Sleep Monitoring in Adults using Wearables and Unobtrusive Technology

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ABSTRACT

Sleep is a complex physiological process that plays a fundamental role in maintaining homeostasis[1] and overall health. It has an internal structure characterized by sleep stages, which is often affected by either the high demands of the current 24-hour society or by different sleep disorders such as sleep apnea. These disturbances to the regular sleep structure have been strongly associated with reductions of cognitive and behavioral performance, attention deficit, depression, nocturia, memory loss, snoring, and cardiovascular diseases. Therefore, it is crucial to identify sleep problems in an early stage before the overall health is compromised in an irreversible way.

Currently, sleep disorders are diagnosed using polysomnography (PSG), which is the gold-standard sleep test usually recorded in a sleep laboratory. This test is often associated with elevated costs and reduced comfort. With this in mind, many studies have focused on the development of wearables and unobtrusive technologies that can be used at home and that can monitor sleep during more than one single night.

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[1] Homeostasis refers to the ability to maintain equilibrium despite internal or external stimuli.

This chapter discusses unobtrusive state-of-the-art sensors and algorithms for sleep monitoring in adults, with special focus on heart rate, respiration, and blood oxygenation monitoring.

1 Physiological background of human sleep

Sleep is a natural, though complex process, which follows an internal architecture of alternating states. As such, sleep cannot be described by a single state of the body. Instead, it consists of different sleep stages. These sleep stages are associated with characteristic patterns at cerebral, cardiac and respiratory level. However, sleep disorders could alter these characteristics. Therefore, the detailed analysis of one's sleep architecture could serve the detection of these sleep disorders.

1.1 Sleep stages

Sleep stages and their characteristics were first defined by Rechtschaffen and Kales (R&K) in 1968 [132]. Later in 2007, the American Academy of Sleep Medicine (AASM) updated these R&K rules and published a manual for sleep scoring and associated events [26]. These sleep scoring rules are based on patterns and wave characteristics found in the electroencephalogram (EEG)[2], the electrooculogram (EOG)[3] and the chin electromyogram (EMG)[4]. To facilitate the analysis, input signals are scored in consecutive windows of 30s, which are referred to as epochs [132]. Every epoch is scored with one of the five sleep stages defined by the AASM. These stages are Wakefulness (W), Rapid Eye Movement sleep (REM sleep) and non-REM (NREM) sleep 1, 2 and 3 (respectively N1, N2 and N3). Usually, stages N1 and N2 are referred to as *light* sleep and N3 as *deep* sleep [138].

Apart from patterns in the EEG, EOG and EMG signals, differences in sleep stages are reflected in the regulation of both branches of the autonomic nervous system (ANS), namely, the parasympathetic nervous system (PNS) and the sympathetic nervous system (SNS) [104]. As such, distinct characteristics can be observed as well at cardiac, respiratory and cardiorespiratory level during NREM and REM sleep. These characteristics have been exploited for the development of ambulatory systems for sleep monitoring. The reason for this is that cardiac and respiratory information can be extracted from the Electrocardiogram (ECG)[5], which can be easily recorded using wearable and unobtrusive technology. This is exactly the focus of this chapter,

[2] The EEG captures the electrical activity from the brain, commonly obtained from the scalp using surface electrodes.

[3] The EOG records the electrical signal caused due to the opposite polarity between the front and back of the eye, which acts as a dipole.

[4] The EMG records the electrical activity of the muscles.

[5] The ECG records the electrical activity of the heart.

therefore, an overview of these characteristics or physiological changes during sleep stages is presented next.

1.1.1 NREM sleep

It is very well-known that during NREM sleep, the PNS activity dominates over the SNS [104]. Compared to wake, the breathing frequency increases, though the variability is reduced. This is accompanied by a reduction in tidal volume[6], resulting in a breathing which is more shallow and rapid [57]. Between different NREM stages, there is no significant difference in tidal volume and breathing frequency, however respiration becomes more regular during deep sleep compared to light sleep [57].

Due to the high activity of the PNS during NREM, bradycardia emerges and the heart rate reaches a minimum during N3 [104, 153]. Additionally, heart rate variability (HRV) is lower during N3 compared to REM and wake, and regular oscillations can be observed during N3. These oscillations are associated with the respiratory sinus arrhythmia (RSA), which is the modulation of the heart rate (HR) with respiration. Spectral analysis of the tachogram during NREM reveals a decrease in the low frequency (LF) band (0.04-0.15 Hz) and increase in the high frequency (HF) band (0.15-0.4 Hz) of the HRV [165].

1.1.2 REM sleep

REM sleep is characterized by muscle atonia, increased physiological activity and the act of dreaming. During this sleep stage, the PNS is more active compared to wake. Nevertheless, phasic fluctuations in SNS and PNS activity occur during REM sleep. As such, important distinctions exist between tonic and phasic REM sleep epochs [114]. During tonic REM, the SNS activity drops even below NREM levels, while during phasic REM, the SNS becomes very active and variable [104]. Characteristic rapid eye movements are also only present during phasic periods.

On a respiratory level, both tonic and phasic REM exhibit a decrease in ventilation due to a reduction in ventilatory drive. In general, the respiratory system becomes unstable as the depth of breathing becomes highly variable [57].

A general increase in cardiovascular instability is an important feature of REM sleep. During tonic REM sleep there is marked bradycardia and hypotension, resulting in a decrease in HR and blood pressure (BP) even below levels of NREM sleep. On the other hand, phasic REM sleep epochs are characterized by great transient increases in HR and BP, produced by a phasic increase in the SNS [20].

These phasic fluctuations during REM sleep result in the instability of cardiovascular and respiratory parameters. Therefore, REM sleep epochs can exhibit a great variety in cardiac and respiratory characteristics among each other. As a con-

[6] Tidal volume corresponds to the volume of air inspired/expired with each breathing cycle.

sequence, the detection of REM sleep epochs present a more challenging task for automated sleep scoring algorithms compared to deep sleep.

1.2 Sleep architecture

For healthy persons, a normal night of sleep consists of five to six cycles, where REM and NREM phases are alternated with occasional awakenings. A hypnogram is the visualization of a person's sleep architecture over time. The hypnogram of a healthy adult is depicted in Fig. 1(a). One cycle typically lasts for 90 to 110 minutes. An initial wake period is followed by light sleep, where a person transients from N1 to N2. Thereafter, deep N3 sleep is reached. The cycle is terminated with a phase of REM sleep. In this fashion, NREM and REM alternate throughout the night, however their relative distribution changes. The duration of NREM sleep decreases and is compensated by an increase of REM sleep. Within NREM sleep, the portion of N3 will drop, though replaced by lighter N2 sleep. During final cycles, N3 may not even occur. The average distribution of different sleep stages throughout the night is given in Table 1. A longer sleep time will lead to an increase in REM sleep. The effect of aging will lead to a decrease in total sleep time as awakenings will occur more often. In patients with obstructive sleep apnea (OSA), the amount of REM and N3 sleep will be heavily affected due to arousals, which result in a fragmented sleep. A hypnogram of an adult with severe OSA is depicted in Fig. 1(b).

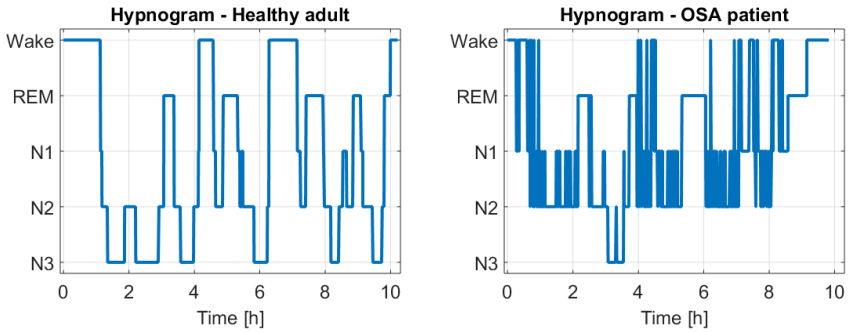

Fig. 1 (a) Hypnogram of a healthy adult. (b) Hypnogram of an adult with severe OSA.

Table 1 Average sleep stage distribution for a healthy young adult.

sleep stage	Wake	REM	NREM	N1	N2	N3
% Time in bed	5%	20-25%	75-80%	2-5%	45-55%	13-23%

2 Polysomnography at a sleep laboratory

The gold-standard test in sleep medicine is the polysomnography (PSG). This test is typically carried out for one night at a sleep laboratory during which several physiological signals are measured while the subject is sleeping with the aim of evaluating one or more aspects of their sleep. Within the most common purposes of a PSG study one can find the evaluation of sleep quality, the identification of sleep stages, sleep-wake activity and the diagnosis of sleep disorders such as OSA.

It is still the common clinical practice to evaluate the PSG by manual scoring of sleep stages and events (e.g. apneas) according to the AASM rules. By using multiple physiological and contextual signals recorded in a PSG, characteristic patterns can be identified, allowing to score these events. The most common signals recorded during a PSG test are listed below. In some cases, these signals can vary depending on the specific sleep laboratory.

EEG: This set of signals is mainly useful in the identification of sleep stages, and hence helps to determine arousals and the wakefulness of the patient. This is done by evaluating characteristic waves in different frequency domains: Delta (3 Hz or lower), Theta (3.5 Hz to 7.5 H), Alpha (7.5 Hz to 13 Hz) and Beta (14 Hz or greater). For example, Delta activity is observed during N3 sleep, Theta activity is characteristic of REM sleep, Alpha activity is used as a marker of relaxed wakefulness, and Beta activity is often observed during wakefulness and drowsiness.

EMG: In a PSG test, the EMG can be obtained from different locations such as the chin and the limbs. The measurement of chin EMG provides an indication of muscle tone, which is reduced with sleep onset and is very low during REM sleep [15], whereas limb EMG can help to identify periodic limb movements, which can be an additional cause of sleep disturbance [15].

EOG: The potential obtained in this signal provides an objective measurement of eye movement and is useful in the identification of REM sleep and the sleep onset. Sleep onset is characterized by slow and rolling eye movements with a symmetric onset and offset, whereas in REM sleep sharp rapid eye movements can be observed which are more asymmetric with a fast onset and a slow offset. [15].

ECG: At least 1 ECG lead (commonly lead II) is recorded during PSG. ECG signals are useful for the identification of cardiac comorbidities but can also provide information on disturbances of the heart rhythm caused by sleep related disorders.

Audio: Recording sounds by using a microphone placed in the neck near the trachea can be used to detect snoring and other tracheal sounds [15]. Recording sound in the PSG room (e.g. the audio registration of the video), on the other hand, can be useful as additional information to verify the nature of arousals and other events.

Respiration: A direct measurement of air flow via a pneumotachograph is the gold-standard method to measure respiration and define apneas [62]. For this method, the use of a mask is necessary, therefore it is only used in combination with therapeutic positive airway pressure (PAP) devices. In clinical practice the combination of a nasal pressure sensor and an oronasal thermistor is the standard used for diag-

nostic PSGs. These measurements are more comfortable for the patient and provide an approximation of the air flow exchange. The end-tidal CO_2 is also an interesting parameter, this is the concentration of CO_2 at the end of an exhaled breath. Reliably measuring the end-tidal CO_2 is, however, difficult. Therefore transcutaneous CO_2 measurements are often used.

Respiratory effort: This is commonly measured by belts around the abdomen and thorax using respiratory inductance plethysmography (RIP). These signals provide information related to the respiratory effort, and hence also play an important role when diagnosing breathing-related sleep disorders.

Oximetry: The standard measurement of the blood oxygen saturation (SpO_2) during a PSG is done by means of an optical measurement in transmission mode. This is typically done with a sensor at the fingertip but can also be measured in alternative locations (e.g. earlobe). The SpO_2 measurement has been defined as a mandatory signal for quantifying the apnea-hypopnea index (AHI) used to measure OSA severity [44] (together with respiration and EEG). This measurement is accompanied by a pulse photoplethysmography (PPG) signal, which also provides cardiac related information such as HR.

Body position and behavioral observation: This provides additional diagnostic information, as some sleep disorders are influenced by the orientation during sleep [15]. Position can be monitored with sensors, but also by video recording, the latter being the most common in standard PSG.

The signals listed above are an important source of information that allow to obtain a complete picture of the person's physiology during sleep. This facilitates the task of diagnosing and following up sleep-related conditions. Nevertheless, it has several disadvantages related to the patient comfort, the test cost and the availability of sleep laboratory beds. The rather obtrusive sensors that need to be attached to the patient, combined with the unusual sleep setting and possible sensor verification from the nursing staff, significantly reduce patient comfort during the night. This leads to a suboptimal setting when aiming to evaluate a typical night of sleep. In addition, the PSG procedure implies a high cost, not only because of the equipment required for the recording of the signals and the sleep laboratory installations, but also because of the need for the test to be supervised and annotated by trained personnel. This high cost causes a limited number of beds available for PSG studies, when compared to the high prevalence of sleep-related disorders. These limitations have motivated the development of sleep monitoring systems for home monitoring, which will not only tackle these challenges but will also allow multiple night monitoring. Devices for home monitoring have the potential to enable a broader patient screening, early detection of sleep-related conditions and a longer follow-up.



Fig. 2 Example of portable PG OOC device for home sleep monitoring. Courtesy of Philips Respironics, all rights reserved.

3 Wearables and unobtrusive technologies for sleep monitoring at home

3.1 Out of center (home) poly(somno)graphy devices

Extended home sleep monitoring can be done using PSG-like devices adapted in size to enable its use at home. These measure a reduced set of the most important physiological signals from a standard in-lab PSG and can be denominated "Out of Center" (OOC) PSG portable devices [44]. When no EEG is included for the correct measurement of sleep, the devices are classified as polygraphy (PG) rather than PSG.

Multiple of these are currently available in the market and can be classified according to the number of signals that are measured. An initial classification scheme based on this principle was proposed by the AASM in 1994 [40]. An updated AASM classification scheme was proposed by Collop et al. [44] in 2011, with the aim to better classify new emerging portable sleep monitoring devices. This classification is done based on measurements of Sleep, Cardiovascular, Oximetry, Position, Effort and Respiratory (SCOPER) parameters. For a review on some of the OOC devices the reader is referred to [62, 44].

An example of a PG OOC device is shown in Fig. 2. These devices allow to monitor some of the main PSG signals at the cost of certain degree of discomfort for the patient, as most require strapping devices to the chest or head and even using a nasal cannula. This remaining discomfort can limit the monitoring time and affect the measurement.

The need for an even higher comfort than the one provided by PG OOC devices, lower cost and longer monitoring time, has led to the recent development of wearables and sensors placed around the patient. These sensors not only measure less signals than an in-lab PSG, but also measure these either in a less obtrusive way or by

applying an indirect measurement of some of the physiological parameters. This has been accompanied by the development of application-specific algorithms based on robust signal processing and machine learning techniques, to monitor some of the main sleep disorders such as OSA.

3.2 Home sleep monitoring with unobtrusive sensors

With the advance and miniaturization of electronics over the last decades, more compact and less obtrusive devices have been developed. These have further enabled monitoring of physiological signals in non-clinical settings in the form of wearables and sensors around the patient. Application specific integrated circuits have played a crucial role in the electronics being used for ambulatory healthcare monitoring.

The main areas of wearables and unobtrusive technologies that are available for sleep-related monitoring in non-clinical settings (i.e. at home) with an increased comfort include: Actigraphy, portable EEG devices, portable ECG devices & patches, ballistocardiography (BCG) devices, radar-based monitoring and capacitively-coupled biopotentials. It is worth noting that these technologies vary in the accuracy of the target measurements and their relevance to specific sleep-related disorders. These bring different levels of increased comfort, while in some cases compromising the sensitivity to artefacts caused by motion, sensor positioning and other uncontrolled factors typical in a home setting.

Although important work has been done in the evaluation of the usefulness of some of these technologies related to specific sleep monitoring purposes, additional validation is still required in order to assess the performance of these technologies on their own, or combined with others, and of application-specific algorithms that have been developed for these. An overview of the different wearable sensor technologies listed above is provided next.

3.2.1 Actigraphy

Actigraphy devices aim to measure the movement from the limbs and/or torso of the person during sleep. The measurement of movement has been identified as important in sleep-related conditions as it can provide information regarding the state of the person, which can be related to physiological changes [105]. In this way, different types of movements can be identified as normal or abnormal and can give information which, if correctly analyzed, can aid in specific diagnosis and sleep characterizations. Parameters that can be estimated from actigraphy measurements include sleep quality, latency, duration, efficiency, fragmentation, circadian rhythm, sleep-wake periods and activity levels [105].

The AASM indicates in their guidelines that actigraphy is reliable in measuring sleep for healthy adults [120]. Nevertheless, these devices only allow to gather general sleep information, as detailed data of sleep-wake physiology are not included [27]. In

addition, there are several limitations in different areas including sensor placement, number of axes and sensors, sensitivity for wake periods [105, 27], data quantification modes, validation and scoring algorithms. A more detailed description of these limitations is provided in [105], as well as an overview of the main contributors to actigraphy scoring algorithms.

The most common measurement of actigraphy is the use of a multi-axial accelerometer worn around the wrist (i.e. wrist actigraphy). Other locations that have been studied include the diaphragm, the chest, the leg/ankle and the trunk [79, 21]. In addition, some smartphone applications use the information from the accelerometer included in the phone when the latter is placed on top of the mattress, but these are expected to be less accurate [27].

Examples of commercially available wrist-based actigraphy devices include the Apple Watch, Biostrap, Empatica, Fitbit, Garmin Vivosmart, Whoop, Xiaomi, Lark and Sleep Tracker. Currently there is a high number of actigraphy wrist-worn devices in the market [105, 140], most of which measure at least one additional physiological parameter, with PPG based heart rate being the most common one. The main differentiators between actigraphy devices are: (a) the availability of raw data for the development of new algorithms; (b) the type of scoring algorithm tackling a specific sleep-related condition; and (c) proper clinical validation against the PSG gold standard.

3.2.2 Portable EEG devices

In contrast with actigraphy measurements, EEG can provide more physiological information. The challenge in portable EEG monitoring is that the unobtrusiveness of these devices is rather limited or implies a compromise in the type of EEG signals that can be acquired, depending on electrode positioning and electrode-tissue interface. Standard EEG monitoring at the PSG laboratory is performed with glued-on electrodes. Frontal, central and occipital derivations are recorded. A full EEG with a complete '10-20' electrode set is barely performed in sleep labs. Nonetheless, the reduced electrode set that is used still implies discomfort to the patient and requires installation by trained personnel.

Because of the lower comfort of using a hat-like device at home during multiple nights, the difficulty for a correct electrode placement, and considering the added value of monitoring EEG for sleep-related disorders, more compact devices have been designed. These devices aim to monitor a limited set of EEG data with a reduced discomfort for the patient. Some of these are available as individually glued electrodes [45] and collect one or two EEG channels together with other PSG signals, but still require training for a correct installation; these could be categorized as OOC PSG-like devices as described in Section 3.1.

Other more portable options include the use of headbands [4, 5, 9, 6, 2] which also record EEG signals from a subset of dry electrodes distributed in the band. Although these collect EEG, not all of them provide the raw data, as some focus on their functionality as a sleep tracker or 'sleep coach', with the purpose of providing



Fig. 3 Example of ECG chest patch.

feedback on the activities previous to sleep, guide respiration exercises, emit tones in different frequencies, amongst other feedback mechanisms that aim to increase the quality of sleep.

Hardware implementations with even higher comfort have been studied by acquiring the EEG signals from around-ear [50, 28] and in-ear [69, 113, 82] electrodes. Some commercial products include these implementations with purposes of productivity increase [172] or as an application-independent platform [107]. Ear EEG has even been tested for sleep monitoring purposes. Results indicate that the automatic sleep scoring using these sensors can reach an accuracy close to that achieved by manual scoring of scalp EEG [113].

3.2.3 Portable ECG devices and patches

Portable ECG monitoring has seen a big advancement in the last decade. Holter monitors that allow to record up to a 12-lead ECG have become smaller, and hence these could be used as part of a solution to perform sleep monitoring at home. Similarly, small form-factor PG devices currently offer the capability of monitoring multiple ECG leads. The main disadvantage in comfort that a Holter or PG device implies, relies on the use of wires connecting individual contact electrodes with the recorder unit.To overcome this, miniature ECG recorders have been developed in the form of a chest patch. These allow to conveniently monitor one lead (or few leads) without the discomfort of using cables by using a relatively small patch as the one shown in Fig. 3. This type of patch can be worn for up to 1 or 2 weeks and enable a more comfortable way of ECG monitoring, which could be of added value for home sleep monitoring. Within the available ECG patches in the market one can find the MCOT [75] from Biotelemetry inc., Zio XT [157] from iRythm, an investigational device from VivaLNK [152], among others.

As an alternative to ECG patches, there are also solutions based on tight chest bands and t-shirts that use dry electrodes, which could also be a source of ECG during a night of sleep monitoring.

These signals also have the potential to be a source of respiratory activity by computing the ECG-derived respiration (EDR), when aiming to perform home sleep monitoring with a reduced subset of signals.

3.2.4 Optical pulse monitoring: PPG & SpO_2

Another way of measuring cardiac activity is by means of an optical pulse readout using PPG in either transmission or reflection mode. This allows to obtain the pulse information, hence providing a source of heart rate monitoring. In addition, given an adequate location of the sensor, the use of the correct wavelengths and dedicated algorithms, SpO_2 can also be monitored.

Besides the standard finger-based PPG/SpO_2 monitors, wearables monitoring PPG generally have the form factor of a smartwatch or smart bracelet with an optical readout in the back. There are currently multiple commercial offerings of smartwatches that monitor PPG, including brands such as Fitbit, Apple, Huawei, Samsung, Garmin, Polar among others. Some of these have lately added SpO_2 functionality to their offering and are even seeking for FDA approval. This addition could play an important role in home monitoring of sleep-related conditions such as OSA. A review of developments and challenges of wearable PPG is provided in [32]. Other investigational devices available in the market that measure PPG signals include small wearable units such as the ones offered by Byteflies [3], which also offer units that can be used for ECG monitoring in the form of a patch.

Compared to ECG signals, PPG signals have a less sharp characteristic and may be more challenging to process when trying to obtain accurate beat-to-beat HR and HRV metrics, but these have the advantage of potentially enabling SpO_2 measurements, which is of added value in sleep-related conditions.

3.2.5 Ballistocardiography and pressure-based devices

Another way to obtain cardiac data is via BCG, which aims to monitor small movements or changes in pressure at the body surface (e.g. chest, back, ...) with the aim of deriving HR and even trying to obtain beat-to-beat HR and HRV. The same principle can be used to monitor respiratory activity, as this causes a change in pressure of the torso in the bed, for the case of sleep monitoring.

The advantage of being able to obtain respiratory and cardiac related signals from one type of sensor has led to multiple companies offering pressure-based sleep monitoring solutions. The company Beddit (now bought by Apple) offers a piezoelectric based sensor [1] that monitors average HR, average breathing rate, snoring sounds (recorded via the microphone of the connected smartphone) and provides metrics of sleep time, bedtime, time to fall asleep, time away from bed, wake-up time and sleep efficiency. Similarly, Withings offers a sleep tracking mat [170] to be placed under the mattress, which detects snoring, performs heart rate and respiration rate tracking and provides a sleep quality assessment within a coaching

program. The company mentions it can also help identify signs of OSA. Another mat-based solution is offered by Emfit, with a sensor also placed below the mattress that aims to measure HRV, respiratory activity and respiratory effort [59]. This sensor is shown in Fig. 4.

BCG setups for heart activity and pressure-based respiratory activity have thus the advantage of not requiring a direct contact with the body. Nevertheless, the extracted heart activity tends to be less accurate than that of an ECG signal (and even of PPG signal) due to the motion-based measurement, as opposed to the electrical or optical based measurements of the ECG and PPG. In addition, motion during sleeping can distort the measurements and patients with high BMI are likely to cause sensor saturation [72]. The question of whether these unobtrusive signals can be used for monitoring specific sleep-related conditions needs to be answered with real-life validation studies.

3.2.6 Radar-based monitoring

A different technology that also aims to monitor the chest movement to extract respiratory and cardiac activity is the use of radar signals. This technology sends radio frequency waves that are reflected at the person's skin. The phase of the signal is modulated by the physiological movement, generating a phase difference between the emitted and received signals, which is then used to calculate the distance changes. The waves are mainly pointed to the chest or the back of the torso. Electromagnetic signals of different frequencies have been used for this purpose, with higher frequency and power resulting in higher sensitivity to small displacements [123]. Carrier frequencies between hundreds of MHz up to more than 200 GHz have been used [92]. More details on the use of radar signals for vital signs monitoring can be found in the work of Kranjec et al. [86], Li et al. [92] and Mercuri et al. [111].

Radar technology has been demonstrated to be able to monitor respiratory and cardiac activity [123, 91, 128]. It has the advantage of monitoring through non-metallic obstacles [86] placed relatively far from the subject. Nevertheless, it is commonly affected by motion artefacts [92] and the acquisition of beat-to-beat HR is more challenging than when using an ECG signal.

Some radar-based solutions are available commercially, including the S+ device by ResMed [135], which monitors breathing and movement, and provides a sleep report based on these measurements. The device has not been tested for the monitoring of specific sleep-related conditions at the moment of writing this chapter, but it is mentioned that it monitors the sleep stages to create a personalized sleep chart.



Fig. 4 Example of pressure-based sensors for heart and respiratory activity.

Similar radar-based devices have been tested with promising results regarding sleep stage classification [41].

3.2.7 Capacitively-coupled biopotentials: ECG & bioimpedance-based respiratory activity

Considering the discomfort of using contact electrodes to monitor biopotentials (e.g. ECG), the capacitively-coupled acquisition of these signals is a technology that has gained interest. The main physiological signals that could be useful in a sleep monitoring setting and can be acquired in a capacitively-coupled manner include the capacitively-coupled ECG (ccECG) and capacitively-coupled bioimpedance (ccBIOZ) for respiration monitoring.

These measurements are done by replacing the skin-electrode galvanic contact by a capacitive coupling, hence enabling monitoring through clothing and bed sheets. In this coupling, the skin forms one "plate" of the capacitor, a conductive surface forms the second "plate" of the capacitor and any non-conductive materials between these conductive surfaces form the dielectric. This completes the standard structure of a capacitor, and hence the connection from the acquisition circuit to the skin is replaced from a galvanic connection to a capacitive coupling. An illustration of a capacitively-coupled electrode interface is shown in Fig. 5.

ccECG acquisition has been explored since 1967 [137], but it is only in the last few decades that it has been more widely explored for a broad number of applications. These applications include sensors placed in the bathroom seat [19, 83, 97], in a wheelchair [129], in a car seat [38, 149, 90, 106], in an airplane sea [147, 146], in an office chair [13, 94, 18, 108] and in a bed [76, 95, 171, 166]. In the field of sleep monitoring, bed implementations have been tested during multiple hours [95, 162, 89], including comparison against polysomnography signals with reported HR coverages of up to 98% [89]. An initial evaluation towards the extraction of features that could be used in the identification of sleep apnea epochs was also done [34].

In the case of ccECG, the signal can be acquired using at least one pair of electrodes, typically accompanied by a third electrode for active noise cancelling, denominated *driven right leg* (DRL). On the other hand, the acquisition of ccBIOZ requires 4 electrodes to perform a '4-point measurement', in which 2 electrodes are used to inject a known amount of high-frequency current through the body, while

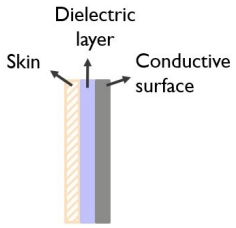

Fig. 5 Illustration of the structure formed by a capacitively-coupled electrode interface for biopotential acquisition.

the remaining 2 electrodes perform a voltage readout. The 4-point measurement has the advantage that the injected current does not flow through the same electrodes used for voltage sensing, hence the impedances at the electrode-tissue interfaces are not included in the measurement.

The acquisition of ccBIOZ has been less studied than the acquisition of ccECG signals. Within the reported research in this field, Abad [11] explored in 2009 the use of contactless BIOZ for bioimpedance spectroscopy (BIS) purposes. In this work, he demonstrated that commercial BIOZ devices are unsuitable for contactless measurements and proposed a multi-frequency current source to be used in ccBIOZ BIS measurements. With the purpose of measuring both ventilation and HR values, Macias et al. [103] reported a ccBIOZ system integrated in a car seat. Here, a 4-point measurement was implemented using textile electrodes on the back of the seat and in the steering wheel (measurements were in galvanic contact at the steering wheel point). Although both cardiac and respiratory activity was acquired under controlled conditions, it was concluded that the system did not achieve acceptable performance due to the capacitive behavior of the electrode-tissue interface.

A more recent system integrating both ccECG and ccBIOZ [37] was demonstrated to successfully acquire these signals in prototypes in the form factor of a car seat and a bed mattress. In addition, the system was shown to be able to provide a flexible interconnection that enables the real-time selection of up to 8 simultaneous ccECG electrodes (i.e. 4 ccECG channels) from an array of up to 64 electrodes, as a solution for the varying quality of the ccECG depending on user position. The prototypes presented in [37] are shown in Fig. 6 as an example of the possible implementations of ccECG and ccBIOZ measurements. It is worth noting that in the specific case of a mattress with the sensors, the mattress can be covered by normal bed linen and the patient can wear standard pyjamas, which significantly increases the comfort when compared to contact-based methods.

Such a multi-electrode approach, together with quality-based signal processing algorithms [34, 33] and optimizations in the electronic design [36, 35, 155, 96] aim to overcome the main challenges of capacitively-coupled signals: the sensitivity to motion related to the varying electrode coupling for different positions or body shapes [46, 167, 17, 175] and the variability of signal quality depending on the electrostatic charges in the surroundings of the patient [46].

Although ccECG and ccBIOZ signals are likely to provide less coverage (in terms of time with high signal quality) than their contact-based counterparts, signal processing and system optimization approaches such as the ones mentioned above are expected to enable the use of the technology for home monitoring during extended periods of time without a compromise in the patient comfort. This is of added value when considering the more realistic scenario of monitoring at home and the increased analysis that an unobtrusive monitoring during multiple nights can allow.

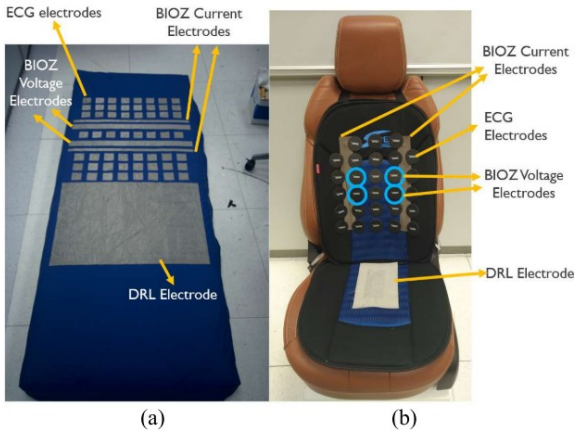

Fig. 6 Example of prototypes acquiring ccECG and ccBIOZ measurements simultaneously. (a) For sleep monitoring (covered by a normal bedsheet when in use). (b) For driver monitoring. Replicated from [37] with permission from the authors.

3.2.8 Multiparametric devices dedicated for sleep monitoring

Taking advantage of the patch form factor used in some of the latest ECG monitors as well as other form factors enabled by miniaturized electronics, devices are now available which aim to combine some of the sensors/techniques mentioned above. This subsection aims to give a brief overview of the less obtrusive devices currently available in the market or being developed, which are specifically tailored for sleep monitoring at home and are significantly different than the PSG-like and PG OOC devices.

The company Beddr offers a small form-factor device called SleepTuner [23] to be placed in the forehead, which monitors actigraphy via a 3-axis accelerometer and uses optical sensors to monitor PPG (including PPG-derived HR) and SpO_2. Based on these sensors, the company's software performs sleep-related analysis which includes sleep duration, position and stopped breathing events. Another patch-based solution is offered by the company Tatch [10], which aims to monitor respiratory effort, flow, oxygen level, heart rate, body position/movement and snoring sounds. The company Onera [7] is currently developing a patch-based solution together with data analytics to enable the 'first at-home medical grade sleep diagnostic patch system'.

The WatchPAT devices offered by Cardio Sleep Solutions [151] allow to monitor actigraphy, SpO_2, chest motion, HR, body position, snoring and peripheral arterial tonometry (PAT), which has been demonstrated to be adequate for the detection of sleep apnea [44]. Other solutions focus solely on the use of applications from smartphones [8, 136]; these mainly aim to quantify the quality of sleep or provide an early assessment of risk for sleep related disorders such as OSA without directly monitoring physiological signals.

4 Machine learning algorithms for Sleep staging at home

Sleep scoring standards are developed mainly based on EEG signals. The current EEG sensor technologies, however, pose a certain level of obtrusiveness. This has motivated the search for alternative sensors and signals, which allow reliable and comfortable monitoring of sleep physiology. As a consequence, the development of novel algorithms for automated sleep staging based on these unobtrusive signals has been an active topic of research. As described in section 3, cardiac and respiratory signals can indeed be more comfortably acquired by emerging unobtrusive sensor technologies compared to EEG based monitoring. Therefore, sleep staging based on cardiac and respiratory signals presents a first leap towards home-based sleep monitoring. These sleep staging approaches are discussed in the following sections. First, the focus is on state-of-the-art algorithms, based mainly on ECG and/or RIP signals extracted from the PSG. Next, an overview of sleep staging algorithms based on data from wearable or unobtrusive sensor technologies is given with special attention to stand-alone actigraphy, BCG and PPG. Finally, an outlook on the signal processing challenges commonly encountered when working with wearable data, and the future research in sleep staging is presented.

Algorithms are compared based on the performance of a 3-class classification task of Wake versus NREM versus REM (WNR). Nevertheless, many studies report a 2-class sleep staging performance, generally being sleep versus Wake. However, different ways exist of combining sleep stages, as Wake and REM share some characteristics and one could define “active sleep” (Wake, REM, N1) versus “quiet sleep” (N2 and N3) [98]). As REM is therefore difficult to classify, a 3-class WNR is preferred for better comparison. Studies in which a 4-class classification task reached superior performance to 3-class classification are also discussed. Typically, this classification task is defined as Wake versus REM versus Light sleep versus Deep sleep (WRLD).

Furthermore, the discussed studies and algorithms have been trained subject independent unless mentioned otherwise. This implies that the training data set does not contain data from subjects which have been included for testing. The studies also report performances by at least an average accuracy and Cohen’s kappa κ score [43]. As such, algorithmic performances can be compared by equal measures. The average accuracy is the percentage of epochs correctly classified compared to the gold standard annotations. The κ score is a measure of agreement which corrects for the level of agreement achieved by chance.

4.1 State-of-the-art algorithms based on cardiac and respiratory signals.

As PSG provides the gold standard for sleep staging, cardiac and respiratory based sleep staging algorithms have been developed based on these PSG derived signals. It allows direct comparison of all PSG signals without synchronization issues. Sleep

stage annotations are directly applicable and high-quality data is assured, thus enabling state-of-the-art performances. In general, sleep staging algorithms are built from a feature extraction phase followed by a classification phase. A multitude of cardiac and respiratory features have been developed in literature, typically modeling the ANS variation in the temporal and spectral space.

For a long time, algorithms reaching state-of-the-art performance used a combination of signals as input. For instance, Harper et al. showed in 1987 that classification performance can improve when combining modalities [71]. Some earlier studies explored sleep staging based on single modalities, such as ECG [173] or RIP [101], with the advantage of requiring less sensors. However, until 2018, performances of these studies were indeed inferior compared to co-occurring studies with multimodal input.

Therefore, these studies published before 2018 and based on a single modality are not mentioned in this chapter. Although, a complete review on automated sleep stage scoring was made by Faust et al. [61]. An overview of discussed papers which reached state-of-the art performance is found in Table 2.

In 2006, Redmond and Heneghan tackled the challenging task of sleep staging based on cardiac and respiratory signals [134]. This was achieved by extraction of temporal and spectral features of the ECG RR-interval (time elapsed between two successive R-waves) and of the respiratory effort signal in standard 30 s epochs.

Table 2 Overview of state-of-the-art sleep stage classification algorithms based on cardiac, respiratory and actigraphy signals. QDA: Quadratic Discriminant Analysis, LDA: Linear Discriminant Analysis, SVM: Support Vector Machines, HMM: Hidden Markov Models, CRF: Conditional Random Fields, Deep NN: Deep Neural Network, LSTM: Long Short-Term Memory networks

Author	**Year**	**Data set**	**Signals**	**Classif.**	**# Rec. Subjects**			**Task**	**Results**	
						Healthy	OSA	# Classes	Acc. [%]	κ
Redmond et al.	2006	private	ECG, RIP	QDA	37	23	14	3 WNR	67	0.32
Redmond et al.	2007	private	ECG, RIP	LDA, QDA	31	31	0	2 WS	89	0.60
					31	31	0	3 WNR	76	0.46
Willemen et al.	2014	private	ECG, RIP, ACT	SVM	85	36	0	2 WS	92	0.69
					85	36	0	3 WNR	81	0.62
					85	36	0	4 WRLD	69	0.56
Domingues et al.	2014	private	ECG, RIP, ACT	HMM	20	20	0	3 WNR	78	0.58
Long et al.	2014	SIESTA	RIP	LDA	48	48	0	3 WNR	76.2	0.45
					48	48	0	4 WRLD	63.8	0.38
Willemen et al.	2015	UCD	ECG, RIP	LDA	25	25		2 WS	74.2	0.37
					25	25		3 WNR	67.0	0.41
Fonseca et al.	2018	private, SIESTA	ECG, RIP	LDA, HMM, CRF	102	102	0	3 WNR	81.8	0.59
					102	0	102	3 WNR	77.0	0.50
					102	102	0	4 WRLD	71.0	0.51
					102	0	102	4 WRLD	70.6	0.46
Wei et al.	2018	SLPDB	ECG	Deep NN	18	16	0	3 WNR	77	0.56
Li et al.	2018	SLPDB, CinC2018, SHHS	ECG	SVM	5793	5793	0	2 NREM vs REM+W	85	0.68
					5793	5793	0	3 WNR	82.0	0.63
					5793	5793	0	4 WRLD	65.9	0.47
Radha et al.	2019	SIESTA	ECG	LSTM	195	195	0	4 WRLD	76.5	0.63
					51	0	51	4 WRLD	78.5	0.60

Furthermore, EDR features and spectral features from the cross-spectrum of the RR and EDR were calculated. As such, the feature set consisted of the power in the LF and HF band of the RR-interval, the EDR, the RR-EDR cross spectrum and the respiratory effort signals. Other features were the LF/HF power ratio of RR, mean RR, standard deviation of RR, difference between the longest and shortest RR interval in the epoch, breath-by-breath correlation and breath length variation. These features served as inspiration for subsequent studies. The accuracy and κ score of the subject-independent algorithm were respectively 67% and 0.32 for a 3-class WNR sleep staging task on healthy subjects. The authors improved the algorithm's performance by a linear discriminant classifier model using a time-dependent a priori probability. The accuracy and κ score then reached 76% and 0.46, respectively [133].

Willemen et al. improved sleep staging performance in 2014 by combination of ECG, RIP and actigraphy [168]. The study was performed on 36 healthy subjects and a total of 85 nights. A set of 13 feature groups was defined for an ECG, respiratory and 1 Hz movement signal, extracted per epoch of 60 s. By transformations, a total of 750 features was obtained and subsequently reduced to 40 task-specific features by forward feature selection. These one-minute epochs were applied for classification, which is different to other studies that commonly classify sleep per 30 s epochs. This one-minute window accounts for the slow dynamics of the breathing rate and heart rate variability, as the HRV Task Force recommends interval lengths of at least 10 times the wavelength of the lowest frequency bound [30]. However, 60 s would only be a reliable choice for the HF band and too short to be fully reliable in the LF band. To validate the classified epochs, the 30 s epochs of the PSGs hypnogram were transformed to 60 s interval values by a set of decision rules. One RBF-kernel support vector machine (SVM) was optimized for different binary classification tasks. Three-class sleep staging of WNR achieved a mean accuracy and kappa of 81% and 0.62, respectively. It is noted that the study population's average age was relatively low: 22.1 ± 3.2 years. Similar results were obtained by Domingues et al., who performed a similar study [56].

Willemen et al. also developed a sleep staging algorithm for OSA patients [169], in which RR inter beat interval (IBI) series, the breathing signal, inter breath interval series and the inspiration-to-expiration ratio interval series were extracted from the ECG and respiratory belt signals for 25 subjects. Sixteen feature groups were extracted from these signals in 60 s epochs. This window length was found to achieve the best results to distinguish apneic from healthy breathing in a study by de Chazal et al. [39]. By detrending first input time series over different intervals and afterwards transforming extracted features, a total of 510 features was defined. A triple layer validation scheme was constructed to train the classifier parameters, perform feature selection and define a test set. The study obtained an accuracy and κ score of, respectively, 70% and 0.41 for WNR classification of OSA patients.

Fonseca et al. compared three of their developed sleep staging methods based on conditional random fields (CRF), hidden Markov models (HMMs) and Bayesian linear discriminants (LDs) [64]. Features were extracted using windows centered on non-overlapping epochs of 30 s, where the window length depended on the feature type. Additionally, they explored the incorporation of time information in

their classifiers and applied their methods on 102 healthy subjects as well as 102 patients with OSA. In general, the best performing classifier was a CRF boosted with time information (CRFt). Although, CRFt performed not significantly better than standard CRF in the case of OSA patients. This can be subscribed to the fact that OSA leads to the decrease of REM and N3 presence and an increase in sleep fragmentation due to arousals associated with respiratory events (i.e., apneas) [139]. Therefore, the presence and progression of their sleep stages might depend more on the occurrence of disordered breathing events than on a healthy sleep architecture. Three-class sleep staging of WNR achieved a mean accuracy and κ of, respectively, 81.8% and 0.59 for healthy subjects compared to 77% and 0.50 for OSA patients. On a healthy data set, the developed CRFt algorithm performs comparable to [168], both for WNR and WLRD classification tasks. With respect to OSA patients, Fonseca et al. reached a substantial improvement in performance compared to [168], in which an accuracy and κ of 70% and 0.41, respectively, was reported. Moreover, the study of Fonseca et al. included only two out of three modalities, which can be seen as an advantage for long-term home monitoring.

In 2018, Li et al. developed a sleep staging algorithm based on a single lead ECG signal from extensive public data sets [93]. They were able to surpass state-of-the-art algorithms using a single modality, however, by extraction of respiratory information from the ECG. First, the authors derived spectrograms of the cardiorespiratory coupling in 5 min windows centered on each 30 s epoch. They applied convolutional neural networks (CNN) on the spectrograms for subsequent feature extraction (i.e. representation learning). Then, the extracted features were combined with hand crafted ECG features into an SVM model. With an accuracy and κ of 81.6% and 0.63 for WNR classification, this model is competitive to [168, 64], albeit with the application of a single modality.

The current state-of-the-art sleep staging model is described by Radha et al. [131], applying exclusively a single lead ECG signal as an input. A set of 132 handcrafted HRV features was fed into an Long Short-Term Memory (LSTM) network. This feature set consisted of time and frequency domain features, entropy and regularity features, and miscellaneous features. To extract the feature vector of a 30 s epoch, a window of 4.5 minutes of IBI data centered around this epoch was considered. The LSTM network type is chosen for its ability to capture long-term temporal dependencies. To determine the optimal number of LSTM layers and cells per layer, 18 combinations were trained and compared. The final model consisted of $2.6 \cdot 10^5$ parameters. This potentially involves a substantial time complexity, however, the study does not mention training time and memory consumption. The model was validated on 195 healthy subjects and 51 OSA patients. The algorithm reached an accuracy and κ of 76.5% and 0.63 on the former and 78.5%, 0.60 on the latter for a 4-class WRLD classification task. Interestingly, authors observed a negative correlation between performance and age, presumably by changes in autonomic function [177] and alteration in sleep architecture [148].

4.2 Sleep staging approaches based on wearable and unobtrusive sensor technologies

The sleep staging algorithms described in the previous section report state-of-the-art performances, yet these were developed on PSG data. In order to monitor patients at home, different wearable or unobtrusive sensor technologies were implemented as described in section 3. Among these, actigraphy, BCG and PPG have played a more important role in sleep staging research and specific algorithms have been developed.

As actigraphy is purely motion based, it is not suitable for refined sleep monitoring. Nevertheless, it presents an established method for sleep/wake classification. These studies are discussed in section 4.2.1 and summarized in Table 3. On the contrary, BCG enables recording of multiple physiological signals: cardiac, respiratory and movement information. This modality has been explored for sleep staging by several studies, which are described in section 4.2.2. Furthermore, PPG has gained interest for sleep research as the classic finger-based recording shifted to a smartwatch configuration. Studies applying PPG in sleep staging are discussed in section 4.2.3. Table 4 gives an overview of discussed papers on sleep staging approaches based on BCG and PPG. Other suitable modalities for wearable or unobtrusive sleep staging such as arterial blood pressure, peripheral arterial tonometry, oximetry, audio, video and temperature are discussed in [138]. Furthermore, radar technology for sleep staging in OSA has been explored by [47].

4.2.1 Actigraphy

Actigraphy or activity-based sleep tracking is a reliable and valid methodology for monitoring sleep-wake and circadian rhythm patterns in healthy adults [99]. The sleep staging capacity of actigraphy is limited as it is known to overestimate sleep time. This is because it cannot differentiate motionless periods of wakefulness from

Table 3 Overview of state-of-the-art sleep/wake classification algorithms based on actigraphy signals. ACT*: surrogate actigraphy; LDA: Linear Discriminant Analysis, QDA: Quadratic Discriminant Analysis

Author	Year	Data set	Signals	Classif.	# Subjects			Results	
						Healthy	Insomnia	Acc. [%]	κ
Devot et al.	2010	private	ECG, RIP, ACT	LDA, QDA	9	9	0	96.1	0.70
			ECG, RIP, ACT		27	0	27	84.5	0.61
			ACT		9	9	0	93.8	0.51
			ACT		27	0	27	78.0	0.39
Long et al.	2013	private	RIP, ACT	LDA	15	15	0	95.7	0.66
Fonseca et al.	2016	private	ECG, RIP, ACT*	LDA	15	15	0	93	0.66
			ECG, RIP, ACT*		40	15	25	87	0.56
			RIP, ACT*		15	15	0	93	0.64
			RIP, ACT*		40	15	25	85	0.5

sleep. On the other hand, it presents a potential tool for unobtrusive screening of certain sleeping disorders. However, the technology is not able to diagnose sleep disorders that involve altered motility during sleep such as OSA [142, 126] and performance will be impacted by disorders altering the ANS [66]. Therefore, actigraphy is usually combined with cardiac and respiratory signals [55, 168, 56]. Devot et al. compared sleep staging using cardiac, respiratory and actigraphy signals to sleep staging based solely on actigraphy. As expected, they obtained superior results with the former approach [55]. In order to minimize obtrusive sensors while preserving classification performance, Long et al. retained the respiratory signal in combination with actigraphy [100] and achieved comparable results as Devot et al. In [63], a surrogate actigraphy signal was estimated from body motion artefacts derived from the ECG and respiratory effort signals. The surrogate signal was combined with RIP or ECG+RIP in a sleep-wake classifier. This approach achieved similar results as classification in combination with the reference actigraphy signal, both in a healthy as mixed population including insomniacs. Authors concluded that in setups where RIP is the only modality, as it is one of the most applied modalities in home sleep monitoring, actigraphy posed a significant added value. In case both RIP and ECG are acquired, the application of actigraphy is redundant.

4.2.2 Ballistocardiography

The following studies have applied a BCG-based bed sensor for sleep staging. Kortelainen et al. used commercial Emfit material to configure a BCG system [85]. From the acquired signal, they extracted the IBI and movement activity. IBI features trained a hidden Markov Model for a WNR task, while the motion signal served as an additional input for wake stage detection. Nine healthy subjects were included in the study, of which in total 18 sleep recordings were acquired. The three-class

Table 4 Overview of state-of-the-art sleep stage classifciation algorithms based on wearables, except for the last two studies including PPG from the PSG. (*) Test and training set contain nights from the same individuals.

Author	**Year**	**Data set**	**Signals**	**# Subjects**			**Task**	**Results**	
					Healthy	OSA	# Classes	Acc. [%]	κ
Kortelainen et al.	2010	private	BCG	18	9	0	3 WNR	79*	0.44*
Migliorini et al.	2010	private	BCG	17	11	0	3 WNR	76.8*	0.55*
Kurihara & Watanabe	2012	private	BCG	20	10	0	3 WNR	78	0.48
Hwang et al.	2016	private	bed sensors	25	12	13	4 WRLD	70.9	0.48
Beattie et al.	2017	private	ACT, PPG (wrist)	60	60	0	4 WRLD	69.0	0.52
Fonseca et al.	2017	private, SIESTA	PPG (wrist)	215	152	0	2 SW	91.5	0.55
				215	152	0	3 WNR	72.9	0.46
				215	152	0	4 WRLD	59.3	0.42
Uçar et al.	2018	private	PPG (PSG)	10	0	10	2 WS	73.4	0.59
Casal et al.	2019	SHHS	PPG (PSG)	5804	5804		2 WS	85.2	-

WNR classification task resulted in an accuracy and κ of 79% and 0.44 respectively. It is noted, however, that the training and test set contain recordings from the same subjects as a leave-one-out cross-validation (LOOCV) was performed on these 18 recordings. This approach could lead to an overestimation of the subject-independent classification performance.

In the same year, 2010, a similar study by Migliorini et al. was published [112]. Seventeen recordings from 11 healthy subjects were acquired, using the commercial Emfit sensor material as well. Similarly, a LOOCV was performed for parameter optimization. The achieved accuracy score was comparable to [85], however, a higher κ of 0.55 was reached. As opposed to Kortelainen et al., authors included features from the respiratory component, which is inherently present in the BCG signal.

Kurihara and Watanabe implemented a pneumatic system based on an air tube and pressure sensor to acquire the BCG. They obtained similar sleep stage performances as Kortelainen et al. using a comparable data set [87].

In 2016, Hwang et al. used a polyvinylidene fluoride sensor for sleep staging in 12 healthy and 13 OSA patients [73]. The motion signal was applied for wake detection, while information extracted from the respiratory signal was investigated for REM and deep sleep (N3). The 4-class classification had an average accuracy of 70.9% and κ of 0.48, where no significant difference was found between the control and OSA populations. Comparing to a later study of Fonseca et al. [64] in 2018, who also applied a WRLD classification on OSA patients, the current method reached similar performance, though by the application of an unobtrusive device.

4.2.3 Pulse Photoplethysmography

Studies on wearable PPG sleep staging can be traced back to 2017. Beattie et al. [22] from Fitbit research performed sleep staging in 60 healthy subjects based on a wrist-worn device, measuring three-dimensional accelerometry and PPG. The interval between peaks of the PPG wave was taken as a surrogate for an ECG-derived IBI. As such, motion, breathing variability and HRV could be extracted from this modality. However, the PPG signal is more sensitive to movement artefacts compared to ECG, especially when worn as a wearable at the wrist. Similar to BCG research by [85], no IBI information could be extracted in periods of heavy motion. In case of unlikely sleep architecture patterns, authors applied a post-processing step by smoothing, e.g. an isolated wake epoch during a long period of deep sleep is converted to the annotation of its surrounding epochs. This assumption is only reasonable when monitoring healthy subjects. After LOOCV, the overall accuracy was 69% with a κ of 0.52 for a 4-class WRLD task.

A similar study was published in 2017 by Fonseca et al. [66]. Although, the study included a larger data set of 152 healthy subjects, from which a validation set was held out for testing. Features and machine learning techniques were similar to their earlier study [65] (later discussed in [64] and described in section 4.1), with the exclusion of respiratory signals. The performance of the current study for both

WNR and WRLD tasks was lower and could partially be subscribed to the reduced number of input signals. However, as the authors have pointed out themselves, a respiratory rate could technically be deduced from the PPG signal [88]. This is potentially beneficial, as it could provide features capturing changes in sympathetic tone, important for detection of REM [66].

Previous studies have performed sleep staging based on wearable PPG in a healthy population. However, sleep staging in a pathological population is essential as total sleep time is an important outcome for severity assessment, e.g. OSA. Uçar et al. [160] and Casal et al. [31] applied sleep-wake classification in an OSA population. As data processing becomes more challenging in a pathological population, non wearable PPG signals were used in these studies. However, it offers the potential of integrating these algorithms with signals from wearable devices.

4.3 Signal processing challenges presented by wearable systems

The signal processing of wearable data is associated with specific challenges. This includes sensitivity to motion and synchronization between the wearable device and PSG system.

First, the presence of motion is ambiguous. On the one hand, movement induces excessive noise in the overall BCG signal, which impedes the IBI extraction and HRV analysis. On the other hand, it provides valuable information on the patient's sleep architecture, similarly to actigraphy. Heavy motion can mainly be subscribed to wake stages and thereby it compensates the loss of information regarding HRV. Moreover, the separation between wake and REM is improved by inclusion of motility information, as the cardiac activity presents similar characteristics during both stages [85].

Furthermore, synchronization between wearable and standard devices is beneficial as it enables quality control of the wearable signal. Comparison of the HR or respiration rate extracted from both devices can act as a quality indicator. Synchronized signals allow direct comparison of predicted and ground truth hypnograms as well.

The synchronization procedure is usually achieved by alignment of tachograms, derived from the heart beats detected in the wearable and from the R-peaks detected in the ECG signal from the standard device [22, 66]. However, in case of heavy motion due to restlessness or sleep disorders (such as OSA), the tachogram is hard to derive and thereby troubling synchronization. In [72], a method for synchronization of BCG recordings of OSA patients was proposed, based on artefacts rather than IBI. First, artefacts were detected in the BCG recordings without training the algorithm on artefact annotations. Then, a segment including several subsequent artefacts defined the artefact template. Next, a corresponding data pattern was sought in the thoracic belt of the PSG to align the segments. Fig. 7 displays a notable artefact pattern found in the BCG signal, which can be linked to a corresponding pattern in the thoracic belt.

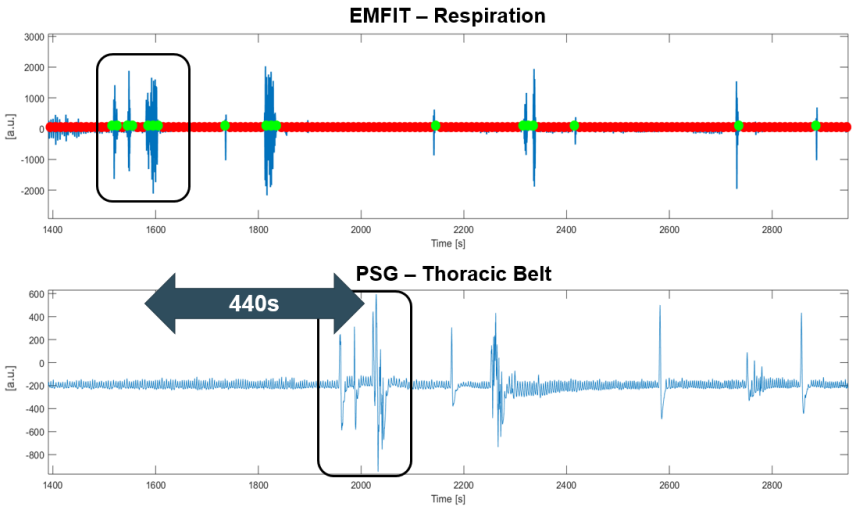

Fig. 7 Synchronization by artefact patterns of an Emfit BCG signal with a thoracic belt signal from the PSG. As wearables are sensitive to motion, tachogram-based synchronization might not always be possible as heart beat detection might be impeded by large artefacts.

Furthermore, it is noted that the equivalence of tachograms derived from the ECG and the PPG or BCG device is only valid in the absence of cardiovascular health problems. For instance, ectopic beats during arrhythmia can be traced by the ECG. In some cases, these beats do not affect the pumping mechanism of the heart. Therefore, these ectopics are sometimes not acquired by the BCG or PPG [85, 66].

4.4 Future research in sleep staging at home

On a future prospect, cardiac and respiratory based sleep staging will be explored by deep learning networks, as intended by [131]. Currently, deep learning based algorithms are more actively developed within the field of EEG-based sleep staging [159, 156, 122]. This entails an algorithmic pipeline where both feature extraction and classification are optimized by extensive neural networks. The advantage is the automated training procedure of the complete pipeline and often superior classification performances. However, one of the requirements to properly develop these algorithms is the availability of large amounts of data. In the field of EEG-based signal processing, data is often provided by the publicly available Physionet Sleep-EDF database [68, 81]. Additionally, it contains EOG, EMG, oro-nasal respiration signals and body temperature. Equivalently, the availability of a large data set containing ECG, respiration and sleep stage scoring could benefit the development of these cardiac and respiratory based algorithms. This would, moreover, allow benchmarking of algorithms, which is currently difficult due to the variety in data sets.

Another potential issue is the suitability of these cardiac and respiratory based sleep staging algorithms for real-time applications. At present, most studies focus on increasing sleep staging performance, which has a theoretical maximum defined by the inter-rater agreement of 82.6% for 5 sleep stages [141]. The developed algorithms often require several minutes or more of sleep data for pre- and post-processing or to include time information. Fewer studies investigate the suitability of algorithms or design them specifically for real-time applications. Real-time processing is, however, not necessary for diagnosis of many sleep disorders, nor do these sleep disorders pose a threat that requires real-time monitoring. Considering the fact that offline monitoring is sufficient for these sleep disorders, relaxes the constraints of newly developed wearable hardware as internal algorithmic processing is not a priority. In contrast, online monitoring is critical in the field of neonatal care. First, it serves to optimize the timing of nurse intervention as to minimize the sleep disturbance of the neonate. This was achieved by sleep staging based on EEG monitoring, though presenting a non-wearable approach [16]. Second, online monitoring is required to generate alarms as motor responses often precede changes in vital signs, such as seizures and apneas. Movements could be real-time detected based on a BCG approach [77]. As unobtrusiveness and real-time sleep staging is crucial in this field, research in neonatal care could complement the field of sleep disorders and its advances in unobtrusive techniques and wearability.

A last challenge concerns the classic 30 s epoch length for annotation, analysis and validation. This epoch length was optimized for EEG-based sleep analysis on paper [102]. At a paper speed of 10mm/s, one page meant a 30 s recording, which served well to visualize spindles and delta waves [51]. The 30 s epoch length was further on recommended by the R&K manual [132]. The sleep stage annotation of such an EEG epoch is defined as the sleep stage which comprises the largest portion of this 30 s. This procedure is efficient for hand scoring and a reasonable approach for a healthy population, in which sleep stages have a certain stability and persist over several epochs [145, 138]. Nevertheless, half-minute epochs are less suited for a population with fragmented sleep (e.g. OSA), which is associated to short-term awakenings, arousals and critical respiratory events. As such, classic sleep staging is less reliable in this population and they might benefit from a smaller time scale in sleep scoring and sleep analysis [145]. Additionally, the probability distribution of a short-term epoch over different sleep stages conveys more information than classical hypnograms, as proposed in [154]. Therefore, current sleep staging algorithms might not only require further validation and adaptation in a variety of age groups and disorders, but also a shift in valuing the gold standard.

5 Detection, screening and phenotyping of sleep apnea in an ambulatory setting

Obstructive sleep apnea is the most common sleep related breathing disorder, it is estimated that worldwide almost 1 billion people are affected by this disorder [25].

However, most of these subjects remain undiagnosed, and consequently untreated. OSA patients experience repetitive complete or partial cessations of breathing during the night which are caused by a narrowing of the upper airway. In many countries, diagnosis of sleep apnea is currently based on manually scoring these events from an overnight in-hospital polysomnography. The AASM has defined a set of scoring rules which are considered as the gold standard for scoring OSA [26]. According to the AASM2012 rules, events are scored if they last longer than 10 seconds. An apnea is scored when an airflow amplitude decrease of more than 90 % occurs, a hypopnea, on the other hand, only requires a decrease in airflow amplitude of at least 30 %, but accompanied by either an oxygen desaturation of more than 3 % or an arousal. The apnea hypopnea index is computed as the number of apneas and hypopneas per hour of sleep. Subjects are diagnosed with OSA if they either have an AHI larger than 5 accompanied with symptoms, or if their AHI is larger than 15, independent of the presence of symptoms [143].

Many researchers have been developing methods for automated in-home screening and diagnosis of sleep apnea. In this section an overview will be given of methods using signals that can be easily acquired in a home environment. The methods will be ordered according to the SCOPER system, which was introduced in Section 3.1. A short overview of the use of these five categories of sensors in the diagnosis of sleep apnea is given below:

1. **Sleep:** A measurement of sleep, for example using actigraphy, will enable the calculation of the hours of sleep, using this measure instead of the recording time leads to a better estimation of the AHI [120]. These methods were the topic of Section 4.
2. **Cardiovascular:** This category includes ECG, PPG and PAT as well as all other measures of the heart rate. Bradycardia can be observed during apneas, followed by tachycardia when breathing is retaken [70], as can be observed in Fig 8. Moreover, these signals can be used to derive an estimate of the respiration and detect autonomic arousals.
3. **Oximetry:** The SpO_2 signal is very useful for OSA screening, since apneas often result in an oxygen desaturation as can be seen from the example in Fig. 8.

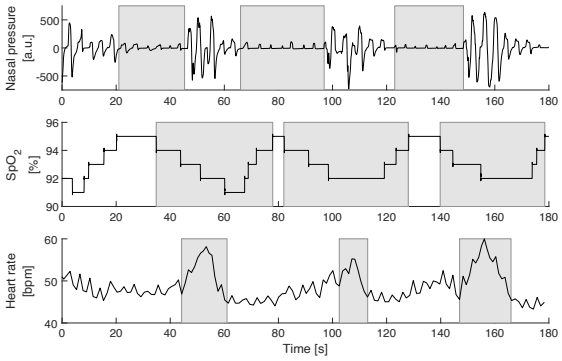

Fig. 8 Example of a segment with apneic events. From top to bottom, the nasal pressure, SpO_2 and heart rate signals are plotted, with respectively, the annotated apneic events, oxygen desaturations and sympathetic activation depicted by the shaded areas.

4. **Position:** Visual and non-visual measures (e.g. using an accelerometer combined with a gyroscope [80]) can determine the body position of a subject. Studies have shown that OSA severity can be position dependent. In fact, a higher AHI and more severe apneas have been observed during supine sleep [124]. Differentiating between lateral and supine sleep could thus help to improve automated OSA detection algorithms. No studies, however, propose to use position measurement on its own for the detection of OSA. Therefore, the analysis of position sensors will not be discussed further.
5. **Effort and Respiration:** The reduction in airflow is the primary effect of apneas. Sensors measuring respiratory effort provide extra information which helps to differentiate between central and obstructive apneas.

An overview of current research and commercial devices for OSA detection categorized according to the SCOPER system can be found in [109]. In this review, sound recording devices were defined as the sixth category, in addition to sleep, cardiovascular, oximetry, position, effort and respiratory parameters. In this section, the focus will be on the detection algorithms, rather than the wearable sensors, which were already discussed in Section 3.

Most OSA detection algorithms consist of 4 main steps: starting with the signal preprocessing phase, next feature extraction, feature selection and finally classification. Two classification problems are studied: event based or subject based classification. In the case of event based classification, the goal is to detect all apneic events within the recording, this is often done by splitting the recording into 1 minute windows. Based on the number of windows classified as apneic, the AHI can be estimated. Subject based classification, on the other hand, extracts features over the whole recording which will then be correlated to the AHI and used to predict the OSA severity category of a patient. In this section, features commonly used for either one of those classification tasks in the framework of OSA detection, will be discussed per SCOPER category. Additionally, studies describing automatically generated features using deep learning, will be briefly discussed in Section 5.5.

5.1 Cardiovascular

5.1.1 ECG

The effects of apneic events on the ECG signal have been known since the 1980s [70, 116], but the research into sleep apnea screening using ECG signals really took a boost in 2000 with the Computers in Cardiology Challenge [115] and the subsequent release of the Physionet Apnea-ECG database [127]. This data set is still one of the most used data sets for ECG based OSA screening. An extensive overview of ECG based methods for OSA screening can be found in [60, 110]. The ECG based screening approaches proposed in [110] obtain subject based classification accuracies of 72-100 % and an area under the curve (AUC) of 89-100 %.

The used features are generally based either on changes in HR [70] or changes in respiration, captured using the EDR [116]. The respiration can be extracted from the ECG since ECG waveform characteristics are altered by respiratory-induced movements of the chest electrodes and changes of the electrical impedance of the thoracic cavity . The simplest measure of EDR is the amplitude of the R waves, but many more elaborate methods have been proposed. A comparative study of 10 EDR algorithms is discussed in [164], where it was shown that the EDR signals computed from changes in the QRS slopes are most robust in the presence of artefacts, changing respiratory rates, and different ECG-recording systems.

OSA detection algorithms typically use statistical, frequency domain and non-linear features extracted from both the HR and the EDR. Recently, measures of cardiovascular interactions have also been identified as relevant for OSA detection.

Statistical features: Different time-domain features of the RR interval time series[7] and EDR have been proposed by De Chazal et al. [48] and are often used in the literature. An overview of these features can be found in Table 5.

Frequency domain features: Multiple methods have been applied to extract frequency information from the heart rate, but the power spectral density and wavelet decomposition [29] are the most popular. Often the power in the standard HRV frequency bands is considered: very low frequency range (0.003-0.04 Hz), low-frequency range (0.04-0.15 Hz) and the high frequency range (0.15-0.4 Hz).

Nonlinear features: An overview of nonlinear parameters used on cardiorespiratory signals for sleep apnea detection is given in [165]. Analysis of the sample entropy of the HRV signal, has shown a reduced complexity for apneic subjects compared to controls [12]. This can be linked to the cyclic pattern of bradycardia and

Table 5 Overview of commonly used ECG time-domain features.

RR	
Mean	μ_{rr}
Standard deviation	σ_{rr}
Serial correlation coefficients (of order k)	$r_k = \frac{\sum_{i=1}^{m}(rr_i - \mu_{rr})(rr_{i+k} - \mu_{rr})}{\sum_{i=1}^{m}(rr_i - \mu_{rr})^2}$
NN50	# adjacent RR-intervals that differ more than 50 ms
pNN50	pNN50= $\frac{NN50}{m}$
Standard deviation of interbeat intervals	SDSD = σ_{rd}, with $rd_i = rr_{i+1}$
Root mean square of interbeat differentials	RMSSD = $\sqrt{E(rd_i^2)}$
Allan factor	A(T)= $\frac{E[(N_{i+1}(T)-N_i(T))^2]}{2E[N_{i+1}(T)]}$ with $N_i(T)$= # beats in the ith window of T seconds
EDR	
Mean	μ_{edr}
Standard deviation	σ_{edr}

[7] Time differences between consecutive R-peaks in the ECG

tachycardia during apneas. Detrended fluctuation analysis has also been applied on the HRV of apneic subjects, but only slight changes in long-term control mechanisms of the heart rate could be observed [165].

Cardiorespiratory interactions: The HRV is modulated by the respiration through the mechanisms called respiratory sinus arrhythmia. It has been observed that the information shared between respiration and HRV decreases during apneas and these reductions have been used as features to detect apneas [163]. An overview of different methods to estimate the RSA from the HRV and a respiratory measurement (e.g. the EDR or a respiratory belt) can be found in [118].

5.1.2 PPG

From the PPG signal, the pulse rate (PR) can be extracted as alternative for the HR. All features proposed for the HR could therefore also be estimated from the PR. Moreover, decreases in the amplitude fluctuation of the PPG (DAP) have been linked to vasoconstriction due to sympathetic arousals at the end of apneas. The use of these DAP events has been studied for the detection of OSA in children [67]. Additionally, characteristics of the PPG waveform such as pulse amplitude, width and slope transit time have been linked to respiration and their behavior can be useful for sleep apnea detection [53].

5.1.3 PAT

The peripheral arterial tonometry [144] sensor was developed for the detection of sleep apnea. It is based on a pulsatile plethysmography signal measured on the finger which can capture vasoconstriction and tachycardia related to apneas. Decreases in PAT amplitude of 33 % in combination with a tachycardia of 15 % were used in [144] for the detection of apneas.

5.1.4 Contactless cardiovascular measurements

Several contactless alternatives for ECG recording have been tested for sleep apnea detection. In [34], a multi-channel contactless capacitively-coupled electrocardiography embedded in a mattress was proposed. The ECG based apnea features defined in [163] were extracted from ccECG signals of healthy volunteers. The HR features achieved high similarity to the features extracted from the reference ECG signal. Signal morphology features, on the other hand showed lower similarity with the reference resulting in problems with the EDR extraction. The similarity in HR features shows the potential of ccECG sensors for the detection of sleep apnea.

Ballistocardiography has also been studied in sleep apnea subjects. In [178], for instance, Zink et al. optimized the algorithm for BCG beat to beat detection in a sleep apnea population and obtained a correlation coefficient R^2 of 0.95 between the

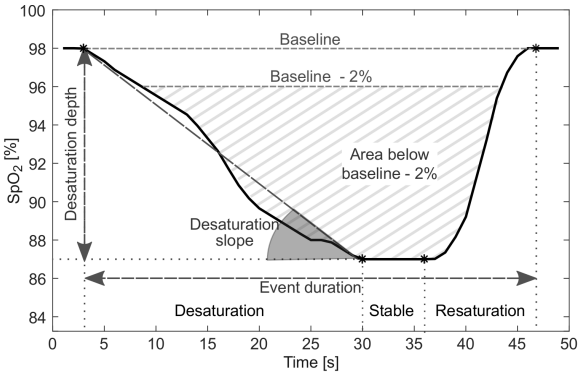

Fig. 9 Overview of desaturation characteristics which can be extracted from oxygen desaturations.

beat-to-beat cycle lengths extracted from the BCG and ECG. Whereas Hwang et al. investigated the correlation between the oxygen desaturation index (ODI, see section 5.2) and HR features extracted from three different BCG sensors [74].

Researchers have also focused on extracting heart rate from radar or infrared (IR) video recordings next to the breathing movements. Zhu et al. have validated IR based heart rate monitoring in sleep apnea subjects and discussed the open challenges in this field [176].

5.2 Oximetry

The SpO_2 signal has been widely studied for sleep apnea screening since it can easily be acquired in a home environment. In clinical practice the SpO_2 signal is often characterized by simple statistics such as the ODI, which counts the number of times a desaturation larger than 4 % occurs per hour of sleep, or time spent below an oxygenation level of 90 % (T90). It has been shown that these simple parameters can reliably confirm moderate to severe OSA, but that a negative test result does not rule out mild OSA [158]. Therefore, researchers have been developing a range of more elaborate SpO_2 parameters in order to detect subtle changes due to apneas. In [158], four categories of commonly used SpO_2 parameters were defined: desaturation characteristics, time series variables, frequency spectrum variables and nonlinear variables.

Desaturation characteristics: The desaturation characteristics include the desaturation depth, duration and area. These can be computed compared to a baseline level, or another reference point. Additionally, these parameters can be calculated on subparts of the desaturation event, e.g. on the downward and upward part separately. Some studies also considered desaturation slopes, or higher order derivatives of the signals [54]. In Fig. 9 an overview of these features is given for an example oxygen desaturation.

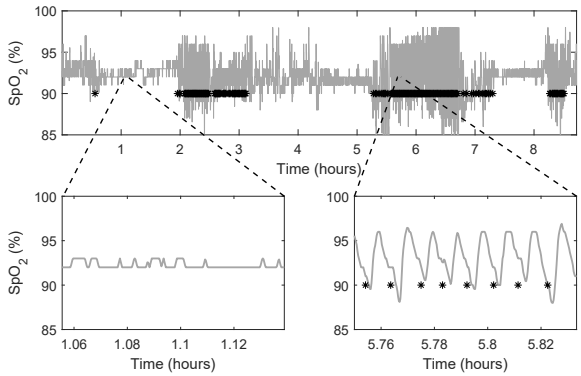

Fig. 10 Example SpO_2 signal of a subject with an AHI of 39.4 in which the apneas (*) are grouped together. In the lower right plot a 5 min apneic segment is shown in which periodicity can be observed in the SpO_2 signal, whereas the left plot shows no periodicity during normal sleep.

Time series analysis variables: These parameters include statistical measures that can be computed over the full SpO_2 signal or window based. These statistics include: the mean, minimum, quantile values, standard deviation, higher order statistical moments, and cumulative time spend below certain SpO_2 values (e.g. T90) [158].

Frequency spectrum variables: Studies have shown that OSA subjects have an unstable or overly sensitive respiratory control system [58]. Therefore instead of going back to a stable breathing pattern after an apnea, often another apnea is triggered. As such, apneas tend to be grouped together, as can be seen from Fig. 10. When the apneas follow each other closely, a periodic pattern of desaturations can occur as is shown in the lower right plot of Fig. 10. Different studies have used the power in the 0.01-0.033 Hz frequency band to capture this periodicity [158]. Other measures of the PSD have been proposed, such as wavelets [117], autocorrelation analysis, or the use of phase rectified signal averaging (PRSA) [54].

Nonlinear analysis variables: The recurrent desaturations during the night also cause the SpO_2 signals to have a higher irregularity, variability and complexity. These can, respectively, be measured using the sample entropy, central tendency measure and Lempel-Ziv complexity [14].

Terrill et al. concluded in their review [158] that the studies which obtained the best OSA detection results used features from multiple of these four categories. These categories thus contain complementary information. However, including more than three to four features in the classifier did not lead to a significant increase in performance. SpO_2 based OSA screening methods typically obtain accuracies of 80-95 % with an AUC of 90-95 %, depending on the used features, data set and AHI threshold [158].

5.3 Effort and Respiration

5.3.1 Airflow

The AASM rules for visuals scoring of apneic events rely mainly on the airflow measured using an oronasal thermal and nasal pressure sensor [26]. Therefore several researchers have developed methods for the automatic detection of sleep apnea on these signals. All drops in peak signal amplitude of more than 90 % are scored as apneas, whereas drops of more than 30 % could represent a hypopnea. These drops are relative to pre-event baseline breathing which is defined as "the mean amplitude of stable breathing and oxygenation in the 2 minutes preceding onset of the event or the mean amplitude of the 3 largest breaths in the 2 minutes preceding onset of the event" [26]. This baseline can be difficult to define for subjects with high AHIs and its definition is ambiguous to be translated into algorithms. Moreover, breathing and movement artefacts will further complicate this baseline extraction for automated algorithms [42]. Therefore, Cioleck et al. proposed a robust airflow envelope tracking using nonlinear filters. Using this reliable baseline, rule-based methods can then be applied to detect apneas and hypopneas when a decrease in airflow amplitude larger than a predefined threshold is observed.

These rule-based methods, however, have as disadvantage that they cannot differentiate if hypopneas are associated with arousals or desaturations. Therefore, more elaborate respiratory features have been proposed in order to capture changes that might have a correlation with arousals or desaturations. Koley et al. proposed statistical features of the respiratory amplitudes and intervals over windows of 8 seconds [84]. Additionally, they extracted the area and length of the respiratory curve and frequency domain features using the PSD. In this study, the deviation of each of the feature values from the subject's mean values were also considered.

5.3.2 Respiratory effort

Similar processing methods can be applied to respiratory effort signals obtained by RIP abdominal and thoracic belts. Despite the absence of airflow during obstructive apneas, the respiratory effort is still present, which challenges the detection of apneas when using this signal modality. However, when the effort is measured in combination with other modalities like airflow or SpO_2, it can be used to differentiate between central and obstructive events [119]. When both the abdominal and thoracic belts are monitored, the thoracoabdominal paradox[8] [26] can also be used as marker for apneic events.

A more extensive overview of methods using airflow and respiratory effort signals to detect OSA can be found in [161, 110]. The methods based on respiration reported

[8] During obstructive apneas the respiratory effort signals from the thoracic and abdominal belts are often out of phase, this phenomenon is called the thoracoabdominal paradox

in [110] obtained subject based classification accuracies of 82-96 % and an AUC of 88-90 %.

5.3.3 Contactless measures of respiration

A lot of research has been conducted towards contactless sensors to measure respiratory effort. Respiratory movements can be extracted by pressure sensors in the mattress. An example of such sensor is the Emfit, discussed in Section 3.2.5. In [72], the use of this sensor for the detection of sleep apnea was investigated. Rather than focusing on the breathing cessations, this study used unsupervised learning (i.e., clustering) to detect breathing distortions in the respiratory signal which are linked to arousals and large chest movements when breathing is regained. The amount of breathing distortions could be correlated to the AHI.

Kagawe et al. [78], proposed a system in which two Doppler radars are installed underneath the mattress in order to measure thoracic and abdominal effort. The system was tested for the detection of sleep apnea, a rule-based algorithm including the detection of paradoxical breathing showed promising results.

In [176], it was shown that the breathing rate can also be extracted accurately from IR video recordings in OSA subjects.

Castro et al. [37], proposed to measure the respiration using a capacitively-coupled bioimpedance sensor embedded in a mattress. This system, however, still needs to be tested on OSA subjects.

5.4 Sound

Snoring is one of the most common symptoms of OSA and differences in acoustic characteristics of snoring have been observed between OSA patients and simple snorers [150]. Moreover, due to apneas, subjects often make grasping and choking sounds. Researchers have developed acoustic features which can be used for the automatic detection of sleep apnea using sound recordings. Solà-Soler et al. have proposed snore intensity, pitch, frequency, and spectral envelope parameters [150]. Their study showed that the snore-to-snore variability of these features was increased in OSA subjects. Moreover, multiscale entropy [24] of audio recordings has also shown to be useful to detect apneas.

5.5 Automatically generated features using deep learning

All features mentioned before are handcrafted, they are extracted based on previous knowledge of the effect apneas have on the signals. The signals might, however, contain more information than these features. Therefore more and more researchers

have moved towards automatic feature extraction using deep learning, avoiding the challenging task of feature engineering. In [121], 21 studies detecting sleep apnea using deep learning were compared. Most studies were based on the ECG signal, but also SpO_2 and respiration were considered. The convolutional neural network (CNN) was the most popular network. It is, however, not clear if this is the best choice, since some studies suggested that recurrent neural networks (RNN) outperformed CNN [121]. The included ECG based methods report global screening accuracies of 79.5-100 %.

5.6 Multimodal OSA detection

Since the scoring rules for sleep apnea are based both on a reduction in airflow and the presence of an oxygen desaturation, the combination of respiration and oximetry has frequently been studied [119, 161]. Moreover, cardiac signals are often added to capture the presence of arousals. Xie et al. [174] investigated the combination of SpO_2 and ECG based features. They concluded that the SpO_2 based classifier outperformed the ECG based one, and that only a slight increase in performance could be obtained when both feature sets were combined. Similar results were obtained in our own study when PPG features were added to an SpO_2 based classifier [53]. Behar et al., on the other hand, tested the combination of oximetry, sound and actigraphy. When comparing the different modalities, oximetry outperformed the other two with a classification accuracy of 85.1 %, but an increase in performance of 3.3 % was obtained when all three modalities were combined.

5.7 Comparison of methods and modalities

When comparing the OSA detection performances which are reported by studies using different modalities, automatic classification using respiratory signals obtained lower performances than ECG and SpO_2 based methods. Although, manual scoring of OSA is mainly based on the respiration. This might be due to a higher noise level in the respiratory signals [110].

ECG-based methods seem to outperform other modalities in single sensor applications. But this might be due to the fact that many ECG based algorithms use public data sets, such as the Apnea-ECG database, which are less distorted by noise and might be easier to classify [110]. When different modalities are compared on the same data set, the SpO_2 signal performs best most of the times [174, 53]. In order to validate the potential added value of deep learning compared to feature-based algorithms, comparative studies on more challenging datasets than the Apnea-ECG data set should be performed.

Another observation is the fact that combining different sensor modalities often does not result in a relevant improvement of performance, probably because one of

the sensors performs quite well and dominates the analysis [110]. When SpO_2 based methods are combined with other modalities, they tend to dominate the performance [174, 53]. Not all apneic events can, however, be detected using the SpO_2 signal since the AASM rules allows scoring apneas when no desaturation is present and hypopneas with only an arousal [26]. Therefore, sometimes the SpO_2 remains stable during apneas. For the databases used in [54], 11.5 % of annotated apneas could not be linked to an oxygen desaturation larger than 1 %. Therefore, further research should be conducted to better merge different modalities in order to detect apneas which were missed by individual modalities. Additionally, combining different modalities improves the classification of apneas into event subtypes (central vs. obstructive) [119].

Although the Apnea-ECG database has stimulated the research into apnea detection methods greatly, most of the recordings only contain ECG signals. The database can therefore not be used to develop multimodal algorithms nor can it be used to compare the performances of different modalities. Moreover, the control group was composed of healthy subjects, instead of subjects with other sleep related complaints which are seen in the sleep lab. Papini et al. have shown in their study [125] a drop in accuracy of 15 % and a drop in sensitivity of 30 % for algorithms trained on the apnea-ECG data set which were tested on a database including a wider spectrum of sleep disorders. These results show that the performance of apnea detection algorithms is strongly dependent on the data set used to train the algorithm. Therefore, one should consider the target population for which the application is being developed and train on a similar data set set with the same pretest probability to have OSA.

Next to the Apnea-ECG data set, the National Sleep Research Resource (NSRR) [49] also provides PSG data sets, of which the Sleep Heart Health Study (SHHS) [130] has been used the most for the automatic detection of sleep apnea. This data set, however, was recorded in the general population, whereas sleep experts advise against OSA screening in the general population, but rather advise to screen groups with a high pretest probability in order to ensure a high post-test probability [44].

The availability of large public data sets, ideally including wearable data recorded simultaneously with the gold standard PSG, is even more important for algorithms based on deep learning. These algorithms are completely data-driven and their performance tends to improve if more data is available.

Another important factor when comparing different algorithms is the used testing method. In order to obtain a fair generalization performance, the test set should be patient independent. However, studies often do not mention specifically if subject independence of the test set was imposed [121]. Especially for cardiovascular signals the classification performance can increase significantly if part of the data from a test set patient was included in the training set, since cardiovascular features can be highly patient dependent.

5.8 Future of sleep apnea screening: beyond the AHI?

Most of the studies developing automated screening algorithms for OSA validate their methods based on the AHI, which is used to define OSA severity in clinical practice. The AHI, however, only takes into account the number of apneas, but not their severity. This might explain why the AHI does not correlate well with the sleepiness of patients nor with cardiovascular outcome [52]. Moreover, when an AHI cutoff of 15 events per hour of sleep is considered, prevalences of up to 50 % can be observed in middle-aged male populations [25]. Therefore, researchers are searching for alternatives for the AHI in order to better phenotype OSA subjects and prioritize them for treatment.

In [58], Eckert reviews phenotypic approaches for OSA, with a focus on the PALM[9] score. This score describes 4 traits causing OSA: an impaired upper airway anatomy, a low respiratory arousal threshold, an unstable ventilatory control system and ineffective upper airway dilator muscles. According to the most dominant trait, other treatments could be proposed. Measures of each of the causes were defined based on gold standard PSG and PAP drops, but should still be tested on wearable measurements.

In [158] and [52], on the other hand, SpO_2 severity parameters are proposed which correlate better than the AHI with the cardiovascular risk of OSA subjects.

This area of research is promising to enhance phenotyping of OSA subjects and in the future these developed parameters could also be extracted from wearables in a home environment.

6 Conclusion

Sleep monitoring used to be a clearly defined domain based on EEG analysis. Bringing sleep monitoring to a home environment resulted into the emergence of a multitude of sensors and sleep staging algorithms. Within this chapter, unobtrusive state-of-the-art sensors and algorithms for sleep monitoring in adults were discussed as alternatives to the costly and uncomfortable in-hospital PSG. These novel technologies have the potential to enable a broader patient screening, early detection of sleep-related conditions and a long term follow-up at home.

Recently developed wearables and sensors placed around the patient were introduced, which measure PSG signals in a less obtrusive way or apply indirect measurements of the physiological parameters. The focus was on devices monitoring heart rate, respiration, and blood oxygenation, but actigraphy and portable EEG devices were also briefly discussed. An important aspect of these recently developed devices is that, although these provide increased comfort and a higher amount of data, the acquired data is of variable quality. This is caused by both the use of these

[9] PALM is an acronym for the measured parameters for each of the 4 studied traits: **P**crit, **a**rousal threshold, **l**oop gain and **m**uscle responsiveness

technologies in an uncontrolled environment, as well as by inherent characteristics of the technologies. In order to be able to exploit these solutions optimally, it is of high importance that research around this topic also includes the development and evaluation of algorithms for an automatic assessment of the quality of the data, as well as compensation methods for data of intermediate quality. Moreover, these novel devices require the development of application-specific algorithms for sleep monitoring.

The evaluation and comparison of sleep staging algorithms depend on many parameters, apart from studied population and algorithmic details. It includes sensor types, applied input signals and mutual combinations. In general, good performances have been achieved based on solely the cardiac signal, being ECG or PPG, as it conveys respiratory information as well. The latest state-of-the-art sleep staging algorithms are furthermore based on deep learning techniques, which are expected to become even more important for future implementations. However, a validation on wearable or unobtrusive signals is often lacking. Therefore, the field of sleep staging at home would benefit from the development of algorithms which consider the limitations of wearable/unobtrusive data from the start.

Obstructive sleep apnea is the most common sleep-related breathing disorder, it however, often remains undiagnosed. Therefore, researchers have been developing OSA detection algorithms using signals that can be easily acquired in a home environment. ECG and SpO_2 based algorithms have obtained the most promising results. However, most of the studies did not include experiments at home. These algorithms should thus be further tested on signals acquired unobtrusively from a home environment. Moreover, not much performance gain has been shown from multimodal algorithms, smarter ways to combine different signal modalities should thus be investigated.

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