *NREM*, using a combination of 41 features including time and frequency domain, and geometric features [141]. Time and frequency domain features extraction methods for sleep studies are briefly discussed in this paper.

1) **frequency domain methods**: consist in counting and assigning the number of N-N intervals that belong to the specific pre-defined frequency ranges.

There exist several methods in the literature that serve in extracting these parameters, such as the classical *power spectral density (PSD)* estimation (also called power spectral estimation), Lomb-Scargle periodigram and wavelet entropy measures [142]. Among them, fast fourrier transform based methods are the most widespread, and they include parametric and non-parametric methods.

- **non-parametric methods** consist in finding a reliable estimate of the *PSD* by performing some operations such as smoothing and averaging, applied directly on the autocorrelation function of the signal or its periodigram. No prior information or assumption is made on how the data is produced. Classic methods include The Barlett [143], The Welch [144] and The Blackman and Turkey method [145]. Being data-driven techniques, non parametric methods offer advantages such as algorithm simplicity and computation speed but require the high amount of data to obtain a consistent HRV analysis.
- **parametric methods** frequency domain parametric methods consist in modeling the data as an output of a linear system that is driven by white noise. Hence, the estimation problem becomes estimating the model parameters. The most widespread method consists in modeling the data using an auto-regressive (AR) model. Several approaches have been proposed to estimate the *AR* model parameters such as Yule-Walker, Burg, foward-backward least squares and maximum likelihood estimators [146]. Alternatives to the *AR* model include maximum entropy spectral estimation, *moving-average (MA)* and auto-regressive *MA* estimators [147], [148]. In special cases, e.g., the signal is relatively short, parametric methods could yield higher resolutions, leading to smoother spectral components. One limitation of these methods is validating the suitability of the chosen model and model complexity (e.g., order).

2) **Time domain methods** it is noteworthy that a time-varying form of *AR* models has also been used in time-domain methods [149]. unlike frequency domain methods, time domain methods for analyzing cardiac variability consist in calculating statisfical parameters from the *ECG* signal over time, hence no signal transformation to frequency domain is required. Although less used than frequency domain methods in general sleep stages identification purposes, time domain methods have been used for specific applications where the variation of interests are more ample than those occurring between sleep stages, such as sleep-related breathing disorders. For instance, authors in [150] have used time domain methods to feed a classifier in order to identify *OSAS* patients. Computed parameters in time domain methods include standard deviation of N-N intervals (SDNN), mean of the standard deviations of all N-N intervals for the consecutive 5-minutes segments (SDNN index), square root of the mean of the sum of the squares of differences between consecutive RR intervals, standard deviation (SD) of the averages of N-N intervals in all 5-minute segments, and standard error of N-N intervals.

B. PRE-PROCESSING, TECHNICAL CONSIDERATIONS AND CHALLENGES FOR UNOBTRUSIVELY ACQUIRING ECG SIGNALS DURING SLEEP

Challenges facing the interpretability of the produced signals during unobtrusive protocols of *ECG* acquisition and the technical considerations that should be taken into account in order to obtain a reliable *HRV* analysis are addressed in this section.

- **Sampling rate:** low or high sampling rate end up with altering the spectrum; the best range can be set between 250 and 500 Hz and in some cases can be higher [151]. For unobtrusive *ECG* acquisition during sleep, 360 Hz has been used by [152] for the electrode placement shown in the Fig. 7(f). In some cases, specially for long term applications, sampling rate should be lowered for several considerations [153]; herein where interpolation techniques can play an important role in reducing the error [154]. It has been shown in conventional hardware acquisition protocols that using proper interpolation techniques gives a margin to lower the sampling rate even to a value of 100 Hz while maintaining an acceptable error [154].
- **Frequency range**: high and low cutoff frequencies must be chosen in a proper way. The choice to be made have to be based on the hardware specifications, specially the type of electrodes used for acquisition in such a way the high cutoff frequency should be lower than the one of the hardware, otherwise points of interests e.g, peaks become less recognizable altering *HRV* analysis. For instance, instead the common 150 Hz cut-off frequency, Ricciardi *et al.* have shown that a better ECG signal tracing quality could be achieved using a 40 Hz high cut-off frequency without altering the clinical interpretation of the ECG, making it the lowest acceptable high frequency [155].
- **Duration of *ECG* recording**: depending on each application, time of *ECG* recording required to perform *HRV* analysis may vary. Accordingly, the right methods of *HRV* analysis are chosen. Usually, comparing the recording length and the wavelength of the lower bound, the first should be somewhat 10 times of the second [156]. Hence, in *HRV*-based sleep staging, duration length related restrictions are satisfactorily met where the recording is long enough, and the whole night *ECG* recording is accounted for in the analysis.
- **N-N interval misdetection**: during the recording, an over-detection of N-N intervals may happen due to technical considerations (software and/or hardware). The end-reason is the occurrence of peaks in the *ECG* signal having amplitudes surpassing the criteria set that make a peak considered as a component of an N-N interval or of a peak couple. Usually for diagnosis purposes, or studies involving *HRV* analysis to sensitively track variability in the aim of concluding or correlating with physiological changes, a high accuracy is needed and such over-detection could be reduced automatically

by application-specific filters [157] and [158]. Thus some detected N-N intervals will be filtered out by the previously mentioned filters. The criteria required for filtration should be determined depending on several factors such as the conditions of the recording, the environment, the types of errors occurring, the tolerance required, etc. Such filters are based on static time-interval thresholding, where the criteria for example consists of filtering out an N-N interval having one fifth the time-value of the preceding one. Alternatives can be adopted for correction whether for automatic filters used for both long and short term recordings, or manual inspection, and manual correction of detected peaks for short-term recording segments [159].

- **Results interpretability**: several factors determine to what extent the results are reliable [160]. One important factor is the analysis domain chosen to elaborate results, e.g., time or frequency domains. For short term applications, frequency domain analysis has shown more correlation with sleep stages when compared to time-domain methods. However, for long-term recording, frequency domain methods are less reliable than the time-domain ones. However, an approach that helps leveraging the benefits of frequency domain methods for long-term applications, consists in decomposing the long term measurement's time in time-equal sequential short segments, then averaging the individual calculated spectral components, before correlating with sleep stages [69]. A special case is when the electrical activity of the heart remains stable or undergoing slight changes in these predefined short segments, which results in the same lack of reliability of the main (long-term) recording.

C. SENSING TECHNOLOGY

ECG measurements in sleep studies have been used with various acquisitions protocols, i.e., electrodes placement, electrodes types, acquisition environments and applications. However, each application requires a specific combination of sensing characteristics depending on several criteria, such as the parameters of interest and precision tolerance. Conventional *ECG* signals acquisition are accompanied by different types of noises introducing unwanted components to the data acquired. However, acquiring *ECG* in unobtrusive sleep applications consist of measuring these low amplitude physiological signals while providing the least contact with the skin of a person sleeping on a mattress, which makes the measurement subject to a higher amount and new types of noise when comparing with the conventional methods of signal acquisition. Hence, specific hardware acquisition is required to handle these challenges in order to preserve a consistent signal quality, e.g, signal-to-noise ratio. Conventional types of artefacts accompanying *ECG* signals include power line interference, electrode contact noise, movement-induced noise, high frequency noise, breathing periodic noise. This section mentions and discusses the sensing hardware that has been used in unobtrusive sleep assessment procedures, the limitations of such designs preventing them to reach industry and what are the missing considerations to make them more realistic [161].

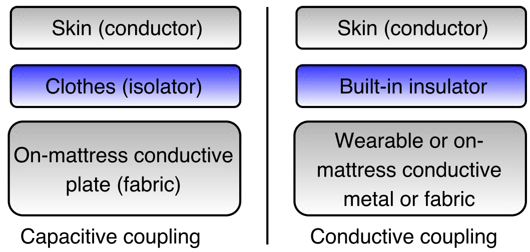

FIGURE 6. Conductive vs. capacitive coupling in the context of sleep studies .

1) CAPACITIVE *ECG* COUPLING

consists in acquiring *ECG* signals using a conductive electrode (plate), while considering the subject's skin as the other parallel conductive plate of a capacitor and his clothes as the capacitor's separative dielectric isolator as shown in Fig. 6. Hence, instead of considering clothes as a barrier to get the signal, they could be considered as a component of the electrical coupling. For some sleep monitoring applications i.e., home monitoring, capacitive *ECG* electrodes could be a potential solution since no direct contact with the body (skin) is allowed. Researchers have explored different scenarios for capacitive coupled acquisitions on several levels, specially in what is related to the size of the skin-electrodes region and electrodes placements [162]–[167].

2) CONDUCTIVE *ECG* COUPLING

Conductive *ECG* coupling has been widely used in both conventional and alternative/unobtrusive methods of sleep assessments [152], [168], [169]. Although it requires a direct contact with the skin in order to acquire *ECG* signals as shown in Fig. 6, the acquisition protocols in which it has been employed have helped meeting some unobtrusiveness requirements in the context of sleep studies. More particularly, researchers have developed unobtrusive *ECG* acquisition scenarios that could meet unobtrusive sleep requirements by introducing wirelessly connected conductive and non adhesive electrodes. This could make longterm *ECG* acquisition possible by not restraining the subject's possible movements or tosses during sleep and avoiding skin irritation and overnight skin-electrodes contact deterioration.

D. OPTIMIZING THE ELECTRODES MAPPING ON THE MATTRESS

Based on the priority of the designers, a compromise between accuracy/SNR, comfort, and autonomy of the system would constraint the choice of electrodes placement. A previous work has been focused on the optimization of the electrode placement for various applications. such as reconstruction of the image of the electrical activity of the heart [170]

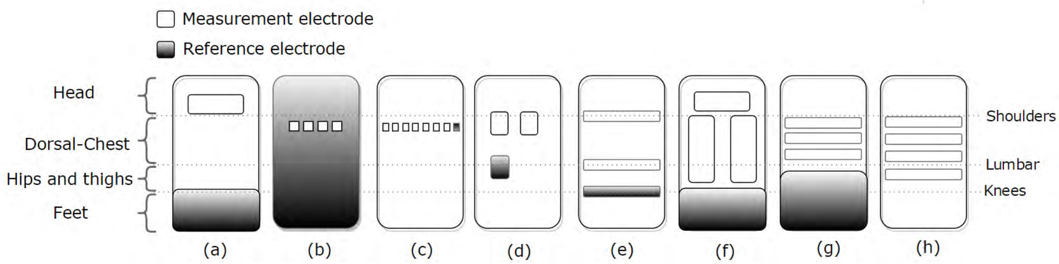

FIGURE 7. Capacitive electrodes placement on mattress in unobtrusive signal acquisition scenarios.

by optimizing the electrodes placement for multi-channel electrocardiography. Also with wearable applications, such algorithms have been applied in order to improve the acute myocardial infarction detection [171]. In addition, automated design of *ECG* measurement systems has been conceived based on the multiobjective optimization approach [172]. Bipolar measurements optimization using a pair of electrodes with different locations involving different interelectrode distances where compared with respect to signal to noise level, signal strength, and inter-patient deviation [173]. Results have shown that for non-diagnostic purposes like the detection of the cardiac beat, the QRS complex remains detectable even for a one fourth of the standard distance between V1 and V2. Since the study has been done in a direct skin-electrode contact acquisition with standard leads, the results do not accurately describe the case of non-contact *ECG* acquisitions used in unobtrusive sleep studies, rather they give a general idea about the correlation between IED and signal behavior.

E. ECG SIGNAL ACQUISITION IN THE CONTEXT OF UNOBTRUSIVE SLEEP STUDIES

A wide range of *ECG* signal processing techniques in the context of unobtrusive sleep studies exists. In the present section, the ones that do not require wearable or wired sensors, i.e., implemented on the mattress, are presented and discussed in what is related to electrodes placements, obtained results, and impacts or constraints imposed on the subject's sleep.

As mentioned before, the choice of the electrodes type is highly correlated with their positioning and the body area concerned during the measurement. If the acquisition involves a direct contact with the skin of the person, then contact electrodes are used, otherwise the use of capacitive electrodes is recommended as they do not require a direct contact and can handle clothes electrical isolation. In the literature, two types of *ECG* sensors positioning were adopted, followed by differences in materials/types, numbers of electrodes and contact area size of the electrodes:

- **Acquisition using neck and feet region:** this type of electrodes positioning derived from the fact that the unveiled body parts of a person wearing normal pyjamas are the hands, face, feet and neck. Being the stable unveiled regions on the bed, the neck and feet were chosen to acquire signals from. Even though contact *ECG* electrodes are best to be used, however conventional wet or dry direct-contact electrodes such as Ag-Agcl are out of selection as the acquisition is chosen to be unobtrusive; hence, capacitively coupled textile electrodes, i.e., using capacitive electordes plates, are used in this electrode positioning.
- **Acquisition using dorsal-chest region:** depending on the wearing clothes specification, one of the two types of electrodes has been used in this electrodes positioning. For instance, where wearing clothes is prohibited, direct contact with the skin is allowed, hence conductive electrodes were used, otherwise capacitively coupled textile or metal electrodes were used.

In 1993, a first study of its kind has been conducted by Ishijima [174] to acquire *ECG* signals following this electrodes positioning. Conductive textile materials were used to perform the acquisition. For the sake of comparison, three types of textiles composed of electrically conductive materials were tested in the acquisition process made of carbon fiber, and nickel plated acrylic fibers where one of them made of span yarn and the second of single filament, respectively. As shown in Fig. 7(a), the textile electrodes were placed on the pillow so positioned under the nape, and on the lower section of the bed sheet to be under the heel of the person, taking into consideration all the constraints imposed such as the appropriate length of textiles and the body parts that should remain in the measuring section. However, respiratory-induced artefacts have not been taken into consideration in his design, because the *ECG* acquisition regions were far from the chest area making the system susceptible to unpredictable and uncorrectable noise. Hence in 1996, Ishijima [175] added two sheets of capacitive electrodes under the chest area of the person to detect the respiratory-induced chest movements through the alternation of capacitance between the two sheets while keeping the same design for *ECG* acquisition as the first study. The change of the capacitance that reflects the respiration movements is fed to a frequency to voltage converter to monitor the capacitance change continuously. Ishijima's work has been the very start in this field of sleep research. Ignoring the movement's artefact and not taking any measure to correct the induced baseline drift makes the system unsuitable to home applications and daily use. Moreover, the system cannot self-adapt with tosses and changes in body position, so *ECG* signal alterations for 5-12 seconds were encountered at each movement. Although such acquisition protocol does not maintain along the night the necessary accuracy to derive cardiopulmonary diagnostic data as it was the intended application, but it successfully detects the heart rate with a percentage of 82 to 93 % during a continuous recording for 7 hours of sleep.

Devot el al., proposed a similar design following the same electrodes positioning of Ishijima as shown in Fig. 7(a), where wearing cloth is permitted for the person [169]. They evaluated the feasibility of correlating frequency domain analysis of *HRV* parameters to sleep staging. Their results, were promising in terms of percentage of classification between *REM* and *NREM* sleep with an average coverage of 81.8% over a night recording; however, this evaluation was based on time segments that do not contain artefacts, which is unrealistic in real applications where no shielded rooms are available in homes, so the percentage of coverage should be measured over all night period without excluding unwanted segments. In addition, the number of successful detection of arousals suffers from a high number of under-estimated instances, again due to the presence of artefacts. Devot and Ishijima's works regarding the placement of *ECG* were comparable to lead III based on einthoven's triangle.

Lim *et al.* proposed another acquisition protocol based on the capacitive sensing where wearing clothes was allowed [166]. Attached on the mattress's chest area, an array of eight conductive electrodes and a reference electrode sheet as shown in Fig. 7(c) are involved in conducting a unipolar measurement for each one of the eight electrodes with respect to the reference sheet. The system has proved to be good for *HRV* analysis with a high coverage of heart rate; drawbacks are the rigidity of the electrodes array because it was protruded in order to assure more stable and higher contact area with the subject, causing soreness to the body region involved in the contact.

Ueno [163] conducted also their experiments based on three capacitively coupled electrodes. The electrodes placement is shown in Fig. 7(d). The system maintained a good *ECG* quality for at least seven hours of sleep. Wu *et al.* conducted three types of experiments to evaluate the performance of monitoring *ECG* with different types of postures for several subjects, and the performance durability on long term monitoring [165]. The electrodes positioning is shown in Fig. 7(e) where a unipolar capacitive sensing is adopted for signal acquisition. High average rate of R-Peaks detection was recorded during eight hours of sleep, with a root mean square error of heart beat detection of approximately one beat per minute. Even though it was not the intended idea of this work, from a signal quality perspective, it is clear that the results obtained make the work a promising solution for capacitive sensing to derive R-Peaks then perform a *HRV* analysis in the aim of inferring sleep stages. However for the perspective of practicality and suitability with real applications, a major drawback of the system that was not cited clearly by the authors emerged after modifying the electrodes size. In the first acquisition protocol proposed, the three electrodes were covering the whole width of the mattress. This has led to an important decrease of the QRS amplitudes detected for some postures and this is mainly caused by the direct contact of the person's hand(s) with the electrode sheets that are meant to be used for capacitive measurement not conductive one. To solve this problem, the authors reduced the width of the electrode sheets length to cover a smaller part of the mattress width to avoid contact with the person's hands. However, the previous statement could be considered as true only if the person was sleeping in the middle of the mattress with his dorsal-chest region covering the electrode sheets. If the person was lying on the very right or left side of the mattress, there is a big chance that his hand(s) contact again the electrode sheets. So, this update made to the system enhanced the signal quality while imposing a constraint on the position and the mobility of the person, so movements are allowed only while staying in the same position, which makes the system impractical for autonomous and long term monitoring. Park *et al.* tried the direct contact approach in which the person is permitted to wear a short-sleeves shirt and short pants in order to maintain a direct contact with the bed sheet conductive electrodes [152]. They explored a new approach using *ECG* signal processing to derive respiration signal from *ECG*. They derived the respiration after a comparison made between two different types of acquisition protocols: one consists of the two electrodes in the shoulder's region which is compared to lead I and the other using the same electrodes positioning used with Ishijima [174], [175] and Devot *et al.* [169] as shown in Fig. 7(f). A high coverage of ECG derived respiration was obtained making a promising step for deriving respiration from *ECG* with a high accuracy. Peltokangas *et al.* [176] have tried the bipolar measurement for heart rate and *HRV* detection. A high average coverage of 95.08% was recorded among all measurements for a total of 158 hours divided on 22 nights (Approximately 7 hours of sleep per night). However the person was not allowed to wear a shirt as the eight conductive fabric electrodes require direct contact with the skin. As a result, the concept of this system was clearly based on prioritizing the success of detection at the expense of the autonomy which makes the solution impractical as a stand alone system for sleep monitoring. Other researchers such as Ishida *et al.* [177], Vehkaoja *et al.* [164], Chamadia *et al.* [178] and Kato *et al.* [179] have proposed somehow similar acquisition protocols based on capacitive electrodes positioning according to Fig. 7(h), (b), (d) and (d), respectively, showing more potential solutions of unobtrusive *ECG* acquisition during sleep.

VI. CONCLUSION AND FUTURE PERSPECTIVES

Cardiac activity, respiration, posture and body movements abide the most measured physiological signals in unobtrusive sleep monitoring techniques. Features include especially the variability of the heart rate that could be projected and studied in several domains, along with respiratory parameters such as rate, regularity and auto-similarity, and body movements and postures features. The majority of the state-of-art works have been using one of these signals to estimate sleep stages accordingly, leading to a weak discriminative power when compared to the conventional *PSG* sleep stages classification. More particularly, existing methods have been able to distinguish between two or three classes, i.e., wake and sleep, or wake, *REM* and *NREM* stages, while the *PSG* classification output is usually a combination of 5 classes, having the discriminative power of separating *NREM* into three stages, i.e., *NREM*1, *NREM*2 and *NREM*3. With the introduction of new techniques of data analysis such as deep machine learning algorithms, a combination of the aforementioned features of unobtrusively measurable physiological behaviors could potentially lead to a well-established automatic and unobtrusive sleep stages classifier system. Future work has to be done in this line of research in order to leverage advancements in computation power and data availability in serving the ultimate goal of sleep studies and provide a wider diagnosis of sleep problems towards a healthy sleep worldwide population.

A. EMERGING SENSING AND EARLY-STAGE TECHNIQUES

A number of the proposed state-of-the-art works remain in their early stage, eventhough some of them have been revealed since decades, and that is due to several factors, including lack of clinical validation and research database. A dedicated work is needed in order to bring these techniques to the medical field, making available a wide range of research opportunities. Early-stage potential techniques of acquiring unobtrusively physiological signals in the application of sleep monitoring include:

1) **Ballistocardiography**: consists of producing graphical representations of cardiac induced repetitive human body movements in order to give insights on the blood injections. It has been first proposed in the early 80's and still not adopted in clinics [180], [181]. Ballistocardiography has several open research areas such as lack of standardization with respect to 1) the measured signal, by proposing a unified nomenclature for peaks and valleys and 2) a unified or a standard site of measurement [182].
2) **Air mattresses:** breathing, body movements and cardiac activities could be detected by the volume change of the pneumatic underneath the subject [183]–[186]. This method has been validated on synthetic data and then clinically only in supine sleeping posture [184]. A range of determinants influence the performance and applicability of such methods and are related to both the acquisition protocol and the subject i.e., inter-posture and inter-subject variability [186].
3) **Ultrasound sensors:** ultrasonic sensors have been used in order to detect breathing rate and body movement activities [187]–[191]. For instance, receiving a modified version of the projected ultrasonic wave can give insights about the frequency of the detected movements, this method of movement detection is also referred to as Doppler technique. Although the advantages provided by this technique, a number of parameters choice make its use subject-specific or sensitive to noise. For instance, an optimal carrier frequency has to be chosen based on the type of targeted body movements that is in some cases, subject-specific, as higher frequencies allow a better sensitivity to small movements [192].
4) **Wireless detection systems:** they include systems that use Wi-Fi signals [193]–[196], microwave antennas [197] and ultrawideband systems [196] in order to detect respiration and body movements activities. They consist of devices that are able to acquire the wireless channel state information of the radio signals in order to measure rhythmic patterns induced by body movements and breathing activities [198]. Some of the drawbacks of these techniques consist in the limited decetable motion range in specific postures, e.g., lateral motions involving a displacement greater than 20cm are not detected in an ultrawideband system for breathing monitoring [196].
5) **Optical fibers based systems:** consist of using microbend fiber optic sensors underneath the subject's mattress in order to monitor breathing and body movements activities in order to extract sleep parameters such as TST [199], [200]. A number of research opportunities are available with optical fibers such as a further analyzing the motion types that could emerge during acquisition and assigning specific retroactive feedback to attenuate the impact, such as in the case of the occuring muscle tremors, that could be a potential disturbance to the acquired information [201] and [202].
6) **Other techniques:** include phonocardiographic sensors [203], static charge beds [204], in-ear EEG sensors [205], etc.

B. RECOMMENDATIONS AND REMARKS FOR FUTURE WORKS

Based on the conclusion and what we presented in this paper, our conclusive recommendations and remarks for future directions can be resumed as follows:

- **Clinical experimentation and database availability:** lack of data is majorly facing two of the most crucial steps towards an unobtrusive sleep monitoring: 1) validation, and hence medical devices monitoring sleep unobtrusively, and 2) teaching machines to perform autonomous tasks, and lessening medical intervention and assistance requirements. A potential line of research leading to advancements in this area consists of conducting clinical experiments in order to collect physiological data during sleep. For instance, a simultaneous data acquisition using both the experimental device and the standard system i.e., PSG, is bound to give the opportunity to researchers to compare, analyze, teach machines and validate with respect to the standard measurements leading to a faster pace of advancements.

- Clinical validation with respect to standards: researchers have been focusing on proposing methods and devices for giving insights on sleep behavior leading to a larger spectrum of unobtrusive sleep monitoring techniques. However, a number of studies have shown that these techniques have been rarely validated with respect to PSG in a significant and reliable way [16], [206]. Clinical validation is an inevitable phase for approving a medical device and adopting it in clinics. Hence, future efforts are bound to work on this line of research in the aim of validating the applicability of a broad range of existing devices and acquisition techniques.
- **Machine learning application in unobtrusively acquired data during sleep:** this line of research consists of using the growing knowledge in machine learning techniques in the application of sleep studies. In an era where both the computation speed and deep neural networks are expanding in a tremendously fast pace, high dimensional unveiled patterns are expected to be leveraged in estimating sleep hypnograms, classify apnea events and score sleep quality [207]. This direction has recently started gaining researchers' interests [208]–[210]. However, the existing works have covered the classification of sleep stages based on obtrusive and conventional data. Hence, this highlights the need to conduct similar research using autonomous physiological functions such as cardiac, breathing and body movements activities in order to bring advancements in unobtrusive sleep monitoring.
- **Assessing conformity of the proposed techniques to norms and regulations:** it is one of the essential requirements resulting in a potential medical device. It consists of a systemic evaluation of the regulations and norms as early as during the design phase to the implementation and validation. As previously established in the paper, rarely the proposed unobtrusive sleep monitoring techniques have succeeded to reach industrial gates, who's outcome is a class-defined medical device. Thus a substantial work has to be done in this area in order to transfer the existing knowledge to the medical field.
- **Exploring hardware, smart clothes, wearables, and E-textiles for data acquisition** Last but not least, exploring potential and new ways of acquiring physiological data without imposing constraints on the subject is a tremendous need in the field of sleep studies. The future work has to be done on two levels: 1) proposing new methods and apparatus: although a wide spectrum of methods and devices have been proposed, proposing new solutions could make it considerably much easier for unobtrusive sleep monitoring to reach the medical field. And 2), improving the existing systems in what is related to hardware performance optimization and parameterization; for instance, improving electrodes positioning in capacitive ECG sensing eventhough by using same electrodes types, has improved potentially the signal quality and HRV analysis, leading to a better correlation with sleep stages [170].

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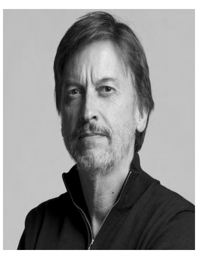

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