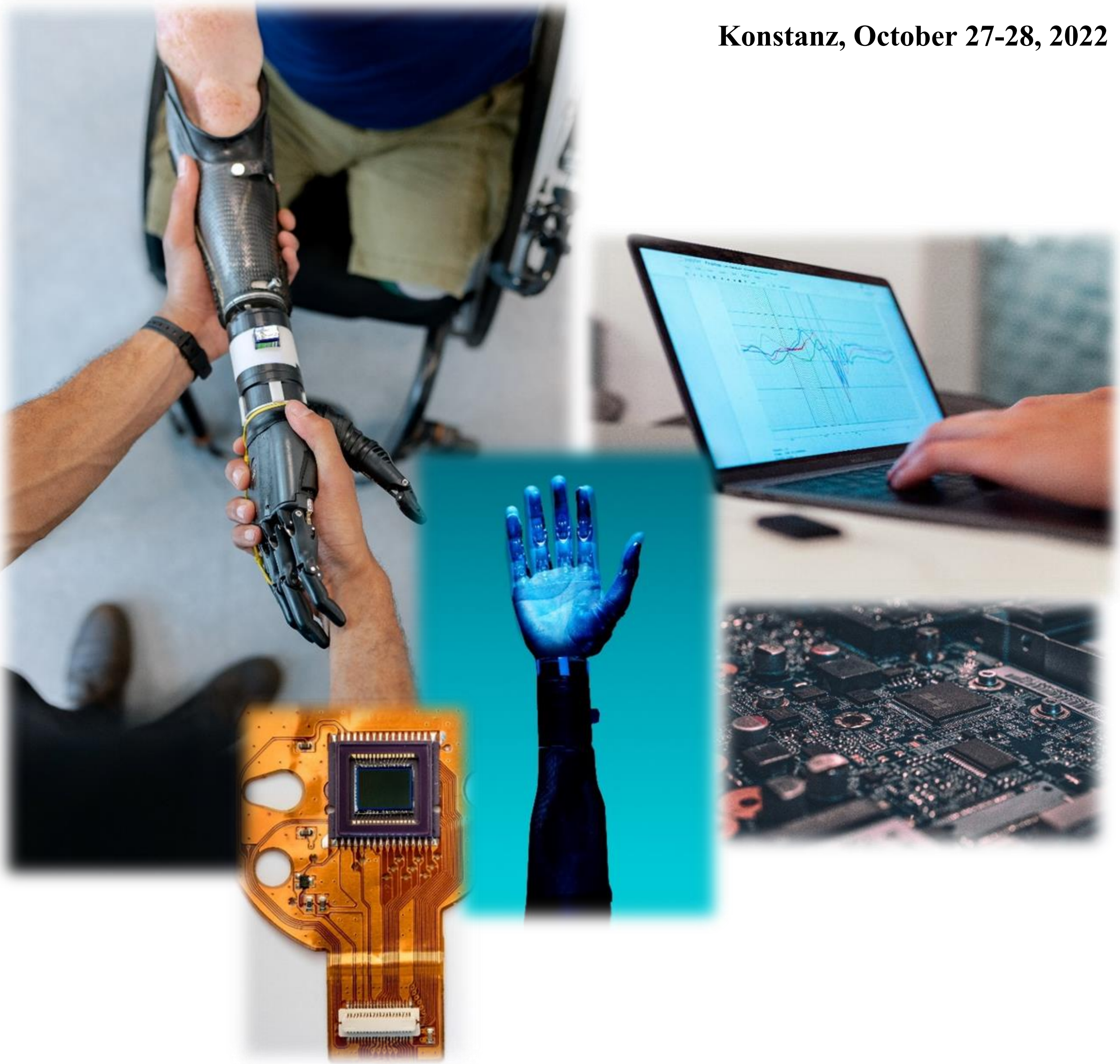
Konstanz, October 27-28, 2022



Hardware and Software supporting Physiological Measurement (HSPM-2022)

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Hardware and Software supporting Physiological Measurement (HSPM-2022)

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Edited by

Ángel Serrano Alarcón and Andrei Boiko

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Contents

Preface

This workshop addressed scientific research and development to acquire physiological signals, process signals, and extract relevant data for further analysis. There are very different domains of application, for example. Tiredness and drowsiness are responsible for a significant percentage of road accidents. There are different approaches to monitoring driver drowsiness, ranging from the driver's steering behavior to in-depth analysis of the driver, e.g., eye tracking, blinking, yawning, or Electrocardiogram (ECG). One of the leading causes of road accidents in Egypt is trucks, buses, cars, motorcycles, and pedestrians, all sharing the same infrastructure. The result is that there are more than 12,000 fatalities in road accidents every year. Thousands are injured, and some suffer long-term disabilities. A similar effect can be observed in Germany for all types of vehicles. According to the Federal Statistical Office, a high percentage of accidents involving personal injury are directly or indirectly caused by drowsiness.

A different application domain is sleep monitoring: Healthy and sound sleep is a prerequisite for a rested mind and body. Both form the basis for physical and mental health. Healthy sleep is counteracted by sleep disorders, the medically diagnosed frequency of which increases sharply from the age of 40. Increasing acceptance can be promoted by monitoring vital signs during sleep over long periods through the exclusive use of noninvasive technologies. In the case of objective measurement, the vital signs are measured to calculate the sleep phases or sleep efficiency and, after applying the appropriate algorithms, to record the sleep quality. About a quarter of all Germans have the feeling of sleeping poorly. The disruptive factors include problems falling asleep or the subjective feeling that sleep is not restful. About half of those subjectively affected have consulted a doctor. Older people and people living alone are particularly affected. There is no doubt that sleep abnormalities can lead to poor performance throughout the day, physical/somatic illnesses, psychological problems, or even premature death. Prevention, early detection, and therapy support are relevant factors impacting the personal quality of life.

The presented approaches have different application domains but share standard methodologies and technologies. Cross-domain thinking and application are essential to successful data acquisition and processing, either with traditional or cutting-edge approaches.

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Konstanz, October 2022

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The workshop has been funded by the German Academic Exchange Service – DAAD within the project "Portable system for detecting and alerting driver fatigue" (project number 57562477).
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Evaluation of Substituting a Sleep Diary by Smartwatch Measurement

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Abstract*. *The importance of sleep for human life is enormous. It affects physical, mental, and psychological health. Therefore, it is vital to recognise sleep disorders in a timely manner in order to be able to initiate therapy. There are two methods for measuring sleep-related parameters - objective and subjective. Whether the substitution of a subjective method for an objective one is possible is investigated in this paper. Such replacement may bring several advantages, including increased comfort for the user. To answer this research question, a study was conducted in which 75 overnight recordings were evaluated. The primary purpose of this study was to compare both ways of measurement for total sleep time and sleep efficiency, which are essential parameters for, e.g., insomnia diagnosis and treatment. The evaluation results demonstrated that, on average, there are 32 minutes of difference between the two measurement methods when total sleep time is analysed. In contrast, on average, both measurement methods differ by 7.5% for sleep efficiency measurement. It should also be noted that people typically overestimate total sleep time and efficiency with the subjective method, where the perceived values are measured.

Keywords -- Objective Sleep Measurement, Sleep Diary, Sleep Efficiency, Sleep Study, Wearables.

I. Introduction

Sleep is essential for human life and well-being. The fact that humans spend, on average, about a third of everyday sleeping emphasises its influence on our life, as human evolution has led to this significant amount of the needed rest time based on its importance [1].

Considering the relevance of sleep for human health, it is crucial to keep its quality high. For that, possible sleep disorders should be identified at the early stage to apply timely and appropriate therapy. Different parameters can be measured and analysed depending on a particular sleep disorder to facilitate diagnosis. In the case of sleep insomnia, one of the standard methods for diagnosis and therapy monitoring is based on using sleep diaries to obtain relevant sleep characteristics. The consensus sleep diary is one of the established tools being applied [2].

A sleep diary can be classified into the category of subjective sleep measurement [3]. This kind of measurement is based on the human perception of sleep and therefore is individual-related [4]. Another sleep measurement approach is called objective and relies on recording sleep-relevant characteristics /physiological parameters with the help of specialised devices [5].

Both measurement methods are used in sleep medicine to diagnose various disorders, and a combination of them might provide a comprehensive sleep analysis [6]. Nevertheless, the question if a substitution of a subjective approach through the objective one could be possible is arising, as the objective method could provide more convenience for a user due to automatical measurement without the necessity of daily filling out the documents as it must be done in case of sleep measurement with a sleep diary [7]. The comparison of these measurement approaches was reported in several publications, e.g., [8] or [9]. However, a particular device should be compared with a subjective measurement recording parameters of interest to provide a reliable conclusion on the possibility of such substitution.

This article aims to evaluate the possibility of substituting a sleep diary with a smartwatch Samsung Galaxy Watch 4 for the measurement of Total Sleep Time (TST) and Sleep Efficiency (SE), being significant characteristics in sleep medicine [10] and correlating with human health [11] and performance [12].

II. Methods

A sleep diary is a commonly used method for the subjective assessment of sleep. Several versions exist, and for the presented in this manuscript study, the German version recommended by the German Society for Sleep Research and Sleep Medicine was used [13].

Various devices for measuring sleep parameters can be used for objective measurement. To ensure comfortable use, the device should disturb the user as little as possible during sleep. A widely used approach is the use of wearables. The choice of the Samsung Galaxy Watch 4, in particular, is based on several reasons:

- The previous models of the Samsung Watch were evaluated for measuring physiological parameters with acceptable results [14].
- The relevant sleep parameters, such as TST and SE,

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can be measured with this device.

- The measurement results can be accessed via a mobile app or downloaded from a user account.
- All settings can be made in advance via the mobile app, and the measurement is fully automatic.
- The watch can ensure a battery life of about 30-40 hours.

TST and SE were chosen for the evaluation because of their significance and informative value. According to [15], there are several ways of determining SE. In the presented evaluation, we used the following Formula 1:

$$SE = TST(Wake\ up\ Time - Time\ trying\ go\ to\ Sleep\ ) * 100\% \quad (1)$$

To perform the evaluation, the field study was planned and executed. Five participants from the age group 20-40 years old were included in the study, and no significant health disorders were known to be present. Before starting the study, the aim and process of the experiment were explained, and all questions were addressed.

The smartwatch and sleep diary were presented and explained to participants on the first day of the study. They had to wear them during the day or at least put them on 20 minutes before going to bed and take them off not earlier than 20 minutes after getting out of bed. Always when the battery state was lower than 35%, the smartwatch had to be charged. A sleep diary was to be filled out directly after going to bed and immediately after waking up to ensure accurate data recording.

III. Results

After performing the study, a set of 75 overnight recordings by a smartwatch and a sleep diary was collected and analysed. The average differences between the subjective and objective measurement approaches were calculated for TST and SE parameters, and following Table 1 demonstrates the obtained statistical values for both characteristics.

TABLE I. STATISTICAL VALUES REPRESENTING THE DIFFERENCES BETWEEN OBJECTIVE AND SUBJECTIVE MEASUREMENT FOR 75 OVERNIGHT RECORDINGS

Characteristic	Mean	Median	SD
Total sleep time	00:32	00:28	00:19
Sleep efficiency	7,50%	7,06%	3,28%

Analysing the findings, one can see that the difference between the two measurement methods is, on average, more than 30 minutes for TST. If this difference can be acceptable for a substitution depends on the particular aim of the sleep characteristics analysis.

In the case of SE measurement, a 7,5% difference appears to be relatively low, which leads to the conclusion that a substitution may be reasonable for this sleep characteristic.

To facilitate a comprehensive and comprehensible representation of the obtained evaluation results, box plots for TST and SE were generated and presented in Figure 1 and Figure 2.

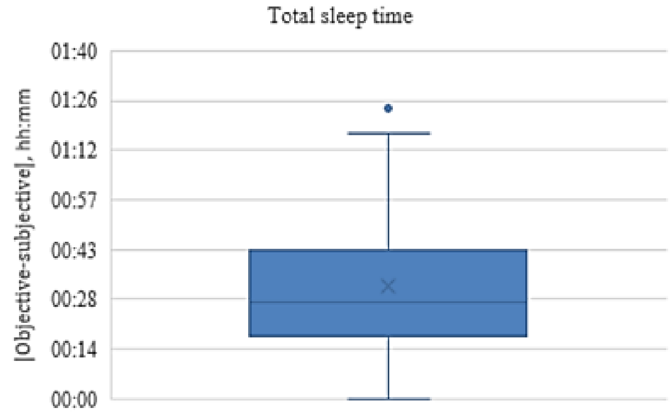

Fig. 1. Box-plot visualising the differences between the objective and subjective measurement of total sleep time for 75 overnight recordings.

Analysing Figure 1, it can be observed that outliers may reach up to 1 hour and 25 minutes of difference for a single night. This leads to the assumption that an exchange of measurement methods cannot be recommended if an accurate measurement is necessary for particular nights.

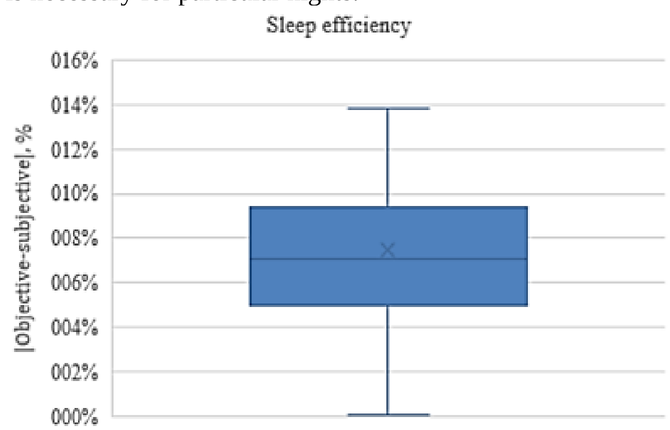

Fig. 2. Box-plot visualising the differences between the objective and subjective measurement of sleep efficiency for 75 overnight recordings.

When analysing Figure 2, it can be seen that the differences between measurement approaches are between 0% and 14%, meaning that the highest reliability of the results in the case of substitution can be achieved by a long-term observation of the SE parameter.

IV. Conclusion and Future Work

Since an automatic measurement of sleep characteristics could increase the convenience for the users and reduce potential missing data, as the measurement could be done fully automatically, the evaluation of the possibility of replacing the sleep diary with an electronic device seems reasonable.

In the work presented in this article, the Samsung Galaxy Watch 4, one of the state-of-the-art smartwatches, was chosen for the objective measurement. It is essential to mention that the findings and conclusions obtained refer to this particular smartwatch and cannot be directly transferred to other hardware devices. To summarise the results, the following statements can be presented as the main conclusions:

- The evaluation of the TST as one of the meaningful sleep characteristics led us to the conclusion that the substitution of the subjective measurement by the objective one and vice versa is unreliable when a high level of accuracy is required. One of the reasons is a substantial underestimation of awake time during the night in the case of the subjective measurement, which leads to an overestimation of TST. This also coincides with other reported findings in this area [16].

- Another parameter that was analysed - SE - seems to be suitable for replacing a sleep diary as a measurement method with a Samsung Galaxy Watch in the case of long-term observation, as the difference between the two approaches is 7.5% on average.

The performed analysis of the findings has allowed us to determine the following steps to be performed within the research line:

- Extension of the number of recordings, as well as the increase of participants number, is one of the main aims. This would allow us to enlarge the significance of the outcome.
- A broader set of parameters might be included in the evaluation, e.g., Time of Falling Asleep or Wakeup Time.
- Other devices might also be introduced in the evaluation, allowing for a certain generalisation of the outcomes. It is known that different measurement and analysis approaches, including algorithms using signals that may be measured in a non-obtrusive way [17-19], are available and can be applied to various devices. Therefore the extension of the set of devices appears to be reasonable.

V. Acknowledgment

This research was partially funded by (a) Carl Zeiss Foundation and the MORPHEUS-Project "Non-invasive system for measuring parameters relevant to sleep quality" (project number: P2019-03-003); and (b) by the German Academic Exchange Service – DAAD within the project "Portable system for detecting and alerting driver fatigue" supported (project number 57562477).

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Designing a Sensor Interface for Cardiorespiratory Measurement in Sleep Monitoring

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Abstract. Sleep is essential to existence, much like air, water, and food, as we spend nearly one-third of our time sleeping. Poor sleep quality or disturbed sleep causes daytime solemnity, which worsens daytime activities' mental and physical qualities and raises the risk of accidents. With advancements in sensor and communication technology, sleep monitoring is moving out of specialized clinics and into our everyday homes. It is possible to extract data from traditional overnight polysomnographic recordings using more basic tools and straightforward techniques. Ballistocardiogram is an unobtrusive, non-invasive, simple, and low-cost technique for measuring cardiorespiratory parameters. In this work, we present a sensor board interface to facilitate the communication between force sensitive resistor sensor and an embedded system to provide a high-performing prototype with an efficient signal-to-noise ratio. We have utilized a multi-physical-layer approach to locate each layer on top of another, yet supporting a low-cost, compact design with easy deployment under the bed frame.

Keywords -- Cardiorespiratory Parameters, Unobtrusive Measurement, Sleep Monitoring.

I. Introduction

According to the United Nations' 2030 agenda for sustainable development goal (SDG) and the World Health Organization's (WHO) 13th general program of work, the aim should be ensuring healthy lives and promoting well-being for all people of all ages as well as setting three interconnected strategic priorities to (i) achieving universal health coverage, (ii) addressing health emergencies, and (iii) promoting healthier populations. Thus, the young and the elderly, the healthy and the disease-affected, should benefit [1,2].

On the one hand, according to statistics, individuals spend up to 80% of their time in indoor spaces such as home, of which we spend almost one-third of our lifetime asleep [3]. On the other hand, homes are the major indoor and private spaces, and with the recent advances in sensors technology, the trend of shifting toward the smart medical home has shown promising output [4].

Integrating inexpensive medical and non-medical sensors and devices in smart homes and combining signal and bio-signal processing using analytical software via artificial intelligence (AI)-based techniques may contribute to an early and valid diagnosis [4].

With advancements in sensor and communication technology, sleep monitoring is moving out of specialized clinics and into our everyday homes. It is possible to extract data from traditional overnight polysomnographic (PSG) recordings using more basic tools and more straightforward techniques. Laboratory PSG, which primarily defines brain states based on electroencephalogram (EEG), is the gold standard of sleep monitoring [5,6].

With the emerging sensor technologies, advances in transforming this private space into a diagnostic space are at hand. This concept is in line with the paradigms of shifting the: (i) subject-to-device in a hospital → device-to-subject in a point of perception, and (ii) diagnosis of symptoms → preventive medicine. This supports the idea of "an accurate forecast for a specific individual longest before the predicted event". Such an approach provides unobtrusive, continuous, and long-term data acquisition for real-time monitoring [4].

Sleep is essential to existence, much like air, water, and food, as we spend nearly one-third of our time sleeping. Poor sleep quality or disturbed sleep causes daytime solemnity, which worsens daytime activities' mental and physical qualities and raises the risk of accidents [7].

The most prevalent sleep disorders are insomnia (the inability to fall asleep) and sleep breathing disorders (repeatedly interrupting normal breathing during sleeping). Other common sleep-related disorders include parasomnias, narcolepsy, periodic limb movement syndrome, and REM sleep disorder. Additionally, it is commonly known that sleep problems make it more likely for healthy people to have multiple chronic diseases at once [8].

Movement analysis and cardio-respiration measurement are the concerns that yield insight into the physiological and health status of the subject as well as the sleep assessment. With improving the sensitivity and availability of the sensors such as force sensitive resistors (FSR), piezoelectric, pressure sensors, and fiber Bragg grating (FBG), unobtrusive, non-invasive, and low-cost monitoring is at hand [9].

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The ballistocardiogram (BCG) is a technique measuring the body recoils when the heart pumps blood into the veins. Modern technical developments have greatly streamlined the measurement and evaluation of these signals and opened up new vistas for their clinical application. Every time the heart beats, the blood moves along the vascular tree, causing changes in the body's micro movements. These changes are then maintained by the body's overall momentum. The BCG is the recording of these motions and is understood to comprise motions in all three axes. It can be quantified as a displacement, velocity, or acceleration signal [10].

The transverse BCG indicates anteroposterior (or dorso-ventral) vibrations, where-as the longitudinal BCG measures the head-to-foot deflections of the body. Longitudinal BCG measurements were the main focus of the initial bed- and table-based BCG systems because they were thought to constitute the biggest projection of the 3D forces brought on by cardiac ejection [11,12].

The FSR sensors, which transduce changes in pressure exerted on its active area in-to changes in its electrical resistance, have been extensively applied in monitoring cardiac activity and respiration measurement at home with the focus of research activities [13].

However, designing and implementing a device that is low-cost, easy to deploy, and high performing remains a concern.

In this work, we design and implement a board interface that facilitates the communication between the FSR sensors and the embedded system for measuring cardiorespiratory during sleep. The prototype is in an efficient form factor, compact, low-cost, extendable, and does not need any technical guidance for deployment, is battery-powered, and operates out of the box.

The rest of this work is presented as follows: in Section 2, materials and methods, including the technical description and approach, are provided. In Section 3, the results are presented briefly, and the advantages of the prototype are highlighted. The work is concluded with the take-home messages and future outlook in Section 4.

II. Materials and Methods

LTspice (Analog device, Wilmington, MA 01887, USA) has been used to simulate the electronic circuit, electrical check, adjust the gain, and tune the boundaries of the filters. Besides, we have used the Easyeda tool to design the hardware layout and a two-layer printed circuit board (PCB) performed in JLCPCB library [14].

A. Electronic Design: Components Selection, Gain, and Filter

Using LT3042, a high-performance, low-dropout linear regulator featuring ultralow noise and ultra-high power supply rejection ratio (PSRR) architecture for powering noise-sensitive radio frequency (RF) applications, we have secured the first level of the circuit.

An instrumentation amplifier (INA) provides a large gain for very low-level signals, often at high noise levels. Therefore, the first level of the circuit is followed by AD8221, a high-performing INA. INA is a particular type of differential input amplifier; its primary focus is to provide differential gain and a high common-mode rejection ratio (CMRR). AD8221 offers a wide power supply range of ±2.3 V to ±18 V, high input and low output impedance, low offset (25μV maximum input), and low noise, i.e., 8 nV/√Hz, @ 1kHz, maximum input voltage noise and 0.25 μV p-p input noise (0.1 Hz to 10Hz). There are three main features for selecting this INA:

(i) The gain can be set by one external resistor,
(ii) The input stage is fitted with buffer amplifiers,
(iii) The output stage is a traditional difference amplifier.

We have adjusted the gain to 100 and filtered the signals with a frequency of greater than 50Hz. However, it could be further adjusted.

B. Form Factor: Deployment, Portability, and Applicability

We have developed a prototype composed of two layers – but extendable, (i) battery-powered embedded system and (ii) an interface board, which links the FSR sensor(s) to the embedded system. We have utilized the multi-physical-layer (MPL) approach. It benefits from the extendable height rather than the x-y plane. Thus, the implemented prototype is in 3D, with extended height and maintaining the x-y dimensions. The interface board is stuck on the top of the embedded system via the board-to-board connectors, yet the top layer supports the extension for sticking further board interface for additional sensor(s).

We have shared the power source and inter-integrated circuit (IIC) bus between the boards and preserved the pins for connecting the sensors to the ADC pins of the embedded system, i.e., Raspberry Pi 4B.

The prototype resulted in a compact and out of box functional hardware design that could be readily deployed under the bed frame. It could be assembled, moved, and adjusted from one bed frame to another, yet compatible with the requirements and does not need re-adjustment nor technical instruction for the assembly (Figure 1).

C. Cost: Efficient and End-User Affordability

The total cost of the device, including the interfacing board, the electronic components, Raspberry Pi 4B, and sensors, remains restricted to 180 Euros, of which the costs of the interfacing board plus electronics components integrated into, is approximately 50 Euros.

III. Results and Discussion

We have designed and implemented a board interface between the measuring FSR sensor(s) and an embedded system to acquire, pre-process, and transmit the data over the wire.

The system consists of a battery-powered embedded system (Raspberry Pi 4B), a board interface, and FSR sensors. The approach used is the multi-physical layer (MLP) utilizing the board-to-board connections in the z direction. This would contribute to the portability of the system and easy deployment via maintaining the x-y dimension fixed and expanding the height. Consequently, the approach improves the form factor leading to a compact system.

The sensor-board-Raspberry Pi 4B communication is through IIC, which have been originally designed for on-board, short-range communications for efficient multi-sensor deployment supporting high frequency and avoiding the sampling rate drop. The layout design led to removing all wire-based communications between the board and the embedded system in order to preserve this goal and achieve the sampling rate in the range of 250-300Hz. This enables the system to use the data without violating the Nyquist rule for phonocardiogram (PCG) analysis

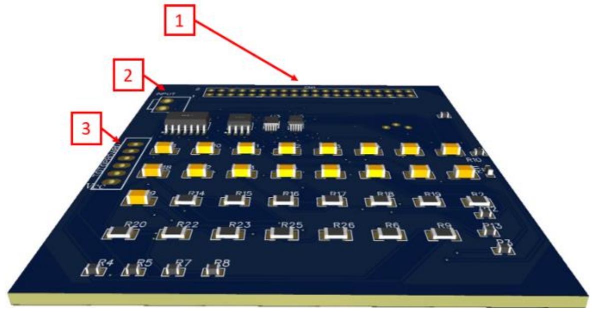

Fig. 1. The sensor board interfaces in two-layer. (1) the shared pins with the Raspberry Pi 4B, (2) the input to the FSR sensor, and (3) the ADC shared pins between the boards.

The sensor board dimension is 70.6 mm × 66.1 mm, which is smaller than the Raspberry Pi 4B with a length dimension of 85.6 mm. The sensor board interface is located on top of the Raspberry Pi 4B through the integrative pins. The total height of the system consists of Raspberry Pi 4B, and board interface is limited to 25 mm.

In addition to sharing the power pins and IIC bus between the two layers, the potential of direct communication between the additional interface board and the embedded system has been anticipated by preserving the sharing ADC pins with each sensor. Thus, the board is expandable up to four board interfaces in the z-direction, extending the height of the whole system up to 55 mm, yet, representing a small box in the dimension of 85.6 mm × 66.1 mm × 55 mm (Figure 2).

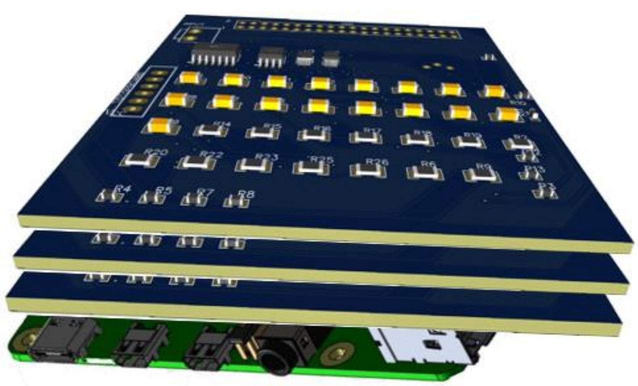

Fig. 2. A schematic of the MPL approach. The battery-powered Raspberry Pi 4B is at the bottom with three additional sensor board interfaces. The approach preserves a compact form factor for easy deployment under the bed frame.

We have already tested the board with one FSR sensor deployed under the mattress and on the bed frame, collecting the data from five subjects in four positions (supine, prone, left, and right shoulder), each for 60 seconds.

The results show that the signal amplitude and signal-to-noise (SNR) have been significantly improved while the form factor of the prototype has shrunk and further advanced.

IV. Conclusion

Using the prototype implemented in this work can facilitate the unobtrusive monitoring of cardiorespiratory parameters using FSR sensors. The prototype supports a low-cost and easy deployment of the sensors under the bed frame for cardiac and respiratory activity measurement, improving the signal quality, sampling rate of up to 300Hz, and a compact and extendable version for further studies.

V. Acknowledgment

This research was partially funded by (a) Carl Zeiss Foundation and the MORPHEUS-Project “Non-invasive system for measuring parameters relevant to sleep quality” (project number: P2019-03-003); and (b) by the German Academic Exchange Service – DAAD within the project "Portable system for detecting and alerting driver fatigue" supported (project number 57562477).

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Apnea-Hypopnea Index Using Deep Learning Models with Whole and Window-Based Time Series

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Abstract. Today many scientific works are using deep learning algorithms and time series, which can detect physiological events of interest. In sleep medicine, this is particularly relevant in detecting sleep apnea, specifically in detecting obstructive sleep apnea events. Deep learning algorithms with different architectures are used to achieve decent results in accuracy, sensitivity, etc. Although there are models that can reliably determine apnea and hypopnea events, another essential aspect to consider is the explainability of these models, i.e., why a model makes a particular decision. Another critical factor is how these deep learning models determine how severe obstructive sleep apnea is in patients based on the apnea-hypopnea index (AHI). Deep learning models trained by two approaches for AHI determination are exposed in this work. Approaches vary depending on the data format the models are fed: full-time series and window-based time series.

Keywords -- Deep Learning, Obstructive Sleep Apnea, OSA, Precision Medicine, AHI

I. Introduction

The classification of physiologically relevant events using artificial intelligence is a flourishing topic in medicine. Concretely, in sleep medicine, there are numerous scientific works in the field of obstructive sleep apnea (OSA) classification [1–4]. Some works use a single time series collected from the patient that represents only one physiological signal to use several physiological signals. [5–7]. Most publications focus on the performance of machine learning models (in terms of the accuracy of the model, sensitivity, etc.). However, not all of them include two crucial aspects when working with biomedical time series of patients suffering from apnea: the explainability of the model and the calculation of the apnea-hypopnea index. Calculating the apnea-hypopnea index is crucial to get to know the severity of a patient suffering from obstructive sleep apnea. Not all developed models take into account the AHI calculation. However, if the models are to be used in a real healthcare environment (in this case, a sleep laboratory), the models should allow the AHI calculation.

In this study, two techniques are explained to calculate the AHI depending on the deep learning model used. The focus is based on the type of input the neural network receives, either window of a certain duration or complete time series. The objective of both approaches is the same, however they present several differences that will be explained throughout this scientific work.

II. Methods

There are a large number of factors to take into account when working with deep learning and time series models. These range from the selection of the model architecture to the dataset used to train the algorithm. Although a priori, it may seem that these factors are not relevant, a correct dataset selection with good quality data and a large number of instances is crucial for success when it comes to deep learning model development tasks.

A. Data set

The dataset is usually determined by the natural setting where the model will be deployed. However, datasets from external data repositories are commonly used. One widely used repository is the Sleep Heart Health Study (SHHS). The data contains time series of patients who may suffer from sleep disorders like sleep apnea. In this case, a time series of seven hours duration can be selected for sleep apnea events classification. The data can be divided into two sets of signals according to the for-mat of the dataset that fed the models during the training:

- Window-based time series classification
- Whole-time series classification

After several tests, the 60-second windows seem to work best for classifying sleep apnea events and especially for calculating the AHI.

B. Model architecture

After a thorough literature analysis, convolutional neural networks are the best per-formers when classifying time series, in this case, OSA events. Several factors should be considered:

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the neural network complexity, the computational cost in training and inference, and the explainability and performance of the models. Based on the two approaches followed in this study, we found the following architectures:

- Window-based time series classification: Fully-Convolutional Neural Net-works (FCNNs)
- Whole time series classification: convolutional neural network for segmentation

C. Explainability of the model

The explainability of the model is crucial when it comes to developing algorithms that will be used in an actual medical environment. The class activation map (CAM) or gradient-weighted class activation mapping (Grad-CAM) technique are some of the methods used for explainability [8,9]. These techniques are easier to implement with window-based time series classification, as it is easier to visualize in 60 seconds than with the full-time series. The explainability of the complete time series classification needs to be further evaluated in order to be able to provide the clinician with all the information about a given decision quickly. However, this is not the scope of this study.

D. Apnea-hypopnea index (AHI)

The widely known formula is used to calculate the AHI:

$$AHI = \frac{Number\ of\ apnea\ and\ hypopnea\ events}{Total\ sleep\ time\ (hours)} \quad (1)$$

Two methods are used to obtain the number of apnea and hypopnea events depending on whether windows or full-time series are used. These methods are described in section 3

III. Results

This work does not pretend to show how to develop a deep learning model to work with time series and to show architectures that yield good results. Once the whole model training process, evaluation of the neural network performance, and model explainability are finished, it is time to calculate the AHI. To get the most accurate AHI possible, the deep learning model must classify as many apnea events correctly as possible. This paper proposes a method to calculate the AHI using the two most typical approaches when working with time series in machine learning, the window-based time series classification and the whole-time series classification.

A. Window-based tune series classification

When working with time series divided into windows of a specific duration, it is al-ways necessary to consider whether overlapping is applied. In this case, where the aim is to classify apnea and hypopnea events in addition to knowing the number per hour, the absence of overlapping is crucial. This way, counting how many events have occurred in the whole sleep time is possible. In this case, selecting 60-second windows helps to include complete apnea events longer than 10 seconds. Information can be lost when dividing the time series into windows. Still, this 60 seconds allows us to classify the patient's sleep minute by minute, and considering that we have time series of several hours, the AHI can be very close to the real one. Therefore, for this approach, the number of events (60-second windows) classified as apnea would be counted and divided by the total sleep time. The fact of not including overlapping allows not counting the same event several times.

B. Whole time series classification

With the segmentation technique, it is possible to identify apnea events with second-by-second accuracy. Regardless of the apnea or hypopnea event duration, such events will be classified without selecting time windows. This fact avoids the loss of information by dividing the time series into windows of a particular period in order to be classified by the deep learning algorithm. However, when it comes to calculating the AHI, it is more complex than windowing. To do so, it will be necessary to identify all the parts of the signal that have been classified as an apnea event (in seconds), along with obtaining the sets where there are more than 10 seconds of an event (if an apnea event is classified as '1' then it would be necessary to look for more than ten consecutive values of '1s'). Once all the sets have been obtained, regardless of their duration, such sets can be counted and divided by the total sleep time. This method will have higher accuracy than the windowing approach. However, it also requires higher accuracy of the neural network so that all the second-by-second events are classified correctly as we can see in Figure 1.

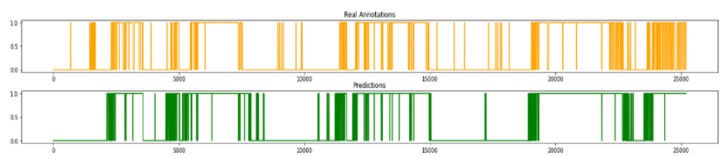

Fig. 1. Real annotations performed by the clinicians and predictions generated by the deep learning model.

IV. Conclusion and Future Work

Although different alternatives exist to work with time series of patients suffering from obstructive sleep apnea and to train deep learning models to classify sleep apnea events, the AHI calculation is limited. In particular, following the two approaches explained in previous sections: window-based and whole time series classification. The techniques described in this paper allow a simple and concise calculation of AHI and help doctors and clinicians to understand the results derived from deep learning models. The aim is to make the models as understandable and accurate as possible so they can be easily implemented in real healthcare settings.

V. Acknowledgment

This research was partially funded by (a) Carl Zeiss Foundation and the MORPHEUS-Project “Non-invasive system for measuring parameters relevant to sleep quality” (project number: P2019-03-003); and (b) by the German Academic Exchange Service – DAAD within the project "Portable system for detecting and alerting driver fatigue" supported (project number 57562477).

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Determination of Accelerometer Sensor Position for Respiration Rate Detection: Initial Research

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Abstract*. Continuous monitoring of a patient's vital signs is essential in many chronic illnesses. The respiratory rate (RR) is one of the vital signs indicating breathing diseases. This article proposes the initial investigation for determining the accelerometric sensor position of a non-invasive and unobtrusive respiratory rate monitoring system. This research aims to determine the sensor position in relation to the patient, which can provide the most accurate values of the mentioned physiological parameter. In order to achieve the result, the particular system setup, including a mechanical sensor holder construction was used. The breathing signals from 5 participants were analyzed corresponding to the relaxed state. The main criterion for selecting a suitable sensor position was each patient's average acceleration amplitude excursion, which corresponds to the respiratory signal. As a result, we provided one more defined important parameter for the considered system, which was not determined before.

Keywords -- contactless measurement, respiration rate, accelerometer sensor.

I. Introduction

One important aspect essential to the healthcare service is the continuous monitoring of the patient's vital signs. This can be done both in the hospital and on an ambulatory basis. However, regular monitoring becomes a barrier to the patient's everyday life. The creation, implementation, and usage of non-contact vital sign monitoring systems make it possible to monitor the patient unobtrusively, solving the abovementioned problem. This can be achieved by installing such a system in the patient's bed, regardless of location - in the hospital or home (even using a regular bed). In this way, this step ensures that indicators can be monitored anywhere [1]. One of the indicators that require such monitoring is respiratory rate. This is because its changes can indicate various severe medical conditions, including sleep medicine [2].

II. Related Works

Different invasive and non-invasive measurement methods can be used to obtain breath information [3-4]. A non-invasive measurement method, it is essential to note the existence of approaches using low-cost and non-contact multimodal sensor fusion, which extracts vital signs related to sleep from radar signals and sound-based context awareness techniques [5]. The various systems in which sensors are combined with the patient bed are also of particular interest. For example, an overview of health monitoring systems for use at the bedside can be found in [1]. Devices based on piezoelectric sensors can be highlighted [6]. In the meantime, Albuhari et al. in [7] presented a force sensor placed under the bed. An unobtrusive vital signs monitoring system used to assess sleep stages is shown in [8]. In addition, there is an accelerometer-based heart rate (HR) estimation system [9-10]. This system is also capable of estimating HR through the use of an accelerometer sensor. The same system is also capable of estimating RR [11].

Meanwhile, the authors of these works point out that the measurement results highly depend on the choice of sensor, the mechanical sensor holder, and its position. However, not all of these system parameters have been addressed. Thus, Conti et al. showed the choice of sensor for further studies [9]. More recently, the process of determining a specific system setup using a mechanical holder to obtain the most accurate measurement results has been presented [11]. However, determining the proper position of the sensor concerning the patient to improve measurement results has still not been given sufficient attention.

This work aims to determine the accelerometer sensor position related to the patient for a non-invasive respiratory rate measurement system using the particular system setup [11]. For this purpose, the patient's amplitude values of the respiratory signal at different sensor positions have been analyzed.

III. Methods

In summary, the system consists of the following parts: the mechanical holder, the sensor, and the computation unit with data storage possibility. All mentioned parts of the system are presented in the following subsections.

A. Mechanical holder

As noted earlier in the previous section, the measurement results are severely influenced by several aspects. One of these is the sensor holder because of its effect on the sensor's oscillation under the mattress. It is essential to ensure that the

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sensor is attached to the hanger; therefore, constant contact between the mattress and the sensor. In this paper, the mechanical holder (presented in Figure 1) is used to fix the sensor.

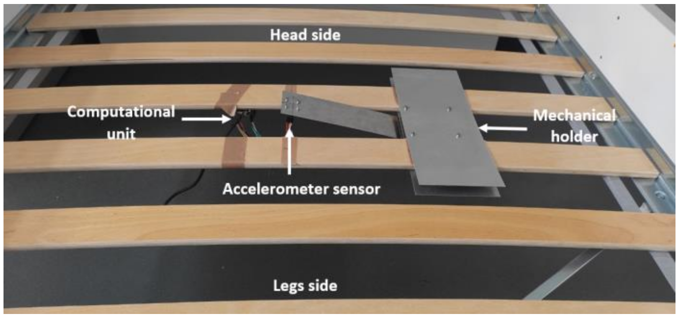

Fig. 1. The mechanical holder for the non-invasive RR measurement system.

The holder has a special adjustment for plate hanger length and thickness in order to obtain acceptable results [11].

B. *Data acquisition*

The system block associated with the signal acquisition should consist of a computing unit transmitting the data to the cloud or server, a storage module for data backup, and a sensor.

The ESP32 module has been selected as the computing unit in this work. This is because this unit is sufficient for data collection from the sensor. This device can support voltages up to 5V according to its technical characteristics. It also fulfills the cost requirements. The ESP32 module sends data to the PC via WiFi using the access point. In addition, a micro-SD module connected to the ESP32 allows each new entry to be locally stored as a backup in case the WiFi connection fails while sending data to the PC.

The ADXL355 accelerometer (Analog Devices) was used due to its good performance ratio between cost and accuracy of data acquisition. Its main features are low noise density, high sensitivity, and programmable digital high and low pass filters. Previously, this sensor has been applied successfully in non-invasive cardiac signal-sensing systems [12].

C. *Signal processing*

The signal processing for RR estimation was implemented in MATLAB. In the first step, the raw data from the ADXL355 (breathing signal) was divided into windows corresponding to the subject's position on the bed at time points according to the experiment protocol. The average breathing amplitude was then estimated for each window and subtracted to compensate for the sensor's gravitational acceleration effect and possible non-ideal positioning. A bandpass and moving average filter were then applied to the signals, with the moving window applied twice to minimize the error of detecting false breath peaks. For the bandpass filter, a frequency range of [0.05; 0.5]Hz has been chosen, sufficient to analyze human breathing at rest. Finally, the average respiratory signal amplitude excursion values for each window and patient position were calculated. The maximum difference between the calculated respiratory amplitude values was estimated to determine the preferred relative sensor position for RR estimation.

D. *Experiment design*

An experiment was performed to identify the most appropriate sensor position related to the patient to detect respiratory rate. In the beginning, the ADXL355 was placed under the bed mattress. The motion sensor was positioned in the bed center at chest level during the experiment. Then positions approximately corresponding to the level of the xiphoid process (solar plexus), diaphragm, and abdominal muscles were used to acquire data from other sensor positions (see Figure 2).

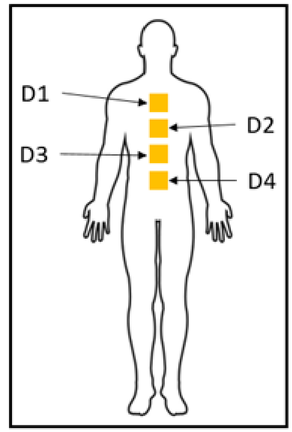

Fig. 2. The scheme of considering sensor distribution.

The sampling rate has been set at 31Hz, sufficient for the breathing signal bandwidth. In the beginning, the subject was asked to lie on the bed in a prone position (i.e., abdominal position), then the measurement was started. In order to record one series of measurements, the subject had to lie for 5.5 minutes in a relaxed state. The subject was also required to change one's body position on the bed in the following sequence: prone position, right side, backside, and left side every 80 seconds. It is important to note that the time window's first and last 10 seconds were removed from the 80-second window during the signal processing phase. One of the reasons is to stabilize the sensor position using a holder mounted under the bed when the person is already lying on the bed. It is also important to achieve a relaxed patient state in the first seconds of the experiment and then obtain data. Thus, a time interval of 60 seconds was estimated for each patient's position. In the data processing phase, this interval would be divided into 30-second epochs for analysis. In addition, this measurement series duration (5.5 minutes) is due to the need to wait a few seconds after all necessary procedures during one series before finishing data recording. After each recorded series of measurements, the position of the transducer was changed according to the order presented above. For this, the patient had to get out of bed. This was also due to avoiding the same patient position during measurements. Moreover, this approach provides more precise data for further evaluation of the sensor position. One series of measurements was performed for each holder set.

IV. RESULTS

The result of this initial research is a definition of accelerometric sensor position that allows us to get acceptable measurement results of respiratory signals from patients. Figure 3 shows typical acceleration signals from one subject's position and one of the considered sensor distributions.

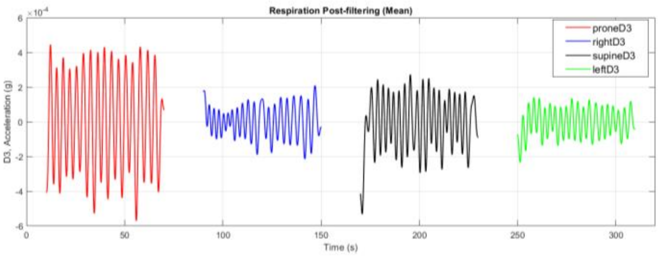

Fig. 3. Example of extracting signal.

In order to determine a proper sensor position concerning the patient, it is important to evaluate the average acceleration amplitude excursion that corresponds to the respiratory signal. The data were collected from 5 subjects (four men and one woman) who participated in the experiment. It is important to note that all subjects had approximately the same body composition. Thus, the amplitude excursion values were calculated from 10 30-second windows for each patient subject position. Table 1 shows the results for normal patient breathing in all considering bode positions and sensor distributions.

TABLE I. AVERAGE ACCELERATION AMPLITUDE EXCURSION

Sensor distribution	**Subject position**			
	Prone	**Right**	**Supine**	**Left**
	Average acceleration amplitude excursion [10^{-4} , m/s^2]			
D1	3.032	1.034	1.317	0.743
D2	3.420	1.157	1.693	1.216
D3	2.384	1.286	2.978	1.368
D4	4.569	1.119	0.879	0.662

The sensor distributions D2 and D3, which correspond to xiphoid process and diaphragm, allow getting the maximal value of considering parameter (average amplitude excursion) based on the presented results. However, it is important to carry out additional measurements and evaluation results to determine the best of these distributions.

V. Conclusion and Future Work

The study determined the preferred position of the accelerometer sensor about the patient for a non-invasive respiratory rate measurement system. Meanwhile, the evaluation of respiratory signals is challenging due to the strong influence of ambient noise. As mentioned earlier, among the factors affecting signal quality are the mechanical design and position of the sensor under the mattress and the minimum number of sensors to achieve high system accuracy.

The mean acceleration values of the amplitude of regular and deep breathing signals were analyzed to determine the proper position of an accelerometer sensor for monitoring the patient respiratory rate. Based on the results, it was determined that the position which corresponds to xiphoid process and diaphragm was the preferred position among those considered in this initial study for further work with the system used in this paper.

Despite many advantages, such as the simple design combined with efficient hardware and unobtrusive measurement capability, the system in question and the study as a whole still has enormous potential for improvement.

For example, more subjects need to be included in the study, which would give a more accurate and complete picture of the measurement results. Equally important is the validation of the results obtained using registered and recognized vital sign monitoring systems (e.g., polysomnography), which would significantly improve the results' quality. Also, no consideration has been given to reviewing and obtaining data from other perspectives. This can be achieved by shifting the sensor some distance away from one or more considered positions. In addition, there is also potential for a signal processing algorithm. One of the possible ways, for example, is to consider the system for heart rate and sleep apnea detection. In other words, there is a need for future research to improve the system, as this research is at an initial stage.

VI. Acknowledgment

This research was partially funded by (a) Carl Zeiss Foundation and the MORPHEUS-Project "Non-invasive system for measuring parameters relevant to sleep quality" (project number: P2019-03-003); and (b) by the German Academic Exchange Service – DAAD within the project "Portable system for detecting and alerting driver fatigue" supported (project number 57562477).

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Non-Invasive Cardiorespiration Monitoring Using Force Resistive Sensor

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Abstract. ***Sleep analysis using a Polysomnography system is difficult and expensive. That is why we suggest a non-invasive and unobtrusive measurement. Very few people want the cables or devices attached to their bodies during sleep. The proposed approach is to implement a monitoring system, so the subject is not bothered. As a result, the idea is a non-invasive monitoring system based on detecting pressure distribution. This system should be able to measure the pressure differences that occur during a single heartbeat and during breathing through the mattress. The system consists of two blocks signal acquisition and signal processing. This whole technology should be economical to be affordable enough for every user. As a result, preprocessed data is obtained for further detailed analysis using different filters for heartbeat and respiration detection. In the initial stage of filtration, Butterworth filters are used.***

Keywords -- FSR sensors, Polysomnography (PSG), signal processing, Butterworth filter, heart rate, respiratory rate.

I. Introduction

Humans spend almost a third part of life sleeping. Sleep is essential in recovering mental and physical health [1, 2]. Getting enough quality sleep is necessary for a person's mental health, physiological well-being, quality of life, and safety. Sleep disorders, medical conditions, and mental health can result from poor sleep quality. Sleep issues affect people of all ages and genders [3].

A Polysomnography (PSG) will document the sleep process in professional medical environments. This technique is used in sleep laboratories where patients are monitored during their sleep. PSG is the primary method to identify possible sleep disorders. Various physiological parameters are recorded: Electro-encephalography (EEG), Electro-oculography (EOG), Electro-myography (EMG), Electrocardiography (ECG), Pulse oximetry, Oral and nasal airflow, Respiration effort [4]. Measuring all of these signals requires being in the medical lab and in the presence of sleep experts, which can lead to patient discomfort.

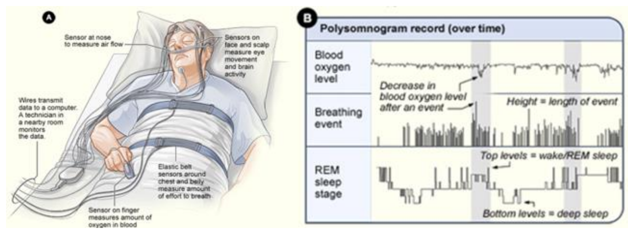

Fig. 1. A) Typical polysomnography measurement B) Current sleep analysis system used in Hospitals [5].

PSG is the standard monitoring method to determine sleep stages and possible sleep disorders [6]. Various information is collected with high accuracy and resolution. However, subjects have to sleep in an unfamiliar environment (sleep lab) and are strictly connected to sensors, which could lead to uncomfortable sleeping behavior compared to regular sleep [7]. Despite the apparent feasibility of the PSG to provide real-time and accurate information about sleep disorders, it introduces some limitations, i.e., complexity, invasiveness, intrusiveness, physical limitation, time-consuming, high cost, and lack of privacy. Furthermore, not all gathered information by PSG are necessary to detect anomalies in sleeping behavior. Therefore, alternative approaches are of high interest [8].

In the proposed approach, a resistive pressure sensor was used to detect the pressure under the mattress. FSRs (Interlink Electronics, Camarillo, California, United States) are sensors that detect physical pressure, squeezing, and weight, which operate on the principle of a variable resistor whose resistance is directly proportional to the applied force. These sensors are easy to set up and are excellent for measuring pressure.

The idea is to do experiments comparing data from the PSG system and data from the FSR sensors with different distributions under the mattress and attempt to answer the question: what is the optimal distribution of the sensors for the heart rate and breathing rate measurement?

II. Methods

The proposed system consists of two blocks of signal

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acquisition and signal processing, verified with an experimental design. All three blocks are presented in the following subsections.

A. *Signal acquisition*

The system includes pressure sensors installed under a bed mattress and a computational unit. The choice of pressure sensors is essential for unobtrusive data measurement. According to [9], pressure sensors have been chosen, particularly the 406 Square Force Sensing Resistor (FSR), to integrate into the system. The sensor's shape is well-suited for installing the bed structure. Moreover, they preserve low-cost and high sensitivity (Figure 2).

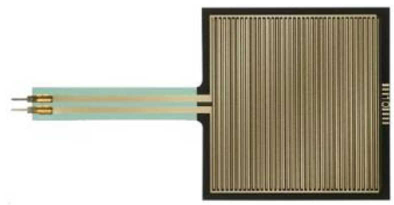

Fig. 2. FSR 406 Resistive pressure sensor.

We aim to identify the efficient sensor distributions and the most contributing sensors in different sleep positions. Several ways of sensor layout under the bed mattress have been investigated earlier [10]. Thus, it is necessary to define the sensor arrangement. Considering preliminary tests and studies, we have come up with the arrangement set of four sensors in a line on the chest level, as it is proven to be more efficient in detecting body movement, which might represent the respiratory and cardiac activities on this line [11].

It is important to note that one line of sensors distributions with a similar arrangement designed, such that this line can be located either at chest level or stomach level, as the belly and thorax exert the most significant pressure on the plane [11]. However, as there are two areas where a person can exert the most pressure during breathing movements, we decided to choose five distributions of sensors to investigate different distributions and study the sensors' contributions to each respiratory and cardiac activity independently (see Figure 3).

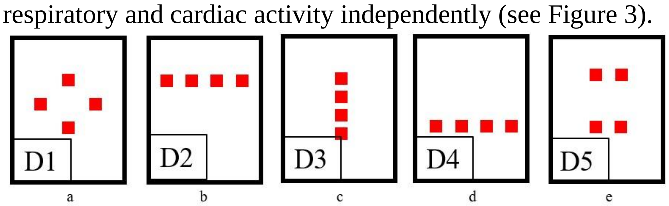

Fig. 3. Distribution of FSR sensors.

The sensors should be connected to a computational unit that will convert the analog signal to digital. Raspberry Pi 4B has been chosen as a computational unit for the system concept because it fulfills the requirements such as low cost, a powerful embedded system, is capable of real-time data acquisition and processing, and supports a wide range of data communication protocols. This is due to the availability of video output, a high processor clock speed, and sufficient RAM. Moreover, Raspberry Pi 4B has several advantages:

- It is small in size, which allows it to be located under the bed.
- It is decisive for signal processing visualization and transmission.

A PSG system with two-electrodes ECG and a Respiratory Inductive Plethysmography belt (from SOMNOmedics GmbH, Randersacker, Germany) for thorax and abdomen signal recording was used as reference data. The ECG, respiration rate, and FSR sensors were recorded with a frequency of 256Hz and 32Hz, and 78Hz, respectively. The FSR sensors and system were deployed under the bed frame. The data collected from FSR sensors were compared with the reference standard sensors.

B. *Experiment design*

During the experiment, four subjects participated in the study. For each subject, four positions (prone, right side, supine and left side) are recorded for 80 seconds in each position. FSR distributed sensors with four sensors and five distributions (shown in figure 2).

The participants were asked to put on the PSG system before lying on the bed, under which the sensors are pre-installed in different distributions, in a prone position. From each position and recording, 10 seconds of beginning and end are cut. It is important for the cleanliness of the data recording in order to ensure removing (reducing) the effect of an artifact. It was also necessary to change position every 80 seconds to the right, supine, and left sides.

C. *Signal processing*

In order to process the data acquired from the FSR and reference sensors, the acquisition, preprocessing, and comparison took place as the following steps:

- Time synchronization of data received from PSG and FSR systems
- Four windows corresponding to the position of the patient on the bed were highlighted (supine, prone, left and right sides)

The analysis of the pre-processed data was performed. For this purpose, second-order Butterworth filters were used for the data from the FSR sensors first: Low-Pass Filter with a cut-off frequency of 0.3 Hz for the respiratory data and Band-Pass Filter: 0.7-5 Hz (low cut and high cut frequencies) for the cardiac analysis.

III. Results and Discussion

We have conducted a preliminary study to process the data and improve our understanding of the FSR sensor's functionality under different positions. We performed the preprocessing, including the offset removal and data synchronization, to perform the next study steps applying different filters to detect heart and respiratory signals. More specifically, time synchronization of two-time series data, separation of four windows of 60 seconds duration, and comparison of recording frequencies. Also, an attempt to apply second-order Butterworth filters to data from FSR sensors.

As this study is at an early stage, it is necessary to analyze the signals against a gold standard to determine the sensors' location to achieve the most accurate results. An example of data visualization is shown in Figure 4. It shows the data from one subject, from the first position (on the chest), and for 10 seconds.

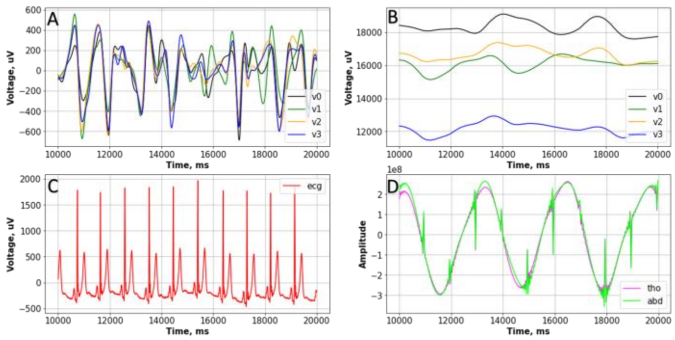

Fig. 4. Data visualization: A) band-pass filter applied to FSR data (vi - sensor); B) low-pass filter applied to FSR data (vi - sensor); C) data from the PSG system for the ECG; D) data from the PSG system for the respiratory signals (thorax and abdomen).

We compared the number of peaks when using the band-pass filter to detect heartbeat (A) with the number of R peaks from the ECG signal (C), it is possible to monitor heart rate. The same can be seen in graphs B and D and it is then possible to detect respiratory rate.

IV. Conclusion and Future Work

As part of this work, it has become possible to monitor a person's heartbeat and breathing through FSR sensors deployed under a mattress. Firstly, the data was obtained from raw data for further analysis. Secondly, compare the number of peaks received from the filtered data from the FSR sensors with the reference data. In the future, however, there will still be areas where further improvements are possible. One possible way to use discrete wavelet transform for spectral analysis of signals for detecting heart rate. So it is possible to evaluate and analyze the data even more precisely. Another possible direction of future work is to use many combinations of sensor locations under the bed. Perhaps a different configuration can be found to allow a more accurate heart and breathing rate estimation.

V. Acknowledgments

This research was partially funded by (a) Carl Zeiss Foundation and the MORPHEUS-Project "Non-invasive system for measuring parameters relevant to sleep quality" (project number: P2019-03-003); and (b) by the German Academic Exchange Service – DAAD within the project "Portable system for detecting and alerting driver fatigue" supported (project number 57562477).

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Generative Adversarial Networks: Project Relevant Overview

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Abstract. Generating synthetic data is a relevant point in the machine learning community. As accessible data is limited, the generation of synthetic data is a significant point in protecting patients' privacy and having more possibilities to train a model for classification or other machine learning tasks. In this work, some generative adversarial networks (GAN) variants are discussed, and an overview is given of how generative adversarial networks can be used for data generation in different fields. In addition, some common problems of the GANs and possibilities to avoid them are shown. Different evaluation methods of the generated data are also described.

Keywords -- Generative Adversarial Networks, Synthetic Data, Machine Learning.

I. Introduction

Nowadays, data is significant in the machine learning community as it is difficult to get valuable data because of privacy laws. Generating synthetic data can help to improve machine learning tools to have more data to train on and to generate better results in classification or other tasks. Generative adversarial networks (GAN) are well-known and established ways to generate data. It is commonly used for image generation. In this work, we will discuss the problems of GANs and which variants of GANs are already used to generate synthetic data for different aspects. This work will discuss GANs, their problems, and the variants that exist to avoid common problems. Then some examples of how GANs are used in the medical field and a short overview of the evaluation metrics will be given.

II. Generative Adversarial Networks

The training of the GAN is based on two networks that are competing. The generator tries to generate values that are synthetic but look real. On the other hand, the discriminator tries to identify the values it gets from the generator as real or fake. The discriminator learns how real data looks like from the real data sample which it get for the training. In every iteration the generator gets feedback from the discriminator, if the generated data is recognized as real or fake [1-7].

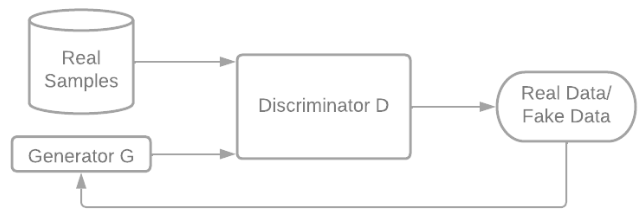

Fig. 1. Structure of a GAN

A. Problems of GANs

A common problem of generative adversarial networks is that the generator may generate samples that the discriminator does not detect as fake. So the generator can remember the characteristics and generate only similar samples where the distribution is insufficient. This is called a mode collapse. Another problem is that if the discriminator is too good, the generator does not get enough information to adjust the procedure. This also can lead to the discriminator and the generator can fail to cover, and so they cannot generate correct results [1,3,5,8,10].

B. Wasserstein GAN

The Wasserstein GAN uses the Wasserstein distance instead of the traditional Jenson-Shannon Divergence for evaluating the real and synthetic distribution. The use of the Wasserstein Distance leads to more stable training of the GAN [3,11].

C. Anonymization Through Data Synthesis using GANs

The difference between a conditional GAN and an ADS-GAN is that the ADS-GAN optimizes each patient's conditioning set and generates new data based on them. On the other hand, the set of variables is predetermined in a conditional GAN. Moreover, to overcome the known limitations of GAN Yoon et al. used a Wasserstein GAN with Gradient Penalty [3].

D. Other GANs Variants

In order to improve the GAN and eliminate its problems, many different GAN versions were developed. For example, there is the Deep convolutional GAN, Cycle GAN, Private Aggregation of Teacher Ensemble GAN, RedGan, METGAN, XGAN, and StarGAN [3,4,8].

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III. Generative Adversarial Networks in the medicine field

In this section, some examples will show there GANs are used in medicine.

A. Dual-Discriminator Fourier Acquisitive GANs

As a classification of disorders based on optical coherence tomography(OPC) with deep learning needs a lot of data. Tajmirriahi et al. extended a GAN model to generate OPC images. By adding a dual discriminator and a dual-adversarial GAN with a Fourier acquisitive, the model can learn spatial and frequency domain characteristics and create higher-resolution images so that more images of realistic diseases like diabetic macular edema can be used for the classification models to learn. This allows the GAN to multitask learning of spatial and Fourier information of the OCT images. This also leads to an increase in stability and prevents the mode collapse of the GAN. The authors described that with this method, the generated data follow the original data pattern [1].

B. X-ray Images from Point Clouds using Conditional GANs

For simulation X-ray images from point clouds, Haiderbhai et al. used conditional GANS to generate x-ray images. They used a depth camera and other sensors to create point cloud images of hands, and then they generated the images with the GAN. These generated pictures should be a prediction of the real X-ray images. They used the Root Mean Squared Error, the Structural Similarity Index Metric, and the Perak Signal Noise Ratio for validation. In all experiments with different point cloud densities, the results were similar, but the points in the cloud were the better the results were, even if only minimally better [2].

C. Generating ECG Data

Harada et al. changed the generator to an RNN based on LSTMs to generate time-series data. The discriminator is also an LSTM layer with an average pooling layer. [5] Another paper tries to use the basic GAN to generate ECG data, but before training the model, Piacemtino et al. transform the time series into images with a data arrangement algorithm so that no information is missing and the standard use of GAN can be continued [6].

D. Using GANs for protecting private data

One key aspect of using GAN in the medical field is to protect the private data of patients but still allow researcher to have enough data for there projects. GAN can be used to generate synthetic data by using dataset of real data. One way to anonymize the generated data is to add noise to the learning process of the GANs generator during the learning process. An other way is to add the noise directly to the data. This process is also called Differential privacy(DP). A popular DP method is the Laplacian mechanism.[12] The anonymized synthetic data can then be shared between different institutions for different research project without compromising the privacy of the patients. And as more data is available more successful results can be accomplished.

IV. GAN Evaluation Metrics

Kolmogorov-Smirnov test, Pearson Chi-square test, Mean Absolut Error, Mean Sum of Squared Differences, image similarity index measure, Fréchet inception, and learned perceptual image patch similarity are the most commonly used metrics to evaluate the similarity of synthetic and real images. The main issue tested with the metrics is if the distribution of the generated data is similar to the original distribution of the data [1,3,4,7]. If the generated data has a relation in between itself it is useful to use the Persons correlation coefficient which can detect a relations between data [13].

For evaluation generated synthetic time series by GANs the Maximum Mean Discrepancy is used often. This method measures the distance between probability distributions of different data samples [14,15]. Another way to evaluate the results of GAN is to use the generated synthetic data in classification models and compare these results with the classification of the real data. If the results should the similar in the best case. Naveed et al. compared also forecasting models with real and synthetic data to evaluate the used GAN [16].

V. Acknowledgment

This research was partially funded by (a) Carl Zeiss Foundation and the MORPHEUS-Project “Non-invasive system for measuring parameters relevant to sleep quality” (project num-ber: P2019-03-003); and (b) by the German Academic Exchange Service – DAAD within the project "Portable system for detecting and alerting driver fatigue" supported (project number 57562477).

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Estimation of Stress Perception Using Mobile Devices and Emotional Stability in Students while Driving in a Simulator

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Abstract. The purpose of this paper is to examine the effects of perceived stress on traffic and road safety. One of the leading causes of stress among drivers is the feeling of having a lack of control during the driving process. Stress can result in more traffic accidents, an increase in driver errors, and an increase in traffic violations. To study this phenomenon, the Stress Perceived Questionnaire (PSQ) was used to evaluate the perceived stress while driving in a simulation. The study was conducted with participants from Germany, and they were grouped into different categories based on their emotional stability. Each participant was monitored using wearable devices that measured their instantaneous heart rate (HR). The preference for wearable devices was due to their non-intrusive and portable nature. The results of this study provide an overview of how stress can affect traffic and road safety, which can be used for future research or to implement strategies to reduce road accidents and promote traffic safety.

Keywords -- Stress, Worries, Heart Rate, Stress Perceived Questionnaire (PSQ).

I. INTRODUCTION

The purpose of this study is to investigate the estimations of stress perception and emotional stability while driving in a simulator while using a mobile device and show the different emotional states and the perceived stress of different drives while. Road safety and stress have a relationship. Drivers may experience stress when they feel they are unable to handle the driving process or are losing control. Stress can be defined as a psychological factor that, on high levels, has long-term adverse effects on the heart [1], and extreme acute levels of stress can induce immune dysfunctions [2] and even trigger panic attacks [3]. These can be hazardous for traffic safety because they can lead to unexpected and difficult-to-manage circumstances. The daily presence of stress is not necessarily seen as a negative element but more a mechanism to cope and react fast to demanding situations [4].

Stress can be defined as a mechanism that is active in the presence of danger or situations that demand height attention and fast response. Stress helps us to react faster to these situations and reorganizes body functions prioritizing functions that help us achieve maximal reaction and performance [4]. Stress is helpful in our daily life to cope with demanding situations, and triggers that can induce stress are called stressors. In additionally to the previously mentioned effects of stress, there are also negative severe long-term effects of high levels of stress like difficulties responding adequately to fiscal, mental, and emotional demands [5-8], also known in burnouts and cardiac diseases [9-10].

II. METHODS

The study consists of five male and female volunteer participants from the university student population. The age range of the participants was between 18 and 35 years old. The selection criteria were: the volunteers had to be healthy, have no cardiac health problems influencing the heart variability, and have good vision. The participants underwent two phases of the experiment, which were conducted using a driving simulator. In the experiment first phase, the volunteer had to answer a Stress Perceived Questionnaire (PSQ) and listen to relaxing music. In the second phase, the volunteers were asked to drive in the simulator, taking on a range of tasks, such as maintaining a safe speed, using the brakes correctly, and navigating a course over a period of 25 minutes.

Additionally, some random situations that induce stress were created. In both phases, the heart rate was collected and stored. Both phases were conducted over a period of 30 minutes.

Each volunteering participant was equipped whit a chest strap that collected different biocidal parameters. In this study, we focused on the Heart rate and R-R Intervals. The R-R interval is the time between two beats. As a result of this study, a tendency between worries and the subject experienced stress while driving in a simulator is expected. Depending on the answers given in the Stress Perceived Questionnaire (PSQ), the volunteer will be categorized into one of the three levels of worries and stress. The results should help to compare the relationship between worries and perceived stress.

The Stress Perceived Questionnaire (PSQ) is one of the most commonly used questionnaires for the estimation of personal stress [11]. In this context, stress is defined as the strain people perceive when they feel their needs are too much to handle.

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The driving simulator used in the study implements realistic car physics and allows the configuration of the behavior of pedestrians and other drivers and customization of the traffic density.

III. Results

The results of the experiment revealed some tendencies of the volunteers, showing that most of the volunteers are generally not very worried (see Fig. 1). Fig. 1 shows that most of the volunteers were in the group with fewer worries from 0 to 33,33% to middle worries and the group of 33,34 to 66,67%. Table 1 shows the percentage of volunteers who have experienced different worries levels. 37,5% of the volunteers have a low level of worries, 37,5% have a medium level of worries, and 25% of people have a high level of worries. Although the participants reported a higher stress level when driving the simulator compared to listening to relaxing music. Table 2 shows the reported stress levels and the measured RMSSSD for each category. Table 2 indicates that 25% of the students have a low level of stress whit in an RMSSD score between 91,043 and 70.430, 25% have a medium level of stress whit in an RMSSD between 70,430 and 49,818 and 50% of the students reported a high level of stress whit an RMSSD between 49,818 and 29,205.

Table 1. Worries of students.

Worries Level	**%**
Low	37,5%
Medium	37.5%
High	25,0%

Table 2. Reported stress of students.

Stress Level (RMSSd)	**%**	**RMSSD**
Low	25,0%	91,043-70,430
Medium	25.0%	70,430-49,818
High	50,0%	49,818-29,205

IV. Discussion

The small sample size of the studies limits the reliability of the results. The results of this study show a tendency that driving in a simulator whit randomized traffic conditions has a negative effect on stress levels. The results could indicate that this situation imposes the driver with extra demands, resulting in an increment of stress. This suggests that drivers that reported a medium or higher level of worries might feel more stressed than those who reported less worried. It appears that drivers with higher levels of worry may experience more stress than less worried drivers. It might also suggest that it is essential to consider the effects of stress and worries when road safety is a concern.

Additionally, it is visible that the calculated RMSSD behaviors are very similar. As seen in table 2, the groups of volunteers that reported higher perceived stress also had a lower RMSSD.

Due to the limited amount of collected data, the effects of driving with different levels of stress and worries and their influence on road safety have to be explored more deeply and in detail. Due to the particular smal data size used in this experiment, it is important to mention that the result might not be generalizable. However, further research is needed and planned to confirm this tendency due to the limited data sample.

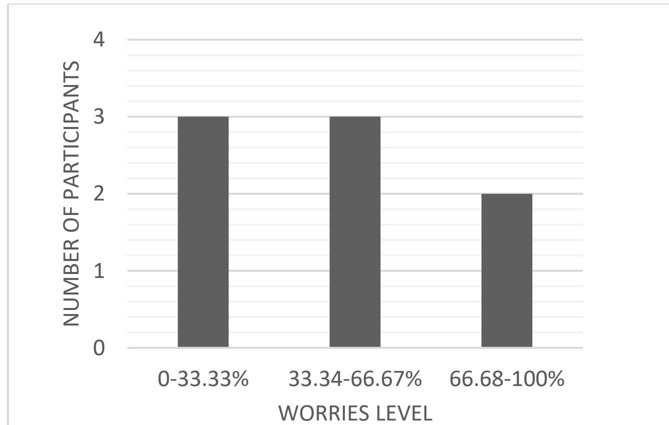

Fig. 1. Distribution of participants

V. Conclusion

Overall this study highlights shortly the importance of understanding the relationship between stress and worries and the need for future research to understand the relationship between stress and worries better. The study also shows the importance of reducing the negative impact of stress on worries.

The results suggest that driving in a simulator with randomized traffic situations can affect stress levels negatively. Additionally, it suggests that worried drivers are more prompt to feel more stress and, consequently, have a higher risk of causing a road accident and reducing traffic safety.

In addition, future studies should also look at the effects of different personality traits on traffic and driver safety and determine the relationship between personality traits and the effects of stress and could explore how interventions such as stress management training or cognitive-behavioral therapy could reduce stress levels and lead to an increment on road safety and safer driving. Finally, future studies can also help to understand how stress manifests differently in various populations and how to tailor intervention strategies depending on different personality traits to address various needs.

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