Unobtrusive Monitoring of Sleep Cycles

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Contributor: Ibrahim Sadek , Juwonlo Siyanbade , Bessam Abdulrazak

Polysomnography is the gold-standard method for measuring sleep but is inconvenient and limited to a laboratory or a hospital setting. As a result, the vast majority of patients do not receive a proper diagnosis. In an attempt to solve this issue, sleep experts are continually looking for unobtrusive and affordable alternatives that can provide longitudinal sleep tracking. Collecting longitudinal data on sleep can accelerate epidemiological studies exploring the effect of sleep on health and disease. These alternatives can be in the form of wearables (e.g., actigraphs) or nonwearable (e.g., under-mattress sleep trackers).

ballistocardiography sleep cycles home monitoring

1. Introduction

Sleep is important for the physical and mental well-being of an individual. The quantity and quality of sleep are generally associated with chronic diseases and health risks such as diabetes, cardiovascular diseases, renal failure, anxiety, and depression [1][2]. The fast pace of modern society and the rapid increase in the aging population have contributed to the population of people being affected by sleep disorders. The Centers for Disease Control and Prevention (CDC) reported that a third of the United States population does not get enough sleep [1]. A similar statistic was reported by the Canadian Men's Health Foundation (2016) stating that 30% of Canadian men are sleep deprived. This is reflective of the global populace as sleep disorders are rapidly becoming a global concern, leading to a range of societal problems [3]. Sleep monitoring is important and could be a lifesaver for people with undiagnosed sleep disorders [4][5]. A major motivation for sleep monitoring is the effect it has on health and well-being [6]. However, the process requires trained sleep technicians to perform polysomnography (PSG).

The PSG is the medical gold standard for sleep studies. It uses various intrusive sensors to record multiple physiological signals during sleep, namely electroencephalogram (EEG), electrooculogram (EOG), electromyogram (EMG), electrocardiogram (ECG), body position, oronasal airflow, photoplethysmogram, abdomen, and thorax respiratory efforts, and others (**Figure 1**).

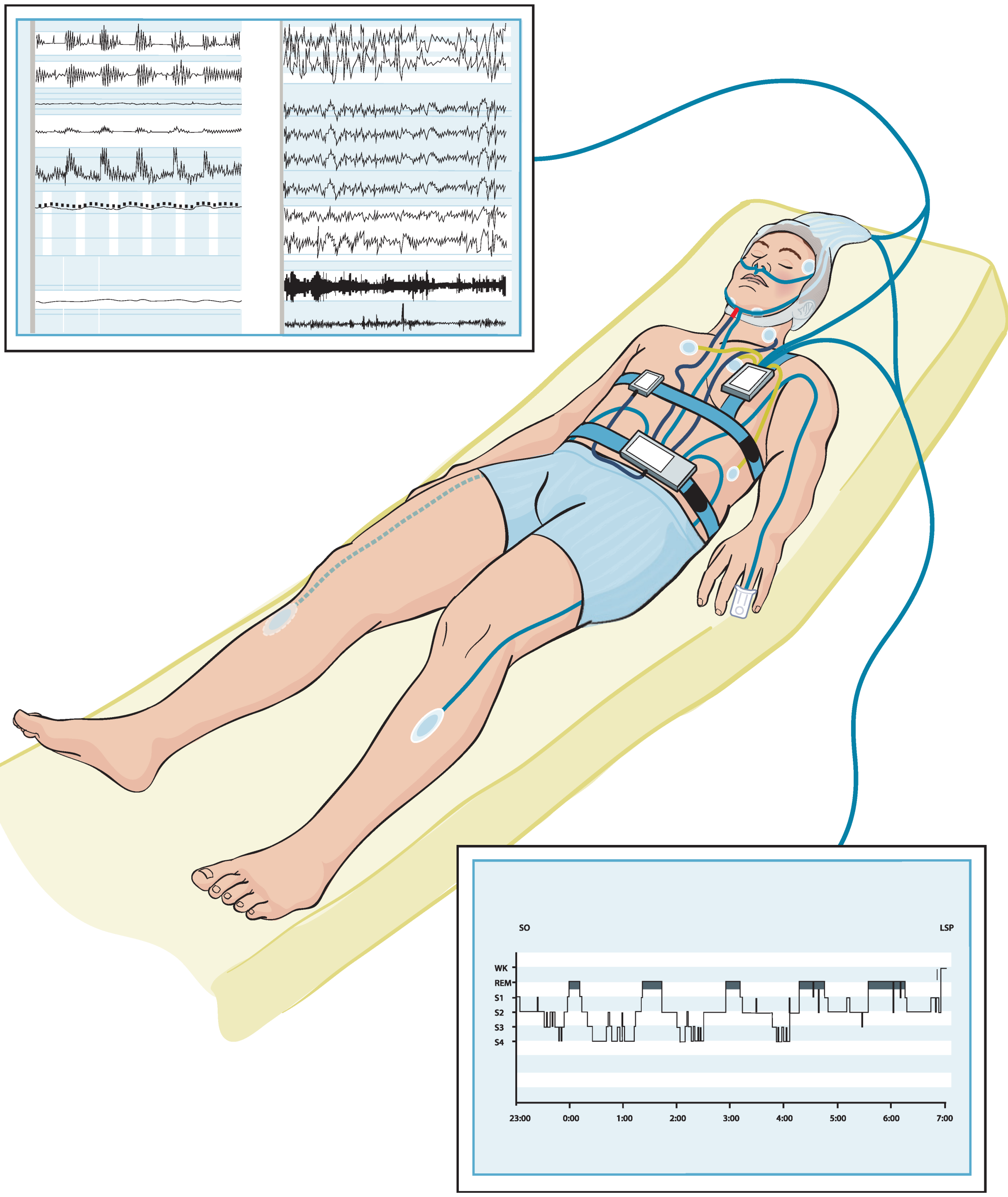

Figure 1. An illustration showing the several sensors attached to a monitored individual during an overnight PSG study.

It is a fairly inconvenient, time-consuming, and expensive technique, used only clinically, and cannot be used for longitudinal sleep tracking [7][8]. The PSG protocol can itself affect the quality of sleep because of unfamiliarity with the environment and the multiple attachments used here. The results (sleep score) include sleep onset latency, sleep efficiency, and sleep stages. The structure of sleep includes various stages characterized by specific physiological changes.

Due to the complexity of PSG, other methods have been proposed as alternatives. Actigraphy (ACT) and photoplethysmography (PPG) are two solutions that enable long-term monitoring and produce a valid assessment of sleep/wake behavior. Metrics derived from longitudinal sleep tracking can help detect and manage various diseases, e.g., cardiorespiratory disorders and dementia [9]. That is, the collection of longitudinal sleep data on a large scale can boost epidemiological studies that examine the influence of sleep on health and disease [10]. There are also less cumbersome approaches to sleep monitoring owing to the advancement, adoption, and integration of technology into healthcare in the form of non-contact systems, wearables, and mobile systems [10][11][12][13][14]. These systems capitalize on the strong correlation between bio-vital signs and sleep.

Researchers have been focusing on creating non-contact sleep tracking methods (e.g., under-mattress sleep trackers shown in **Figure 2**) that can achieve closer outcomes to PSG [15]. These systems can potentially be used for sleep-quality monitoring. Examples include systems working on the principle of ballistocardiography (BCG) (Sadek et al. [16]), strain gauge (Lima et al. [17]), seismometer (Li et al., 2018), ultrasonic (Hsu et al., 2017; Tran et al., 2019), ultra-wideband system (Kang et al., 2020), RF signals (Liu et al. [4]), fiber optics (Koyama et al. [18]), and smart textiles (Zhou et al. [19]).

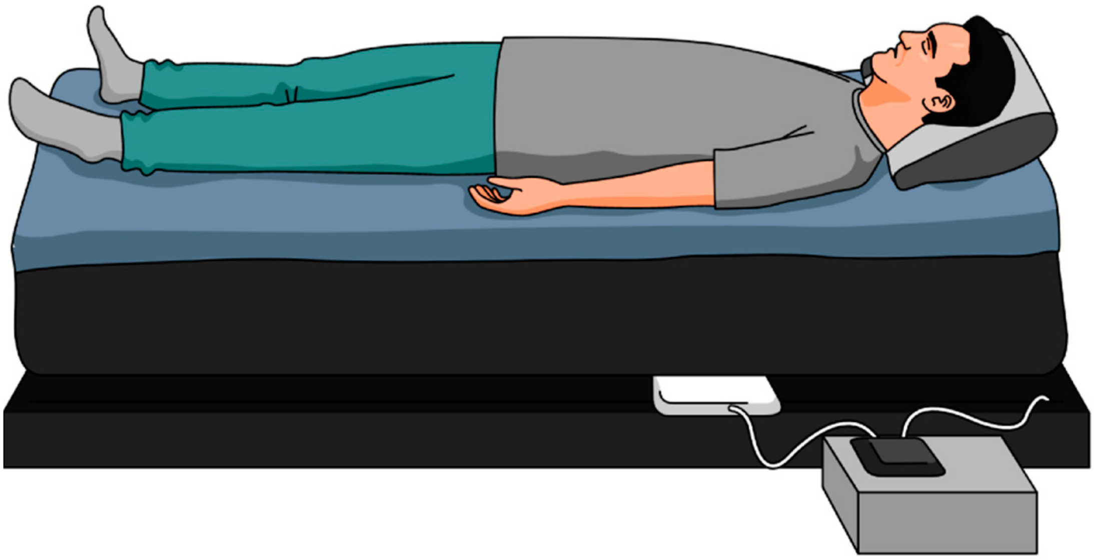

Figure 2. An illustration showing the location of a contactless sensor under the mattress of a monitored individual.

2. Current Insights of Sleep Monitoring Methods

It can be noted that there is an increasing interest in sleep monitoring (in particular, sleep cycles) using unobtrusive sensors. Due to the unsuitability of PSG for in-home monitoring, researchers have developed and are developing various unobtrusive systems as alternatives, leveraging on recent technological advancements. Generally, proposed sleep monitoring methods are based on one or a combination of the following: respiratory cycle, cardiac cycle, body movement [20]. It was also observed that the majority of the proposed systems are limited to three-stage sleep classification [20]. Although the results from the abovementioned studies are encouraging in terms of accuracy, commercial devices cannot produce identical results to PSG. It makes sense because EEG-based systems are the most accurate for detecting all the stages of sleep [21].

That said, the ease and relative performance of actigraphy-based devices for sleep and sleep-cycle monitoring has given rise to numerous wearable devices and smartphone-based technologies. Actigraphy devices enable the user to wear dedicated sensors to help track vital signs and movements while sleeping. It is shown that the use of wearable devices for sleep-cycle monitoring is feasible but inaccurate compared to the gold standard PSG [22][23][24]. This is because even in healthy adults accelerometry has high sensitivity but low specificity for sleep detection. These devices often tend to underestimate or overestimate some key parameters such as TST, sleep efficiency, wake, or the transition between the sleep stages [22][23][24]. Patients with sleep disorders, or those who are chronically sleep-deprived, are more likely to suffer from fragmented sleep and reduced ability to understand their functional impairment. Therefore, wearing sleep trackers with incorrect readings could have adverse effects on these patients. This happens because most patients do not realize that the claims of these devices typically outweigh the science to support them as devices to measure and improve sleep. As a result, the importance of precise measurements cannot be overstated [23].

A recent study by Chinoy et al. [25] has shown that off-the-shelf sleep trackers (i.e., Fatigue Science Readiband, Fitbit Alta HR, EarlySense Live, ResMed S+, SleepScore Max) provided mixed results for sleep stage classification and the trackers tended to perform worse on nights with poorer/disrupted sleep. Similarly, Roomkham et al. [26] have come to the same conclusion that further studies are needed to assess the longer-term performance of sleep trackers, namely, the Apple Watch in natural conditions, and against PSG in clinical settings. Furthermore, Kholghi et al. [27] concluded that EMFIT QS failed to distinguish sleep stages against PSG and additional development is needed before using EMIFT QS in clinical settings. Moreover, studies have shown that although smartphone-based sensing systems are simpler and less expensive, they correlate poorly with the PSG [28].

Frankly, it is impractical to compare or generalize the accuracy across sleep trackers, specifically for under-mattress sleep trackers. This inconsistency occurs because the morphological characteristics of acquired BCG signals are device dependent. Besides, the signals can be different between and within subjects [24][29]. As a result, there is a need for a comprehensive and open dataset of BCG signals that will enable researchers to utilize them in their environments and improve the field into an accepted technique suitable for clinical studies [20]. To date, there is only one publicly available dataset of BCG signals; the purpose of the dataset was to assess the ability of the BCG to monitor changes in cardiovascular function [30].

Inventors have proposed, produced, and presented several methods (models and devices) for sleep monitoring by acquiring physiological data unobtrusively. However, the efficacy of a few systems was clinically validated. Experiment-wise, most of the studies are limited to a small sample of healthy individuals [26]. Thus, a broader scope of participants should be taken into consideration during future proposals and assessments of sleep-cycle tracking systems. This is because factors such as gender, age, profession, and social class affect the quality of sleep (Cappuccio et al. [31]).

Despite the above criticism, commercial sleep trackers can provide continuous and long-term monitoring of patients' sleep quality for days and weeks, which is impossible in hospitals. In other words, they can be used as predictive screening methods before performing the sleep studies [20]. For example, Sadek et al. [32] have shown the efficiency of an under-mattress sleep tracker for long-term monitoring of specific sleep parameters, namely, wake-up time, bedtime, and time in bed. These parameters were trended over time, and the authors were able to detect anomalies and notify corresponding caregivers.

Typically, under-mattress-based sensors can monitor the sleep quality of patients without interfering with their daily activities. However, this may not always be the case for wearable sensors considering vulnerable populations with behavioral symptoms. To explain, if the sensor is not waterproof, it has to be removed before showering. In addition, if the sensor has a short battery life, it needs to be removed frequently for charging. These situations will undoubtedly distract patients and similarly disrupt the data collection [33][34]. The choice between wearable and non-wearable sensors should be based on the medical conditions of each patient group. Hence, there will always be a trade-off between data continuity and patient comfort [33].

3. Conclusions

With the rising interest in sleep monitoring generally and the clinical need for sleep cycle monitoring, there is an opportunity for researchers and commercial organizations to produce systems that will provide reliable and valid sleep information. Sleep monitoring is a very critical medical issue that could avert negative consequences on the life of individuals. It could potentially reduce the volume of fatigue-related work injuries, health issues, underperformance, road accidents, and aid health workers in managing sleep disorder patients. The performance and features of the systems examined here are encouraging. They could be set up for remote sleep-cycle monitoring and long-term studies, and they are easy to use. Unlike the gold standard-PSG, they are unobtrusive and contactless.

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