UNIVERSIDAD DE SEVILLA

DEPARTAMENTO DE LENGUAJES Y SISTEMAS INFORMÁTICOS

Design and development of comprehensive digital solutions with application in the medical field: Human sleep analysis

International Doctoral Dissertation presented by

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February 2022

Acknowledgements

I would like to express my gratitude to my PhD supervisors Prof. Dr. Ralf Seepold and Prof. Dr. Juan Antonio Ortega Ramírez. They made this result possible through their shared experience, attention, and time invested in this work. Thanks to their constant support, I have been able to develop myself not only as a researcher but also as a person, which is of great importance in life.

A big thank goes to my parents and grandparents who have always believed in me, and thanks to them, I have become the person I am. I am also grateful to my brother for the fact that I can always be sure that I can rely on his help in any situation.

I would like to express special thanks to my wife Silvia, for whom the time of my doctorate was not always easy, but who has nevertheless kept me motivated, supported, and understood me the whole way from the beginning. Without her, I would not have been able to accomplish this task, and therefore her role cannot be valued highly enough. Of course, I would also like to thank my son for filling my life with new meaning, and thanks to him, my motivation has increased even more.

To all my current and former work colleagues, I would like to thank you for being able to put up with me and giving me numerous pieces of advice. I won't be able to name all of you here, but special thanks go to Daniel, who has been two metres ahead of me in the office all these years but has also always been available outside of it to support me. I would also like to thank Agnes for contributing many helpful ideas, especially in the early years, and always being available to talk to. I would also like to thank Lucas for his support and Patrick for motivating me every time we met.

Prof. Dr. Natividad Martínez Madrid also played an important role in my development - first during my study, but also afterwards. Thanks to her, I have met several people who have changed my life, and I thank her for that. The Berlin colleagues from Charité, Prof. Dr. Thomas Penzel, and Dr. Martin Glos - thank you for sharing your experience and knowledge. It was essential for the research work that was done. I would also like to thank my colleagues from Italy – Prof. Dr. Massimo Conti and Prof. Dr. Simone Orcioni, for always helping me research-wise and as friends. Also, in Spain, there was always support from colleagues - special thanks to Juan José, but also from my friends and relatives of my wife, who are now also part of my family.

Thank you to everyone I have mentioned but also to everyone else I have met in my life – many of you had some impact on it.

ABSTRACT

The influence of sleep on human life, including physiological, psychological, and mental aspects, is remarkable. Therefore, it is essential to apply appropriate therapy in the case of sleep disorders. For this, however, the irregularities must first be recognised, preferably conveniently for the person concerned. This dissertation, structured as a composition of research articles, presents the development of mathematically based algorithmic principles for a sleep analysis system. The particular focus is on the classification of sleep stages with a minimal set of physiological parameters. In addition, the aspects of using the sleep analysis system as part of the more complex healthcare systems are explored. Design of hardware for non-obtrusive measurement of relevant physiological parameters and the use of such systems to detect other sleep disorders, such as sleep apnoea, are also referred to. Multinomial logistic regression was selected as the basis for development resulting from the investigations carried out. By following a methodical procedure, the number of physiological parameters necessary for the classification of sleep stages was successively reduced to two: Respiratory and Movement signals. These signals might be measured in a contactless way. A prototype implementation of the developed algorithms was performed to validate the proposed method, and the evaluation of 19324 sleep epochs was carried out. The results, with the achieved accuracy of 73% in the classification of Wake/NREM/REM stages and Cohen's kappa of 0.44, outperform the state of the art and demonstrate the appropriateness of the selected approach. In the future, this method could enable convenient, cost-effective, and accurate sleep analysis, leading to the detection of sleep disorders at an early stage so that therapy can be initiated as soon as possible, thus improving the general population's health status and quality of life.

TABLE OF CONTENTS

LIST OF FIGURES

PART I

PREFACE

CHAPTER 1

INTRODUCTION

Given that the dreaming brain must perform these remarkable contortions - creating a world, living in it, responding to it, and then carefully blocking all the responses in a manner that does not cross the threshold of awareness - it is no wonder that this dreaming brain seems to be more active than the waking brain.

William C. Dement

1.1 Research Motivation

Each of us spends a significant part of our lives in sleep. Nevertheless, the importance of sleep for good health is still often underestimated, although numerous studies have already demonstrated that the influence of sleep on a well-functioning including mental, psychological, and physiological state of the human body is essential [1, 2]. Therefore, it is of great importance to study and to analyse sleep and in case of abnormalities to initiate appropriate treatment.

Various sleep disorders can lead to health problems if left untreated. One of them is, for example, chronic insomnia, which affects between 10% and 30% of adults all over the world [3]. In the case of the elderly, the observed incidence is even higher - according to [4], between 30% and 48% are suffering from it [4]. Another common sleep disorder is obstructive sleep apnoea (OSA) which is one of the sleep-related breathing disorders. According to current estimates, it affects about 936 million people between the ages of 30 and 69 worldwide using an Apnoea-Hypopnoea-Index (AHI) criterion of five or more events per hour based on the American Association of Sleep Medicine (AASM) criteria [5]. Restless legs syndrome (RLS) is as well a widespread sleep disorder with the general prevalence rates ranging from 4% to 29% of adults, averaging 14.5 ± 8.0% across different available studies [6]. In addition, there are several other sleep disorders that should be identified and treated in the affected population whenever possible to minimise possible negative health consequences [7]. Further information regarding sleep disorders can be consulted in section 2.1.

Besides the health impact, sleep disorders also bring significant economic consequences. Several factors are responsible for this, and some are not obvious, though they should nevertheless be considered. As an example, we can consider the data of incurred costs due to inadequate sleep from Australia, presented in Table 1 for the 2016-2017 financial year [8]. The table provides information on various categories of costs and their origins and includes both financial and non-financial ones for the comprehensive representation.

Table 1.1: Breakdown of the costs of inadequate sleep in Australia by various categories (the financial year 2016–2017) [8].

	Costs of various categories of inadequate sleep including costs of conditions associated with them			**Total**
	EDS-SD	**EDS-Other**	**Insufficient Sleep**	**($ billions)**
	($ billions)	**($ billions)**	**($ billions)**	
Financial costs ($ billions)				
Health	0.50	0.52	0.22	1.24
Productivity				
Reduced employment	1.27	2.69	1.26	5.22
Premature death	0.24	0.26	0.11	0.61
Absenteeism	0.36	0.94	0.43	1.73
Presenteeism	0.73	2.22	1.68	4.63
Subtotal	2.60	6.11	3.48	12.19
Informal care	0.11	0.18	0.12	0.41
Other (nonmedical accident costs)				
Workplace accidents	0.05	0.16	0.08	0.29
Vehicle accidents	0.36	0.98	0.85	2.19
Subtotal	0.41	1.14	0.93	2.48
Deadweight loss	0.38	0.75	0.43	1.56
Total financial costs	4.00	8.71	5.17	17.88
Nonfinancial costs ($ billions)				
Loss of well-being	21.41	5.14	0.78	27.33
Total costs ($ billions)				
Financial + Nonfinancial	25.41	13.85	5.95	45.21

EDS = excessive daytime sleepiness; SD = sleep disorders.

For detailed sleep analysis and evaluation of the individual sleep stages, a standard procedure called polysomnography (PSG) is typically used and performed according to the guidelines of the American Academy of Sleep Medicine (AASM) [9]. Several physiological signals are recorded continuously during sleep when performing a PSG procedure [10]. Each of the above signals undergoes changes depending on the current sleep phase. Evaluation of these changes thus allows classification of the individual's stage of sleep at any given time. More details on PSG measurement are presented in section 2.2.1.

Despite the feasibility of an accurate analysis of sleep using PSG, some aspects should be considered that bring with them several disadvantages as well as complications:

- A sleep laboratory where PSG recording is performed is not a natural sleep environment for patients. In addition, several electrodes, sensors, and cables are attached to the subjects' bodies, as can be seen in Figure 1.1, causing discomfort that can affect sleep patterns [11].
- At least 22 analysis connectors are needed for the analysis in a standard case, which can also cause logistical and economic cost problems [12].
- The time and personnel costs required for recording, processing, and analysing the data are high [13].
- The number of available sleep laboratories and sleep physicians is limited [14], resulting in a delay in the care of patients with sleep disorders. However, this care is crucial as a large number of undiagnosed sleep disorders can lead to serious health problems [15].

These issues indicate that PSG remains a limited method and that several aspects require improvement in the development of sleep analysis systems.

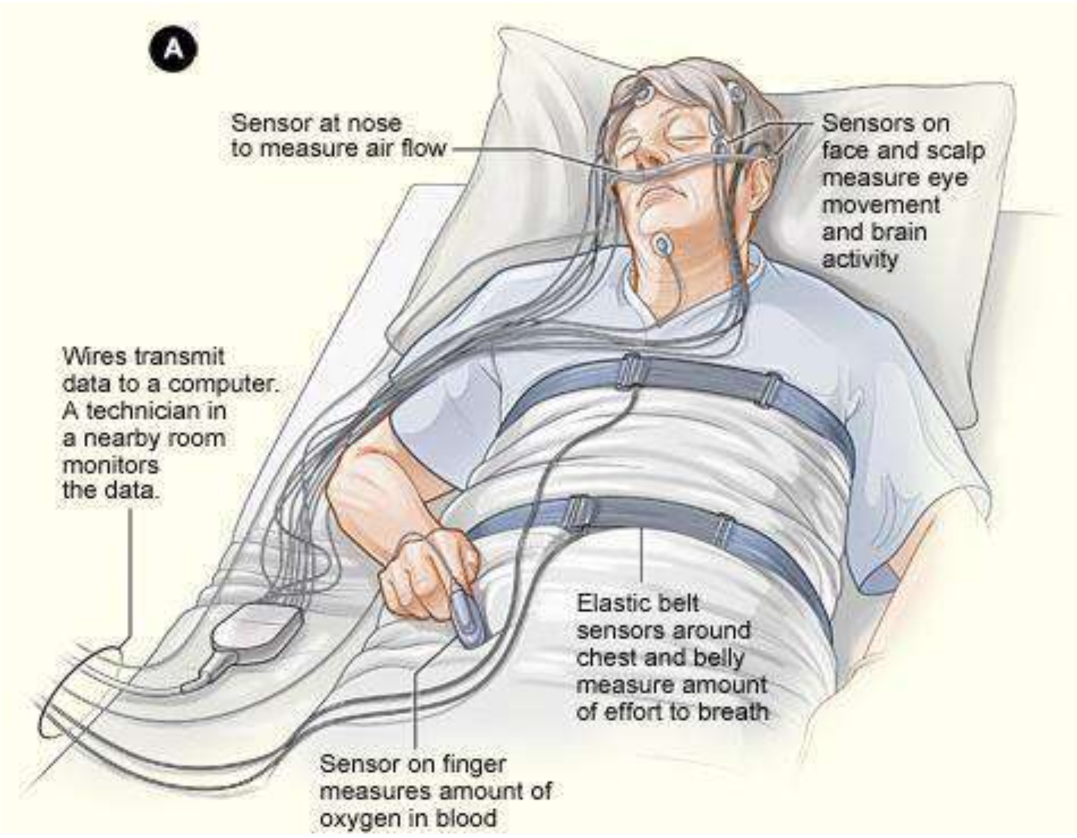

Figure 1.1: Typical polysomnography measurement[1]

[1] http://www.nhlbi.nih.gov/health/dci/images/sleep_studies.jpg

It is evident from several scientific works that physiological parameters, such as breathing or movement, also vary during different sleep phases and could be used for the identification of various sleep disorders [16, 17]. These signals could potentially be recorded with less effort and more convenience for patients. However, such a solution requires the expertise of several disciplines: medicine, signal acquisition, processing, and analysis. Nonetheless, such development remains reasonable and promising, as, in the future, this approach should enable convenient, cost-effective, accessible to everyone and accurate sleep analysis, leading through broad application to the detection of possible sleep disorders at an early stage so that therapy can be initiated as soon as possible, thus improving the health status and quality of life of the general population.

1.2 Research Methodology

The methodology of this research is based on the standard scientific research technique [18], was adapted according to the objective, and includes the following phases:

1. **Research on state of the art.** During the first phase, the literature review was performed in order to specify the research question and to get a comprehensive overview of existing methodologies, systems, and scientific backgrounds in the field of sleep study.

2. **Conception/Modelling.** Based on the previously performed literature analysis, the first concepts and mathematical models for sleep analysis were designed in this phase.

3. **Prototyping.** According to theoretically developed/improved models, the prototype implementation of the sleep analysis system was performed.

4. **Development and execution of studies.** Research studies with the developed prototype were designed to facilitate the following evaluation of the implemented prototype.

5. **Evaluation/analyses of results.** The obtained results of the prototype work were evaluated in this phase.

6. **Improvement of technology/model.** According to the evaluation results, improvements were made to the technologies/model to enhance the outcomes and increase the scientific value of the research.

Phases 3-6 have been repeated to improve the quality of the research outcome.

1.3 Research Question

The following research question that leads this doctoral dissertation was determined during the first phase of the used methodology:

> *What mathematically reasoned methodologies have the potential to be evolved and deployed to provide convenient, affordable, and accurate sleep analysis?*

From this, research objectives can be derived, which are outlined next.

1.4 Research Objectives

This doctoral thesis aims to create a solid scientific basis for developing sleep analysis systems for widespread use, thereby improving the well-being and health condition of the population in the long term. These are among others:

- Prepare the scientific background for developing an algorithm for the classification of sleep stages based on signals that can be acquired non-invasively.
- Determine a minimal set of physiological parameters required for the distinction of sleep stages with a sufficient level of accuracy. It must be considered that the signals should be recorded in the absence of direct contact with the body.
- Design the features for further algorithmic processing based on the analysis of physiological signals during sleep and their correlations with the current sleep stages.
- Identify which type of systems can be used for a non-obtrusive recording of the relevant signals detected during sleep.
- Verify whether the same type of systems can be applied for a broader range of sleep-related analytics, including for instance the detection of sleep apnoea.

1.5 Success Criteria

Success is achieved when the research question is addressed, which includes completing the previously defined objectives of the research. For this purpose, scientific studies should have been conducted to evaluate the developed mathematically reasoned methodologies in the area of a sleep study. The evaluation should have shown the applicability of the selected methodology of sleep analysis for achieving qualitatively adequate results.

Translated to the exact goals of this doctoral research, the success would be the detection of sleep stages at the level that exceeds state of the art, which can concern both the set of parameters used and the accuracy of detection.

1.6 Thesis Outline

The structure of the doctoral thesis is as follows:

Chapter 2 presents the problem of existing methodologies and algorithmic approaches in sleep analysis and provides the relevant basic information on the topic of this doctoral dissertation.

In Part II are presented the selected published journal articles that directly address the research question and the objectives of the dissertation. These articles were published in Clarivate Journal Citation Reports (JCR) journals.

Additional published scientific articles are included in Part III. These articles provide further details of the research conducted and present significant additional findings related to the research objectives. The publications include, among others, proceedings of the conference of the category B (CORE) – KES and book chapters in book series from Q3 in SCImago Journal & Country Rank.

Finally, in Part IV, conclusions are drawn, important observations are presented, and potential future work is discussed.

CHAPTER 2

SLEEP ANALYSIS SYSTEMS

The idea behind digital computers may be explained by saying that these machines are intended to carry out any operations which could be done by a human computer.

Alan M. Turing

2.1 Introduction

As described in the previous chapter, sleep is essential for human health. Therefore, in case of irregularities, appropriate therapies should be prescribed. For this, however, the sleep disorders should first be detected, and for this purpose, different approaches can be used. In order to better understand what kind of systems are suitable to be used for this, one should first gain a general understanding of the signals that are to be measured and the disorders that are to be identified. Following is presented the relevant basic information about the physiological signals, arts of measurement, and sleep disorders that are of importance in developing a system for sleep analysis.

2.1.1. Sleep Disorders

Currently, there are over 80 known sleep disorders according to the AASM classification [19]. These disorders can be divided into six main categories:

- Insomnias
- Sleep-Related Breathing Disorders
- Central Disorders of Hypersomnolence
- Circadian Rhythm Sleep-Wake Disorders
- Parasomnias
- Sleep-Related Movement Disorders

In addition, there is a seventh category: "Other sleep disorders", which includes all other sleep-related symptoms or events that do not meet the standard definition of a sleep disorder.

All of these sleep disorders have specific characteristics that allow them to be distinguished. The standards described in detail in [20] should be applied to diagnose them. As a support for this, technical solutions can be used to measure a number of physiological parameters. Subsequently, with appropriate processing and analysis, the recorded signals can be used for the diagnosis. Sections 2.2 and 2.3 further detail possible technical solutions and appropriate algorithms.

2.1.2. Arts of Sleep Parameters' Measurement

The methods of measuring sleep characteristics may be classified into two major groups - objective and subjective measurement [21]. In the case of objective measurement, the relevant values are recorded with electronic devices and evaluated afterwards. For this purpose, various types of sensors can be used, such as a system that is a combination of a pressure sensor and a triaxial accelerometer [22]. This type of system can be used, for example, to detect heart rate, respiration, sleep phases, movement, the position of the person, sleep apnea, and sleep time, and to calculate other parameters from these data using an appropriate algorithm. Besides, a smartphone's sensors can also be used for the objective measurement of sleep quality [23]. However, using of smartphones brings some disadvantages, such as the need to place the phone near the person in the bedroom or the increased battery consumption during the night. In addition, there are differences in the sensors installed in different smartphones, which may have as a result that the measurement data may differ by diverse devices.

As for the subjective measurement, it is based on recording the sleep parameters perceived by the subjects. Questionnaires and/or sleep diaries are used for this purpose [24]. Mobile apps can also play the role of electronic sleep diaries. In [25], a comparison of a classic paper-based sleep diary with an electronic version and the actigraphy measurement was made and presented. The evaluation showed that electronic sleep diaries might have an advantage over paper-based versions. The comparison of the results of sleep quality measurements with objective and subjective methods was made in [26]. As a result, a correlation between both types of measurement was confirmed.

Further details on subjective and objective measurement of sleep characteristics and the evaluation of the comparison of these two arts of measurement may be found in the article “Comparison of sleep characteristics measurements: a case study with a population aged 65 and above” presented in Part III of this doctoral dissertation. The performed study has disclosed the correlation between different ways of measurement for several sleep characteristics, indicating where the objective measurement could substitute the subjective one.

2.1.3. Physiological Signals

When talking about types of physiological signals relevant for sleep analysis, they can be divided into a couple of main groups. These are the following:

- Heart-related signals.
- Respiratory signals.
- Movement signals (including eye movement).
- Brain activity signals.

- Other signals (blood oxygen saturation, video/audio signal, temperature, etc.).

These groups may, in turn, be subdivided into further subgroups. For example, respiratory signals can be divided into respiratory flow and respiratory effort.

The majority of the classical methods of measuring the above signals need direct contact with the human body, for example, to measure electrical impulses, as presented in section 2.2.1. Other alternative methods can provide a more convenient measurement for the subjects. More details are shown in the following section 2.2.2 and the article "Recognizing Breathing Rate and Movement While Sleeping in Home Environment" in Part III of this thesis.

2.1.4. Sleep Stages

Analysing the measured physiological signals, one can, among other things, carry out recognition of the sleep stages. The first standardised division of sleep into sleep stages was made in 1968 according to the Rechtschaffen and Kales (R&K) method [27]. Sleep was divided into 30-second intervals - "epochs" - and each epoch was assigned one of the sleep stages:

- Stage W – wake/wakefulness
- Stage 1 (S1)
- Stage 2 (S2)
- Stage 3 (S3)
- Stage 4 (S4)
- Stage REM – Rapid Eye Movement

Stages 1-4 can be combined into one NREM (non-REM) stage. In addition, some epochs could be marked as "Movement Time" (MT) if the movement makes exact identification of the sleep stages in the recordings impossible.

As new insights into sleep have been gained over time, it has become necessary to provide a new guideline for terminology, recording method, and scoring rules for sleep-related phenomena. This happened in 2007 when AASM published a new Guideline, which has been constantly updated since then, and the current latest version is 2.6, which was released in 2020 [9]. Among other things, a new division of sleep stages was proposed:

- Stage W – wakefulness
- Stage N1/NREM1 (formerly S1)
- Stage N2/NREM2 (formerly S2)
- Stage N3/NREM3 (formerly S3+S4)
- Stage R/REM – Rapid Eye Movement

The comparison of the scoring of sleep stages between both standards has been the subject of several scientific publications, including [28] and [29].

In the practice of sleep analysis, the sleep stages N1-N3 are sometimes combined into one NREM Stage. Another division to be encountered in scientific papers is Wake / Light Sleep (N1+N2) / Deep Sleep (N3) / REM (R). Exact detection of the (short) wake phases during the night and the exact time of falling asleep and waking up are of importance for the sleep analysis.

In healthy people, there is a characteristic sequence of sleep stages: after falling asleep, several stages of light sleep and deep sleep usually follow before a REM sleep stage ends the respective cycle. On average, a sleep cycle lasts about 90-110 minutes and is completed four to five times per night. However, the duration of the periods of sleep stages and each sleep cycle can also vary. In the normal course of the night, the REM phases typically become longer and the deep sleep phases shorter in healthy people, whereas there are also age-related differences [30]. To get a general idea of the course of sleep, an example of a visualisation of a sleep profile is provided in Figure 2.1.

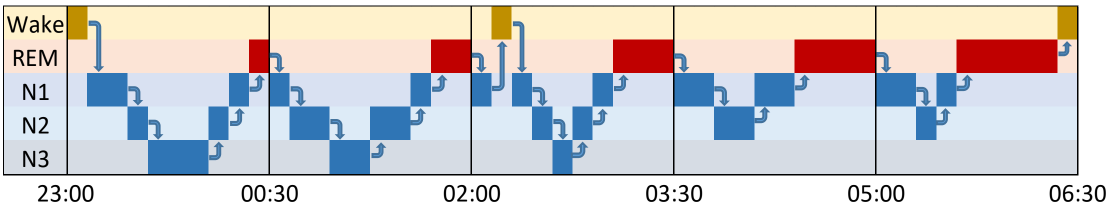

Figure 2.1: Example of approximate sleep cycle during the night

2.2 Hardware architecture

Different types of hardware systems can be used to provide a recording of physiological signals. They can be differentiated by the signals recorded but also by the sensors used. Other hardware-implemented modules, such as signal pre-processing or amplification, can also differ significantly and influence the final result. Since sleep analysis has been carried out for decades, some gold standard methods have been developed, mainly used in sleep laboratories. Nonetheless, the development of alternative approaches, which are expected to have some advantages, is going on in parallel. In the following, both traditional and novel hardware methods are presented that could be used to record physiological signals for subsequent sleep analysis.

2.2.1. Classical Approaches

The main method for measuring sleep behaviour, established for many years, is polysomnography (PSG) [31]. The hardware system for performing the PSG consists of several components explained in the following. Typically, there is a central component that receives and stores data from different sensors. Some kind of pre-processing is also possible on the central unit. Other components, the sensors used to record the signals in a PSG are as follows:

- Electroencephalography (EEG) records brain activity. Electrodes placed on the head are used for this.
- Electrocardiography (ECG) is a method that detects the small electrical signals caused by the heart muscle on the skin, which gives the electrical activity of the heart over time. Electrodes are placed on the chest for measurement.
- Electrooculography (EOG), on the other hand, uses the electrodes to detect and measure the potential that exists between the back and front of the human eye. This measurement allows the recognition of the behaviour of the eyes.
- Electromyography (EMG) is used to record muscle activity, which also records the signals with the help of the electrodes.
- Blood oxygen saturation is measured using pulse oximetry, for which the sensor is typically placed on the fingertip.
- Both respiratory flow and respiratory effort are often measured. The sensors can be used, which have contact with the body accordingly, such as nasal cannulae and chest/thoracic belts.
- In addition, other sensors can be used, such as a position sensor to determine the person's position or a video camera to enable video recordings for detailed analysis.

The recorded signals are stored and subsequently analysed. The number of sensors applied permits accurate analysis of several parameters but certainly also brings discomfort for the user because most sensors have direct contact with the body. Moreover, the sensors are mostly wired, and cables run along the human body, which causes additional restrictions. Another disadvantage is the high material and personnel costs required to prepare, perform and analyse the recordings.

Another widely used method for analysing sleep behaviour is actigraphy [32]. In this case, a motion sensor (e.g., an accelerometer) is used for the measurement. The sensor is typically placed on the wrist, although several alternative positions exist. Actigraphy can be used to determine levels of activity/inactivity, which, after appropriate analysis, allows conclusions to be drawn about the person's sleep/wake states. From this, one can calculate some relevant sleep parameters, such as the number of awakenings, total sleep time, per cent of time spent asleep, total wake time, or per cent of time spent awake. An example of an actigraphy recording visualisation is given in Figure 2.2. Here, a recorded day was divided into 15-minute intervals for the visualisation.

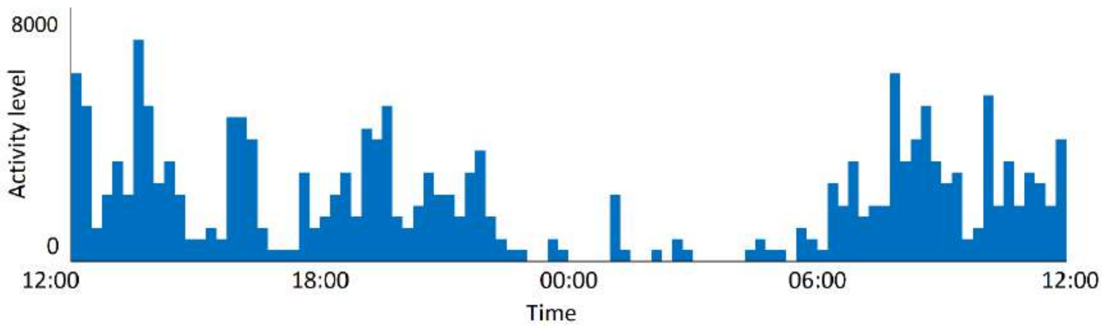

Figure 2.2: Example of the actigraphy recording visualisation

Actigraphy has the advantage that only one sensor is needed for the recording, which increases the comfort for the user. It can also provide around-the-clock monitoring as the person can wear the device with the sensor on their wrist throughout the day. Despite these positive features, actigraphy also has several aspects that are disadvantageous. No exact detection of sleep stages is possible, but only sleep and wake states. These states are also detected with a limited level of accuracy (although relatively high at over 80%) and low specificity (0.33) [33]. Furthermore, it cannot measure respiratory signals, which makes this method inappropriate for diagnosing multiple sleep disorders.

2.2.2. Alternative Techniques

Due to traditional systems' several disadvantages, new methods are continuously being researched to overcome them. At the same time, the quality and informative value of the measurements should remain at a high level. Another possible application of the alternative methods could potentially be continuous sleep monitoring or monitoring in a home environment, where not only sleep/wake states are to be distinguished. PSG would be inappropriate in this case because the wiring and placement of the sensors require a trained person, which can cause several difficulties in continuous use. Moreover, if one were to sleep for several days, weeks, or months with many sensors directly attached to the body, the acceptance of the method would most likely be low.

When selecting the appropriate architectures, an analysis of the hardware components but also of the changes in physiological signals during sleep is necessary. This requires deep research and knowledge from several disciplines.

In alternative systems, sensors that are not used in classical approaches can be used. It is also possible to use some combinations that differ from traditional ones. In this way, a higher comfort level for the user can be achieved by placing a smaller number or less intrusive sensors on the body. For example, in [34], the actigraphy was combined with the respiratory effort signal recorded with respiratory inductance plethysmography. One of the important research directions in the domain of sleep analysis is to find the hardware components that can be used comfortably and with minimal effort for the user. These aspects, among others, have been investigated in the journal article "Digital health and care study on elderly monitoring", which can be found in Part II of this PhD thesis.

In order to achieve maximum comfort, the placement of the sensors other than on the person's body would be of great advantage. One of the variants would be the use of the radar, as proposed, for example, in [35]. However, such systems have several disadvantages. For example, the radar often has to be placed very close to (or directly above) the user, which in turn makes it much less comfortable to use. Furthermore, the radars are very sensitive to the user's movements and position, and in the case of obstacles in between (which can also be a body part), the measurements become inaccurate easily. Another important point is a complex calculation, which requires appropriate resources. The question of acceptance can also be problematic when using radars, especially in the home environment. To the best of my knowledge, there is currently no radar-based system that would allow reliable, highly accurate recordings of physiological signals continuously throughout the night in a real environment. However, research keeps going, and new results may change the situation.

Another type of physiological signal recording could be provided by a camera-based system. An infrared camera could also be used for this, as presented in [36]. However, cameras are very sensitive to direct line of sight contact with the object being recorded. Therefore, clothing and blankets as well as the position of the person can significantly affect the quality of the measurement of the physiological signals. Acceptance of cameras, especially in private bedrooms, is also a factor that should not be underestimated.

Wearables or smartphones can also be used to record the signals, which can be relevant for detecting sleep stages [37] and sleep apnoea [38]. The integrated sensors are used for this, which provide the data for the following processing.

Another category of sensor placement following the high comfort of the user are sensors that are attached to the bed and not to the person. Several types of sensors can be used for this purpose that could measure different physiological signals. One of the examples would be ballistocardiography (BCG), where the heart signal is measured indirectly through movements. For this purpose, the accelerometers can be applied, as described, for example, in [39]. Other types of sensors can also be used, such as polyvinylidene fluoride (PVDF) film sensors, which can be placed between the mattress and bed sheets [40]. This way of measurement facilitates the recording of respiratory, heart, and body movement signals, which were also selected for detailed further investigation.

Ideally, the sensors should be placed in a manner that does not influence the normal sleep routine. One of the variants is to place the sensors under the mattress (e.g., in the positions as it is presented in Figure 2.3). This variant was also chosen for the work carried out within the framework of this dissertation, which necessitated research into the characteristics of the signal coming through the mattress, its filtering, and amplification for further processing. The results of the performed within the scope of the PhD thesis research, development, and the measurements carried out with it are presented in the article "Recognizing Breathing Rate and Movement While Sleeping in Home Environment" in Part III of this document. Furthermore, several other scientific works on the identification of heart, respiratory, and body movement signals with the following scientific publications on this topic were made within the performed research; the list of the articles are presented in Annex A.

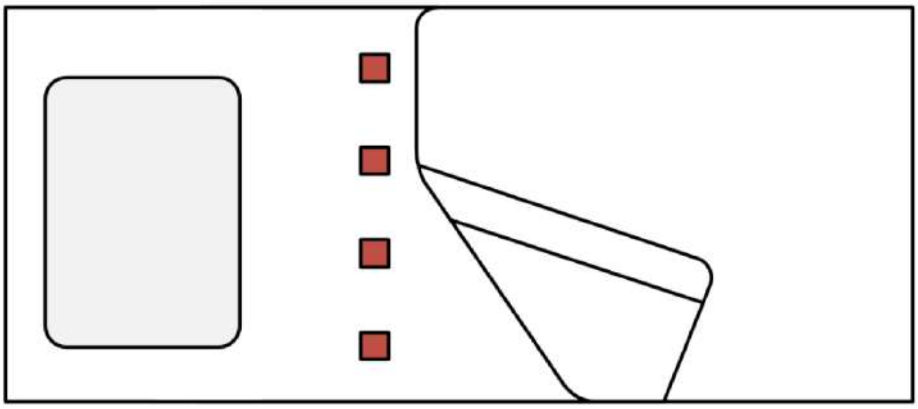

Figure 2.3: Possible placement of sensors under the person

2.3 Algorithmic Approaches in Sleep Analysis

The recorded and pre-processed by the hardware signals are then to be algorithmically processed to be able to draw key conclusions about sleep. This can be, for example, the recognition of sleep phases during sleep or the identification of sleep apnoea events. It is also possible to recognise other sleep-relevant parameters employing a corresponding analysis for subsequent providing of the results to an interested person that might be, for instance, a user directly or a physician. Only sleep apnoea and sleep stages detection methods are presented in the following subsections, as the total number of possible applications with corresponding algorithmic approaches is so large that such description would go beyond the scope.

2.3.1. Sleep apnoea identification

Sleep apnoea detection is a prominent field of sleep analysis. As mentioned in section 1.1, OSA is a common sleep disorder that affects hundreds of millions of people [5]. However, central sleep apnoea (CSA) also has a prevalence of 0.9% and can lead to complications [41]. For the detection and differentiation of OSA and CSA (mixed form and other breathing-related events such as hypopnea are also possible), mainly respiratory flow, respiratory effort, and oxygen blood saturation are analysed according to AASM criteria [9]. Snoring or PCO_2 (in the case of hypoventilation measurement [9]) may also be of interest, as well as position, cardiovascular information, and detection of sleep state (or at least sleep time) [42]. Traditionally, methods that follow the rules described in [9] are used for detection, which can also be linear algorithms, as the rules are clearly defined.

In the case of alternative measurements, where either a smaller number of parameters or other signals (such as tracheal sounds [43] or BCG [44]) are measured, other algorithms may be used that have more complicated background logic.

These can be, for example, neural networks [45], Gaussian Processes (GP) [46], or support vector machines (SVM) [47]. Nevertheless, other algorithms as well can be applied. A comprehensive review of 84 original research articles on obstructive sleep apnoea detection is presented in [48], while a general overview of alternative approaches in sleep apnoea diagnosis has been made in [49].

An alternative method for the detection of sleep apnoea events and namely the analysis of respiratory signals recorded without contact using sensors placed under the mattress was also developed within the framework of this PhD thesis and is presented in the article "Embedded system for non-obtrusive sleep apnoea detection" in Part III.

2.3.2. Sleep stages classification

The main focus of this PhD thesis was on the detection of sleep phases, which were briefly presented in section 2.1.4. The detailed research conducted on state of the art has shown that there are several groups of methods that allow the signals to be analysed. Furthermore, different signals can also be considered as input for the analysis. Some research describes algorithms that will enable detection of sleep stages based on the signals recorded during traditional polysomnography, described in section 2.2.1. An example of this type of signal is the EEG signal, the analysis of which is described in [50, 51]. Such algorithmic systems allow for relatively high accuracy (86.7% for W, N1, N2, N3, and REM in [50]) but require a recording that cannot be performed in a contactless way which has some disadvantages as described before.

Based on the assumption mentioned in section 2.2.2 and confirmed by preliminary prototype development, that the recording should be performed with maximum comfort for the user and thus heart, breath, and motion signals can be acquired, the decision was made to use these three signals as input.

When it comes to methods of analysing the signals, for example, an SVM can be used to automatically identify sleep and wake phases, as described in [52, 53]. In [52], wrist and chest actigraphy were analysed in combination with heart rate variability (HRV) for sleep classification. The accuracies obtained for the group of 18 healthy adult subjects are almost the same - 78 % and 77 % for, respectively, chest and wrist actigraphy in combination with HRV. However, HRV requires very exact identification of R (or J in the case of BCG) peaks, which can be challenging due to the contactless art of measurement favoured for the PhD research. In [53], besides SVM, other classifiers that can be used for sleep phase detection were analysed: K-nearest Neighbor and Naïve Bayes. The best classification results were obtained with the Naïve Bayes classifier with a precision of 70.3%, a recall of 71.1%, and overall accuracy of 72.2%.

Neural networks are another group of methods that can be applied to detect sleep stages. Numerous scientific papers have analysed different signals using this approach. The work already mentioned [50] used cascaded long short-term memory recurrent neural networks (LSTM) to identify sleep stages. LSTM is a frequently used method, which is also described in [54] for the analysis of HRV. In general, LSTM can be said to be an advanced version of recurrent neural network (RNN) architecture. One of its advantages is that it can model chronological sequences and their long-term dependencies more precisely than conventional RNNs. Nonetheless, RNNs can also be used to analyse signals to detect sleep phases. An implementation is presented in [55], where heart rate and wrist actigraphy recorded with a wearable were analysed.

A review of scientific papers using deep learning techniques for sleep phase detection is presented in [56]. For further analysis of automatic sleep phase detection techniques in the last decades, [57] and [58] can be consulted.

Analysing the changes during sleep in the heart, breath, and movement signals that were selected for this PhD research, a regression analysis can be applied to find a correlation with the corresponding sleep phases. Since in this case, there are several input signals that can be presented as independent variables, and as a result, the sleep phases should be detected, which can be presented as a limited number of categories of a dependent variable, one of the variations of logistic regression and namely Multinomial Logistic Regression (MLR) could be selected as one of the appropriate methods [59]. This approach, which brief visualisation is presented in Figure 2.4, was also taken for the development of an algorithm for the detection of sleep phases in this doctoral thesis, among other things because, in this implementation, there is not only a rigid assignment of an epoch to a sleep phase, but in the output, the probabilities of being in each sleep phase are represented for each epoch. This circumstance makes further processing with the improvement of the results easier and more flexible.

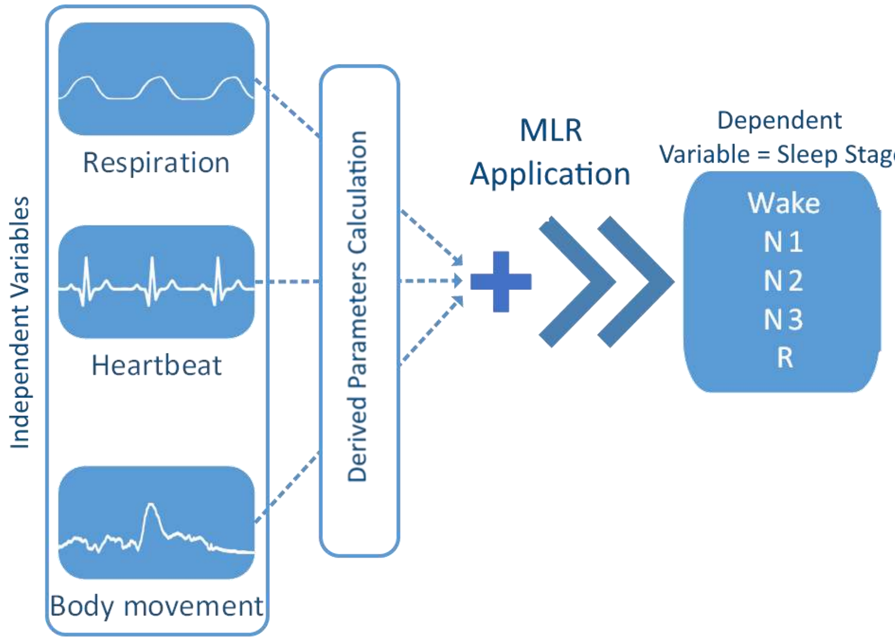

Figure 2.4: General visualisation of the proposed MLR approach

The first results of the research and development of an algorithm for the recognition of sleep and wake states based on the MLR method are presented in Part III of this document in the article "Recognition of Sleep/Wake States analysing Heart Rate, Breathing, and Movement Signals". The detection of wake/light/deep/REM sleep stages was also achieved, as presented in the article "Automatic sleep stages classification using respiratory, heart rate and movement signals" in Part II. A further detailed description of the method used, including the explanation of the calculation of the parameters derived from the input signals to increase the accuracy, can also be consulted in these articles.

Considering the circumstance that especially recognition of heart signal can be challenging due to the fact that every heartbeat produces only a small movement, which amplitude is significantly lower than provoked by breathing or body movements signals, the doctoral research has been directed towards finding the possibility of recognising the sleep stages exclusively through the analysis of breathing and movement signals. To do this, it was important to closely examine the variations in physiological signals during sleep and develop appropriate features for the algorithm input. After thorough research, this has been achieved, and the results are presented in Part II in the article "Estimation of Sleep Stages Analyzing Respiratory and Movement Signals".

PART II

SELECTED RESEARCH WORKS

Automatic sleep stages classification using respiratory, heart rate and movement signals

Overview

This article deals with the estimation of sleep stages through the analysis of movement, heart, and respiratory signals. For this purpose, parameters/features derived from the signals were selected, calculated, and then used as input for the MLR model.

Context

This publication resulted from research conducted over the first two years of the PhD study. During these years, thorough literature research was carried out, as well as the first developments of the algorithms were based on the knowledge gained. The experience gathered during the research stays in Seville (Spain), and Ancona (Italy) has significantly contributed to achieving these results. Furthermore, the active work in international projects, such as the IBH Living Lab Active and Assisted Living, has supported the development.

Journal information

The Journal "Physiological Measurement" was selected for the submission of this paper. This journal is indexed in JCR with the current Impact Factor of 2.833. Detailed ranking for the last five years is presented in the following Table.

Category	*Biophysics*		*Engineering, Biomedical*		*Physiology*	
JCR Year	JIF Rank	JIF Quartile	JIF Rank	JIF Quartile	JIF Rank	JIF Quartile
2020	41/71	Q3	53/89	Q3	41/81	Q3
2019	39/71	Q3	49/87	Q3	43/81	Q3
2018	45/73	Q3	41/80	Q3	48/81	Q3
2017	45/72	Q3	39/78	Q2	55/83	Q3
2016	49/73	Q3	37/77	Q2	50/84	Q3

This is the Accepted Manuscript version of an article accepted for publication in *Physiological Measurement*. IOP Publishing Ltd is not responsible for any errors or omissions in this version of the manuscript or any version derived from it. The Version of Record is available online at https://doi.org/10.1088/1361-6579/aaf5d4.

Automatic Sleep Stages Classification Using Respiratory, Heart Rate and Movement Signals

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Abstract

Objective: This paper presents an algorithm for non-invasive sleep stage identification using respiratory, heart rate and movement signals. The algorithm is part of a system suitable for long-term monitoring in a home environment, which should support experts analysing sleep. *Approach*: As there is a strong correlation between bio-vital signals and sleep stages, multinomial logistic regression was chosen for categorical distribution of sleep stages. Several derived parameters of three signals (respiratory, heart rate and movement) are input for the proposed method. Sleep recordings of 5 subjects were used for the training of a machine learning model and 30 overnight recordings collected from 30 individuals with about 27,000 epochs of 30-second intervals each were evaluated. *Main results*: The achieved rate of accuracy is 72% for Wake, NREM, REM (with Cohen's kappa value 0.67) and 58% for Wake, Light (N1 and N2), Deep (N3) and REM stages (Cohen's kappa is 0.50). Our approach has confirmed the potential of this method and disclosed several ways for its improvement. *Significance*: The results indicate that respiratory, heart rate and movement signals can be used for sleep studies with a reasonable level of accuracy. These inputs can be obtained in a non-invasive way applying it in a home environment. The proposed system introduces a convenient approach for a long-term monitoring system which could support sleep laboratories. The algorithm which was developed allows for an easy adjustment of input parameters that depend on available signals and for this reason could also be used with various hardware systems.

Introduction

The human body is more fragile than people think. In order to survive, it requires sleep just as much as food, water, or oxygen. This is a basic principle of human physiology that has been borne out by thousands of research studies.

In general, sleep is a state where our bodies and minds rest and rejuvenate [SPR09]. It is obligatory for our normal physiological, mental and emotional functioning during the awake hours. The belief that it is possible to have just a couple of hours of sleep a night over a long period of time without suffering any negative consequences is a common misconception [NAT11]. It is categorically beyond doubt that when sleep contains even slight abnormalities, the aftermath can lead to physical illness, psychological problems or an untimely death [LEE12].

A popular misconception is that adults have to sleep at least 7 to 8 hours every night to be rejuvenated properly, while children require far more hours of sleep [NAT11]. However, this is only standard recommended advice; sleep requirements are individual for every person [NAT11]. In addition, getting many hours of sleep does not always guarantee a healthy and rested state, because the crucial point here is not the quantity, but the quality [NAT11].

In order to get reliable data on the quality of a person's sleep, the sleep stages and their sequence and durations have to be analysed. Usually such studies are executed in sleep laboratories. The established standard procedure for sleep stage quantitative evaluation is the overnight polysomnography (PSG) following the guidelines of the American Academy of Sleep Medicine (AASM) [CHO13].

Motivation

The execution of PSG generally means that during sleep a human body will be connected to at least 22 laboratory wire attachments [CHO13], which explains why the PSG is quite a costly and time-consuming procedure [ETT10]. Moreover, being in the sleep laboratory is always unfamiliar and disturbing for the subjects, so there could be some discomfort because of the electrodes and the issue of movement limitation. All of these conditions would impact the person's regular sleep behaviour [LEB01]. It is safe to say that the sleep during the PSG monitoring often has differences compared to sleeping at home.

Moreover, the fact, that different sleep stages have an appreciable effect on heart rate, breathing and movement [HAY12, KUR12, LON14], provides good reason to combine these parameters to develop the sleep stage classification algorithm.

Furthermore, there are a limited number of sleep medicine specialists who can provide healthcare and support sleep study [SIN15]. Additionally, in order to conduct sleep studies for all the patients who require them without incurring long waiting periods, the number of sleep laboratories and experts would have to be immense. At the same time one of the most important health problems that humanity faces lies in the terribly high amount of undiagnosed sleep disorders [LEE12]. Besides that, polysomnography-based sleep scoring is a very expensive procedure [BER15]. This is why low-cost, non-invasive, home-based diagnostic systems for sleep study, in particular for categorical distribution of sleep stage parameters, would provide substantial additional support for stationary sleep laboratories.

Objective

This project aims to develop a new approach to the classification of sleep stages. The novelty of this approach would be the set of parameters (including the derived parameters) used for the sleep stage recognition. Whereas traditional testing (e.g. polysomnography) requires examining many parameters, our aim is to develop a system which uses as few appropriate parameters as possible for input. Choosing the parameters would require serious consideration of the two main points:

- the chosen parameters must differ by behaviour patterns during the particular sleep stages;
- these patterns have to be represented by mathematical equations and then converted to algorithms.

As a result, a software application to implement the sleep phase analysis and automatic evaluation will be designed. The foundation for the sleep stages recognition should be provided by mathematical description and transformed into programming code.

The developed algorithm should work with the bio vital parameters that must be available to be collected by using non-invasive methods. In an effort to get recordings of sleep states that are natural and genuine, the experimental subjects must be provided with a feeling of sleeping in their usual environment. [GAI18]

The system for sleep phase classification described in this article should be designed to classify the sleep stages using the signals from PSG recordings.

State of the Art

Research on the topic of non-invasive sleep stage classification methods has been discussed in a number of scientific publications [PEN16, HAY12, KAM12, KUR12, LON14, TAT15] around the globe. This case study is focused on just those few publications that provide the relevant content for this work. Research studies that were conducted by using heart rate, body movement or respiration as vital signals for sleep classification and sleep cycles investigation are of particular value. The scientific papers listed below mostly dealt with these complex issues, so only the parts significant to this project will be described.

The ECG itself, heart rate and heart rate variability can be used to analyse and detect sleep stages [PEN16].

In [AKT17] wrist and chest actigraphy were compared in combination with heart rate variability for sleep classification. In this study a support vector machine (SVM) was used for the automatic identification of sleep and wake stages. The achieved accuracies for the group of healthy adult 18 subjects are nearly equal - 78% for chest and 77% for wrist actigraphy jointly with HRV.

One study [HAY12] describes a method for the sleep and wake stages classification based on just the ECG signals and a neural network algorithm. To develop and analyse the obtained results, they used 16 PSG recordings from the MIT-BIH polysomnographic database. First of all, to pre-process the data they built the RR series from the QRS annotation files to help calculate the heart rate variability (HRV). At the next stage, the Extreme Learning Machine (ELM) neural network algorithm with a single hidden layer was used to classify the wake and sleep phase [GBH06]. In order to distinguish between wake and sleep phases, the algorithm was trained on two scenarios:

- Subject-specific classification
- Subject-independent classification

In the first scenario, the time periods were selected from every single night's recording and fed into the ELM algorithm. Two-thirds of the whole sample recording was used for that. Next, one-third of the night recordings were used to test the algorithm's performance. As for the subject-independent classification, the researchers used epochs from all subjects to train the ELM. After training the algorithm, a recognition rate of approximately 90 percent was achieved. Predictably, the subject-specific rates are a bit better (93.33%) than the subject-independent ones (90.03%).

An automatic algorithm to determine REM sleep on the basis of the autonomic activities reflected in heart rate variations was developed in [YOO17]. The heart rate variability was calculated from ECG using R-R intervals and an adaptive threshold was applied to ascertain the REM stage. The average accuracy was 87% for the evaluation of 25 healthy and OSA subjects.

In another scientific study the concept of using data about body movement for sleep cycles estimation was investigated [KAM12]. The experiment was conducted by studying 16 healthy people who slept through the night with electrodes attached to their bodies. A detection device (NapVIEW) with a NaPiOn infrared motion sensor was used to detect body movements. It was placed on the bedside 50 cm from the subject's head. Along with this, the body movement density (BMD) was defined as the amount of body movements per time unit as an index of sleep transition. In sum, this study showed that BMD cycle is strongly linked to sleep cycle. And to evaluate sleep cycles we can use body movement data instead of brain activity or other parameters. Moreover, it was concluded that a BMD cycle is less affected by individual variations and it is therefore a better index than the absolute value of BMD.

One particular research study [KUR12] describes another two algorithms and methods for sleep stages estimation. Their classification experiment was conducted with the help of 10 healthy adults with a mean age of 22.2 years. The main goal of this project was to find a non-invasive method to obtain the vital parameters and classify the subjects' sleep stages into the categories WAKE, REM and NREM1 - NREM4. To achieve this, the scientists developed an air mattress with a highly responsive pressure sensor. It allows the measuring of respiration, heartbeat and body movements. They created an algorithm based on the idea that all sleep stages have certain characteristics regarding body activity and that body signals behave differently in the different sleep stages. In Tables 1 and 2 the different characteristics of REM and NREM sleep, which are important for this article's purposes because of using similar features, are listed.

Table 1: Characteristics of REM sleep [KUR12]

N	Characteristics
1	Brainwaves similar to those in NREM1 and WAKE are found
2	Decreasing of incidence ratios of delta wave and spindle
3	Disappearing of the tension of anti-gravity muscles
4	Appearing of rapid eye movement
5	Increasing of frequency of heartbeat and respiration while simultaneously becoming less rhythmic, blood pressure becomes high.
6	REM sleep occurs once every 90 to 100 minutes on average (adults)
7	Concentration of body movement before and after REM stage

Table 2: Characteristics of NREM sleep [KUR12]

N	Characteristics
1	The incidence ratio of delta waves is more frequent with the deeper sleep
2	In the NREM2 stage spindle waves are recognized
3	When sleep deepens from the WAKE stage, body movements become smaller and less frequent
4	The deeper the sleep, the less frequent the heart rate
5	NREM1 occasionally is found after NREM3, NREM4, or REM stages with large body movement

In the end, this experiment got 51.6% agreement with the classification results done by sleep experts within 6 stages (WAKE, REM, NREM1,2,3,4) and 77.5% within 3 stages (WAKE, REM, NREM).

Furthermore, there are various studies (e.g. [LON14, TAT15]) where respiration behaviour during sleep hours has been examined. One study [CHU07] tried to classify REM sleep based on respiration rates. The researchers aimed to develop a new user-friendly method for the sleep-wake-monitoring called "bed actigraphy" (BACT), which was presented in an earlier study [CHO07]. To achieve the goal, a system with four load cells fixed at the bottom of the bed legs was built. In order to assess the methods, the researchers studied 3 healthy participants – 2 males and 1 female between 27 and 32 years old. Their sleep cycles were analysed and classified in a specialized sleep center with PSG, according to the scoring manual of Rechtschaffen and Kales. There are peaks between expiration and inspiration during a fixed period of time called *window size*. It was determined to further compute the average respiration rate, after which the maximum peak inside this window was outlined as a peak point. The comparison clearly illustrates that the respiration rate is more irregular and increased during REM sleep stage than in other categories. Using an appropriate threshold level, the researchers determined the REM stages for all 3 participants. The percentages of correct predictions for these stages were 87.9%, 69.1% and 69.7%. It was concluded that respiration is a suitable parameter to classify REM and NREM sleep.

All the studies explored above proved that the examination of the bio vital parameters, particularly respiration and heartbeat, and additionally body movement during sleep has a potential to evaluate several sleep stages. However, the scientists tried to obtain multiple patterns of heart rate variability and respiration during special sleep phases using different mathematical approaches. Moreover, one study has shown that the occurrence of body movement during sleep provides the ability to make conclusions about the sleep cycles.

To evaluate the sleep stages, special sleep phases and sleep cycles, simple mathematical algorithms along with a more complicated neural network algorithm were used. The resulting findings were promising. But they have also indicated that the estimation of sleep stages without recording brain activity and eye movements (as is done in PSG) is too imprecise. In addition, a perfect match with estimated results of the experts is not possible because the judgment standards of the R-K method include ambiguities. Thus, it can lead to different sleep stage classifications in some parts of sleep recordings due to the subjective interpretations of particular sleep-stage evaluators [KUR10].

Nevertheless, it is still vital to develop a non-invasive and as accurate as possible solution for sleep stage recording and estimation, in order to support the complex PSG procedure in the future.

Statistical Methods

To calculate the strength of correlation between one dependent variable and a series of other changing independent variables, regression analysis is used as a statistical measure. It is known that regression is the most widely used statistical evaluation and its applications occur in almost every field [DCM12]. In this method, the dependent variable, which has to be analysed or predicted, is usually denoted by Y. In order to do so, one or more other independent variables related to variable Y and denoted by $X_1, X_2, ..., X_n$ must be estimated [AVE98].

Though, it is not necessary for these independent variables to be statistically independent of each other [BEL91]. Therefore, the information about the dependent variable carried by the independent variables has to be presented through a mathematical function, which will define the existing relationship as accurately as possible [AVE98]. Such a mathematical function must be found.

When there is a need to analyse and adjust a nominal outcome for multiple independent variables, the multinomial logistic regression (MLR) is used. It is a special form of logistic regression that falls under the multiple regressions category. The usage of MLR presumes that one of the categories has to be designated as the reference. Which category is chosen as the reference will affect the procedure for reporting the results, but not the mathematical answer itself. The MLR model compares all categories of the dependent variable to the reference category for each of the independent variables. The number of such comparisons is equal to one minus the number of categories of the dependent variable. Basically, the MLR models the logit (logarithm of an odd) of being in one of the outcome categories compared to being in the reference group [KAT11].

In this case, the odds ratio is equal to the antilogarithm of the logistic regression coefficient. In multinomial regression, the odds ratio presents the information on how the probability of being in one category versus being in the reference group is influenced by the change of independent variable. If a value of the odds ratio is greater than 1, then as an interval-independent variable increases, the value of probability increases too. In other case, if the odds ratio is less than 1, then there is an opposite scenario in place – the value of probability decreases when an interval-independent variable increases [KAT11].

The outcomes of categorical dependent random variables denoted as $Y \in \{0, 1, 2 ... k\}$, are modelled by MLR. According to the model, a conditional mean of the dependent categorical variables is the logistic function of an affine combination of independent variables, which is usually denoted as x and is defined as

$$E\left[Y \middle| x\right] = \sigma\left(c^T x\right)$$

for some unknown vector of c coefficients, and where

$$\sigma\left(x\right) = \frac{1}{1+e^{-x}}$$

is the logistic function. Then, MLR finds the vector of coefficients c that maximizes the probability of observations.

In turn, maximizing the probability, which is defined as

$$\prod_{i=1}^{n} Pr\left(Y = Y_i \middle| X_i\right)$$

is equal to maximizing the log-probability, which is estimated as

$$\sum_{i=1}^{n} \log Pr\left(Y = Y_i \middle| X_i\right).$$

This leads to the simplified function for maximizing the probability

$$l\left(c\right) = -\sum_{i=1}^{n} \log\left(1 + e^{-1^{y_i} * c^T x_i}\right).$$

The standard error of coefficient *i* is calculated as

$$se(c_i) = ((X^T AX) - 1)_{ii},$$

where the Hessian of $H = -X^T AX$ and $A = diag(a_1, \ldots, a_n)$ is the diagonal matrix with $a_i = \sigma(c^T x) * \sigma(c^T x)$ [GAR16].

Finally, the so-called *Wald z-test* defined as

$$z_i = \frac{c_i}{se(c_i)}$$

is necessary to test the significance of predictors in the logistic regression. In this case, the Wald p-value for coefficient *i* gives the probability of seeing a value at least as extreme as the one observed, considering that the null hypothesis $(c_i = 0)$ is true.

The formula for Wald p-value of *i* coefficient is

$$p_i = Pr\left(|Z| \geq |z_i|\right) = 2 * \left(1 - F\left(|z_i|\right)\right)$$

where *F* is the cumulative density function of a standard normal distribution [GAR16].

Methods

The existing research studies have confirmed that there is, indeed, a correlation between the various behaviour patterns of bio vital signals – respiration, heartbeat and body movement – and the different sleep stages. This correlation can be used as a base for sleep stage recognition with an appropriate algorithm. Not only does this include the aforementioned parameters themselves, but also parameters derived from them are able to be used in the algorithm for calculations. The selection of a convenient method and its application will now be described.

Approach

In order to build on the successful studies and promising results of several publications presented in part earlier in the section "State of the art", this project aims to combine existing methods for the purpose of creating a new algorithm which will be able to analyse sleep phases based only on the following parameters of human body:

- heartbeat
- respiration
- body movement

The choice of these parameters is not accidental. Each of them can potentially be measured using non-invasive methods. This method will help to ensure that the sleep recording process does not jeopardize the accuracy of results or disturb the subjects' sleep.

All 3 signals mentioned below are taken from polysomnography records of the Charité dataset[1]. In this study, the heartbeat signals were substituted by ECG and, for the respiration signals, a thoracic (VTH) inductive plethysmography record was used. The body movement signal was replaced by the signal called *Beweg*, which is monitored by a 3D acceleration sensor in a recording device placed on the chest of the subject. For that, a 3D actigraphy sensor integrated into a PSG-System "SOMNOscreen PLUS" is used. It has the following properties: amplitude resolution = 16bit, accuracy = ±5%, Sampling-rate = 32 Hz, frequency range = 0,07 – 1kHz. Baseline wandering should be excluded by the lower frequency range and also not significant for the end results as only the changes of the signal and not the absolute value will be analysed and furthermore, baseline wander has a much

[1] Charité dataset consists of 230 hours of sleep recordings from the Sleep Medicine Center at Charité Universitätsmedizin Berlin (Germany) Center of Sleep Medicine, in which 30 individuals (an equal number of male and female participants) with no significant health disorders were studied.

lower amplitude than significant movements. For every axis the mean value of movement for every second is calculated and stored:

$$X = \frac{1}{n}\sum_{i=1}^{n}|x_i - x_{i-1}|$$

$$Y = \frac{1}{n}\sum_{i=1}^{n}|y_i - y_{i-1}|$$

$$Z = \frac{1}{n}\sum_{i=1}^{n}|z_i - z_{i-1}|$$

with n=32 (sampling-rate), and after that the activity was computed as:

$$Body_i = \sqrt{X^2 + Y^2 + Z^2} \ .$$

The part of the software which is responsible for the classification procedure is based on the statistical regression method – MLR. Therefore, both dependent *(Y)* and independent $(X_1, X_2, \ldots, X_n)$ variables have to be estimated. The dependent variable *Y* signifies the several sleep stages. As for the independent parameters, they must be defined as derived parameters from the vital parameters mentioned earlier – heartbeat rate, respiration and body movements. In other words, HRV is a derived parameter from the heartbeat rate parameter and could be used as a predicting variable for parameter *Y*.

In this study, to implement the MLR model, ten derived parameters were selected, which would reflect the behaviour of a number of sleep phases. All derived parameters were calculated for 30-second time periods k_i of the particular sleep recording.

The chosen derived parameters from the heartbeat signals are:

- heart beat interval – mean RR interval between successive heart beats for every 30s epoch (HBI)
- number of heartbeats per 30s (HB)
- heart rate variability – mean difference of successive RR interval lengths per 30s (HRV)
- R - algorithm (RA)

The RA algorithm stands for the R(k)-algorithm [KUR12]. The values of R(k) increase during REM stage. The reason for this behaviour is that the frequency of respiration and heartbeat accelerate during REM sleep (see Table 1), but at the same time these signals become less rhythmic [KUR12]. It is calculated as

$$R(k) = \frac{1}{2q+1}\sum_{i=-q}^{q}\left|H_{k+i}^{former} - H_{k+i}^{latter}\right|,$$

where the discrete time for every 1 min (starting from the first minute of the record and ending at the last one) is defined as k, H_{k+i}^{former} and H_{k+i}^{latter} are the heart rate values from the former and latter 30 seconds of the time interval $(k+i)$ and *i* represents the movement inside the window (moving average) with the size $2q$. In this work according to [KUR12] q=10 was used

A derived parameter from body movement is the mean value of body movement (BM) signal. It is defined as

$$BM(k) = \frac{1}{n}\sum\nolimits_{i=0}^{n-1} Body_i$$

with *n* equal 30 (the number of body-movement records for one 30-second epoch – one movement record per second – see above) and $Body_i$ is calculated as the square root of (X*X+Y*Y+Z*Z) with X, Y and Z the values of signals per axis of a 3D actigraphy-sensor as described above.

Furthermore, the mixed derived parameter from body movement and heartbeat signals, known as DA, was chosen. It represents the D(k)-algorithm [KUR12]. This algorithm was developed based on the knowledge that when moving from the wake stage to deeper sleep, body movement decreases and at the same time its frequency drops (see Table 2). DA represents the combination of changes in movement and heartrate and is calculated as

$$DA(k) = \log_2 \frac{A_k^{body}}{A_k^{heart} + A_k^{body}}.$$

A_k^{body} and A_k^{heart} are the mean amplitudes of the body movement and heartbeat signals for the time *k*. The proposed formula uses a logarithm to reduce the effect of large fluctuations in body movements and to enhance slighter movements of the body.

The derived parameters for the respiration signal are:

- Mean respiratory depth of inhalation (P_{sdm})
- Mean respiratory depth of exhalation (T_{sdm})
- Median respiratory volume during breathing cycles (V_{br})
- Median respiratory volume during inhalation (V_{in})

These parameters were chosen because these two variants of respiration characteristics are included in the sleep stage calculation. The P_{sdm} and T_{sdm} features take into account the mean respiratory depth and its variability at the same time, in terms of inhalation and exhalation. The V_{br} and V_{in} parameters are the volume-based features that should reflect the changes of respiratory effort signals [LON14].

Here is the mathematical representation of the derived respiration parameters:

$$P_{sdm}(k) = \frac{median(p_1, p_2, \ldots p_n)}{IQR(p_1, p_2, \ldots p_n)}$$

$$T_{sdm}(k) = \frac{median(t_1, t_2, \ldots t_n)}{IQR(t_1, t_2, \ldots t_n)}$$

$$V_{br}(k) = median\left(\sum\nolimits_{s_x \in \Omega_1^{br}} s_x, \sum\nolimits_{s_x \in \Omega_2^{br}} s_x, \ldots, \sum\nolimits_{s_x \in \Omega_k^{br}} s_x\right)$$

$$V_{in}(k) = median\left(\sum\nolimits_{s_x \in \Omega_1^{in}} s_x, \sum\nolimits_{s_x \in \Omega_2^{in}} s_x, \ldots, \sum\nolimits_{s_x \in \Omega_k^{in}} s_x\right),$$

where $p = p_1, p_2, \ldots, p_n$ and $t = t_1, t_2, \ldots, t_n$ are the peak and trough sequences from a chosen time window (in this case – 30 seconds), the kth breathing cycle is declared with Ω^{br}_k , the kth inhalation and exhalation cycles with Ω^{in}_k and Ω^{ex}_k with k consecutive breathing cycles ($k = 1, 2, ..., K$).

The possibility that all derived parameters could in some way depend on each other is not problematic since there is no need for the independent variables to be statistically independent of each other [BEL91].

Exploratory Data Analysis (EDA) was used to identify the significant features among 10 proposed derived parameters. According to its results, several classification attempts were executed with different sets of features. However, reducing the number of features to 7 or lower (e.g. excluding RA, VBR and HRV according to results of EDA) led to a reduction of accuracy (about 10-30%). Excluding 1 or 2 parameters (e.g. VBR and RA) did not have any significant effect on accuracy (with the current amount of test persons). As a result, a decision was made to include all 10 of the derived parameters because their calculation did not make the algorithm significantly more difficult, but did retain the high accuracy of the results. Furthermore, to accurately evaluate the influence of derived parameters on the system work, it wold be necessary to increase the number of test subjects in the study substantially. In other case, because of the individuality of each person and just minimal differences by excluding of 1-2 features, it is not possible to estimate the importance of every feature for the overall results.

To increase the accuracy of classification results, the transition patterns between different sleep stages were taken into consideration by the implementation of the algorithm described in this paper. As Schlemmer et al. [SCH14] has proved, some transitions between sleep stages are much more probable than others and at the same time some of transitions have a probability of nearly zero. In the first implementation of the algorithm the emphasis was placed on the not probable transitions. As the algorithm works with probabilities, it allows the inclusion of additional adjustments, which increases accuracy without having to adhere to strict rules. In this case the algorithm decreased the probability of the examined sleep stage by 10% to 15% (a higher percentage would have a negative effect if the previous stage was incorrectly classified), if its appearance probability according to the transition pattern is almost equal to zero. This approach has led to an increase of the accuracy of the proposed algorithm by up to 3% compared to the implementation without considering the transition probabilities.

Implementation

In order to calculate the derived heartbeat parameters HB, HBI, HRV and RA, the exact time (in respect to the start of the record) of R-peaks, which occurred within 30-second epochs, must be identified and extracted. Therefore, to remove the disturbances (e.g. baseline wander) from the ECG, data filter techniques have to be used along with methods to remove artefacts. To achieve this goal, a linear high-pass filter (HPF) algorithm [CHE03] was implemented in the project. Due to the usage of HPF, the low-frequency noise sources of the ECG signals, such as *P* and *T* waves, and the baseline wander will be suppressed. The HPF-method used here is represented mathematically as:

$$y_1[n] = \frac{1}{M} \sum_{m=0}^{M-1} x[n-m],$$

where *x[n]* is the input data and *M* represents the filter length. For the presented implementation the value of parameter M was determined to be 5 according to [CHE03].

Figure 1 shows an overlap of the typically unfiltered (blue) and filtered (red) ECG signals for the same time interval. As the figure indicates, the key pillar of the HPF-method lies in the fact that the filter does not shift the signals on the axis *X,* which otherwise could cause the occurrence of incorrect time values of the R-peaks. Therefore, the lower frequency noise sources of the ECG signal and the baseline wander will be suppressed with the help of the HPF-method.

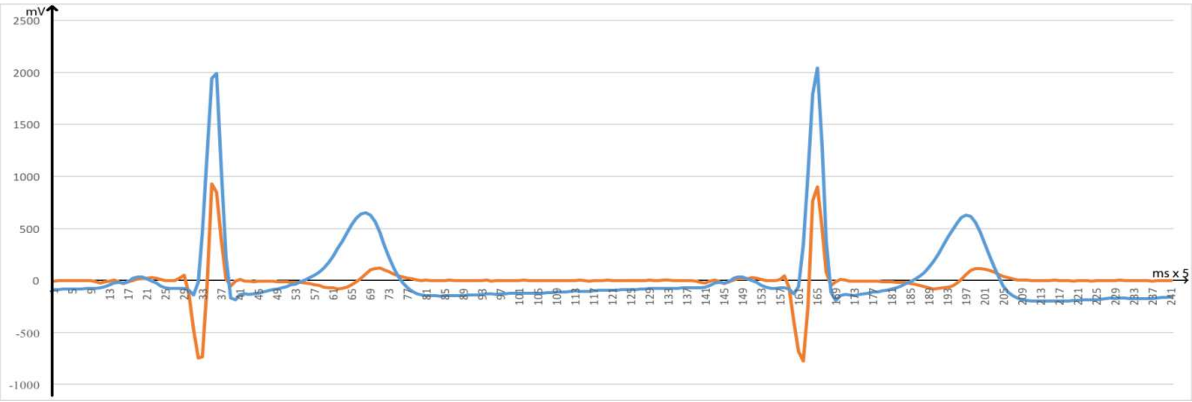

Figure 1: Overlap of the same ECG signal interval

After removing the artefacts from the ECG signal with a HPF-filter, the next stage of calculation is to identify the timestamps of all R-peaks. The following step is to estimate the derived parameters and to store, for further computations, the lists of all derived parameters for every subject in a CSV-File. The values from each list are calculated in ratio to the derived parameter average signal. Each list is sorted in chronological order and every entry contains the values for a 30-second epoch. For instance, in the column HRV are determined values for every epoch, calculated as the difference (in ms) between HRV per actual 30s and the average HRV of the full sleep record. The first 10 minutes of the recording of one subject are presented in Table 3 to illustrate the possible deviation of derived parameters. As can be seen in the table, the deviations can be very diverse even for the same sleep stage, but the results of current research confirm that it is still possible to find some dependencies with appropriate mathematical model. This makes sleep stage recognition based on these parameters a challenging, yet promising method.

Table 3: Extract of the file Param.csv, including the results of the first 10 minutes of a subject.

Index	HB	HRV	HBI	BM	TSDM	PSDM	VBR	VIN	RA	DA	AllStages	FourStages	ThreeStages
1	19,234	19,87	-18,031	361,135	-88,419	-85,571	-22,398	0,974	-26,582	-78,349	1	1	1
2	3,121	3,222	-2,095	-7,022	-3,863	38,145	-27,179	-32,812	-6,312	-17,725	1	1	1
3	-0,101	-0,108	-2,352	-12,769	7,2	0,854	-23,869	-13,121	-11,14	-13,394	1	1	1
4	3,121	3,222	-3,133	-18,379	78,726	-33,214	-21,294	-5,255	19,782	-4,734	1	1	1
5	-0,101	-0,108	-3,37	-29,668	56,493	-28,998	-13,939	14,367	58,445	8,257	2	2	2
6	3,121	3,222	-2,122	-20,911	-35,676	-27,311	-20,559	-19,075	40,053	-0,404	2	2	2
7	-0,101	-0,108	-2,627	-29,736	34,384	-34,394	-15,778	14,78	-27,579	8,257	2	2	2
8	-0,101	-0,108	-0,757	-20,5	-1,307	-11,514	-11,732	13,721	-86,397	-4,734	2	2	2
9	-0,101	-0,108	-1,115	-24,263	-64,183	-63,253	-12,468	-14,441	-88,39	-0,404	1	1	1
10	-3,324	-3,438	2,523	-33,636	-18,537	-52,984	-4,744	25,011	-83,562	12,587	2	2	2
11	-3,324	-3,438	1,897	-37,057	7,611	46,315	5,554	29,109	-8,266	16,918	2	2	2
12	-6,546	-6,768	2,766	-35,552	37,512	-8,966	2,244	31,983	81,59	8,257	3	2	2
13	-0,101	-0,108	1,361	-35,825	26,288	-33,008	-1,434	32,808	18,786	16,918	3	2	2
14	-0,101	-0,108	-2,16	-20,158	42,802	-8,722	-2,17	27,197	-30,529	-4,734	3	2	2
15	25,679	26,53	-20,673	137,134	-84,719	-26,599	-34,535	11,507	-6,427	-61,027	1	1	1
16	-3,324	-3,438	0,36	-23,237	-9,815	-11,252	-15,41	-0,374	-12,098	-4,734	1	1	1
17	-3,324	-3,438	3,234	-31,447	-40,002	-40,316	-12,468	15,027	-50,685	8,257	2	2	2
18	-3,324	-3,438	1,897	-37,673	-50,225	-54,089	-8,79	15,206	-99,004	16,918	2	2	2
19	-3,324	-3,438	1,641	-37,741	-45,882	-47,399	-2,17	18,921	-29,533	16,918	2	2	2
20	-3,324	-3,438	3,519	-34,936	2,249	-23,919	10,335	29,673	-55,628	12,587	2	2	2

The list column 'Index' represents the consecutive number of sleep epochs, then values of derived parameters are listed. 'AllStages' contains the sleep stages obtained by the experts, according to the RK-method. The column 'Four-Stages' shows more results of those specialists; however, the categorization is divided into the stages WAKE (1), Light- and Deep Sleep (2 and 3) and REM (4). The column "ThreeStages" represents the experts' results which are categorized into the stages WAKE (1), NREM (2) and REM (3).

Regression analysis is a complex process and difficult to implement in a research project. Furthermore, algorithms have already been implemented in various programming environments [BOC18], [BR18]. Therefore, there was no need to develop completely new algorithms or implementation strategies. To achieve the goals of this project, free software and the programming language *R* (v.3.3.1) for statistical computing and graphics were utilized. The use of *R* was justified because of its ability to provide a wide range of statistical variety (classical statistical tests, linear and nonlinear modelling, time-series analysis, clustering, classification, etc.) and various graphical techniques. Also, *R* is compatible with and runs on a wide variety of UNIX platforms, Windows and MacOS [RF17]. Integration of *R* into the developed software was done using the corresponding free access libraries.

The merged derived parameter list of five files (representing 5 subject recordings) represents the training data, which then is used as a training set for the MLR model in *R*. In addition, category variables have to be set as factor variables. "Wake" was chosen as the reference category for the MLR analysis because it is the only 'stage' not included in the bigger category "Sleep" containing REM, Light Sleep and Deep Sleep stages. The *multinom* method of *R software* is used to fit the multinomial log-linear models to maximum probability estimations. Finally, the significance of the parameters can be analyzed with the 2-tailed Wald-z test [UCL18]. The most important part of this project is the *R* prediction-method, called *predict*. It requires the fitted model and the data frame to predict the probability of each stage belonging to a particular category. The predicted results are supposed to be stored in a separate .xls file.

Results

This project is focused on analysing the sleep records from the Charité clinic in Berlin[2]. In the main study, about 230 hours of recordings from the Sleep Medicine Center at Charité were analysed. The data originates from the sleep recordings of 30 individuals (the amount of male and female participants is equal) with no significant health disorders. The average age was 38.5 +/- 14.5 years old and the BMI of participants averaged 24.4 +/- 4.9 kg/m². The sleep stages of each PSG recording were manually measured in 30 second time intervals based on the Rechtschaffen and Kales method. As a result, the classification was made for three stages: WAKE, NREM and REM, and for four stages: WAKE, Light Sleep (i.e., NREM 1 and NREM 2), Deep Sleep (i.e., NREM 3 and NREM 4) and REM.

Using real data from a sleep laboratory for system evaluation can help to confirm the accuracy of the theoretically developed algorithm in a practical setting. Therefore, firstly, the results of the statistical estimations with regard to the mean and quartiles of the derived parameters were listed to show their behaviour in the 4 main sleep phases – WAKE (W), Light Sleep (LS), Deep Sleep (DS) and REM (R). In the next step, the MLR model fitting process was described. Finally, the results of the regression analysis in 3 and 4 classification categories were displayed for the provided data.

In this project, the recordings were strictly separated into the types of data – training and tests. Firstly, the recordings of five subjects were entered into the model for the Charité-dataset for the training. Then, for classification, the recordings of the remaining 30 subjects were used. Average age, height, weight and state of health of subjects in both datasets had no significant differences. At the same time, the training dataset has also covered the values with deviation (in both directions but without outlier) from the average. The male/female ratio was also similar.

The proposed first version of the algorithm was implemented for the classification of sleep stages of healthy adults. The tests also used adult subjects with no record of sleep disorder.

In total, 27,662 time intervals were recorded, each with a length of thirty seconds. The classification matrices for the Charité subjects in sleep stages 4 and 3 are shown in the Tables 4 and 5. In the end, the results for the overall classification rate were:

- with 4 stages – accuracy: 58%, Cohen's kappa: 0.50;
- with 3 stages – accuracy: 72%, Cohen's kappa: 0.67.

[2] Thomas Penzel, Dr. rer. medic. Martin Glos; initial study was carried out in Charité - Universitätsmedizin Berlin Center of Sleep Medicine Charitéplatz 1, D-10117 Berlin (Germany).

Each row of the matrix contains the rates for both the classified and misclassified time intervals. For example, the first row in Table 4 indicates that 2649 intervals were correctly classified as the phase *WAKE*. The next entry displays the 1146 intervals classified as *LS* phase, but it was actually *WAKE*, and so on.

Table 4: Classification results. Four stages.

		Stage (developed SW-System)			
		WAKE	LS	DS	REM
Stage (expert)	WAKE	2649	1146	480	219
	LS	1686	10023	1700	942
	DS	168	3041	2104	58
	REM	628	1328	151	1339

Table 5: Classification results. Three stages.

		Stage (developed SW-System)		
		WAKE	NREM	REM
Stage (expert)	WAKE	2472	1642	380
	NREM	2060	16004	1658
	REM	748	1101	1597

Tables 6 and 7 present the percentage of correct classification of sleep stages for each stage in particular. It can be seen, that in 4 stages, WAKE and Light Sleep is recognised with the highest accuracy, whereas the error rate at the Deep Sleep and REM stages is high, so an improvement in accuracy will be required.

Table 6: Correctly classified stages. Four stages.

Rights	58 %
Mistakes	42 %
WAKE	59 %
LS	70 %
DS	41 %
REM	36 %

Table 7: Correctly classified stages. Three stages

Rights	72 %
Mistakes	28 %
WAKE	56 %
NREM	81 %
REM	42 %

Discussion

Supporting sleep professionals with the help of non-invasive system for long-term sleep study in the home environment is the goal of this research. In particular, this paper discusses the software part of the system.

There are two main points, which represent the novelty of this work: the unique set of derived parameters which can be calculated from bio-vital signals and measured in a non-invasive way, and the use of multinomial logistical regression for the classification (which enables the possibility of easy algorithm adjustment – e.g. the consideration of transition patterns). The following paragraphs will elaborate on these points in more detail.

To implement an automatic sleep stage analysis and evaluation in this project, the appropriate software was developed. This program had the task of automatically classifying a sleep phase in 30 second time intervals based on the vital parameters – respiration, heartbeat and body movement signals from raw PSG recordings. Moreover, for this technique to be transferable into later studies with the sensor set mentioned above, the signals from them would not be translated with the raw values of the recordings. The goal was to create an algorithm which would present the parameter signals through the relation to parameter's average signal. The reason for the development of this method is to make evaluations which consider the differences in individuals. After the experiment was finished, the classification results were compared with the pre-estimated whole-night PSG recordings.

The core of the software is the algorithm for sleep stage recognition using respiratory, heart rate and body movement signals. The results achieved so far are the following: 58% correct recognition rate for Wake, Light (N1 and N2), Deep (N3) and REM stages and up to a 72% hit rate for Wake, NREM and REM stages. Sleep recordings of 30 subjects were used for the evaluation. The outcomes obtained are promising, but improvements are still possible and they will be developed in order to obtain results which are closer to PSG application.

There are several reasons for low accuracy of recognition in the REM stage. One of them is its similarity with WAKE sleep concerning breathing. Another more significant reason is that the REM stage is shorter than other sleep stages. Therefore, every incorrectly recognized epoch of REM sleep has percentagewise a high degree of influence on accuracy of recognition of this stage, whereas accuracy of the whole system will be less affected. Yet another reason for low accuracy of recognition is that the algorithm tends to recognise the next epoch as being the same as the previous one, if its features are similar. That being the case, since REM follows the LIGHT stage, the first "transitional" epochs are often misclassified due to the presence of similar characteristics (heart rate and breathing).

The primary result of this project is that the selection of parameters (set of derived parameters from respiration, heart rate and body movement) has proved its validity. The theoretical foundation described in the chapter State of the Art has inspired this line of thinking and the results of this study have justified it. It is important to keep in mind, that there are still conceivable improvements to be made to the algorithm which could increase the accuracy of results, but would not change the main concept. Furthermore, these parameters can be obtained in a non-invasive way with a hardware system (e.g. with sensors placed under the bed's mattress) that can be installed by non-experts, which would be important for a home sleep study system.

Reducing the amount of derived parameters by using only 3 base features (heart rate, respiration rare and movement) will not lead to significant benefit for the proposed algorithm because the calculation of derived parameters does not need a high degree of computational power.

To evaluate the introduction of respiration as a bio vital signal for sleep stage classification, the test was executed with the same dataset but without using the respiratory signal. The following results were achieved: general accuracy for WAKE/LS/DS/REM decreased to 53% and WAKE/NREM/REM to 64% (compared to 58% and 72% with respiratory signal). More importantly, the recognition rate of the REM stage diminished to about 15% for both sets of stages, which is not acceptable.

The first attempt to use the balanced proportion of classes in the training dataset was made (WAKE/LIGHT/DEEP/REM = 25%/30%/25%/20%), but the total accuracy was decreased by 2% for WAKE/LIGHT/DEEP/REM and was not significantly changed for WAKE/NREM/REM stages. Nevertheless, the increase in the recognition rate of the REM stage has indicated the potential of this approach.

The classification into three (Wake, NREM, REM) and four (Wake, Light, Deep, REM) sleep stages had to be performed according to the research goal. Multinomial logistical regression (MLR) is the classification method that was chosen here because it allows a categorical distribution of values. One dependent variable (in this case – sleep stages) has as input a set of different independent variables-parameters, and they may even overlap. More details are presented in the chapter Statistical Methods. Using MLR as a base for categorical distribution of sleep stage parameters will be used to enhance the process in the future, as it enables an easy and fast adjustment of the algorithm that depends on the requested input parameters. Even if just three bio vital signals are used in the method described, different derived parameters can be calculated when dependent variables are used in the regression model. Moreover, the adaptability of this algorithm allows for quick modifications if other bio vital signals are available for the study.

Though the selection of suitable parameters for the model was one of the challenging tasks, it has led to satisfactory results. However, some improvements are still possible, for instance the identification of other derived parameters that can be obtained in a non-intrusive way. Selection of the most suitable parameters can be proposed on the basis of theoretical research, but proof is only possible after analysing the results of numerous studies. Even with a distinguished background in qualitative analysis, it would be necessary to test the proposed set of parameters with real data in order to confirm the theoretical assumptions. The reason for this is the complexity of biological processes in the human body which have a variety of effects on bio vital signals, which can be used as inputs for the algorithm.

The consideration of transition patterns between different sleep stages was restricted to only one rule. Introducing other rules in respect to the transition matrix would increase the risk of reducing accuracy because if the previous sleep stage were incorrectly recognised, it would affect the classification of the next stages.

The strategy of this approach has been confirmed as being a highly credible method for yielding successful sleep stage classification with the help of a greatly reduced set of parameters. The number of test subjects could be increased in order to collect and evaluate a higher amount of data. For this reason, further studies with different sets of input parameters and a higher number of subjects are in planning. During the study, several possible algorithm improvements were identified, and amongst others, the implementation of *trust anchors* will be investigated. The chapter Conclusions and Future Work focuses on this and other possibilities.

Comparing the results of this work with other studies, it is important to keep in mind that input signals for the system presented here could be obtained in non-invasive way. Most of the scientific articles on sleep stage classification (e.g. [SUP17], [KAR18]) describe systems using Electroencephalography (EEG) as input. Using EEG can provide higher accuracy, but requires placing the sensors direct on the test subject's head, which would be not acceptable for a non-invasive system. Therefore, the most similar approach to use for comparison would be ballistocardiography or other methods using respiration, heart rate and movement signals as input. In [MEN10] an accuracy rate of about 0,79 was achieved, but only the classification of NREM and REM stages was determined and WAKE stage was excluded. The research system proposed here also includes WAKE stage, which explains the slightly lower total accuracy, but nevertheless provides increased usefulness as a sleep stage identification system.

Another paper [SAM14] describes an unobtrusive sleep stage classification system using a pressure-sensitive bed sheet which achieved 70% precision for WAKE, NREM and REM stages. With our system, we obtain a higher rate of accuracy and it was tested on a higher number of overnight PSG recordings (30 compared to 7).

The number of features used in [LON14] is higher (14/13 compared to 10 in our method) and the results are equal without subject-specific normalization and just about 3% better with subject-specific normalization, but as mentioned before with a higher number of included features.

In [AKT17] an accuracy rate of about 0.78 was achieved with a lower number of features. However, the proposed method can identify only SLEEP/WAKE stages, and in addition, an assumption was made to include NREM1 as a part of the WAKE stage. In the proposed in this paper method not only SLEEP/WAKE, but also WAKE/NREM/REM and WAKE/LIGHT/DEEP/REM classification is done, which is a different and much more complicated task. However, a comparison with the results from [AKT17] can be easily done using the already obtained results (having SLEEP=LIGHT+DEEP+REM). In this case even without adjusting the algorithm to recognise only SLEEP/WAKE stages, the approach presented in this paper got better results: accuracy: 0.84, sensitivity: 0.59, specificity: 0.89 and kappa: 0.46 compared to Acc=0.78, Se=0.85, Sp=0.48 and K=0.30 in [AKT17].

The fore-mentioned results and the abundant opportunities for advancement in sleep stage classification prove the potential of the concept presented here and the necessity for further research on this approach. The comparison with the state of the art articles has confirmed the quality of achieved results, having a better relation "amount of features" / "correctly classified sleep stages".

Conclusions and Further Work

The results obtained in this study (72% accuracy, Cohen's kappa – 0.67 for Wake, NREM and REM stages) prove that the algorithm developed for this project represents a truly promising method for sleep stage classification using just a few bio vital parameters: heart rate, respiration and body movement. It is also obvious that there are several ways to improve the classification algorithm. The first possibility is to define more derived parameters and examine them according to their significance in the MLR-model. For instance, the additional inclusion of sample entropy as an independent variable could potentially improve the model.

Also, the classification data could be revised in a second step. If a particular category is predicted with a lower percentage, the time intervals directly preceding and following it could be re-analysed in order to improve the overall classification rate. Besides this, the intervals which were classified with a high-confidence level could act as trust anchors. They could adjust the percentage values for the category membership of their neighbours.

Moreover, to further improve the software system, all the probabilities from the sleep stage transition matrix will be examined and two-step transitions [SCH14] will be introduced.

Furthermore, an investigation is planned to study the effect of a currently unbalanced number of samples of different sleep stages on the accuracy of the method [TIM09]. One of the possible solutions could be to consider the balanced proportion of classes (WAKE, NREM, REM) for training dataset with executing of following test classification, but this point should be deeply investigated, as the first results have indicated.

The reduction of used derived features is also planned for the future when executing studies with higher numbers of test subjects would be possible.

Another approach to the classification of sleep phases is the implementation of a multi-layer neural network algorithm with the MLR model in the first layer, though it is still questionable whether the neural network analysis would improve the classification rates. Thus, it should be considered, but thoroughly examined and scrutinized.

A perfect match of the evaluated results with the findings of a sleep medicine professional is not possible due to the R-K method's judgment standards, which include ambiguities. However, all in all it is still desirable to develop a more accurate and, more importantly, non-invasive solution for the problem of recording and estimating the sleep stages. It would help to find alternative methods which could, in time, substitute for the more complex PSG procedure.

This research is part of an intended far larger study aiming to develop a monitoring system for home-based sleep analysis. It was particularly focused on designing a software solution that can classify the sleep stages. As mentioned earlier, the ultimate goal is to obtain the signals of particular bio vital parameters via a set of pressure sensitive sensors placed under the mattresses of study subjects. This approach should presumably ensure that the sleep recording process does not disturb the sleep of the study participants. Furthermore, to get proper recordings of a natural sleep state, the subjects must feel as though they are sleeping in a normal bed in familiar conditions.

The planned system will include both software and hardware parts. The hardware portion will provide data collection and pre-processing. The data recording will be done through a set of sensors and necessary filters will be applied directly to the hardware to record movement, breathing and heart rate signals. After that the information will be automatically transferred to a server, where the software will take care of further operations. It will be processed there and analysed by the developed sleep stage algorithm. The interpretation of the acquired results has to be made by medical professionals. After completing the development and integration of all the system parts, the resulting monitoring system could provide useful diagnostic support to sleep professionals and enhance the field of sleep medicine by offering a convenient way to perform preliminary sleep studies in the home environment.

Acknowledgements

We thank the Interdisciplinary Center for Sleep Medicine of Charité Clinic in Berlin and in particular Dr. rer. medic. Martin Glos, Beate Diecker and Claudia Biro for supporting the study. We would also like to thank Agnes Klein for her help, which was very important for the development of the system.

This research was partially funded by the EU Interreg V-Program "Alpenrhein-Bodensee-Hochrhein": Project "IBH Living Lab Active and Assisted Living", grants ABH40 and ABH66.

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Digital Health and Care Study on Elderly Monitoring

Overview

The paper addresses the problem of designing sustainable home healthcare systems for the elderly. Particular focus is given to sleep analysis as one of the important parts of such systems.

Context

This publication was prefaced by multiple scientific publications in the area of "Healthcare Technologies" and active participation in several international projects on the given topic. Practical experiences from the projects and knowledge obtained from in-depth research have resulted in this publication. The findings of a study carried out within the framework of the international project "IBH AAL: Home Health Living Lab" were evaluated and scientifically supported. The research stays in Ancona (Italy) and Seville (Spain), among others, have provided essential knowledge that has been crucial in the implementation of this research.

Journal information

A Special Issue "Sustainable Technology and Elderly Life" of the Journal "Sustainability" was selected for the submission of this paper due to the relevance of the topic "Elderly Healthcare". This journal is indexed in JCR with the current Impact Factor of 3.251, and its ranking for the last five years is presented in the following Table.

Category	*Environmental Sciences*		*Environmental Studies*		*Green & Sustainable Science & Technology*	
JCR Year	JIF Rank	JIF Quartile	JIF Rank	JIF Quartile	JIF Rank	JIF Quartile
2020	124/274	Q2	59/125	Q2	6/9	Q3
2019	120/265	Q2	53/123	Q2	6/8	Q3
2018	105/251	Q2	44/116	Q2	3/6	Q2
2017	121/242	Q2	51/109	Q2	3/6	Q2
2016	119/229	Q2	47/105	Q2	4/6	Q3

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Digital Health and Care Study on Elderly Monitoring

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Abstract: Sustainable technologies are being increasingly used in various areas of human life. While they have a multitude of benefits, they are especially useful in health monitoring, especially for certain groups of people, such as the elderly. However, there are still several issues that need to be addressed before its use becomes widespread. This work aims to clarify the aspects that are of great importance for increasing the acceptance of the use of this type of technology in the elderly. In addition, we aim to clarify whether the technologies that are already available are able to ensure acceptable accuracy and whether they could replace some of the manual approaches that are currently being used. A two-week study with people 65 years of age and over was conducted to address the questions posed here, and the results were evaluated. It was demonstrated that simplicity of use and automatic functioning play a crucial role. It was also concluded that technology cannot yet completely replace traditional methods such as questionnaires in some areas. Although the technologies that were tested were classified as being "easy to use", the elderly population in the current study indicated that they were not sure that they would use these technologies regularly in the long term because the added value is not always clear, among other issues. Therefore, awareness-raising must take place in parallel with the development of technologies and services.

Keywords: home health systems; sleep monitoring; sustainable technologies; technology acceptance

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Citation: Gaiduk, M.; Seepold, R.; Martínez Madrid, N.; Ortega, J.A. Digital Health and Care Study on Elderly Monitoring. *Sustainability* **2021**, *13*, 13376. https://doi.org/10.3390/su132313376

Academic Editors: Ana Iglesias, Jorge Morato, Sonia Sanchez-Cuadrado, Fernández Panadero María Carmen and Mihajlo (Michael) Jakovljevic

Received: 14 October 2021
Accepted: 24 November 2021
Published: 2 December 2021

1. Introduction

According to the United Nations, technologies are one of the enablers of achieving sustainability objectives around the world [1]. Concerning the health monitoring of the elderly, new technologies can provide new ways to improve the quality of life for these people without worsening conditions for future generations, which is the goal of sustainable development. In recent years, there has been a steady evolution of home health systems, with a concurrent increase in understanding that sustainability is essential for the development of new systems [2]. Among the reasons for this is that they are able to provide several benefits to different user groups. For example, home health technologies could be used in rural areas where traditional healthcare providers are more challenging to reach. This could lead to decreasing the necessity of travelling to hospitals/family doctors, resulting in resources being saved. These types of technology could be especially beneficial for the older generation. As a result, they could serve to increase the quality of life of this population [3] and could also simultaneously reduce inequality, which is one of the goals stated by the United Nations [1].

Furthermore, home health technologies could be used, for example, to continuously monitor the health conditions of older people in their home environment [4]. This could result in people staying in their own homes longer rather than moving to an assisted environment, as described in reference [5]. According to the United Nations, this would help to overcome economic and social challenges, which is also one of the sustainable development goals set by the United Nations [1].

The topic of sustainable technologies for the elderly has seen significant developments in recent years, as described in reference [6]. In that study, scientific publications in this domain were analysed, and the conclusion that was drawn indicated that technologies for the elderly can, among other things, improve connections with society and health professionals but could also enable the early detection of health problems and could enhance wellbeing.

Another paper [7] describes digital services in relation to the sustainability of elder care. It also concludes that technologies can provide many benefits if used appropriately. However, it is not always necessary to develop and use new technologies because older technologies can be used in new and innovative ways in certain cases.

There are already numerous devices on the market that can be used to measure various biomedical or health-related signals and values in patients, including, for example, heart signals, blood oxygen saturation, respiration, muscle movement, temperature, falls, and sleep patterns [8,9]. To date, these devices and their associated applications have only been used to a limited extent for various reasons. In practice, it is apparent that assistive technologies face a multitude of barriers [10]. They usually only offer isolated solutions: each device often has its own app and data collection method. There is great potential for these technologies if they choose to use integrated data (fusion of data), which is hardly the case at present.

However, the barriers to these types of applications are not only technological or business-related. Two other aspects play a significant role: first, the user has to consider about data protection: how are the data transmitted and stored? Specifically, how are they stored and used in the data centre (in the "cloud" of the service providers)? How can privacy be protected through anonymization or pseudonymization, if necessary, but how can they also serve the advancement of science? Particularly, these questions represent a major cross-border challenge, as they are heavily dependent on national legislation.

On the other hand, current devices and systems do not always consider the aspects of user-friendliness sufficiently (both in terms of usability and user experience) [11–16]. These systems need an intuitive concept of use, often not only for the patient but also for his or her social environment or (informal) caregivers, patient groups, or other social groups. This is organized and perceived differently in different countries and therefore represents a further challenge. The accessibility of technologies is another significant point to consider [17].

Numerous scientific publications have dealt with the topic of the technology acceptance model to answer the question of which aspects of implementation and use lead to an increase in acceptance [18,19]. The results of this research should provide a scientific basis for planning how certain technologies are used.

The presented work focuses on a conceptual home health system that emphasizes certain health domains that can be implemented with AAL approaches. Stress and sleep are the baseline health phenomena for the analysis of technologies. The choice of areas is not arbitrary and is justified by their relevance. Stress is perceived as an extreme burden by up to 30% of the population; it leads to serious chronic diseases or is prevalent in many cases [20]. It is known that a large proportion of sleep disorders is related to stress, some of which are already chronic, and only 35% of US citizens describe their sleep quality as being "good", while 22% describe it as "moderate", and 12% describe it as "poor" [21]. Furthermore, obstructive sleep apnoea is believed to affect approximately 936 million people between the ages 30–69 years old worldwide, according to an AHI criterion of five or more apnoea events per hour and the AASM criteria [22]. Many sleep disorders, such as sleep apnoea, could be detected with a home sleep monitoring system, allowing early therapy and ultimately enhancing health and quality of life [23,24]. Other sleep disorders, particularly in the elderly, are increasingly recognized as essential challenges, and methods for overcoming these problems are being investigated [25]. To improve personal well-being, various rehabilitation techniques could be used preventively or therapeutically. The effect of rehabilitation could, in turn, provide indirect or, in some cases, direct feedback through the measurement of stress and sleep parameters [26].

The importance of the selected topics is also confirmed by the presence of other publications such as [27], where systems that are not only able to monitor stress and sleep but that are also able help users in the struggle against stress and poor sleep quality are described. In this work, the system design is described in detail, and an evaluation is performed with eight subjects, the results of which demonstrated positive feedback from the users as far as the system's usability is concerned.

To be successful and user friendly, sustainable health services should be universal and should accompany the patient or user through the entire cycle: counselling, planning, implementation, operation, and support. People are in charge of providing such services, and AAL technologies support and offer those services. Fairness, non-discrimination, and user acceptance strongly influence the sustainability of solutions, but cost-effective implementation and pricing models and transparency also play an important role [28].

The main objective of the present work is to find out which aspects play an important role in the development of health monitoring systems for the elderly to enable their sustainable use as well as the simultaneous increase of user acceptance. To facilitate 24 h monitoring, two types of devices were selected for assessment: one that can be placed in the bed to monitor vital signs during the night, and another that is worn on the arm to measure heartbeats during the day. General and as well as device-specific recommendations should also be drawn up as best they can. Another important research question to be clarified is whether existing home health technologies (objective measurement) can ensure a sufficient level of accuracy in the recording and analysis of health parameters compared to the sleep medicine questionnaires (subjective measurement) that are commonly used in multiple areas in measuring, for example, sleep quality. Another objective is to investigate whether older people are in favour of the use of sustainable technologies if the relevant aspects are taken into account during their implementation.

2. Materials and Methods

Because the objectives of this work can best be achieved through an evaluation of practical implementation, conducting a field study with a subsequent analysis of the results was chosen as the primary approach. In the following subsections, the general study design is first presented in detail, followed by an explicit description of the methods used to address study queries. It is important to mention that the presented domain "Sleep" was analysed both quantitatively and qualitatively, whereas the domain "Stress" was included exclusively in the qualitative measurement. For this purpose, a device was used that represents, by example, the group of devices for cardiac activity measurement that can also be used for stress measurement after the appropriate analysis, which is explained in more detail in the last subsection of the "Materials and Methods" section. However, direct stress measurement was not carried out in the context of the described study. This has led to differences in the level of detail in the description of these two areas.

2.1. Study Design

Since a specific target group was identified for the study, the following inclusion criteria were elaborated for application in the selection of study participants:

- Age over 65 years old.
- Most of the household work is completed independently.
- In addition, the following exclusion criteria were considered:
- Unable to perform leg training seated with an exercise trainer for about 20 min for a maximum of 10 days over a two-week period.
- Unable to stand up, walk 3 m, walk back 3 m, and sit down again without the active assistance of another person.
- Unable to understand and complete paper format questionnaires.

- Advanced dementia.

A group of 10 individuals (five men and five women) participated in the study. One of them lived in a residential community for older adults, and nine others lived in their own homes. The mean age of the participants was 72.5 years age, with a standard deviation (SD) of 6.2. The mean weight of the study participants was 80.8 kg (SD = 12.6), while the mean height was 167.6 cm (SD = 7.9).

To the best of our knowledge, the study participants did not have severe acute illnesses. They received all of the study information in advance (for example, a detailed description of the procedure, study objectives), and participation was voluntary and could be terminated at any time without giving a reason. All of the study participants received a written consent form, and the participants read and signed a data protection form after the study organizers had answered any remaining questions. The study procedure, including study information and consent forms, was reviewed by ethics officers from the HTWG Konstanz and the University of Applied Sciences Kempten, Germany.

The expected duration of the study was 14 days. On the first day, the study organizers installed and explained all of the necessary technical solutions in the participants' homes:

- The sleep monitoring device was placed under the mattress across the bed. According to the device's instruction manual, its position should be approximately below the chest area, as described in reference [29].
- The device for monitoring the heartbeat was put on the arm of the test person, and the organizers explained how to use and charge it.
- A third hardware element was installed at the subjects' homes to ensure that the used devices had proper Internet connectivity through an access point with an Internet-capable sim card. Therefore, the system was able to function autonomously and was not dependent on the Wi-Fi network of the test subjects.

Furthermore, interviews with general questions (age, sex, height, weight, and health status) were also conducted on the first day of the study. Any possible questions about the study procedure or the use of the equipment were also answered. To conduct the study as realistically as possible, the subjects were asked to continue with their regular daily routine and to contact the organizers only if they had any questions or problems. The questionnaires to be completed every day were explained and given to the subjects:

- Sleep diary.
- Graphical questionnaire on sleep quality.

The participants used the devices for 14 days. During this time, they were visited every 3–4 days by one of the study organizers (public welfare AWO staff) to check if everything was going well or if there were any problems or questions.

On the last (15th) day of the study, the study organizers collected the technical solutions, and the final questionnaires were filled out together with the participants in the form of an interview:

- Pittsburgh Sleep Quality Index.
- Questionnaire to assess the acceptance of the technologies used, including free-form comments.

All the devices and questionnaires mentioned above are presented in detail in the following sections.

2.2. *Subjective and Objective Measurement Using Home-Health Technologies*

As mentioned above, one of the study's objectives was to determine whether existing technologies can guarantee results that are sufficiently accurate compared to health-related questionnaires. For this purpose, sleep analysis was selected as an essential health field that can also be monitored in a home environment [30]. There are two significant types of measurement for sleep-related data: objective and subjective [31]. In the case of subjective measurement, the person's perception is measured. Typically, different questionnaires or sleep diaries are used for this purpose [32]. In objective measurement, health-related values are measured with the appropriate sensors [33].

In sleep medicine, subjective measurement is often used to measure some parameters, such as sleep quality in the detection and treatment of insomnia [34]. Therefore, it was essential to determine whether an objective measurement was able to provide results that were comparable to subjective measurement. For this purpose, we compared the two types of measurement over two weeks [31]. We asked the test subjects to fill out a daily questionnaire determining their sleep quality for subjective measurement. For this, we prepared a graphical representation of sleep quality, as shown in Figure 1 [31]. Subjects were asked to mark the spot on the graph that best corresponded to their perceived sleep quality each morning. After collecting the completed questionnaires, the graph was divided into ten sections, and a number between 1 and 10 corresponding to sleep quality was derived.

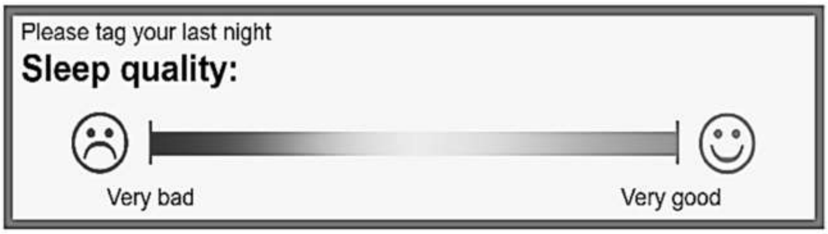

Figure 1. Graphical questionnaire to determine sleep quality. Reprinted with permission from Gaiduk et al. (2021). © Springer 2021 [31].

The technology that was used to measure objective sleep quality was the EmFit QS+ system [35]. This device has been described and evaluated in several scientific publications [36,37]. It uses a ballistocardiography approach and can measure several sleep-related parameters (such as heart rate, respiratory rate, sleep quality, and identification of sleep stages). One of the important points that was considered when selecting the technology was the possibility of automatic functioning without the need for user action. The following formula, Formula (1), which proposed by the EmFit company and evaluated in several scientific publications, was used to calculate sleep quality [31,35–37]:

$$\begin{aligned} \mathit{Sleep\ Quality} = {} & [(\mathit{total\ sleep\ duration} + (\mathit{duration\ of\ REM} * 0.5) + (\mathit{duration\ of\ DeepSleep} * 1.5) \\ & -8.5 * (0.5 * \mathit{awake\ duration}\ /\ 3600 + \mathit{number\ of\ awakenings}\ /\ 15)]/10 \end{aligned} \tag{1}$$

The result is a value between 0.1 and 10, which can be directly compared to the subjective measurement of sleep quality described above. We conducted and finally evaluated the recordings with the selected device for the two weeks of the study, which is described in detail in the "Results" section. Any other system that provides a measurement of sleep duration [38] and sleep stages [39] could be used instead of the device used to calculate objective sleep quality.

The use of technologies for the subjective measurement of health-related parameters is also possible. For this purpose, technologies (for example, smartphones, smart watches, or tablets) can be used to fill in the questionnaires [40,41]. This can bring advantages in achieving direct and automatic data transmission and evaluation because of the electronic form of the data collected from the first moment. However, this approach was out of the scope of the study performed and could be considered in future work.

We selected sleep analysis as an example field of home health technologies for the study. To address whether this field is relevant for determining health status, we decided to use a recognized method for determining sleep quality. This would allow us to determine if there is an underdiagnosis of sleep-related disorders that could be overcome with the broad approach of sustainable technologies. Our method of choice was the Pittsburgh Sleep Quality Index (PSQI) [42]. It is commonly used for the assessment of sleep quality in sleep disorders, especially insomnia. This is a recognized questionnaire in professional circles and has undergone multiple evaluations [43,44]. We used a German version of the questionnaire proposed by reference [45].

Standardization in the true sense does not exist for the PSQI. PSQI classification results from the cut-off value of 5; it was calculated in the original work [42] based on the classification of people with sleep disorders and healthy individuals. A total of 18 items are used for quantitative evaluation. They were assigned to seven components, each assuming a value range from 0 to 3. The total score results from the summation of the component scores and can range from 0 to 21. A higher score corresponds to a lower quality of sleep. There is an empirically determined cut-off value (of 5) that allows a division into "good" and "bad" sleepers. A representative study for the German-speaking area [46] surveyed 1049 participants. Here, a proportion of 32.1% of the participants had a PSQI total score > 5. This survey might be used to compare the findings within our study.

2.3. *Acceptance of Technologies by the Elderly*

Since the acceptance of technologies plays an essential role in their widespread use, this aspect was addressed in the study. Based on the literature review, several points were selected to be considered during the implementation period in order to enable an evaluation afterward:

- The technologies should be self-explanatory and should not require extensive training.
- The devices should function automatically as much as possible;
- The devices should be comfortable and safe to use.

To allow a comprehensive analysis, the following methods were selected:

- Surveying with a questionnaire.
- Free conversations with test participants to receive unstructured feedback.
- Systematic analysis of occurrences and irregularities during the study.

In preparing the questionnaire, an emphasis was placed on ease of use, safety during use, and readiness and suitability of the technologies for regular use. It was also planned to analyse whether there were any difficulties with the use of the devices and the reasons for those difficulties. For this purpose, in addition to answering the standardised questions, the test subjects were asked to provide a free comment (related to the respective device) in case of irregularities/problems with one of the devices being used. Questions were asked during the visits that took place over the 14 days and on the last day, together with the final questionnaire.

To evaluate the acceptance of technologies for different health-related concerns, the system was used that not only included the EmFit QS+ sleep analysis device described above but also included the Polar OH1 heart rate monitor. This kind of device (photoplethysmography based on PPG) can be applied to measure stress levels, which was not performed as part of the presented study. Currently, heart rate variability is often used to detect stress [47,48]. However, existing studies have shown that heart rate variability may be often substituted by pulse rate variability (which can be obtained by PPG measurement), especially at rest [49]. Moreover, some studies have presented the possibility of stress detection by analysing pulse rate variability [50]. However, it is important to note that the Polar OH1 device in this study was used exclusively for qualitative and not quantitative measurement and should only represent a wearable that should be placed on the upper or lower arm and that could be used for stress measurement after appropriate analysis. During the study, the OH1 was to be placed on the right upper or lower arm daily for a fortnight. When the sensor was close to the provided smartphone with the app installed and when new data were available, it paired with the application, and the data were collected for future analysis. The test subjects only had to place the sensor on the upper arm and turn it on by pressing a button. It was also necessary to charge the sensors at night. No other actions were required from the test subjects.

3. Results

After the quantitative analysis of the sleep measurement as well as the qualitative analysis of the devices for both the sleep and heart rate measurements were conducted, a set of results was obtained, which are presented below.

The difference between subjective and objective sleep quality measurement was analysed. Figure 2 shows a corresponding box plot diagram for the ten participants. The vertical axis represents the average differences between subjective and objective measurement for all of the subjects who participated in the study. We can see a clear tendency to underestimate subjective sleep quality compared to the value measured with the electronic device. This underestimation remains relatively stable, with a median value of approximately 13% and a mean value of approximately 10%. However, there are also individuals for whom the difference between objectively and subjectively measured sleep quality is notably more significant. This fact should be taken into account when planning the use of technologies to measure sleep quality. For two subjects, there are significant differences in the number of objective and subjective measurements available. For these subjects in particular, there can be discrepancies in the evaluation of the differences between the subjective and objective measurement, which can also lead to some variation in the results. With the total number of available recordings (115–objective and 90–subjective), it is nevertheless to be assumed that the results are also transferable to the overall population, which is also confirmed below with the calculation of margin of error.

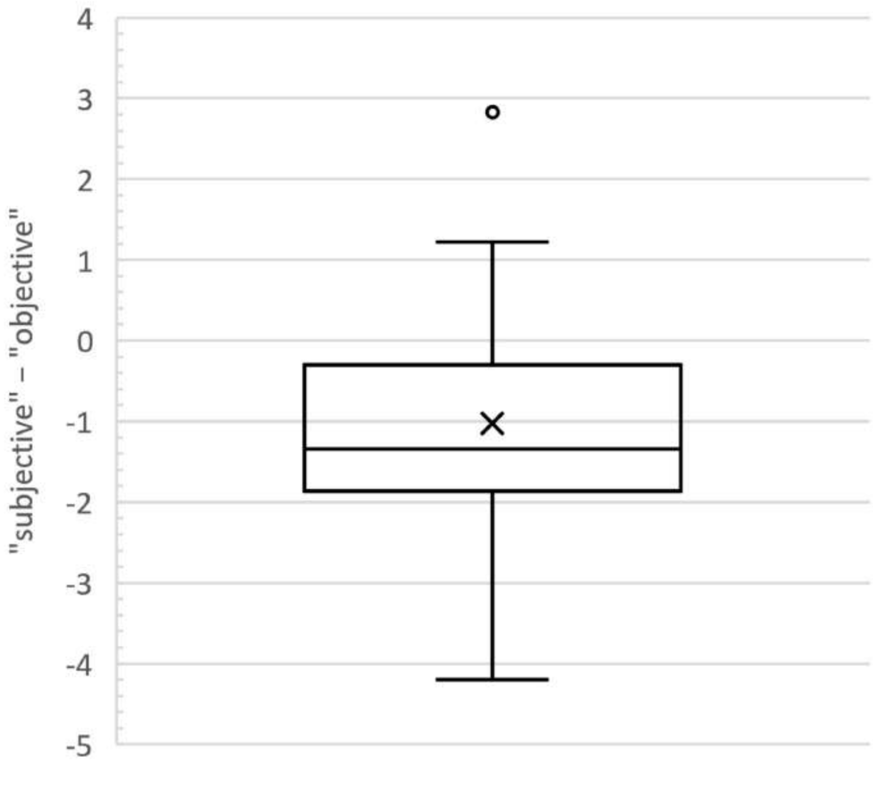

Figure 2. Analysis of the differences between objective and subjective measures of sleep quality for ten subjects. Negative values—subjective sleep quality is underestimated.

To give an idea of the possible differences between objective and subjective measures of sleep quality, the comparison of the measured values (possible values are in the interval from 1 to 10) for a subject with the most significant differences participating in the study is shown in Figure 3.

It can be seen that the median value of sleep quality for the total two-week study period is more than twice as high for the objective measurements taken with the help of an electronic device (approximately 9.2 points of sleep quality) than it is for the subjective measurements taken with the questionnaire (approximately four points of sleep quality). When analysing these results, one can identify two main reasons for this difference: firstly, if there is a large difference between the number of recordings available for both (objective and subjective) measurement methods, then there is more a likelihood that the difference that is measured is greater; secondly, since different parameters are measured in the objective and subjective measurements, the perceived sleep quality may differ significantly from the measured one because measurement with a device cannot take into account all aspects that have an impact on human perception. People typically do not divide sleep quality into the sum of parameters but perceive an overall impression.

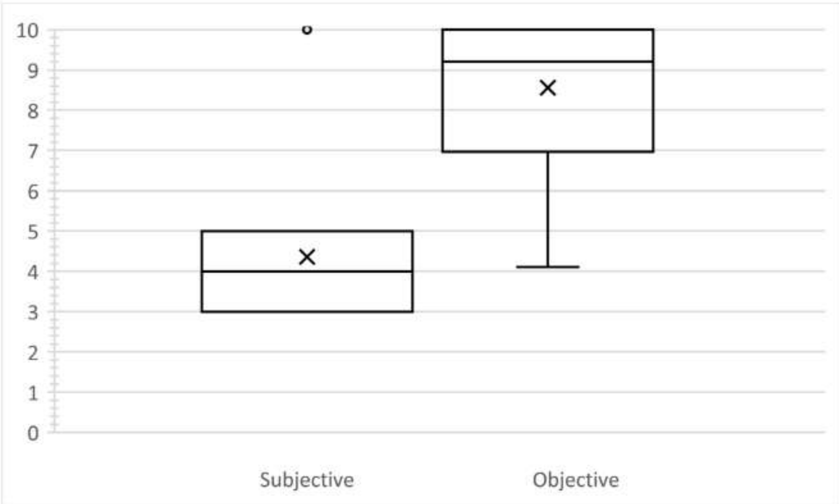

Figure 3. Comparison of subjective and objective measurements for a subject with the most significant differences between two measurement methods.

The results of the PSQI survey are shown in Table 1. From this, it can be seen that there were significantly more people identified themselves as "bad" sleepers than in the previous study reported in reference [46]. There may be several reasons for this, such as:

- The study by reference [46] analysed a broad demographic. In our study, only subjects over 65 years of age were included. Therefore, the results may differ significantly due to the different age groups.
- About 20 years has passed between the study conducted by reference [46] and our study. During this period, the prevalence of sleep-related disorders may have been changed.

Table 1. PSQI screening results.

PSQI Value	Percentage
≤5	40%
>5	60%

The results of the interviews that were conducted at the end of the study are presented in box plots in Figures 4 and 5. Furthermore, the results are analysed and discussed in the following text.

As a result of the analysis of the box plots in Figure 4, the following conclusions can be drawn:

- There was no agreement among test participants on whether they would use the devices regularly. It should be noted that the devices were used over a two-week period, which, among other things, means that the subjects did not have long-term experience with the devices and therefore could not assess whether they would use the devices regularly in the long term well.

- The questions regarding the complexity of the devices, ease of use, and the need for support to use the devices, there is a clear trend in the answers, which is more in favour of the devices being relatively easy to use independently without external support. Moreover, despite the novelty of these types of devices for the subjects, no unnecessary complexity was perceived. According to the technology acceptance model, these points indicate that the proposed concept can increase acceptance [51].

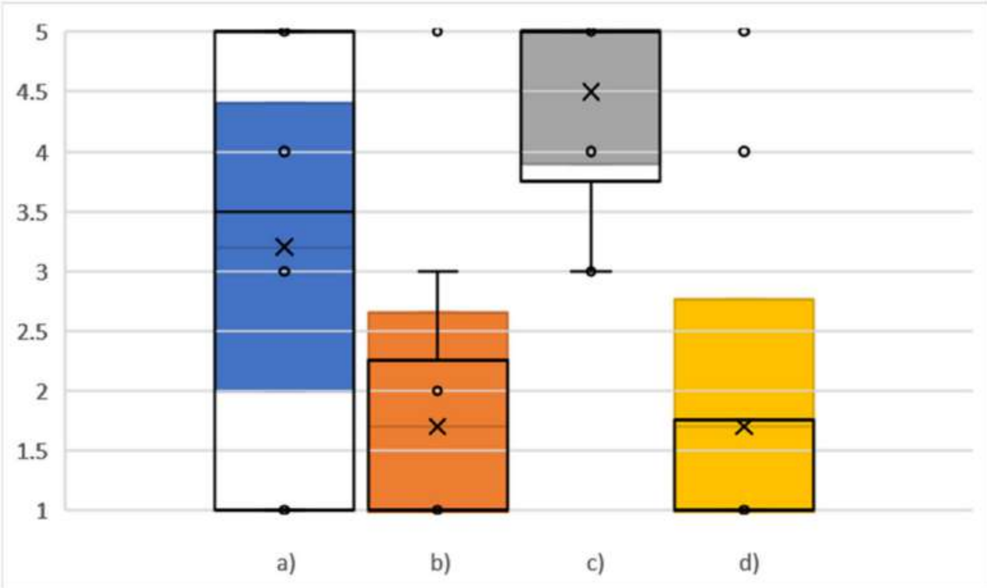

Figure 4. Box plot of the interview results. 1—totally disagree, 5—strongly agree: (**a**) I can imagine using the devices regularly. (**b**) I find the devices to be unnecessarily complicated. (**c**) I find the devices easy to use. (**d**) I think I would need technical support to use the devices.

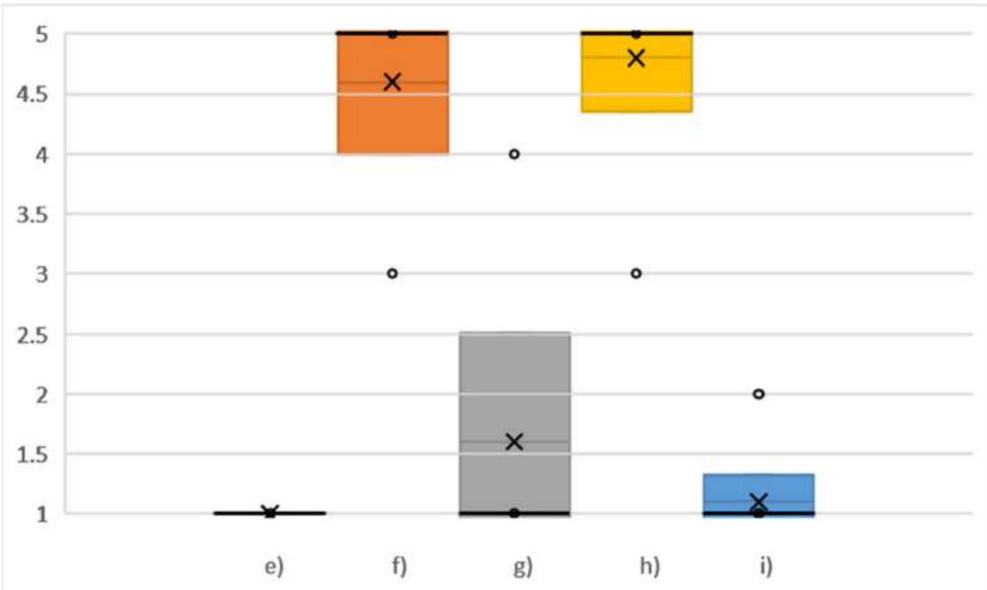

Figure 5. Box plot of the interview results. 1—totally disagree, 5—strongly agree: (**e**) I find that there are too many inconsistencies in the devices. (**f**) I can imagine that most people learn to handle the devices quickly. (**g**) I find the operating of the devices very complicated. (**h**) I felt very safe using the devices. (**i**) I had to learn many things before I could handle the devices.

Analysing Figure 5, one can see that at several points, an obvious conclusion can be drawn that:

- The subjects do not believe that there are too many inconsistencies (confusing or unclear functions or components) with the devices utilized.
- According to the subjects' opinions, the majority of people can quickly learn how to handle the devices.
- The operation of the devices is not very complicated according to the subjective perception of the test participants. However, it should be noted that several people noticed some irregularities in the functioning of the proposed devices, which are described in detail below.
- There was no concern about safety while using the equipment. This means that the perceived risk of using the technologies was relatively low, which according to references [52,53], is essential for the acceptance of technologies.
- It was possible to use the devices without having to learn much new information beforehand. In summary, from the answers to question (e), question (b), and question (c), it can be concluded that the presented concept, where the subjects had to interact with the devices as little as possible, gives a sense of simplicity to users, which can also lead to an increase in the acceptance of such systems [54–56].

When interpreting the results obtained from the surveys, it can be said that the two-week study periods provided the test subjects with sufficient information to be able to assess the ease and safety of using the devices, which can be seen from the fairly clear answers. On the other hand, the strong variance and tendency towards "not sure" in the answers to the question of whether the test participants could imagine using the devices regularly shows us that a significantly longer period of use or familiarization is necessary in order to obtain a clear answer to this question.

Another point that can be observed is the fact that there is at least one outlier in the majority of answers to the questions. There may be different reasons for this. One of them is that it is possible that some questions were misunderstood, resulting in a reverse answer being given. For example, instead of "strongly agree", the answer becomes "strong disagree". This could be caused by the fact that some questions deliberately include two variants in questionnaires to make sure that people answer the questions consciously, the so-called control mechanism. In individual cases, it can lead to misunderstandings or show us that people answer some questions without understanding them precisely. In general, however, it helps to exclude the questions that are not carefully considered by the participants before answering to be excluded from the analysis. Another explanation for the presence of the outliers could be the fact that the individual rare occurrences with the devices, which only happened to a single person, led to this being very distinct from the majority opinion. This could be, for example, a technical malfunction that only occurs once to one person.

A total of 10 participants participated in the study due to the targeting of a specific group of users and the use of not only questionnaires but also the use and installation of the hardware for several devices to be used over a fortnight. Considering this fact, the question arises as to whether the difference to the expected results by the entire population would differ greatly. This point needs to be subject to deep scientific discussion in order to make a well-founded statement. In the following, this question is analysed and supported by statistical evaluation.

To forecast a maximum possible deviation between the results of a study carried out with a sample (ten people in our case) and the entire population, the parameter called "margin of error" is typically used. We have also followed this scientifically recognized approach. According to references [57,58], we calculated the value of the margin of error for each question. For that, (2) was used:

$$d = t\sqrt{\frac{N-n}{N-1}}\sqrt{\frac{S^2}{n}} \tag{2}$$

where t is the Student's t-critical value for normal distribution, N is the size of the population, n is the sample size, and S is the population standard deviation.

Considering the fact that the population size is substantially larger than the used sample size, $\sqrt{\frac{N-n}{N-1}}$ tends towards «1». Due to the impossibility of calculating the standard deviation of the entire population, S can be replaced by s (standard deviation of the sample). Taking into account the mentioned factors, Equation (1) can be transformed as follows:

$$d = t\frac{s}{\sqrt{n}} \tag{3}$$

The t value for the sample size of 10 with 9 degrees of freedom and for the significance level α = 0.05 (for the confidence level of 95%) can be found in the corresponding table and is equal to $\pm$2.262156 (two-tailed). Knowing this, the margin of error for every question was calculated with Equation (2).

The results with a confidence level of 95% are presented in Table 2. The possible range of a mean value for the entire population according to the calculation of the margin of error is represented in Figures 4 and 5, with a coloured rectangle representing each question. Analysing that, even in the case of the maximum possible deviation of the mean value for the entire population from the sample mean according to margin of error calculation, for all of the interview questions except for "I can imagine using the devices regularly", the values still indicate clear agreement or disagreement with the corresponding question, which was also the case for the sample from the current study. This is due to the fact that the responses are very homogeneous and provide us with a clear picture, even with the available number of test persons. Out of that, taking into account the performed margin of error calculation, the results of the study conducted with 10 subjects may be extrapolated to an entire elderly population and can provide a significant scientific added value due to the clear and explicit distribution of the responses. Therefore, it can be stated that no meaningful difference in the results is expected in cases where the study is performed with a large sample size, even for the entire population.

Table 2. Margin of error calculation.

Measure	Question								
	(a)	**(b)**	**(c)**	**(d)**	**(e)**	**(f)**	**(g)**	**(h)**	**(i)**
SD	1.6865	1.3375	0.8498	1.4944	0.0000	0.8433	1.2649	0.6325	0.3162
Mean	3.2000	1.7000	4.5000	1.7000	1.0000	4.6000	1.6000	4.8000	1.1000
Sample standard error	0.5333	0.4230	0.2687	0.4726	0.0000	0.2667	0.4000	0.2000	0.1000
Margin of error	1.2065	0.9568	0.6079	1.0691	0.0000	0.6032	0.9049	0.4524	0.2262

Similarly, the margin of error value can be calculated for the obtained difference between objective and subjective measurement. Performing the calculations according to (3), the margin of error for this measurement with 10 subjects is equal to 1.35, which means that for a 95% confidence level, the mean value of difference for the entire elderly population would be within the interval −2.37–0.33 (−1.02 for the sample of 10 subjects). This means that even in the case of the maximal possible deviation of the mean value of the difference between the objective and subjective measurement, there will still be a clear correlation between these two methods of measurement for the entire population, and the difference will be between 3.3% and 23.7% (0.7–21.1% for a 90% confidence level). This allows one to extrapolate the results of the study conducted with 10 subjects to the entire elderly population with the confidence level mentioned and by considering possible deviations. Based on a statistical evaluation performed using the margin of error calculation, the study results with 10 subjects provide high qualitative and scientifically significant results. It is also important to mention that although only 10 subjects participated in the study, the total number of test nights for the calculation of the difference between subjective and objective measurements was equal to 140, which is a significant number and also increases the reliability of the results that were obtained, as the exact number of evaluation nights (and not only the number of subjects) is relevant for the calculation of the differences between the two types of measurement.

Although the survey results have shown that test persons see the proposed technologies as easy to use, some irregularities can be observed when analysing the available recordings. As shown in Table 3, neither for the objective measurement nor for the subjective measurement of sleep quality are all recordings for all 14 days of the study available.

Table 3. Availability of measurements per person (study duration—14 days).

Measurement	**Subject**									
	1	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**
Subjective	8	10	14	9	11	13	7	7	5	6
Objective	7	6	14	14	14	14	9	10	13	14

If we visualize the number of available recordings as in Figure 6 and analyse them, we can see significantly more recordings with the objective method. This is because the test participants did not have to make any extra effort. After all, the device automatically took recordings. In the case of subjective measurement, the subjects had to tag a perceived sleep quality on their own. However, even in terms of the objective measurements, there were some days where there were no recordings. According to the interviews that were conducted, there were two main reasons for this: the subject did not sleep in the bed that night, or the device was turned off from the power socket, which was not necessary but allowed. Sometimes, as the subjects self-reported, they forgot to plug the device back into the socket before going to bed.

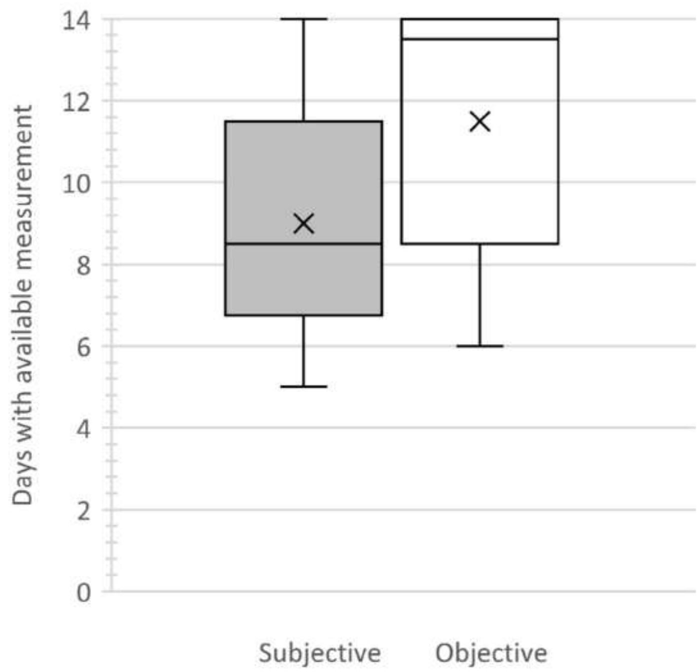

Figure 6. Box plot representing the number of days with available measurements for all subjects for both approaches.

There was only one person who filled out the questionnaire on all 14 days. All of the device recordings were also available for this person. Furthermore, although the questionnaire was created, there was an attempt to make it as simple and as motivating as possible. That is why the graphic form was chosen. It follows that the more effort a method requires from the user (even if it is minimal), the more incompleteness there will be in the data collected.

It is important to address the fact that there is a certain imbalance between the number of objective and subjective measurements in order to assess whether this led to a distortion of the results when evaluating the differences between the objective and subjective measurements presented above. We have a total of 115 nights for the objective measurement and 90 nights for the subjective measurement, which corresponds to a difference of only about 20%. For the majority of people, there are more objective measurements than subjective ones. However, it is important to note that there are also people who have more subjective measurements than objective ones, which means that the differences in evaluation can exist in both directions, but this affects the overall evaluation less than a one-sided shift in the number of measurements. Since the total number of nights is significant (as there is an imbalance exactly in the number of night measurements and not in the number of subjects) in our study and since the evaluation is already statistically significant both at 90 and 115 nights independently, it can be assumed that this imbalance only plays a minor role in the overall evaluation. Another important point is that the difference in the number of subjective/objective measurements is relatively small for most subjects. Only in two subjects (9 and 10) are significant differences present in the number of objective and subjective measurements. These two subjects are mainly responsible for the imbalance (18 out of 25 nights of total difference). With these subjects in particular, there are indeed discrepancies in the evaluation. However, the overall evaluation should remain statistically significant.

Another important finding is that 50% of the test subjects noticed anomalies in the functioning of the home health devices. After a detailed analysis of these reports, it turned out that the main reason for this was the Polar OH1 heart rate measurement device. There were two main problems with it:

- Firstly, the switching button was tiny and partially placed in the device's body. This made it difficult for the subjects to press the button, especially when their fine motor skills were not perfect.
- The second problem was the lack of direct feedback from the device. Therefore, the test subjects did not immediately recognize whether the device was already switched on or not. After evaluating the test results, we found that several recordings were only a few seconds long. This means that the subjects switched on the device, but because they were unsure whether it worked, they tried to switch on the device again, which eventually led to the device being turned off.

It is important to note that the evaluation mainly tried to cover the general points that would also be transferable to other technologies, e.g., the automatic functioning of the system without the need of user actions or the need for feedback from the device will be equally relevant for other technologies. Nevertheless, it is not excluded that, in case of using another system, there may be some differences, which are also listed further in limitations.

4. Conclusions

The study allowed us to collect and analyse relevant data on the use of technologies for older adults. Several conclusions that provide new information to the scientific community can be drawn from the evaluation and are presented below.

One of the questions to be addressed in the study framework was whether an objective measurement with an electronic device could replace a subjective measurement of sleep quality, which is typically conducted through the use of a questionnaire. The analysis that was carried out confirms the possibility of this substitution when it comes to evaluating the sleep quality of a group of people and when the overall average result is of interest. For example, it could be used to conduct a comprehensive study of sleep quality in a region or among a specific subset of people. Considering the accuracy obtained for each person, a substitution is not recommended because it has been shown that the differences between the two measurement methods may be extreme in some infrequent exceptional cases. It is important to note that the results of the study do not mean that a subjective measurement will produce more accurate results. It only means that in some people, the results will differ significantly, and in the practice of sleep medicine, a subjective measurement of several sleep parameters has been the most commonly used method (e.g., for the detection of insomnia [59]). Therefore, this method is a standard procedure, and because it has been used for such a long time, health care professionals have a great deal of experience in evaluating and interpreting these kinds of measurements. For some other measurements, objective measurement methods are used in sleep medicine, for example, for the detection of sleep phases [60]. Therefore, a combination of subjective and objective measurements can currently be recommended to obtain a comprehensive analysis of sleep that includes its different characteristics.

Another critical point examined in the study is whether the elderly are comfortable with the existing technologies for measuring health-related parameters and which aspects should be considered when implementing home health systems.

The concept of implementing the technologies created for the study had a few key points:

- The use of devices that required minimal action on the part of the users. For example, no actions are required except (voluntary) for the unplugging and subsequent re-plugging of the sleep analysis device into the power socket. In the case of the device measuring heart rate during the day, only pressing a button was necessary, and the evaluation of the study showed that even this minimal necessary action led to problems. A possible solution would be to use a device with a more prominent and easier-to-use button to turn it on.
- The technologies should be self-explanatory, and no complex training or support from a third person should be necessary. This goal was achieved according to the results of the interview, as explained in detail below.
- When using electronic devices, there should be a sense of safety. This means that the devices should not contain any parts that could be considered dangerous. Additionally, users should be assured that when using the technologies, they cannot be easily broken. For this, the devices should be robust enough and have as few as possible easily breakable parts.

Another point that was not considered when planning the concept, but which became apparent during the evaluation, is that direct feedback from the devices to the user would increase the feeling that the device was working correctly. This would also help to avoid certain operating errors. The experiences during the study are in line with the usability heuristics known from reference [61].

A significant result was obtained when subjectively measuring sleep quality with PSQI—60 % of the test subjects were identified as "bad" sleepers. This clearly shows that the broad use of sleep monitoring technologies would enhance early diagnosis because many test subjects were not even aware that they might have sleep problems that could be treated. Additionally, currently, when the constant development of technologies and algorithms allows new and less invasive methods to detect sleep stages [62], it is possible to make this early detection easier and more convenient for users.

By directly comparing objective and subjective measurement methods, it can be seen that in the case of automatic measurement using technologies, it is possible to expect better data completeness and consistency than the manual filling out of questionnaires. This may ultimately lead to more relevant data being collected and analysed early, improving the quality of life and possibly the users' health.

The test subjects used the provided devices for a fortnight and finally gave their assessment during an interview. The results allowed us to conclude that the proposed concept is a successful model in terms of the simplicity of independent device operation o and a sense of security when using them. However, the test subjects were not sure as to whether they would use the devices regularly. One explanation for this is that the benefits of using these devices are not always clear to the subjects—there was feedback that they did not think that using these devices would improve their quality of life. To overcome this barrier, a sustained educational effort is needed to communicate clearly and understandably the potential benefits the elderly population using such types of technology. Without this development of motivation to use the technologies, widespread use is complicated, even though handling is not necessarily a big problem, as the conducted study has shown.

There are some limitations in the work presented:

- Only a few technologies could be used and evaluated within the study framework. Therefore, it cannot be excluded that the results could deviate with a different selection of devices. However, it is always necessary to select a specific subset of technologies because it is impossible to test all available devices at once.
- The number of test subjects was limited to 10. In order to obtain statistically relevant data, the period of 14 days was chosen for the study, resulting in a total of 140 person-days of study. In addition, the same proportion of male and female test subjects was ensured. Furthermore, the proposed study contained a certain type of usability testing, which included questionnaires and a free-form interview to understand if there were any problems with the usability of devices. According to reference [63], only 10 ± 2 subjects are necessary to discover 80% of usability problems. Moreover, the analysis of the transferability of the results to the entire population of persons aged 65 and older with the approach of the statistical parameter "margin of error" was carried out and presented in the section "Results". The margin of error scientifically confirmed the significance of the results that were obtained.
- Since the study target group was people aged 65 years of age and older, the results cannot be directly transferred to other age groups.
- The technologies were not connected to a common platform that could be accessed by the participants directly. Therefore, it was impossible to assess whether the possibility of directly viewing the results of the recordings by the test subjects could have a positive impact on acceptance.

To overcome the limitations mentioned above and to gather additional valuable information, the next step could be planning and organizing a new extended study. This could involve more subjects and could allow a wider range of technologies connected to a common platform to be tested. Furthermore, further work could be conducted on the selection and design of questionnaires for the collection of relevant data for analysis.

Author Contributions: Conceptualization, M.G., R.S. and N.M.M.; methodology, M.G.; validation, M.G; formal analysis, M.G.; investigation, M.G.; resources, M.G. and R.S.; data curation, M.G.; writing—original draft preparation, M.G.; writing—review and editing, R.S., N.M.M. and J.A.O.; visualization, M.G.; supervision, R.S. and J.A.O.; project administration, R.S., M.G.; funding acquisition, R.S. All authors have read and agreed to the published version of the manuscript.

Funding: This research was funded by the EU Interreg V-Program "Alpenrhein-Bodensee-Hochrhein": Project "IBH Living Lab Active and Assisted Living", grants ABH40, ABH41, and ABH66. This research was also partially funded by the Carl Zeiss Foundation (project number: P2019-03-003), by the German Federal Ministry for Economic Affairs and Energy, ZiM project "Sleep Lab at Home" (SLaH) grant: ZF4825301AW9 and grant PGC2018-102145-B-C21, funded by MCIN/AEI/10.13039/501100011033 and by "ERDF A way of making Europe", funded by the Ministry of Science, Research and the Arts Baden-Württemberg and supported by the Open Access Publication Fund of the HTWG Konstanz University of Applied Sciences.

Institutional Review Board Statement: Ethical review and approval were waived for this study, based on the review by ethics officers from the HTWG Konstanz and the University of Applied Sciences Kempten, Germany.

Informed Consent Statement: Informed consent was obtained from all subjects involved in the study.

Acknowledgments: We thank the caregivers of the Workers' Welfare Association (AWO) Schwarzwald-Baar e.V. for their contribution in conducting the study.

Conflicts of Interest: The authors declare no conflict of interest.

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Estimation of Sleep Stages Analyzing Respiratory and Movement Signals

Overview

The article focuses on classifying sleep stages, evaluating exclusively respiratory and body movement signals. The findings have validated such a possibility with results that outperform the State of the Art.

Context

This publication is a result of several years of intensive research in the field of signal processing and sleep study combined with the practical experience of project work. It is a logical progression from a number of previously completed and published scientific works. The research stays abroad (especially in Ancona/Italy at Università Politecnica delle Marche), and interdisciplinary cooperation have played a key role in achieving the results that have made this publication possible. In addition, participation in several research projects, such as the Home Health Living Lab, EDITH, or Sleep Lab at Home, has provided the necessary scientific experience in the area of a sleep study to achieve the research objectives.

Journal information

The "IEEE Journal of Biomedical and Health Informatics" was selected to submit this article because of its worldwide leading positions in research areas of interest. This journal is indexed in JCR with the current Impact Factor of 5.772 (Q1 in four categories). The ranking details for the last five years are presented in the following Table.

Category	*Computer Science, Information Systems*		*Computer Science, Interdisciplinary Applications*		*Mathematical & Computational Biology*		*Medical Informatics*	
JCR Year	JIF Rank	JIF Quartile	JIF Rank	JIF Quartile	JIF Rank	JIF Quartile	JIF Rank	JIF Quartile
2020	28/161	Q1	17/111	Q1	5/58	Q1	4/30	Q1
2019	15/156	Q1	12/109	Q1	5/59	Q1	1/27	Q1
2018	19/155	Q1	16/106	Q1	6/59	Q1	4/26	Q1
2017	18/148	Q1	14/105	Q1	6/59	Q1	4/25	Q1
2016	20/146	Q1	16/105	Q1	7/57	Q1	5/24	Q1

Estimation of Sleep Stages Analyzing Respiratory and Movement Signals

Maksym Gaiduk, Juan José Perea Rodríguez, Ralf Seepold, Natividad Martínez Madrid, Thomas Penzel, Martin Glos, and Juan Antonio Ortega

***Abstract*— The scoring of sleep stages is an essential part of sleep studies. The main objective of this research is to provide an algorithm for the automatic classification of sleep stages using signals that may be obtained in a non-obtrusive way. After reviewing the relevant research, the authors selected a multinomial logistic regression as the basis for their approach. Several parameters were derived from movement and breathing signals, and their combinations were investigated to develop an accurate and stable algorithm. The algorithm was implemented to produce successful results: the accuracy of the recognition of Wake/NREM/REM stages is equal to 73%, with Cohen's kappa of 0.44 for the analyzed 19324 sleep epochs of 30 seconds each. This approach has the advantage of using the only movement and breathing signals, which can be recorded with less effort than heart or brainwave signals, and requiring only four derived parameters for the calculations. Therefore, the new system is a significant improvement for non-obtrusive sleep stage identification compared to existing approaches.**

***Index Terms*—biomedical signal processing, regression analysis, sleep stages, sleep study.**

I. Introduction

SEVERAL studies show the importance of sleep for maintaining good health [1, 2, 3]. They emphasize its duration as an essential key factor to good physiological function [2] and warn about the harmful consequences resulting from abnormalities in the sleep duration [3]. These can be physical and psychological problems, several disease states, and even higher mortality. In this regard, we look to the formulated conclusion given by [2], whereby sleep quantity and sleep quality determine its restorative function and allow us to maintain a good health state. Several aspects should be quantified to assess the quality of sleep, including identifying different stages, their sequence, and the duration of each of them. A standard procedure allows evaluating each sleep stage. This procedure is called polysomnography (PSG), and it is performed following the guidelines of the American Academy of Sleep Medicine (AASM) [4].

During PSG, electroencephalography (EEG), electrocardiography (ECG), electromyography (EMG), and electrooculography (EOG) signals are recorded continuously during sleep [5]. This set of parameters is established because each of the signals changes during each phase of sleep. Thus, the combination of the obtained results allows classifying the subject's stage at each moment.

Although PSG provides an environment for sleep recording and analysis, its implementation is faced with a set of limitations related to:

- logistical and economic cost problems due to the requirement of at least 22 analysis connectors for usual implementation [5, 6];
- the high effort of time and personnel for processing and analyzing of data [7];
- non-natural sleep environment in a sleep lab as well as discomfort due to several electrodes, sensors, and cables attached to the subject's body affecting sleep pattern [8].

Furthermore, there is a limited number of sleep medicine specialists and sleep laboratories [9], which leads to delays in starting the care of patients with sleep disorders. This care is critical because of the large number of undiagnosed sleep disorders resulting in serious problems, even in death [3].

Because non-invasive sleep stage classification is a relevant research topic, many scientific publications can be found on the

This research was partially funded by the EU Interreg V-Program "Alpenrhein-Bodensee-Hochrhein": Project "IBH Living Lab Active and Assisted Living", grants ABH40, ABH41 and ABH66. This research was also partially funded by EDITH Research Project (PGC2018-102145-B-C21,C22 (AEI/FEDER, UE). Thomas Penzel was partially supported by the Russian Federation government mega-grant № 075-15-2019-1885.

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This article has been accepted for publication in IEEE Journal of Biomedical and Health Informatics. This is the author's version which has not been fully edited and content may change prior to final publication. Citation information: DOI 10.1109/JBHI.2021.3099295

subject (e.g. [10-16]). However, they use different vital signals as the input for the classification algorithm. A relatively small part of algorithms can work with only movement and breathing signals, as it is done in our approach. We will present several publications relevant to this research case. The main focus will be on research studies conducted using body movement and respiration as vital signals to recognize sleep stages. Scientific papers utilizing other input signals (e.g., heart rate variability (HRV) in [12] or EEG in [15]) are beyond the scope of this literature review.

Using body movement data for the identification of sleep stages is proposed in [13]. Sixteen healthy people have participated in the experiment. They slept through the night with electrodes attached to their bodies. NapVIEW with an infrared motion sensor was used as the device to detect body movements, placed about nineteen inches away from the subject's head. With this device's help, the body movement density (BMD) was calculated as the number of body movements per time unit to be used as an index of sleep transitions. The results of this study have confirmed the strong relation of BMD with sleep stage transitions. Besides that, the argument has been made that a BMD cycle is less affected by individual variations, and it is, for this reason, a more accurate index for sleep cycle identification than the absolute value of BMD.

Body movement and breathing can be used to classify sleep stages, as presented in [17]. Twenty-five features based on the respiratory signal (depth-based and volume-based) were designed, and the accuracy of 72.3% with Cohen's kappa of 0.34 was obtained for the classification of Wake/NREM/REM stages without subject-specific normalization. If only fourteen best features were used, the accuracy of 71.7% and Cohen's kappa of 0.32 are reported. A considerable correlation between the respiratory signal and sleep stages was demonstrated in [17], a study that constitutes its importance as research on non-invasive sleep phase identification.

Moreover, ultra-low-power reflected radiofrequency waves could be used to determine sleep/wake states according to [16]. The proposed algorithm is based on an analysis of movement and, to a lesser extent, respiration signals. The system's evaluation was performed on 113 subjects (94 males, 19 females with an average age of 53±13years). The accuracy of 78% and Cohen's kappa of 0.38 compared to PSG measurement were achieved.

One study [14] presents the comparison of wrist and chest actigraphy combined with HRV to identify sleep stages. Even if this approach uses HRV and movement signal, it is relevant for our work because of a movement role in identifying sleep stages. A support vector machine (SVM) was proposed as the approach for the classification of sleep and wake stages. The methodology was tested on a group of 18 healthy adult subjects. The accuracies of about 77% for wrist and 78% for chest actigraphy combined with HRV were achieved.

As the respiration signal is analyzed to identify sleep stages, it is essential to know if obstructive sleep apnea (OSA) affects identification accuracy. Otherwise, an algorithm providing accurate results for the patients without OSA could have decreased accuracy for the persons with OSA. This research point was investigated in [18], where the accuracy of 70.9% was achieved, and no significant differences in the identification of sleep stages for non-OSA and OSA groups were noticed. This matter allows transferring the classification results obtained with non-OSA test groups to OSA patients. However, the difference cannot be excluded entirely due to different possible sleep phase identification algorithms.

In [11], an approach of identification of Wake/NREM/REM states is presented. The input signals are respiration and movement, and the extracted out of these signals features used for the classification of sleep stages are the following: respiration rate variability, respiration rate, leg movement, body movement, posture, and body orientation features. The signals used for the algorithm's functioning can be obtained in a non-obtrusive way, for example, using the pressure-sensitive e-textile bed sheet, as it was done in [11]. The experiment with seven subjects (3 male, 4 female, age: 21-60 years old) was performed to evaluate the approach using three different classifiers: K-nearest Neighbor, Support Vector Machines, and Naïve Bayes. The best classification results were achieved using the Naïve Bayes classifier with the precision of 70.3%, recall of 71.1%, and total accuracy of 72.2%.

To overcome the limitations and the problems of a classical PSG approach mentioned above and of alternative presented solutions, the main research aim of this study is defined as a development of techniques for pre-processing and analyzing data in order to detect sleep-related pathologies, with simplified procedures apt even for personnel who are not especially qualified and without the need of expensive laboratory installation. In sum, the diagnostic system under examination is low-cost, and its minimally invasive data collection methods help maintain normal sleep conditions, which in turn increase the accuracy of results.

Considering these premises, we have developed a technique to analyze and classify the sleep stages. The main innovations of our proposal are:

1) reduce the directly recorded signals exclusively to breathing and body movement. Thus, we can reduce the invasive action (compared to EEG or ECG measurement) on the subject to a minimum. Furthermore, these signals may be obtained without necessity of involving trained staff;
2) only four parameters, derived from measured signals, to characterize the sleep stages. This aspect represents a quantitative advantage over existing techniques in which up to more than ten parameters are required [5, 10];
3) develop a new derived parameter, based on the premises of logistic regression that relates two of the primary biological signals: the patient's breathing as well as movement.

The Materials and Methods section contains three subsections. In the Statistical Methods subsection, we will explain the quantitative basis to evaluate the parameters characterizing sleep stages. Once we have described our proposal's quantitative scope, we describe our proposed method in the Proposed Model subsection, justifying both the selection

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of the parameters and the coefficient proposed to optimize the results obtained. In the Implementation subsection, we describe the details of the implemented model. The obtained results are then presented in the Results section and discussed in the Discussion section. Finally, we mention the possible improvement options and plans for future research in the Conclusion and Outlook section.

II. Methodology

A. Statistical Methods

This section describes the statistical methods used in our sleep analysis model and justifies this study's preference for statistical methodology. Furthermore, a qualitative explanation of the statistical method is carried out, and the equations used in our model are defined.

The proposed software system is designed to identify sleep stages out of breathing and movement signals. For that, a set of sensors measuring both these signals (e.g., as described in [19, 20]) can be used to quantify a subject's biosignals. These sensors generate numerically quantifiable electrical impulses, *the sample values*, which change at each of the sleep stages. However, although the values change at each stage, it is only possible to perform a sleep analysis after numerical processing using statistical methods. After processing, a set of *the derived parameters* is obtained, with which it is possible to analyze the evolution of sleep.

From a statistical point of view, the derived parameters are *independent variables*, while the sleep stages are identified as *dependent variables*. A research review was conducted to select the appropriate statistical approach. It showed that several studies had proposed different statistical methodologies to determine the correlation between independent variables (derived parameters) and dependent variables (sleep stages), with regression-based analysis providing the best results compared to other statistical approaches [21, 10]. Notably, in regression-based analysis, the dependent variable is predicted or obtained from a modulated weighting of the available independent variables [22].

Regardless of whether a specific correlation can be established between independent variables, the main objective in the field of regression analysis is to establish a mathematical relationship between dependent and independent variables [22]. Depending on the numerical characteristics of the independent variables, there are different statistical methods to obtain this relationship between dependent and independent variables. In our study, we are going to focus on multinomial logistic regression (MLR). MLR is an extension of the logistic regression with which it is possible to manage independent variables (*the derived parameters*) in multiple categories. This choice is due to two factors: the first is that the outcome of a multicategory variable (a variable that can achieve a limited number of categories) needs to be predicted as a function of the independent variables; the second is that these independent variables form a random conditional field or set [23]. In the case of sleep studies, a set is related to vital functions such as breathing or movement of the subject under study. Another advantage of MLR compared to many other algorithms is the fact that the output is not presented as just one value with the detected sleep stage but as a set of probabilities for all sleep stages for each epoch. This allows a further processing and adjustment of the results.

Quantitatively in MLR, the odds ratio is the logistic regression coefficient's antilogarithm, which simplifies the calculations and allows a better obtaining of the dependent variables. It should be noted that the odds ratio presents information on how the change of independent variable influences the probability of being in a category versus being in the reference group. If an odds ratio value is greater than 1, then as an independent variable in the interval increases, so does the probability value. Otherwise, if the odds ratio is less than 1, then there is an opposite scenario - the probability value decreases as an interval-independent variable increase [24].

To quantify the description made of MLR, we will introduce the equations that we will implement in our study. To carry out this task, we will designate the results of the categorical random dependent variables as $Y \in \{0, 1, 2 \ldots k\}$.

According to MLR, the conditional mean of the dependent categorical variables is defined as a logistic function, of a related combination, of independent variables, usually called x. The relationship is defined as

$$E[Y|x] = \sigma(c^T x), \quad (1)$$

where c is the vector of unknown coefficients and where the logistic function, σ, satisfies:

$$\sigma(x) = \frac{1}{1+e^{-x}}. \quad (2)$$

Considering (1) and (2), it is possible by means of MLR to determine the coefficients vector c that maximizes the probability of observations. This operation is defined as

$$\prod_{i=1}^{n} Pr(Y = Y_i|X_i), \quad (3)$$

which is equal to the maximization of the probability of registration, which is estimated as

$$\sum_{i=1}^{n} log\, P\, r(Y = Y_i|X_i). \quad (4)$$

This expression is used to formulate the simplified function to maximize the probability:

$$l(c) = -\sum_{i=1}^{n} log\left(1 + e^{-1^{y_i * c^T x_i}}\right). \quad (5)$$

Additionally, in MLR, the standard error coefficient is of particular importance, which is calculated as

$$se(c_i) = ((X^T AX) - 1)_{ii}, \quad (6)$$

where the Hessian of $H = -X^T AX$ and $A = diag(a_1, \ldots, a_n)$ is the diagonal matrix with $a_i = \sigma(c^T x) * \sigma(c^T x)$ [25].

Finally, to know the maximum probability, it is necessary to test the predictors' meaning in the logistic regression [23, 10]. For this purpose, the *Wald z-test* [25] defined by the equation is usually used:

$$z_i = \frac{c_i}{se(c_i)}. \quad (7)$$

Knowing this last coefficient, it is necessary to demonstrate the predictors' meaning in the logistic regression. The value of the so-called *Wald p-value* for the coefficient i is used. The probability of obtaining a value at least as extreme as the observed one is determined, for which the null hypothesis has

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to be imposed, that is, $(c_i = 0)$.

The formula for the value of the *Wald p-value* for the coefficient i is

$$p_i = Pr(|Z| \geq |z_i|) = 2 * (1 - F(|z_i|)), \tag{8}$$

where F is the cumulative density function of a standard normal distribution [25].

B. Proposed model

The characteristics of the proposed model are described here. We will justify the choice of the parameters derived for identifying each of the three sleep stages and how we can drastically reduce the number of these parameters from 10 to 4 compared to the previous research [10]. We will also introduce a new coefficient that allows us to compare two sources of information, breathing and body movement; we will justify the formulation of this coefficient and describe how this new coefficient can improve the accuracy of the results obtained.

Several investigations have revealed a relevant fact from the analytical point of view: *there is a direct correlation between biosignal patterns, quantifiable using electronic sensors, and the different sleep stages*. Thus, from this correlation of sleep stages-biosignal patterns, it is possible to detect and quantify the wakefulness-sleep situation in which a subject of study can be found. To carry out this task, it is necessary to implement recognition algorithms analyzing parameters obtained from biosignals, quantify and detect the different sleep stages. Some of the essential characteristics of biosignals are summarized in Table 1 extracted from [26-29].

TABLE I
RELEVANT CHARACTERISTICS OF SLEEP STAGES [26-29]

Stage	Characteristics
Wake	Respiration is typically stable and more frequent than in the NREM (especially in Deep Sleep) stage. Typically, more movement than in NREM (especially in Deep Sleep) and REM stages.
NREM	When sleep deepens from the WAKE stage, body movements become smaller and less frequent. The deeper the sleep, the less frequent the heart rate and respiration. After some instability in respiration during the Light Sleep stage, respiration becomes more stable when sleep deepens.
REM	Heartbeat and respiration become more frequent and less rhythmical. Body movement is typical for the epochs just before and directly after the REM stage. Anti-gravity muscles lose the tension, and therefore, the movement is typically absent.

As a result, we have developed a minimally invasive identification approach in which we only need two sources of biosignal data: (a) body movement, (b) respiration.

This selection is based on specific changes in physiological features of the human body caused by sleep. When moving from the wake stage to deeper sleep, both a body's movement (amplitude and frequency) and, at the same time, a heart rate are being decreased [26], so only one of these two data sources needs to be used. To achieve our goal of using signals that can be obtained with less effort and more comfort, we have decided to use a movement signal and refrain from using a heart signal. Furthermore, after a transition from NREM to REM stage, body movement is typically decreased even more or absent [27]. The absence of movement in the REM stage also helps distinguish it from the WAKE stage with a high level of accuracy.

Additionally, to obtain more accurate results, we use a respiratory signal and have developed a new derived parameter, integrating body movement and breathing. This will be described later and presented in (16). It is known from [26] that respiration becomes more frequent and less rhythmical in the REM stage, leading to changes in respiratory volume and supports the differentiation between NREM and REM stages.

To quantify body movement in our model, which builds on the research developed by [10], the average value of the position changes for all three axes will be calculated according to the equations:

$$X = \frac{1}{n}\sum_{i=1}^{n}|x_i - x_{i-1}| \tag{9}$$

$$Y = \frac{1}{n}\sum_{i=1}^{n}|y_i - y_{i-1}| \tag{10}$$

$$Z = \frac{1}{n}\sum_{i=1}^{n}|z_i - z_{i-1}|, \tag{11}$$

where x_i, y_i, z_i and x_{i-1}, y_{i-1}, z_{i-1} are the sensor coordinates in the current and correspondingly previous moment.

From the (9), (10), (11), we calculate the instantaneous position of the body at the moment i as the modulus of the changes in coordinates, i.e.:

$$Body_i = \sqrt{X^2 + Y^2 + Z^2}, \tag{12}$$

where X, Y and Z are the signal values for each axis of a 3D activity sensor used in the study. If the signal provided by the sensors measuring movement is 1-dimensional, it can be directly used as the input for (13).

The derived body movement parameter is defined as the mean value of the body movement (BM) signal. It is defined as

$$BM(k) = \frac{1}{n}\sum_{i=0}^{n-1} Body_i, \tag{13}$$

where n is the number of body movements and $Body_i$ is described in (12).

Additionally, to quantify respiration, we will consider the recommendations given by [17, 10]. In these studies, up to four parameters are formulated from the data provided by the breathing sensors. The innovation of our proposal is that we only need two of these parameters to obtain satisfactory results. Performed tests with different sets of breathing-related parameters have indicated no significant improvement of the classification rate in increasing the number of used derived parameters. Therefore, in our proposal, we will only need

- Mean respiratory depth of exhalation (T_{sdm})
- Median respiratory volume during inhalation (V_{in})

The choice of these parameters is conditioned by several clinical studies in [17, 26] in which the importance of considering mean respiratory depth, mainly in terms of exhalation, is highlighted, so we have chosen T_{sdm}, as well as the Median respiratory volume during inhalation, should already reflect the changes of respiratory effort signals and these, in turn, are related to the stages of sleep [26]. Selecting only two parameters instead of the four proposed by [26] does not imply loss of information since the biosignal data are related to each other [30], so a proper selection allows knowing all the information, as we will demonstrate in the Results section.

Here is the mathematical representation of the derived breathing parameters,

$$T_{sdm}(k) = \frac{median(t_1, t_2, \dots t_n)}{IQR(t_1, t_2, \dots t_n)}, \quad (14)$$

$$V_{in} = (k) median\left(\sum_{s_x \in \Omega_1^{in}} s_x, \sum_{s_x \in \Omega_2^{in}} s_x, \dots, \sum_{s_x \in \Omega_k^{in}} s_x\right), (15)$$

where $t = t_1, t_2, \dots, t_n$ are the sequences of peaks and troughs of a selected time window, IQR is the interquartile range for the given sequences of peaks, the k^{th} inhalation and exhalation cycle is defined through Ω^{in}_k with k consecutive breathing cycles ($k = 1, 2, \dots, K$) and S_x is the respiratory effort value.

It is important to note that not absolute values of the derived from respiratory signal parameters are significant for the correct functioning of the proposed algorithm, but their changes over time. Furthermore, all signals are being subject-normalized and do not contain raw values. Therefore, even not calibrated sensors (e.g., inductive plethysmography) can be used for signal recording.

However, with these three parameters, defined in (13), (14), and (15), it is impossible to obtain precise results that allow the determination of the sleep phase. In order to avoid this problem and achieve a higher precision from the three derived parameters, we formulated a new derived parameter BV_{in} which represents the combination of the inhalation parameters V_{in} and the $BM(k)$ according to the equation,

$$BV_{in} = ln \frac{BM(k)}{BM(k)+V_{in}}. \quad (16)$$

This choice is not arbitrary but is based on two fundamental conclusions: the first is that when the subject under study evolves from the waking stage to that of a deep sleep, the movement of the body decreases, and the depth of breathing increases [17, 26] so that the combination in the form of a coefficient will improve the accuracy of detecting the sleep stage. The amplitudes of the breath and body movement signals can vary significantly between subjects. To standardize these deviations, $BM(k)$ is divided by $BM(k) + V_{in}$ The second is that using the coefficient as an argument for a logarithmic function reduces the large fluctuations associated with body movement, as highlighted by [26].

Tests were also conducted in which all selected parameters were excluded from the algorithm one by one. This resulted in a reduction in accuracy of about 10-15%, with no clearly detectable differences depending on which parameter was excluded.

Thus, by calculating three derived parameters and a fourth obtained from them, we will demonstrate that accurate results are obtained, as presented in the section Results.

C. Implementation

In our study, we have implemented a classification model based on the statistical technique of MLR, in which we identify as dependent variable (Y) the various stages of sleep, while the independent variables ($X_1, X_2, \dots, X_n$) are the biosignal parameters which in our case are derived out of breathing and body movements, as described in the section Proposed Model. To calculate the derived parameters, the data obtained with a sampling rate of 32Hz was split into epochs of 30 seconds each.

The general structure of the system modules is presented in Figure 1. First, the input signals are pre-processed to facilitate further elaboration, then the derived parameters are calculated, and the calculation of probabilities of sleep phases for every epoch is performed. After each step, the results of the

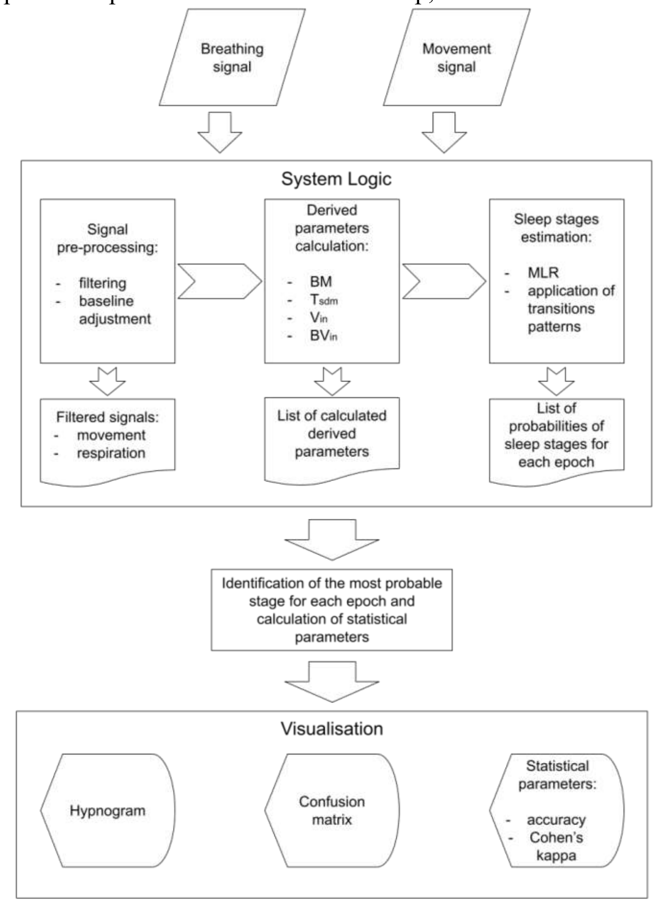

Fig. 1. System structure.

calculations are saved in a separate file to enable a subsequent analysis of the operations carried out and simplify the exchange of system modules if required. The next step is to determine the most probable sleep phase for each epoch and finally to visualize the results.

The input signals can be recorded independently or as a part of a polysomnography study. For breathing signals, a chest inductive plethysmography (RIP) record may be used. Other sensors that can record respiratory signals, including changes in their amplitude, can also be applied [e.g. 19, 20]. Body movement signals can be replaced by a signal monitored by a 3D acceleration sensor in a recording device placed on the subject's chest. Another option for the measurement of movement signal could be pressure sensors placed under the mattress [19]. The baseline wandering should be excluded from the lower frequency range and not be significant for the final results, as only the changes in the signal will be analyzed and not its absolute value. Also, the baseline shift has a much smaller amplitude than body movements. A median filter was applied to the respiratory signal to remove short, high-amplitude body movements. Afterward, a rolling mean filter was applied to get a cleaner signal, which was beneficial for calculating the selected derived parameters.

To increase the accuracy of the classification results, the

This article has been accepted for publication in IEEE Journal of Biomedical and Health Informatics. This is the author's version which has not been fully edited and content may change prior to final publication. Citation information: DOI 10.1109/JBHI.2021.3099295

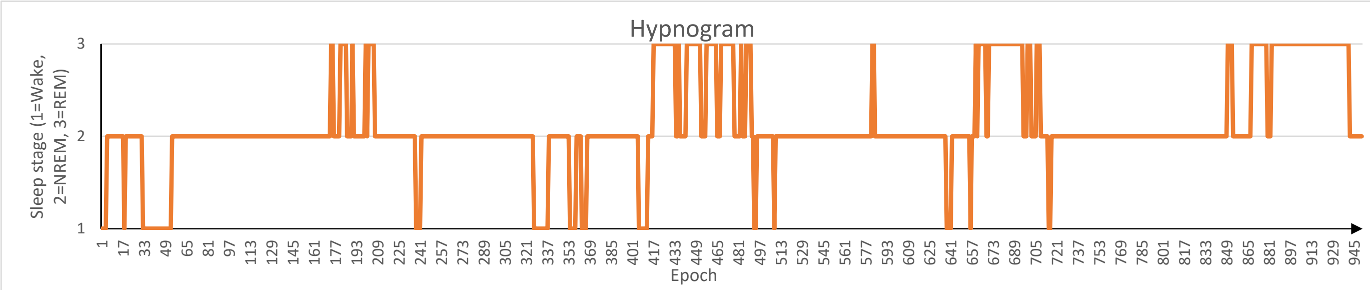

Fig. 2. Results of classification of sleep stages for one subject visualized as a Hypnogram.

transition patterns between the different sleep stages were taken into account in implementing the algorithm described in this work. As shown in [31], some transitions between sleep stages are much more likely than others, and at the same time, some transitions have a very low probability. In the first implementation of the algorithm, the emphasis was placed on non-probability transitions. As the algorithm works with probabilities, it allows additional adjustments, increasing accuracy without having to comply with strict rules. In this case, the algorithm reduced the probability of the examined sleep stage by 10-15% (a higher percentage would negatively affect the total classification accuracy if the previous stage were incorrectly classified) if its probability of occurrence according to the transition pattern is almost zero. This approach has led to an increase in the proposed algorithm's accuracy by up to 3% compared to implementation without considering transition probabilities.

III. Results

The evaluation of the algorithm's work was performed with the use of the dataset provided by the Charité[1] clinic in Berlin. The experimental procedures involving human subjects described in this paper were approved by the Institutional Review Board of the Charité-Universitätsmedizin Berlin (application number: EA1/320/114). The overnight recordings of 35 persons (with a total length of about 260 hours) were available for evaluation. The participants' average age was 38.6 +/- 14.5 years old, and the BMI averaged 24.4 +/- 4.9 kg/m². The number of male and female subjects was similar, and no significant health disorders were known for the test persons. The used PSG recordings were previously manually analyzed by sleep medicine physicians, and every 30-second epoch was tagged with the corresponding sleep stage (Wake, N1, N2, N3, REM). As the classification algorithm operates with three stages (Wake, NREM, REM), the stages N1, N2, and N3 from the PSG recordings were merged to the evaluation's NREM stage.

The available dataset was strictly separated into training and test subsets. The training dataset consisted of sleep data of randomly selected subjects (after separation male/female) with a total amount of about 100 hours of recordings. Typically, the NREM sleep stage is the prevalent one during sleep, resulting in classification errors due to unbalanced classes in the training dataset. Therefore, it was necessary to balance the subset used for the system training, which was performed during the evaluation preparation phase. The test dataset included about 160 hours of overnight recordings of 20 subjects, which corresponds to 19324 epochs, 30 seconds each. Both subsets had a similar male/female ratio, and the average BMI of the included subjects did not have a significant discrepancy.

Visual representation of sleep stages estimation is presented in Figure 2. It can be seen that there are multiple rapid transitions from one state to another at some points in time. It happens because there is no algorithm for averaging the results of sleep stage classification implemented, and every single epoch is directly visualized according to calculated values.

Table 2 represents the classification results of the developed algorithm compared to the expert classification. The rows of the table contain the number of epochs corresponding to each sleep stage according to the expert's evaluation, whereas the columns represent the results of classification by the developed algorithm. The main diagonal indicates the number of sleep epochs, where the results of both classifications (by experts and algorithm) are in accordance.

The achieved general accuracy is equal to 73% following the expert's classification. More statistical measurements are presented in Table 3.

In addition to the classification accuracy, we estimated Cohen's kappa parameter, which is commonly used to measure agreement between several observers (in this case – methods). Its calculated value for the developed classification algorithm compared to the results of experts' classification is 0.44.

TABLE II
Classification Results

Stage Expert	Stage developed system			
	Wake	NREM	REM	Total
Wake	1256	862	604	2722
NREM	1104	11081	1691	13876
REM	211	730	1785	2726
Total	2571	12673	4080	19324

TABLE III
Statistical Measurements

Overall accuracy	73.0 %	
	Recall	Precision
Wake	46.1 %	48.9 %
NREM	79.9 %	87.4 %
REM	65.5 %	43.8 %

[1] Initial study was carried out in Charité - Universitätsmedizin Berlin Center of Sleep Medicine Charitéplatz 1, D-10117 Berlin (Germany).

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IV. Discussion

This manuscript research aimed to provide a scientific base for the development of a sleep study system that could be used in medical or home environments. Monitoring movement and breathing of recumbent subjects in a non-obtrusive way is less challenging than monitoring heart signals (especially HRV) [32]. It was imperative to develop an algorithm that could classify sleep stages relying on only these two signals for input, the target of the performed research.

The achieved general accuracy of algorithm function of 73% indicates that the goal of this challenging task was met. The developed algorithm recognized the NREM stage with high recall of about 80%, which is higher than for both other stages – Wake and REM. The overestimation of the NREM phase can partially explain its prevalence in a typical sleep pattern. Even using a balanced training dataset did not completely solve this problem. Another critical point is that human respiration and movement during the Wake stage just before falling asleep and during the NREM1 stage, which is a part of the NREM stage performed in this work evaluation, are very similar [33]. It may lead to misclassification of the Wake stage as the NREM stage and vice versa. Significant differences in accuracy for different sleep stages are also typical for other systems (e.g. [11, 40]).

Another factor that has a strong influence on the results is the quality of the input signals. When analyzing the recognition rate per person, it was detected that there are some recordings where the results are significantly worse than the average. Accordingly, such exceptional cases have driven down the average accuracy and average Cohen's kappa value. After a thorough analysis of such recordings, it was found that the signals had significant differences from other typical recordings. Figure 3 shows a comparison of two recordings of approximately 130 minutes each of the respiratory signal compressed in time. The upper graph in Figure 3 illustrates a typical recording (accuracy of classification 76%) in which the amplitudes of the respiratory signal have few outliers and can therefore be adequately analyzed by the algorithm. However, when looking at the lower graph in Figure 3 (classification accuracy 49%), one can notice that the signal is volatile and contains many disturbances that make it almost impossible to analyze the amplitude of the signal (and also its volume) in numerous signal sections.

Nevertheless, the developed algorithm has proven that the accuracy of the classification of sleep stages remains adequate even with the inclusion of such limiting cases. If we would exclude this kind of cases, we could significantly increase the accuracy. However, the presented work aimed to test the functionality of the developed system under natural conditions, which also means the inclusion of low-quality signals.

Cohen's kappa value of 0.44 (which is "fair to good" according to [34]) may be considered a good result because a very high value can be challenging to achieve for epoch-by-epoch sleep stage identification. To clarify, even for the AASM scoring standard, the evaluation by different experts has an overall level of agreement of 82% with Cohen's kappa equal to 0.76 [35]. It is, however, important to mention that in [35], five stages were considered. It is expected that a sleep stage identification with only movement and breathing signals as input will have lower levels of accuracy and Cohen's kappa than the gold standard, which uses PSG signal as input.

The main novel point proposed in this study's approach is that it uses only the signals that can be obtained in a non-obtrusive way: movement and breathing [19, 20], for which a unique set of parameters was designed. For that purpose, comprehensive literature research and statistical analysis were performed. The new combination of derived parameters and MLR-approach, extended by algorithms for considering transition probabilities from one sleep stage to another, has led to the development of a new unique software solution for identifying sleep stages.

A significant amount of research on automatic sleep stage classification is based on using the EEG signal as the algorithm's input [36-38]. As EEG can be recorded only in an obtrusive way with electrodes attached to the subject's head, these researches are not directly comparable with that presented in this article's approach.

Another large subset of sleep research considers the identification of sleep stages, having the heart rate or ECG signal as the input. In [39], the authors used the ECG signal and respiration effort. The accuracy of 80% for the classes Wake,

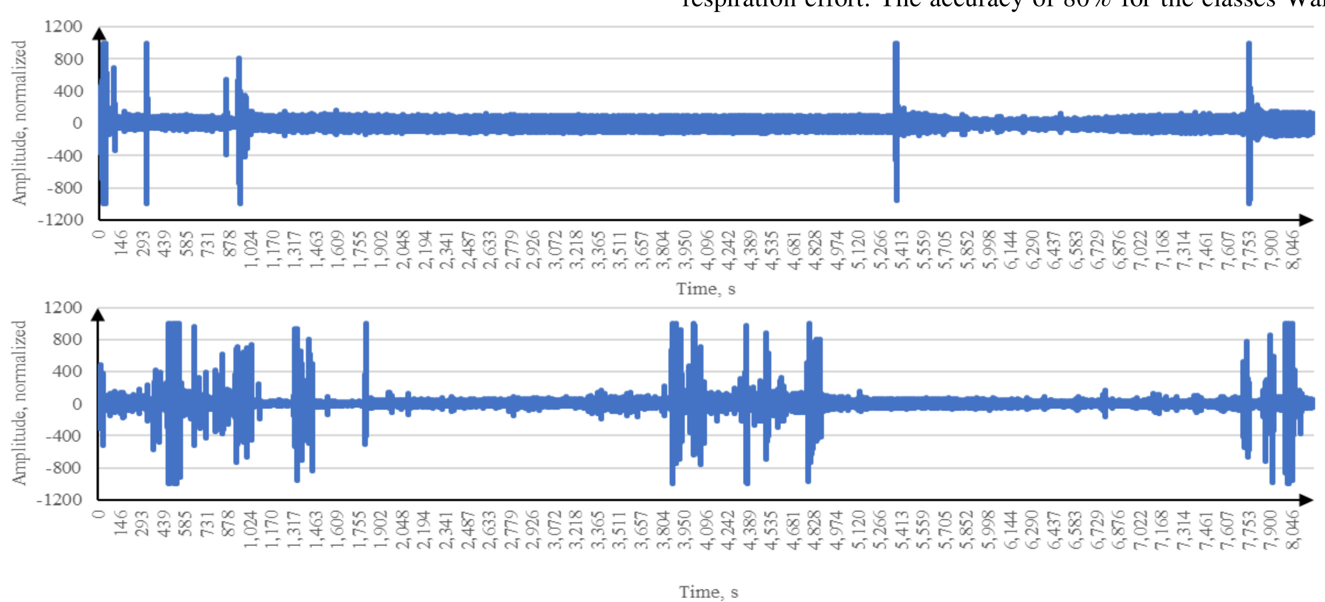

Fig. 3. Respiration signal. Normal (upper) and faulty (lower) recordings.

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NREM, and REM is slightly higher than in our approach. However, it would not be possible to perform the measurement described in [39] in a non-obtrusive way because the ECG signal is being measured directly by placing electrodes on the human body. Therefore, our method has a significant advantage as the necessary signals may be measured in a contactless way as described in [19, 20], while reporting only a slight reduction of accuracy. Another crucial advantage of our approach is using only four features, compared to 80 in [39], which means faster processing and less computing power needed, which is essential for the embedded systems.

To continue, the approach described in [40] uses the HRV signal derived from the ECG. The achieved accuracy of 72,6% for subject independent classifier is slightly lower than the accuracy of the method presented in our paper. Though the accuracy is comparable, our method is preferable since it uses only respiration and movement signals (which can be obtained contact-free). Furthermore, the algorithm's number of features used is significantly lower than proposed in [40] (4 against 41).

Breathing and body movement signals are used as the input in [16] approach, making it similar to our method concerning analyzed signals. However, only Wake/Sleep states are recognized in [16], whereas our system identifies Wake, NREM, REM sleep stages. The accuracy of 78%, with a Cohen's kappa of 0.38 stated in [16], compared to 73% of accuracy with a Cohen's kappa of 0.44 in our experiment, confirms the quality of our results. The number of recognized stages in our method is higher, albeit with a marginal decrease in accuracy, and it achieved a better Cohen's kappa value.

The reported results in [17] regarding the accuracy of 72.3% with Cohen's kappa of 0.34 (25 features), and accuracy of 71.7% with Cohen's kappa of 0.32 (14 features) for the classification of Wake/ NREM/REM stages without subject-specific normalization is lower than in our work. Our work also presents data using fewer used features (4 against 25/14), another advantage over other studies. The respiratory signal is used in [17] as the input for the algorithm.

Compared to the approach presented in [11], our method uses the same input signals but indicates better results: 73% accuracy against 72%, using only four features compared to more than 30 in [11]. Furthermore, a significantly higher number of overnight recordings was used to evaluate our experiment (20 against 7), which illustrates the results' stability.

It is important to note that a reduction in the number of the used features is especially relevant when it does not have any negative impact on the accuracy of detection because the effort required to calculate the features is moderate. The results of the comparison with state-of-the-art solutions presented above confirm that our system can use a small number of parameters and demonstrate high accuracy at the same time.

Although the results of the work carried out are promising, some limitations should be addressed:

- The number of recordings for the training was limited, and therefore it cannot be excluded that with a significantly larger quantity, the training results could be different.
- Changes in the signal in the process of recording (e.g. due to the displacement of the RIP belts) can lead to a reduction in accuracy.
- The available recordings were divided into 30-second intervals, which is also typical for sleep analysis. However, transitions from one sleep stage to another can also occur within these intervals, which was not considered in the current implementation of the algorithm.
- Although the possibility of substituting the devices for recording the movement and respiration signals is pre-planned, it was not possible to use and compare several alternative devices for the recording within the scope of the study conducted. Therefore, it cannot currently be claimed that the results of the algorithm's work will be identical for different signal sources.

V. Conclusion and Outlook

The development of an algorithm for identifying Wake/NREM/REM sleep stages was performed, and the accuracy of 73% with the Cohen's kappa value of 0.44 was obtained. These results confirm the proposed approach's appropriateness for the defined use case with only breathing and movement signals as the input. Further investigation on this method promises the algorithm's improvement and, consequently, more accurate results of system work.

One possible way to enhance the algorithm's performance is to continue investigating the best set of used derived parameters and the development of new ones. However, this needs an in-depth investigation of the importance of different features and values in the general sleep stages recognition algorithm. This work was done, but further improvements should still be possible and are planned for future projects.

Moreover, other sleep stages recognition approaches could be combined with the one proposed in this study to get an extended algorithm, which would obtain the final identification results as a mix of two or more methods, e.g., MLR + neural network. In this case, the epochs with the same identified stages by both approaches could be used as "trust-anchors," and the epochs before and after them could be identified more precisely, considering the transitions between the different sleep states [28]. Having three or more combined approaches, the decision system could be implemented, determining the final sleep stage identification result as the election by the majority of algorithms.

As shown in the Discussion section, the quality of the input signal plays an essential role in the correct classification of sleep stages. Therefore, in the future version of the system, it is planned to label the recordings with the disturbed signals and, if necessary, to remove some parts of the signal from the analysis and to provide a corresponding notification if no signal correction should be possible.

Signal reconstruction for improving the quality of the signal is a topic in itself and could also be included in future research. This would make it possible to perform a good detection of sleep phases even in parts of the signal where no reliable evaluation was initially possible.

Another possible direction of future work is to develop a standalone system tuned to a home environment [41], which requires developing a hardware part of the system to complement the software. This development's significant progress is already made and presented in several scientific publications [19, 42]. The final aim is to gain a system that would recognize sleep stages and sleep apnea, available for use in a home environment without high financial and personnel costs. Furthermore, the system should be comfortable to use, which has led to selecting the signals that can be obtained in a non-obtrusive way – movement and breathing. This kind of system could be widely used to provide the necessary information to medical professionals, thus enabling early detection of sleep problems and ultimately improving the population's quality of sleep.

ACKNOWLEDGMENT

We thank the Interdisciplinary Center for Sleep Medicine of Charité-Universitätsmedizin Berlin and in particular Beate Diecker and Claudia Biro for supporting the study.

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PART III

OTHER RELEVANT RESEARCH WORKS

EMBC '19

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Recognition of Sleep/Wake States analyzing Heart Rate, Breathing and Movement Signals*

Maksym Gaiduk, *Student Member, IEEE*, Ralf Seepold, *Senior Member, IEEE*, Thomas Penzel, *Senior Member, IEEE*,
Juan A. Ortega, Martin Glos and Natividad Martínez Madrid, *Member, IEEE*

***Abstract*— This document presents an algorithm for a non-obtrusive recognition of Sleep/Wake states using signals derived from ECG, respiration, and body movement captured while lying in a bed. As a core mathematical base of system data analytics, multinomial logistic regression techniques were chosen. Derived parameters of the three signals are used as the input for the proposed method. The overall achieved accuracy rate is 84% for Wake/Sleep stages, with Cohen's kappa value 0.46. The presented algorithm should support experts in analyzing sleep quality in more detail. The results confirm the potential of this method and disclose several ways for its improvement.**

I. INTRODUCTION

Sleep is a state in which our body rests and recuperates [1]. For human's normal physiological, mental and emotional functioning during waking hours, it is necessary to have a good sleep. There is a common belief that it is possible to have only a few hours of sleep per night over a long period of time without suffering negative consequences, which is just a misconception [2]. In fact, even smaller sleep abnormalities can result in psychological problems or physical illness. [3].

Most adults have a sleep duration of 7 to 8 hours each night to regenerate properly, while children should have much more sleep. Indeed, the sleep requirements are very individual for each person. In addition, many hours of sleep do not always guarantee a healthy and restorative state, because the crucial point here is not quantity, but quality. [2]

Sleep studies for obtaining trustworthy data on a person's sleep quality are usually carried out in sleep laboratories. For this procedure, the gold standard method is the overnight polysomnography (PSG) according to the guidelines of the American Academy of Sleep Medicine (AASM) [4]. This method is a resource-consuming and high costly procedure [5]. Several electrodes have to attach to the head in order to record EEG, EOG, and EMG signals for sleep staging [4]. In addition, sleeping in a sleep laboratory and sleeping at home in a familiar environment are two different situations. These reasons can affect the sleep structure and sleep quality of the person in sleep laboratory [6].

However, there are several scientific studies, confirming the relationship between the movement, breathing and heart rate with the sleep stages [7, 8, 9]. And these parameters can be obtained in a more comfortable way, than the PSG [10]. Using these bio vital data, with the appropriate algorithmic background, at least initial investigation of sleep-wake structure as a diagnostic step could be performed in home environments. This would enable to investigate sleep in a much higher number of persons than it is possible nowadays. Although, with this tools the need for sleep laboratories and the sleep experts remain very relevant for a full medical diagnostic of sleep, but medical doctors will receive important information for choosing the appropriate diagnostic and therapeutical pathway in patients suffering from sleep disorders. The main aim of presented project work is to develop a software system supporting a recognition of Sleep/Wake states when analyzing few human body signals, which could be obtained in a non-obtrusive way. According to [7, 10, 11, 12] heart rate, breathing and movement data are qualified signals.

II. STATE OF THE ART

Classification of sleep stages is a topic of a high number of scientific articles [8, 9, 13]. This summary mentions just a few but relevant publications due to their similarity in input signals.

As in [11] presented, ECG, heart rate variability (HRV) and heart rate itself could be used for the recognition of sleep stages. HRV and actigraphy (both, wrist and chest sensor) for the recognition of Wake and Sleep states is presented in [14]. 78% of correct recognition rate for the chest and 77% for wrist actigraphy in combination with HRV were achieved in this research.

The article of [7] presents an approach for the identification of Wake and Sleep states using the ECG signal

* This research was partially funded by the EU Interreg V-Program "Alpenrhein-Bodensee-Hochrhein": Project "IBH Living Lab Active and Assisted Living", grants ABH40, ABH41 and ABH66.

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24th KES International Conference on Knowledge-Based and Intelligent Information & Engineering Systems KES2020

M. Cristani, C. Toro, C. Zanni-Merk, R. J. Howlett and L. C. Jain (Eds.)

10.1016/j.procs.2020.08.001

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24th International Conference on Knowledge-Based and Intelligent Information & Engineering Systems

Comparison of sleep characteristics measurements: a case study with a population aged 65 and above

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Abstract

Good sleep is crucial for a healthy life of every person. Unfortunately, its quality often decreases with aging. A common approach to measuring the sleep characteristics is based on interviews with the subjects or letting them fill in a daily questionnaire and afterward evaluating the obtained data. However, this method has time and personal costs for the interviewer and evaluator of responses. Therefore, it would be important to execute the collection and evaluation of sleep characteristics automatically. To do that, it is necessary to investigate the level of agreement between measurements performed in a traditional way using questionnaires and measurements obtained using electronic monitoring devices. The study presented in this manuscript performs this investigation, comparing such sleep characteristics as “time going to bed”, “total time in bed”, “total sleep time” and “sleep efficiency”. A total number of 106 night records of elderly persons (aged 65+) were analyzed. The results achieved so far reveal the fact that the degree of agreement between the two measurement methods varies substantially for different characteristics, from 31 minutes of mean difference for “time going to bed” to 77 minutes for “total sleep time”. For this reason, a direct exchange of objective and subjective measuring methods is currently not possible.

Keywords: Sleep study; sleep quality; PSQI; sleep efficiency

1. Introduction

Sleep is an essential part of our life that, on average, takes up to one-third of every day [1]. Taking care of it is crucial for our health, as sleep is necessary for the recovery of our body as well as the brain. The two main components of sleep are duration and quality. Furthermore, sleep quality can also be seen as a combination of several characteristics

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1877-0509
10.1016/j.procs.2020.09.297

like the length of time to fall asleep, a number of awakenings at night, etc. [2]. It is known that sleep behavior changes with the age [3]. Among other things, the structure of the sleep stages, sleep efficiency, and sleep duration are typically different for elderly persons compared to younger ones.

In general, methods for measuring sleep quality can be divided into two large groups - subjective and objective measurement [4]. In objective measurement, the values are recorded and analyzed with electronic devices. Different types of sensors and methods for calculating the sleep quality can be used, such as a combination of a triaxial accelerometer and a pressure sensor [5]. In this work, a system was developed that can detect heart rate, breathing, REM/non-REM sleep phases, movement, the position of the person, sleep apnea, and sleep time, and from these data, it calculates the sleep quality with a self-developed algorithm. However, this system uses an accelerometer that has to be placed on the body. This can interfere with normal sleep patterns. The validation of the results by reference measurements was not clearly described in the article. The recognition of breathing rate and movement while sleeping is also one relevant method [6]. For objective measurement of sleep quality, the sensors on the smartphone can also be used as presented in [7]. In this case, three types of smartphone sensors were used: microphone, accelerometer, and light sensor. The smartphone was also used for keeping the sleep diary (derived from Pittsburgh Sleep Quality Index - PSQI [8]). It achieved a 81.48% of accuracy in the classification of "poor" and "good" sleepers. However, using the smartphone to measure sleep quality has some disadvantages, such as the need to place the phone close to the person in the bedroom and increased battery consumption during the night. Moreover, the sensors in different smartphones are not the same, which means that the results may differ between them.

Subjective measurement is based on recording the perceived sleep quality of the subjects. Questionnaires and/or sleep diaries are used [9]. Electronic sleep diaries are often developed as mobile apps. [10] compares a paper-based sleep diary versus an electronic version, and versus a measurement with an actigraph was made. It was concluded that electronic sleep diaries could have an advantage over classic paper-based versions. Another digital sleep diary was presented in [11]. Users perceived the proposed system as practical, but it was found that user experience and motivational effects should be considered when developing the system. In [12] the results of sleep quality measurements were compared with objective and subjective methods, and a correlation was confirmed. However, such important characteristics as "total tome in bed" or "sleep efficiency" were not considered, and the results of some test persons differ significantly so that a combination of the two methods can be useful.

For the detection of sleep disorders (especially insomnias), it is important to pay attention to such sleep characteristics as sleep efficiency, which is also directly linked with sleep duration [13]. Sleep efficiency is defined as the ratio between total time in sleep (sleep time) and the total time in bed (bedtime). It is known that insomnias are more common and sometimes get more distinct in the elderly [14]. Sleep efficiency can be measured objectively (based on electronic device recording) and subjectively (based on the feeling and memory of the person). For the recording of subjective feelings of bedtime and sleep time, the PSQI questionnaire is commonly used [8]. For the electronic measurement, different types of systems can be used, for example, based on the measurement of heart rate, breathing, and movement signals, as described in [15]. In this work, a system based on a multinomial logistical regression approach was developed and tested. The overall achieved accuracy rate is 84% for Wake/Sleep stages, with Cohen's kappa value 0.46.

Several studies targeting the improvement of sleep quality in older adults can be found (e.g., [16, 17]). However, to identify the persons with sleep quality problems and to monitor the progress of therapy, an easy-to-use method for broad application is necessary. Therefore, automatically obtaining the results of measurements, making it possible to test essential sleep characteristics for a high number of older adults could support the enhancement of sleep quality for this age group.

However, the results of measurements with the help of devices and based on the subjective feeling of a person may have some discrepancies [18], which should be investigated to check the possibility of substitution of questionnaires by automatic measurement with the help of electronic devices. Investigation on this question for the subjects from the age group 65+ is the main aim of the study presented in this manuscript.

2. Methodology

2.1. Test subjects

A total of 10 elderly persons (five males and five females) has participated in the study. Nine of them were living in their flats and one in a shared apartment for the elderly. All subjects were over 65 years old with mean value (MV) equal to 72.5 and a standard deviation (SD) of 6.2. The average height of participants was 167.6cm (SD=7.9), and the average weight was equal to 80.8kg (SD=12.6). They were able to carry out the majority of the homework themselves and did not have any severe acute diseases. All participants could understand and respond to the interview questions and were not suffering from advanced dementia. They were given all the study information in advance, and participation was voluntary.

2.2. Measurement methods

For the measurement of sleep characteristics, two approaches were implemented: (1) questionnaire for the measurement of subjective feeling of participating persons, and (2) electronic device for the measurement of sleep characteristics in an objective way.

For the questionnaire-based approach, Pittsburgh Sleep Quality Index (PSQI) was selected [8]. The main reason is that the PSQI is presently the only standardized clinical instrument that covers a broad range of indicators relevant to sleep quality with strong positive evidence for reliability and validity (hypothesis testing) [19]. [20] used the German version of the questionnaire. It asks retrospectively for two weeks about the frequency of sleep-disturbing events, the estimation of sleep quality, regular sleep times, sleep latency and sleep duration, sleep medication intake, and daytime sleepiness. A total of 19 items are used for quantitative evaluation. They are assigned to 7 components, each of which can assume a value range from 0 to 3. The total score results from the summation of the component scores and can vary from 0 to 21, whereby a higher value corresponds to reduced sleep quality. There is an empirically determined cut-off value (of 5), which allows classification into “good” and “poor” sleepers.

Currently, different devices for sleep tracking can be found. Some of them are based on actigraphy [21]; others use piezoelectric sensors [22] or execute analysis of the acoustic signals [23]. For the study described in this document, the Emfit QS+[1] sensor, using a ballistocardiography approach, was chosen [24]. This device can be used for sleep tracking, monitoring general characteristics, like time going to bed, total sleep time, time in bed, and light/deep/REM sleep[25]. It is a contact-free sensor, which can be placed under the mattress to ensure the typical sleep pattern of the users without disturbing their sleep. Furthermore, this device works fully-automatic and does not require any action by the participant of the study other than plugging into a power outlet. This was an essential point for the selection, as one of the study goals is to check if it is possible to execute the measurement of sleep characteristics in an automatic way with a minimal number of necessary actions by users and medical staff. All the data collected with the electronic device can only be accessed by the study organizers.

2.3. Study design

Participants were informed in advance about the procedure of the study. On the first day, the study organizers installed electronic devices in the participants’ homes. The Emfit device was placed beneath the mattress across the bed under the chest area according to the device manual. Interviews with general questions (like age, sex, height, weight) were also conducted on the first day of study. The test persons were asked to continue with their regular daily routine and to contact the organizers only in case of troubles. The devices were kept by participants for 14 days, during which time they were visited every 3-4 days to check if everything was going well or if there were problems or questions. On the 15th day, the devices were collected by the study organizers, and the PSQI questionnaires were filled out together with the participants. The measurements were executed for 14 nights, and the questions of subjective measurement were also referred to the same 14 days.

[1] https://www.emfit.com

2.4. Data evaluation

All completed questionnaires were manually processed, and all data were entered into a database. The following sleep characteristics were obtained directly from the questionnaire: time going to bed, sleep onset latency, getting up time as well as total sleep time. PSQI index, total time in bed, and sleep efficiency were calculated according to the guidelines of the German Society for Sleep Research and Sleep Medicine. Calculation of total time in bed:

$$\text{Total time in bed} = \text{getting up time} - \text{time going to bed} \quad (1)$$

Sleep efficiency (quotient of sleep time and bedtime) was calculated as follows:

$$\text{Sleep efficiency} = \frac{\text{Total sleep time in hours}}{\text{Total time in bed in hours}} \times 100\% \quad (2)$$

The sleep records created by the electronic device were downloaded using the developer web interface. Time going to bed, total sleep time, and total time in bed is directly available in the overnight recordings. Sleep efficiency was calculated according to Equation 2. In order to obtain results for a period of 14 nights, which are comparable to PSQI, the average values for the mentioned above sleep characteristics (time going to bed, total sleep, total time in bed, and sleep efficiency) for all 14 nights were calculated.

3. Results and Discussion

As several essential sleep characteristics have been measured during the study, the results section will also be divided into six subsections for the detailed presenting of the results. First, the results of two used types of measurements will be introduced: PSQI measurement and measurement with an electronic device (Emfit). After that, several relevant sleep characteristics measured with both measurement approaches will be presented.

3.1. PSQI measurement

Table 1 presents the PSQI measurement results for 10 subjects. The most relevant characteristics for the comparison with a measurement executed by hardware devices are “Time going to bed”, “Total sleep time”, “Total time in bed” and “Sleep efficiency”. PSQI index is used to distiguish poor and good sleepers [8]. According to this approach, subjects with PSQI index higher than five are identified as poor sleepers. Hence, 6 out of the 10 persons who participated in the study have poor sleep quality.

Table 1. PSQI questionnaire results.

Subject	1	2	3	4	5	6	7	8	9	10
PSQI Index	5	4	11	6	3	1	6	6	9	7
Time going to bed	22:00	22:45	21:00	00:00	21:00	22:00	21:00	20:00	00:30	00:00
Sleep onset latency (SOL)	00:15	00:30	01:30	00:10	00:10	00:30	01:00	01:00	01:20	00:10
Getting up time	07:30	07:30	06:30	06:00	07:45	06:30	08:00	09:00	08:00	06:30
Total sleep time (TST)	8:00	7:00	6:00	5:30	9:00	8:00	7:00	8:00	5:30	4:30
Total in bed time (TIB)	9:30	8:45	9:30	6:00	10:45	8:30	11:00	13:00	7:30	6:30
Sleep efficiency (SE)	84%	80%	63%	92%	84%	94%	64%	62%	73%	69%

3.2. Electronic device measurement

The results of monitoring with the Emfit device, used for the objective measurement of sleep characteristics, are shown in Table 2. The comparison of measurement results of this approach with the PSQI questionnaire is presented in the following sections.

Table 2. Electronic device measurement results.

Subject	1	2	3	4	5	6	7	8	9	10
Time going to bed	22:25	22:26	21:13	00:28	20:48	21:22	20:55	20:56	01:18	01:06
Total sleep time (TST)	06:37	08:34	07:50	04:57	09:37	08:30	10:16	10:22	05:20	05:06
Total in bed time (TIB)	07:13	09:37	09:09	05:40	10:41	09:31	11:24	11:21	06:25	05:56
Sleep efficiency (SE)	92%	89%	86%	88%	90%	89%	90%	91%	83%	86%

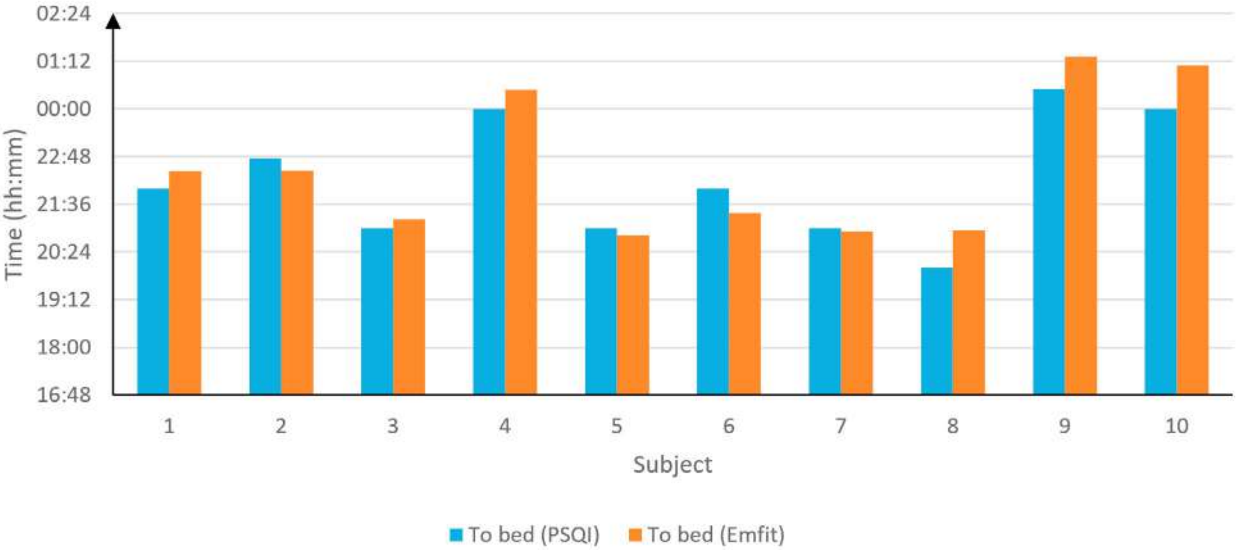

Fig. 1. Average time going to bed.

3.3. Time going to bed

The time going to bed for the ten subjects measured with the PSQI questionnaire and electronic device is presented in Fig. . Test persons could indicate the going to bedtimes with very high accuracy, which was confirmed by objective measurement results.

The average deviation of the time going to bed between PSQI and Emfit measurements is 31 minutes.

3.4. Total time in bed

The total time in bed was also estimated very well by the majority of test persons. This can be appreciated in Fig. . One of the possible reasons for the bad estimation by subjects 1 and 8 could be that for these two subjects (as well for subjects 2 and 7), records of an electronic device are available for less than eight days of study. Therefore, the calculated average time in bed could differ from the real situation.

The average deviation of this parameter for both measurement approaches is equal to 51 minutes for all subjects and 35 minutes in case subjects 1 and 8 are excluded.

3.5. Total sleep time

Only 50% of test subjects also have a reasonably good estimation of total sleep time. Fig. presents the visualization of this sleep characteristic measurement. These circumstances were also expected because estimating the time spent sleeping is naturally more difficult than total time in bed or going to bed. The availability of a maximum of

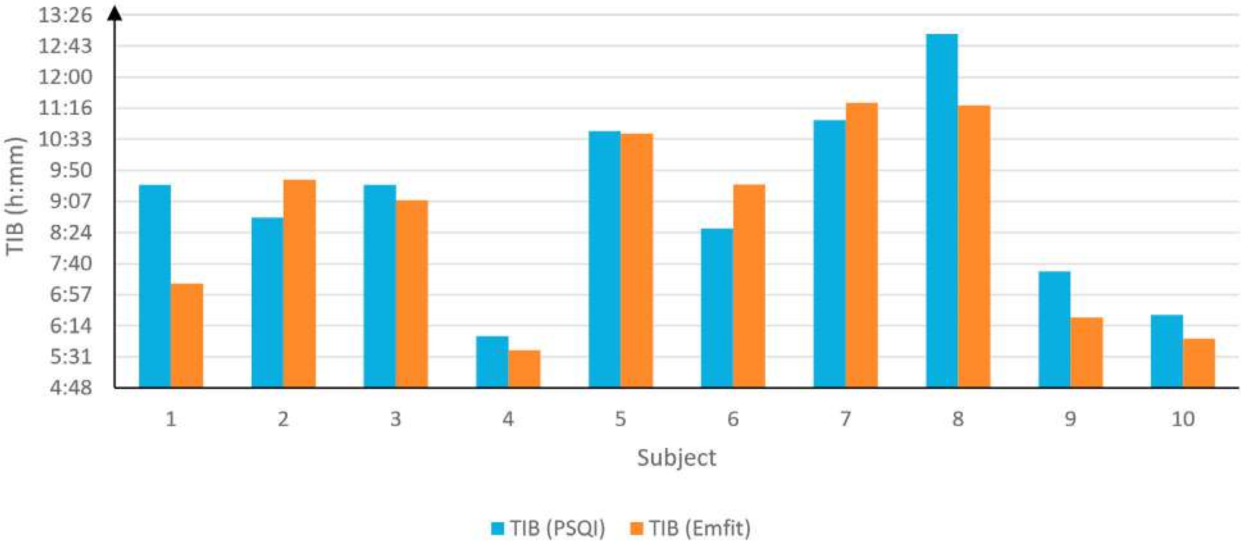

Fig. 2. Average total time in bed (TIB).

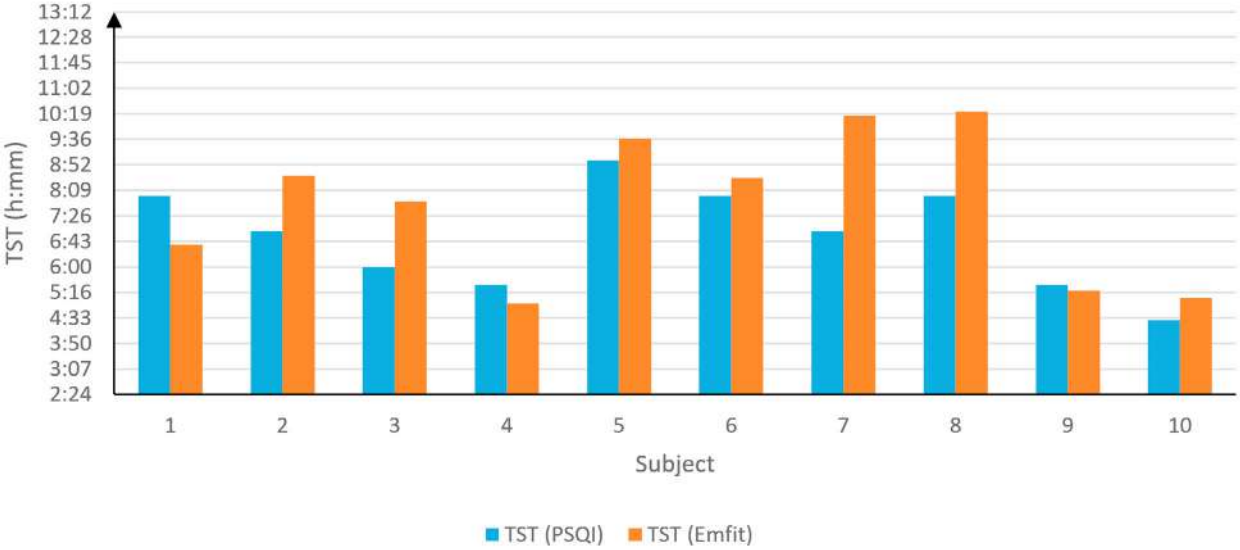

Fig. 3. Average total sleep time (TST).

7-night records (and not all 14) for subjects 1, 2, 7, 8 may have affected the outcome. Nevertheless, the tendency of underestimating the sleep time can be recognized. This fact is also known from other studies [ ].

In the case of the total sleep time measurement, the average deviation between objective and subjective measurement is higher than for the previous two sleep characteristics. It is equal to 77 minutes for all subjects, but it is 54 minutes excluding the subjects 7 and 8 from the statistics, because of a lower amount of available Emfit records for these persons.

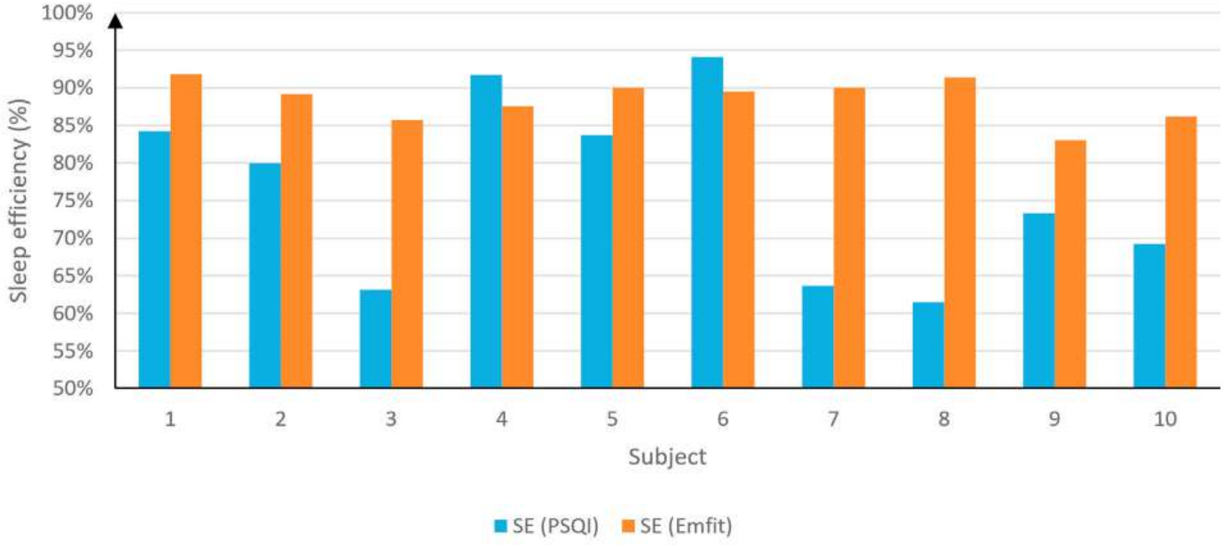

Fig. 4. Average sleep efficiency (SE).

3.6. Sleep efficiency

The presented in Fig. graph of sleep efficiency measurement for both approaches indicates a clear tendency of underestimating this characteristic by the test persons. However, the results of measurement with an electronic device can also be affected by the behavior of test persons – e.g., a continuing lying in bed with no or just a little movement (which can be typical for some persons, especially for less active elderly persons) could be wrongly recognized as sleep by the utilized device.

Comparing the sleep efficiency measured by an electronic device and by PSQI questionnaire, the average deviation between them is equal to 14% for all test persons and 9% in case of exclusion of subjects 7 and 8 for the reasons of missing records for more than the half of nights of the measurement period.

3.7. Comparison of objective and subjective measurement

As seen in previous sections, the results of objective measurements obtained using electronic devices and outcomes of questionnaires based subjective measurements are very similar for some characteristics, but they differ significantly for others. The mean and median deviation between objective and subjective measurement, as well as standard deviation (SD) are presented in Table .

Table 3. Difference between objective and subjective measurements.

Characteristic	Mean	Meadian	SD
Time going to bed (hh:mm)	00:31	00:26	00:20
Total sleep time (TST) (hh:mm)	01:17	01:00	00:59
Total in bed time (TIB) (hh:mm)	00:51	00:43	00:40
Sleep efficiency (SE)	14%	9%	10%

4. Conclusions

The study described in this manuscript has confirmed that measurements of sleep characteristics with the help of a questionnaire and electronic devices have a certain level of agreement. However, this level of agreement differs for the particular attribute measured. For example, the time of going to bed can be estimated very well, whereas total sleep time is much more difficult to estimate, as can be seen in Section 3.7.

The main conclusions that have been reached are the following:

- There is a clear tendency of underestimating the total sleep time in case of subjective measurement. Furthermore, the difference between objective and subjective measurement is significant for some subjects, while for others, it is quite small. Therefore, the direct substituting of subjective measurement of this sleep characteristic by an electronic device and vice versa is currently not possible, as the deviation is very person dependent.
- Times of going to bed reported by persons and measured by the device have a high level of accordance. Hence, the conclusion can be done that these approaches are compatible with this type of measurement.
- The correlation of total time in bed measurement using both presented approaches is of a high level with infrequent exceptions. From this, it follows that the subjective one could substitute objective measurement of this characteristic, but only for statistical evaluation of a group of persons and not for a sole subject, as in this case, there is a chance that exactly this person would be the exception case.
- In the case of sleep efficiency, no agreement between the PSQI and the Emfit device measurement was found. One of the reasons is that this characteristic is not measured directly, but calculated from time in bed and total sleep time. Therefore, the imprecisions of both these parameters' measurements are affecting the calculation of sleep efficiency value and result in lower accuracy.

In summary, it can be said that the results of the objective and subjective measurement for the characteristics "time going to bed" and "total time in bed" are very similar, while for "sleep efficiency" and "total sleep time" there are significant differences.

The executed study has permitted to come to the presented above conclusions, but improvements can still be made. First, increasing the number of participating persons could help to achieve more accurate statistical outcomes. For the same reason, the number of nights to be evaluated could be enlarged. Including more devices (based on different technologies) for the measurement could make the outcome more general and less device-dependent. Moreover, of course, separating the test groups in more subgroups (e.g., depending on the age or sex) could provide more targeted results. However, it would be possible only in combination with the first proposed improvement – increasing the number of participants.

Acknowledgements

This research was funded by the EU Interreg V-Program "Alpenrhein-Bodensee-Hochrhein": Project "IBH Living Lab Active and Assisted Living", grants ABH040, ABH041, ABH066 and ABH068. We also thank the caregivers of the Workers' Welfare Association (AWO) Schwarzwald-Baar e.V. for their contribution in conducting the study.

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Smart Innovation, Systems and Technologies 143

Ireneusz Czarnowski
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Intelligent Decision Technologies 2019

Proceedings of the 11th KES International Conference on Intelligent Decision Technologies (KES-IDT 2019), Volume 2

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ISSN 2190-3018 ISSN 2190-3026 (electronic)
Smart Innovation, Systems and Technologies
ISBN 978-981-13-8302-1 ISBN 978-981-13-8303-8 (eBook)
https://doi.org/10.1007/978-981-13-8303-8

This Springer imprint is published by the registered company Springer Nature Singapore Pte Ltd.
The registered company address is: 152 Beach Road, #21-01/04 Gateway East, Singapore 189721, Singapore

Chapter 28
Home Hospital e-Health Centers for Barrier-Free and Cross-Border Telemedicine

Ralf Seepold, Maksym Gaiduk, Juan Antonio Ortega, Massimo Conti, Simone Orcioni and Natividad Martínez Madrid

Abstract The goal of the presented project is to develop the concept of home e-health centers for barrier-free and cross-border telemedicine. AAL technologies are already present on the market but there is still a gap to close until they can be used for ordinary patient needs. The general idea needs to be accompanied by new services, which should be brought together in order to provide a full coverage of service for the users. *Sleep* and *stress* were chosen as predominant diseases for a detailed study within this project because of their widespread influence in the population. The executed scientific study of available home devices analyzing sleep has provided the necessary to select appropriate devices. The first choice for the project implementation is the device EMFIT QS+. This equipment provides a part of a complete system that a home telemedical hospital can provide at a level of precision and communication with internal and/or external health services.

28.1 Motivation

Some of the AAL technologies for healthcare services have been around for a long time and yet they have barely made it into patients' homes. Some of the barriers are technological and are based on the lack of integration of data from devices (including

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I. Czarnowski et al. (eds.), *Intelligent Decision Technologies 2019*,
Smart Innovation, Systems and Technologies 143,
https://doi.org/10.1007/978-981-13-8303-8_28

Lecture Notes in Electrical Engineering 627

Sergio Saponara
Alessandro De Gloria *Editors*

Applications in Electronics Pervading Industry, Environment and Society

APPLEPIES 2019

Springer

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ISSN 1876-1100 ISSN 1876-1119 (electronic)
Lecture Notes in Electrical Engineering
ISBN 978-3-030-37276-7 ISBN 978-3-030-37277-4 (eBook)
https://doi.org/10.1007/978-3-030-37277-4

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The registered company address is: Gewerbestrasse 11, 6330 Cham, Switzerland

Chapter 38
Recognizing Breathing Rate and Movement While Sleeping in Home Environment

Maksym Gaiduk, Ralf Seepold, Natividad Martínez Madrid, Simone Orcioni and Massimo Conti

Abstract The recovery of our body and brain from fatigue directly depends on the quality of sleep, which can be determined from the results of a sleep study. The classification of sleep stages is the first step of this study and includes the measurement of vital data and their further processing. The non-invasive sleep analysis system is based on a hardware sensor network of 24 pressure sensors providing sleep phase detection. The pressure sensors are connected to an energy-efficient microcontroller via a system-wide bus. A significant difference between this system and other approaches is the innovative way in which the sensors are placed under the mattress. This feature facilitates the continuous use of the system without any noticeable influence on the sleeping person. The system was tested by conducting experiments that recorded the sleep of various healthy young people. Results indicate the potential to capture respiratory rate and body movement.

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S. Saponara and A. De Gloria (eds.), *Applications in Electronics Pervading Industry, Environment and Society*, Lecture Notes in Electrical Engineering 627,
https://doi.org/10.1007/978-3-030-37277-4_38

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Embedded system for non-obtrusive sleep apnea detection*

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***Abstract*— This document presents a new complete standalone system for a recognition of sleep apnea using signals from the pressure sensors placed under the mattress. The developed hardware part of the system is tuned to filter and to amplify the signal. Its software part performs more accurate signal filtering and identification of apnea events. The overall achieved accuracy of the recognition of apnea occurrence is 91%, with the average measured recognition delay of about 15 seconds, which confirms the suitability of the proposed method for future employment. The main aim of the presented approach is the support of the healthcare system with the cost-efficient tool for recognition of sleep apnea in the home environment.**

***Clinical Relevance*— This approach can be used for continuous non-obtrusive apnea monitoring in the home environment.**

I. Introduction

Humans spend a big part of everyday sleeping. Sleep is unavoidable for the normal functioning of the human organism. To restore our body and brain for daily life, it has to be healthy. However, for healthy sleep, not only the duration of sleep is essential, but its quality [1].

The usual approach for the analysis of sleep behavior is a study in the sleep laboratory. In this case, the overnight polysomnography (PSG) according to the guidelines of the American Academy of Sleep Medicine (AASM) is applied [2], which is very accurate but time and cost consuming procedure. PSG is a golden standard for a sleep study, which includes attaching several sensors to the human body for the measurement, among other things of EEG, ECG, EMG, and EOG signals [3].

Another critical point is that traditional PSG study is typically executed in a sleep laboratory and not in a home environment. Therefore, the continuous observation of a patient at home is almost not possible to organize. For this reason, cost-efficient systems for use in the home environment could support sleep experts in analyzing a sleep quality, even if the accuracy of measurements in a home environment cannot achieve the level of PSG in a sleep laboratory. In [4], a review of actual health monitoring systems using sensors on bed or cushion was done.

Sleep apnea is one of the sleep disorders, which is present by 3% to nearly 50% of the population, depending on sex and age [5,6]. It has different effects on our everyday life; for example, the daytime sleepiness was reported by about 25% of patients with obstructive sleep apnea (OSA) [7]. Fatigue or unrestful sleep was indicated by a higher amount of persons [7].

II. State of the Art

Recognition of OSA is a topic of several scientific publications. Different approaches are presented in the following shortlisting of actual research on this topic.

The sound was analyzed in [8] to recognize the OSA/events. It was processed using Voice Activity Detection (VAD) algorithm, which has measured the energy of the acoustic signal during the breathing and holding the breath. The accuracy of about 97% for the silence phases lasting 15s or longer in the quiet environment using the professional microphone was achieved in the experiment with 50 participating persons.

In [9], the signal from bio-radar placed about 2,5 m from the test persons was used as the input of the system. The wavelet information entropy spectrum is a base for the algorithm implementation. The achieved accuracy for ten participating test subjects was equal to 93,1% comparing to the Polysomnography measurements. In a further research of the same group, they have applied the developed algorithm on the PSG respiratory recordings instead of bio/radar and achieved an accuracy of 96,1% for the detection of apnea events [10].

* This research was partially funded by the EU Interreg V-Program "Alpenrhein-Bodensee-Hochrhein": Project "IBH Living Lab Active and Assisted Living", grants ABH40, ABH41 and ABH66 and by the Spanish Ministry of Science, Innovation and Universities: EDITH Research Project (PGC2018-102145-B-C21,C22 (AEI/FEDER, UE)).

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PART IV

FINAL REMARKS

CHAPTER 11

CONCLUSIONS AND FUTURE WORK

Mathematical reasoning may be regarded rather schematically as the exercise of a combination of two facilities, which we may call intuition and ingenuity. The activity of the intuition consists in making spontaneous judgements which are not the result of conscious trains of reasoning. [...] The exercise of ingenuity in mathematics consists in aiding the intuition through suitable arrangements of propositions, and perhaps geometrical figures or drawings.

Alan M. Turing

11.1 Conclusions

The research and work conducted have made it possible to elaborate a mathematically based foundation for the development of a comprehensive sleep analysis system that provides valuable outcomes with a minimal number of measured signals. Field studies have also been carried out to address the challenges of implementing health monitoring technologies in a home environment.

As part of the work carried out, algorithms were elaborated based on a comprehensive analysis of physiological signals during sleep. Several rounds of evaluation of the developments took place, and in each case, new insights were gained, which were analysed in detail and allowed for further refinement. The most recent results have shown that the detection of sleep-relevant parameters (especially sleep stages) by analysing only respiratory and movement signals is possible and a promising method. These signals could be recorded contactless and thus conveniently for the user. The results achieved surpass the current state of the art and thus represent an important scientific finding. The findings were presented to the scientific community in numerous publications and scientific sessions.

Other matters were also addressed, even if on a smaller scale, besides the research on the main topic - sleep stage classification. Among other things, the initial design of hardware for a non-obtrusive recording of physiological signals was carried out, which necessitated research into signal pre-processing and signal recording methods. The aspects of user comfort, simplicity of use, and cost factors were as well taken into account. Identification of other sleep-related aspects/events was also not disregarded. For example, an important issue of sleep apnoea detection was considered, and initial results were obtained. The composition of these addressed points shows a comprehensively conducted work in the subject area of sleep analysis, which represents a consideration from different directions to enable an overarching scientifically based system design.

The work carried out has shown the importance of interdisciplinary cooperation because, in topics that overlap different fields of knowledge, an exchange of expertise plays a significant role, in this case, it was necessary from both the computer science and medical fields. Even if such combined approaches imply a certain degree of difficulty, at the same time, they allow to reach novel insights and thus push science further, opening new perspectives.

11.2 Future Work

The research work carried out, through the comprehensive analysis of the current state of knowledge and thanks to new developments achieved during the work, has revealed several aspects that could be focused on in future work.

As far as the recognition of sleep stages is concerned, these are the following points:

- One could use a multistage procedure in which multinomial logistic regression (MLR) would be the first stage and the calculated probabilities of being in each sleep stage in each epoch would be the input for the following stage. As a second (or further) stage, for example, the long short-term memory model (LSTM) could be used, which was identified as a promising approach during the literature review. Other neural networks and their combinations could also be employed as some of the stages of the system. In order to find an optimal combination, comprehensive research should be conducted to bring together the advantages of different approaches.

- The detection of the sleep stages could be done in parallel with using the different approaches instead of consecutively. Afterwards, an algorithm could be applied to compare the results and the final determination of the assignment of the corresponding sleep stages to each epoch. This could be a selection by the majority (if more than two algorithms were used in the first phase), also adding additional coefficients and considering the probabilities obtained as a result of the MLR model application.

- Since the quality of the input signals plays a significant role in further analysis, signal pre-processing could be enhanced. For this purpose, among other things, the detection of the parts of the signals that have insufficient quality could be improved. As a next step, the signal could be reconstructed at the corresponding points or, if this is not possible, excluded from the analysis to avoid the negative influence on the recognition of the sleep stages of the near epochs.

- By further analysing the characteristics of physiological signals during sleep, other derived parameters from movement and respiration signals could be designed. They should improve the recognition of the individual sleep stages, and thus the accuracy could be increased. Research including statistical analysis with the following mathematical description of large amounts of recordings is needed to achieve this improvement.

- The age-relevant aspects of the recognition of sleep stages should be addressed in more depth to enable differentiated analysis. Other aspects, such as gender or health status, could also be considered in the selection of suitable mathematical models for interpreting physiological signals after previous research.

There are also other extensive works planned for future investigation:

- Additional research on the physiological signals to advance the algorithms for sleep apnoea detection will be carried out. The main focus will be on the analysis of the signals, which will be recorded non-obtrusively.

- The automatic calculation of additional sleep-relevant parameters based on the preliminary work already carried out could be another possible direction for further advancement. Examples of such parameters are the calculation of sleep efficiency, sleep quality (which needs its own extensive research), or recognition of restless leg syndrome.

- The process of recording the signals during sleep without disturbing the user is to be further researched. Different variants of this acquisition are to be prototypically implemented and evaluated.

- Ultimately, the goal is to design a system that could be applied for a comprehensive and user-friendly sleep analysis through multifaceted research. The most important aspects of being considered are comfort, safety, usability, accuracy of the recording, the calculation of sleep-relevant parameters, and detection of important events at the lowest possible cost. This could enable the widespread use of such systems in the future, which could contribute to the early detection of health problems, which in turn would positively influence the well-being and state of health of the entire population through appropriate therapy at the right time.

APPENDIX A

CURRICULUM

A.1 Research Papers

A.1.1 JCR indexed Journals

1 M. Gaiduk, T. Penzel, J.A. Ortega, R. Seepold, "Automatic Sleep Stages Classification Using Respiratory, Heart Rate and Movement Signals", In: *Physiological Measurement*, 39(12):124008, 2018.
DOI: 10.1088/1361-6579/aaf5d4
Impact Factor of 2.833.
Q3 in three categories.

2 M. Gaiduk, R. Seepold, N. Martínez Madrid, J. A. Ortega, "Digital health and care study on elderly monitoring", In: *Sustainability*, 13(23):13376, 2021.
DOI: 10.3390/su132313376
Impact Factor of 3.251.
Q2 in two categories.

3 M. Gaiduk, J. Perea Rodríguez, R. Seepold, N. Martínez Madrid, T. Penzel, M. Glos, J. Ortega, "Estimation of Sleep Stages Analyzing Respiratory and Movement Signals", In: *Journal of Biomedical and Health Informatics*, 26(2):505-514, 2022.
DOI:10.1109/jbhi.2021.3099295
Impact Factor of 5.772.
Q1 in four categories

A.1.2 Other scientific articles (incl. conference proceedings)

Maksym Gaiduk has presented his research findings in international conferences over 20 times. In order to maintain a clear overview, the conferences are not listed additionally, as the contributions were also published in the corresponding proceedings and are listed below in the list of publications.

1. M. Gaiduk, R. Seepold, and N. Martínez Madrid, “Classification of sleep stages: commonly used methods and main aims for the improvement*” In: Analysis of Biometric Parameters to detect relationship between stress and sleep quality (AnBiPa 2016), November 4, 2016, Università Politecnica delle Marche, Ancona, Italy*, 2016, pp. 15–17.
2. A. Klein, N. Martínez Madrid, R. Seepold, and M. Gaiduk, “Sleep phase identification based on non-invasive recordings,” in *Analysis of Biometric Parameters to detect relationship between stress and sleep quality (AnBiPa 2016), November 4, 2016, Università Politecnica delle Marche, Ancona, Italy*, 2016, pp. 11–13.
3. M. Gaiduk, I. Kuhn, R. Seepold, J. A. Ortega, and N. Martínez Madrid, “A sensor grid for pressure and movement detection supporting sleep phase analysis,” in *Bioinformatics and Biomedical Engineering, 5th International Work-Conference (IWBBIO 2017), Granada, Spain, April 26–28, 2017, Proceedings, Part II, (Lecture Notes in Computer Science; 10209)*, Cham: Springer, 2017, pp. 596–607.
4. M. Conti, S. Orcioni, N. Martínez Madrid, M. Gaiduk, and R. Seepold, “A review of health monitoring systems using sensors on bed or cushion,” in *Bioinformatics and Biomedical Engineering, 6th International Work-Conference (IWBBIO 2018), 25th-27th April 2018, Granada, Spain - (Lecture Notes in Computer Science; Vol. 10814)*, Cham: Springer, 2018, pp. 347–358.
5. M. Gaiduk, R. Seepold, S. Orcioni, M. Conti, and N. Martínez Madrid, “Non-invasive sleep analysis with intelligent sensors,” in *Smart-Future-Living-Bodensee: Proceedings of International Workshop, 24. November 2017, Hochschule Konstanz*, 2018, pp. 23–26.
6. M. Gaiduk, R. Seepold, and T. Penzel, „Sensor-Netz-basiertes System für die langfristige Schlafanalyse im häuslichen Umfeld“, Abstracts der 26. Jahrestagung der Deutschen Gesellschaft für Schlafforschung und Schlafmedizin e.V., „Schlaf ist Medizin!“, 11.–13. Oktober 2018, Nürnberg - (Somnologie, 2018, Vol. 22, Suppl. 1).
7. M. Gaiduk, R. Seepold, and E. Rodríguez De Trujillo, “Sleep position recognition in home environment,” in *Fachtagung "Smart Day 2018", Organiser: Smart Home & Living Baden-Württemberg e.V., 7. Nov. 2018, Villingen-Schwenningen*, 2018, pp. 21–24. [Online]. Available: http://nbn-resolving.de/urn/resolver.pl?https://www.shl-bw.de/fileadmin/documents/SmartDay/Tagungsband_Smart_Day_2018.pdf
8. M. Gaiduk, B. Vunderl, R. Seepold, J. A. Ortega, and T. Penzel, “Sensor-Mesh-Based System with Application on Sleep Study,” in *Bioinformatics and Biomedical Engineering, 6th International Work-Conference (IWBBIO 2018), 25th-27th April 2018, Granada, Spain - (Lecture Notes in Computer Science; Vol. 10814)*, Cham: Springer, 2018, pp. 371–382.
9. S. Orcioni, M. Conti, N. Martínez Madrid, M. Gaiduk, and R. Seepold, “A review of health monitoring systems using sensors on beds or cushion,” in *Smart-Future-Living-Bodensee: Proceedings of International Workshop, 24. November 2017, Hochschule Konstanz*, 2018, pp. 45–48.

10. E. Rodríguez De Trujillo, M. Gaiduk, and R. Seepold, “An approach for a sleep tracking system,” in *Informatics Inside connect(IT), Informatik-Konferenz an der Hochschule Reutlingen, 9. Mai 2018*, Reutlingen: Hochschule Reutlingen, 2018, pp. 111–112. [Online]. Available: https://infoinside.reutlingen-university.de/wp-content/uploads/2018/09/2018-Tagungsband-bw.pdf
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12. R. Seepold, M. Gaiduk, T. Penzel, and N. Martínez Madrid, “Contactless detection of sleep phases with the help of regression analysis,” in: *40th Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC'18), 18-21 July 2018, Hawaii Convention Center Honolulu, HI, USA*, 2018.
13. M. Gaiduk, R. Seepold, N. Martínez Madrid, J. A. Ortega, and T. Penzel, “Non-invasives System für die kontinuierliche Schlafanalyse,” *6. Ambient Medicine® Forum „Assistive Technik für selbstbestimmtes Wohnen“, 19.-20. February 2019, Hochschule Kempten, Tagungsband*, pp. 23–28, 2019.
14. M. Gaiduk, R. Seepold, and T. Penzel, “Softwaresystem zur Erkennung von Schlaf- und Wachzuständen basierend auf der Analyse von Herzfrequenz-, Atem- und Bewegungssignalen,” in *Abstract der 27. Jahrestagung der Deutschen Gesellschaft für Schlafforschung und Schlafmedizin e. V., „Die innere Uhr“, 07.–09. November 2019, Hamburg (Somnologie, 2019, Vol. 23, Suppl. 1)*, 2019, S2-S2.
15. M. Gaiduk, R. Seepold, T. Penzel, J. A. Ortega, M. Glos, and N. Martínez Madrid, “Recognition of sleep/wake states analyzing heart rate, breathing and movement signals,” in *41st Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC 2019), 23-27 July 2019, Messe Berlin, Germany*: IEEE, 2019, pp. 5712–5715.
16. M. Jurić, M. Gaiduk, and R. Seepold, “Influence of Illuminance on Sleep Onset Latency in IoT Based Lighting System Environment,” in *Bioinformatics and Biomedical Engineering, 7th International Work-Conference (IWBBIO 2019), May 8-10, 2019, Granada, Spain, Proceedings, Part I (Lecture Notes in Bioinformatics; 11465)*, Cham: Springer International Publishing, 2019, pp. 429–438.
17. S. Orcioni, R. Pellegrini, R. Seepold, M. Gaiduk, N. Martínez Madrid, and M. Conti, “mHealth for therapeutic adherence,” in *EMBC Workshop "Telemedicine and Telemonitoring in AAL Home Environments", 41st Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC 2019), 23 July 2019, Messe Berlin, Germany*, M. Conti, G. Lebedev, N. Martínez Madrid, S. Orcioni, and R. Seepold, Eds., Reutlingen: Hochschule Reutlingen, 2019, pp. 25–28.
18. E. Rodríguez De Trujillo, R. Seepold, M. Gaiduk, N. Martínez Madrid, S. Orcioni, and M. Conti, “Embedded system to recognize movement and breathing in assisted living environments,” in *Applications in Electronics Pervading Industry, Environment and Society: APPLEPIES 2018, 26. - 27. September 2018, Pisa, Italy, (Lecture Notes in Electrical Engineering; Vol. 550)*, Cham: Springer International Publishing, 2019, pp. 391–397.
19. M. Sandybekov, C. Grabow, M. Gaiduk, and R. Seepold, “Posture tracking using a machine learning algorithm for a home AAL environment,” *Intelligent Decision Technologies 2019, Proceedings of the 11th KES International Conference on Intelligent Decision Technologies (KES-IDT 2019) - Volume 2 ; (Smart Innovation, Systems and Technologies ; 143)*, pp. 337–347, 2019, doi: 10.1007/978-981-13-8303-8_31.

20. R. Seepold, M. Conti, N. Martínez Madrid, C. Aironi, S. Orcioni, and M. Gaiduk, "Die Ballistokardiographie misst die Herzfrequenz anhand der mechanischen Körperschwingungen aus der Herzbewegung.," Somnologie, 2020/10/01 2020, doi: 10.1007/s11818-020-00267-4.
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A.2 Awards

1) In November 2021, Maksym Gaiduk was awarded as the author of the best article among young scientists at the international workshop "Social Innovation in Long-Term Care through Digitalization (LTC-2021)" in Ancona, Italy.
2) In 2021, the paper "Estimation of Sleep Stages Analyzing Respiratory and Movement Signals", published in *Journal of Biomedical and Health Informatics,* for which Maksym Gaiduk is the first and corresponding author, was selected as the best paper of July 2021 and third-best paper of the year at Escuela Técnica Superior de Ingeniería Informática (ETSII) of the University of Seville.

A.3 Research exchanges

During my PhD study period, I have spent several months on international research exchanges:

1) Sevilla (Spain). April 2017 (9 days). During this stay, several meetings with research groups of the School of Computer Engineering (ETSII) of Seville University took place to exchange the experience and develop common research directions.
2) Ancona (Italy). October 2017 (3 weeks). The aim of this stay was knowledge and experience exchange with research groups from Università Politecnica delle Marche.
3) Bratislava (Slovakia). October – November 2017 (1 week). This stay aimed to exchange knowledge and experience with research groups from the University of Bratislava.

4) Bucharest (Romania). September 2018 (3 days). The three-day meeting with the representatives of the research groups of universities from 5 countries.
5) Sofia (Bulgaria). August 2019 (4 days). The four-day meeting with the representatives of the research groups of universities from 5 countries.
6) Ancona (Italy). September – December 2019 (3 months). I was hosted by Prof. Massimo Conti in Università Politecnica delle Marche. My stay was supported by the University of Seville. During this exchange, new developments were performed, and a research study with 20 participants using the developed by us system was designed and conducted.

My usual place of residence was in Germany, and my regular workplace was at the HTWG Konstanz (Germany). However, during this time, I had had numerous research stays in Seville (Spain) with a total duration of over two months.

A.4 Projects participation

1. Title: "IBH AAL: Home Health Living Lab (HHLL)"

   Main Researcher: Ralf Seepold

   Granting Entity: EU Interreg V-Program "Alpenrhein-Bodensee-Hochrhein"

   Period: 2018-2021

   Reference: ABH066

2. Title: "IBH Living Lab Active and Assisted Living"

   Main Researcher: Guido Kempter

   Granting Entity: EU Interreg V-Program "Alpenrhein-Bodensee-Hochrhein"

   Period: 2016-2021

   Reference: ABH040, ABH041

3. Title: "Development of Online Learning Environment for e-Health (DOOLEE)"

   Granting Entity: The European Commission: ERASMUS + Program

   Period: 2018-2020

Reference: 2017-1-BG01-KA203-036310

4. Title: Evolucionando hacia los Gemelos Digitales en el Ámbito de la Salud (EDITH)

   Main Researcher: Juan Antonio Ortega Ramírez

   Granting Entity: Spanish Ministry of Science, Innovation and Universities. (Ministerio de Ciencia, Innovación y Universidades: Plan Estatal de Investigación Científica y Técnica y de Innovación 2017-2020 Generación Conocimiento - Proyectos I+D+I)

   Period: 2020-2021

   Reference: PGC2018-102145-B-C21

5. Title: ZIM project "Sleep Lab at Home (SLaH)"

   Granting Entity: German Federal Ministry for Economic Affairs and Energy

   Period: 2020-2023

   Reference: ZF4825301AW9

6. Title: "Non-invasive system for measuring parameters relevant to sleep quality"

   Main Researcher: Ralf Seepold

   Granting Entity: Carl Zeiss Foundation

   Period: 2021-2024

   Reference: P2019-03-003

A.5 Open Science

One of the important tasks of science is to use knowledge to improve the condition of human beings. In this sense, the accessibility of the scientific results achieved is of great importance. In accordance with this, an effort has been made to make the research results accessible to everyone as far as possible, resulting in a large part of the publications being published according to the open-access principle, including one of the JCR journal articles.

A.6 Others

1) Maksym Gaiduk was actively involved in developing the cooperation between the Ubiquitous Computing Lab at HTWG Konstanz and research group IDINFOR at the University of Seville. This cooperation has led, among other things, to several research staff exchanges, numerous organised Special Sessions at international conferences, and joint investigations.
2) Maksym Gaiduk was one of the organising committee members of the International Workshop "Smart-Future-Living-Bodensee" in Konstanz (Germany) in November 2017.
3) Maksym Gaiduk was a member of the organisation committee of GRSS-2018 in September 2018.
4) Maksym Gaiduk was a chairman of Special Session "Telemedicine for Smart Homes and Remote Monitoring" at the international conference IWBBIO 2019.
5) Maksym Gaiduk has been the deputy project leader of the international project "IBH AAL: Home Health Living Lab (HHLL)" over a period of 7 months in the year 2019.
6) Maksym Gaiduk is a reviewer for the JCR-indexed scientific journal "Transactions on Biomedical Engineering" (Q1).
7) Maksym Gaiduk is a reviewer for the JCR-indexed scientific journal "IEEE Access" (Q1).
8) Supervising of 4 Bachelor and Master Theses was done by Maksym Gaiduk.

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