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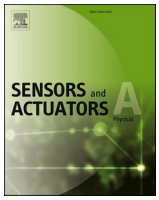

Smartphone-based and non-invasive sleep stage identification system with piezo-capacitive sensors

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ABSTRACT

A non-invasive, wireless, smartphone-based electronic measurement system for sleep stage identification is presented in this work. Ballistocardiograph signals are collected by two piezo-capacitive thin film strips located on the mattress base. Suitable analog conditioning circuits and digital pre-processing techniques are applied to obtain the heart and breathing rates (HR, BR), and an activity index (ACT) related to the body movements during the sleep. An initial calibration stage is proposed where analog signal amplification is fitted to each subject, from which activity index is derived. Features considered for machine learning classifications were the mentioned data and the time variabilities of HR and BR represented by the features R(k) and B(k), respectively. Support Vector Machine (SVM) and K-Nearest-Neighbour (KNN) classifiers are employed in both flat and hierarchical classification scenarios for Wake – Non Rapid Eye Movement – Rapid Eye Movement (WAKE/NREM/REM) sleep stage identification. Twelve healthy subjects were recorded with the developed system using a polysomnograph (PSG) as reference data. When compared with PSG, the presented system achieved an average accuracy of 69 % using only three features: R(k), B(k), and ACT, highlighting an 88.2 % recall for NREM stage identification. These findings suggest that accounting only for time variability features and activity, satisfactory results can be provided as a complementary alternative for sleep stage identification, with a smartphone-based electronic system designed as an affordable, versatile, and simple tool for household applications.

1. Introduction

Sleep constitutes one of the fundamental principles of human physiology since it allows our bodies to rest and to disconnect from the external environment, which have been proved to be very beneficial for human health [1,2]. The prevailing consensus suggests that a night duration of seven to eight hours is adequate for maintaining the body aware and active during the day [3]. Nonetheless, it is imperative to recognize that the significance of sleep extends beyond mere quantity; the quality of sleep is equally pivotal [4,5]. In order to determine its quality, the analysis of sleep stages overnight is usually carried out. The sleep in human animals consists of two differentiated states of existence: REM (Rapid Eye Movement) or Non-REM (NREM). The NREM stage is further divided into three stages [6] or four [7], depending on the classification guide consulted. These stages can be correlated with observable indicators such as bodily movements, breathing patterns (BR) and heart rate (HR) during the sleep cycle [8,9]. The analysis of transitions between these stages and the overall continuity of the sleep duration are critical factors for quality sleep determination.

Traditionally, research on sleep quality has implied the use of

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polysomnography (PSG) techniques as the gold standard. PSG utilizes electroencephalogram (EEG), electro-oculogram (EOG), electromyogram (EMG), electrocardiogram, and pulse oximetry, as well as airflow and respiratory effort, to evaluate for underlying causes of sleep disturbances. This implies the application of electrodes and wires distributed across the subject's body throughout the night, which could lead to some limitations related to time, discomfort and high associated costs [10]. In recent years, several researchers have advocated for the development of simpler and user-friendly equipment for sleep data recording [11–16]. Most of the research in this field is focused on monitoring HR, BR and body movements since these parameters exhibit a strong correlation with the classification of sleep stages, thus providing the basis for the enhancement of classification algorithms [9,17,18].

Ballistocardiography (BCG), a non-invasive technique, has garnered attention in the past decade as a valuable means for assessing sleep quality [19]. This technique provides information from the mass movements, (i.e., acceleration of blood during diastole and systole over the body) [20]. Signals extracted through diverse BCG sensors facilitate the determination of key physiological parameters of the subject such as HR, BR and activity while sleeping or in a horizontal position [21]. The implementation of BCG techniques has contributed to reduce possible discomfort regarding other medical equipment, such as the PSG. Optical, inertial, capacitive, pressure, and triboelectric sensors has been used to obtain BCG signals for sleep monitoring [19,22,23]. Alternative non-invasive sleep monitoring techniques reported in the literature involve the use of cameras with thermal imaging analysis [24,25]. However, these methods necessitate a bulky structure around the bed for subject monitoring.

Sleep analysis represents a promising field of research, holding significant potential for the prevention and amelioration of health issues stemming from sleep deprivation and disorders, such as apnea, parasomnia, or restless legs syndrome. Sleep is a biological footprint, and even basic aspects of our metabolism, genetics, and brain development can be understood through sleep studies. Some of them have harnessed different techniques for the analysis and interpretation of acquired data, such as Kalman filter [8] or convolutional neural networks [26]. In the wake of the ascendancy of machine learning and classification algorithms, many authors have sought to establish correlation between overnight-captured physiological parameters and sleep stages using multinomial logistic regression (MLR) [9], Support Vector Machine (SVM), Naive Bayes (NB), Classification and Regression Trees (CART) [27] or K-Nearest Neighbours (KNN) [28], among other techniques. Notably, one of the most promising methodologies is Leave-one-out cross validation (LOOCV), wherein a single entire night record is reserved for testing while the remainder are employed for training. This algorithm is a computationally expensive technique; however, the obtained results are more reliable and unbiased in terms of performance [29–32]. Some reported works combine LOOCV with multi-layered hierarchical structures, a combination proven to enhance detection accuracy [28,30,33].

In this work, aiming at a versatile and compact solution for home application, a non-invasive and cost-effective electronic system for BCG sleep stages analysis is proposed (Fig. 1). The equipment includes two piezoelectric polyvinylidene fluoride (PVDF) sensors, widely acknowledged for their efficacy in BCG signal extraction [11,34]. Additionally, the system integrates conditioning electronics for signal transduction, amplification, levelling, and filtering. The system uses a computationally optimised classification algorithm, seamlessly integrated into a custom-designed smartphone application. This application provides in-situ results of overnight sleep stages without the need of supplementary equipment. This customised algorithm significantly reduces the number of required features extracted from HR, BR and activity signals in comparison to other classification algorithms. Single layer and hierarchical classification settings have been tested, providing very similar performance. The hierarchical structure of the algorithm comprises two layers. The initial layer discerns wake from sleep (including both REM/NREM stages), converting the analysis into a binary classification problem. After the first classification, the second layer distinguishes from the sleep classified epochs between REM or NREM stages. The home-based system proposed in this paper demonstrates a total accuracy of 69 %, with a recall of 88 % for the NREM stage identification.

2. Description of the system

2.1. In-Bed contactless and wireless system

Polymer-based piezoelectric sensors offer a flexible and conformal solution for dynamic strain monitoring. This kind of sensor has shown up in multiple presentations for diverse applications from sleep tracking to vehicle traffic monitoring. Among the polymers known for their

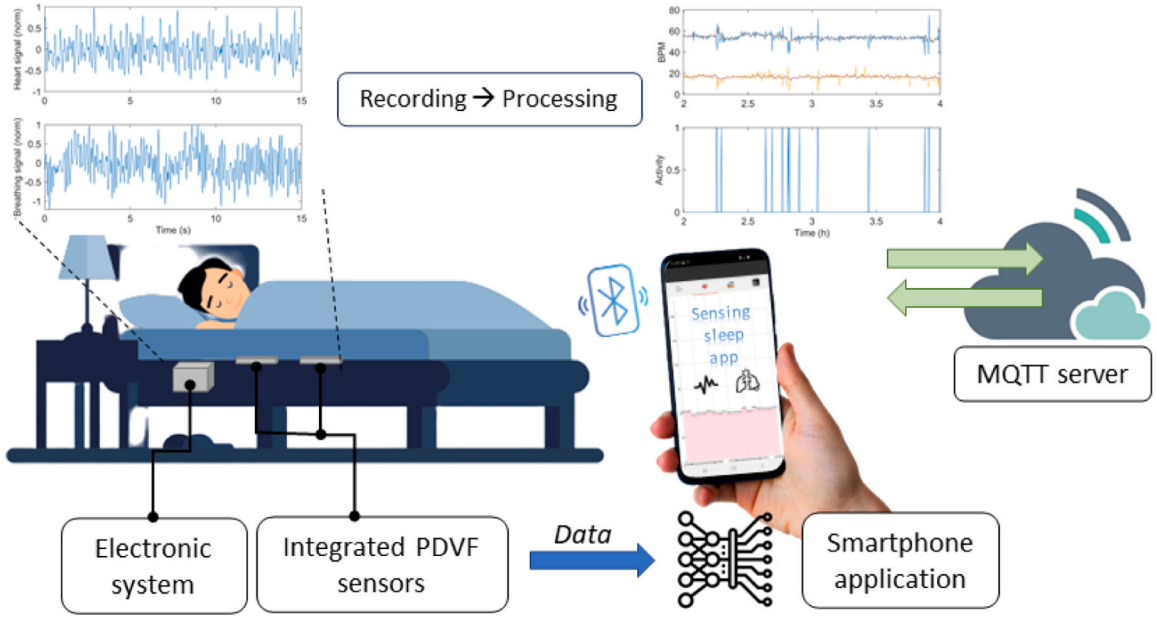

Fig. 1. Overview of the proposed in bed system for sleep stage classification. Raw and processed signals are shown together with details of the developed hardware, smartphone app and cloud server for data sharing.

piezoelectric properties, PVDF stands out for its excellent response to small vibrations. Therefore, piezo capacitive films made of PVDF were selected as sensors in this work, specifically the so-called Sleep Monitor Strips, model 10184000–01 (TE connectivity Ltd., Switzerland). Each strip consists of a capacitive structure with silver ink metal electrodes and PVDF as polymeric insulator, with an active area of 698.5 mm long and 3 mm wide, and total thickness around 50 μm, making it exceptionally flexible and imperceptible when positioned beneath the body. This sensor generates a charge or voltage between its electrodes even under minimal physical pressure. Thus, the small vibrations produced by heartbeat and breathing movements result in voltage variations. The film, with a capacitance around 7 nF (at 1 kHz), exhibits a high sensitivity to vibrations of 15 mV/με.

The hardware system design is aimed to conditioning the piezoelectric sensors output signals, to be digitalized, and further processed by the microcontroller. Fig. 2(a). illustrates the block diagram of the hardware device setup that can be divided into four different stages: PVDF piezo capacitive films, analog conditioning, microcontroller and power supply.

In this prototype, two PVDF piezo capacitive films are included: one for HR and activity detection and another for BR. Typically, using BCG, a single channel could be enough for both BR and HR detection. However, extensive testing involving participants with varying gender, physical constitution, and weight, revealed instances where a strong breathing signal could potentially mask heart beating, contingent upon body position. Consequently, two independent analog conditioning channels have been included in the design to ensure reliable data detection: HR channel and BR channel. Extensive tests guided the optimization of sensor placement under the mattress, aiming at an effective separation and high quality of HR and BR signals. As shown in Fig. 2(b), the optimal locations were identified as being over the bed base under the chest region (HR channel) and the abdominal region (BR channel). The sensors are connected to the rest of the hardware via two standard jack audio connectors.

Two identical charge amplifiers are used as the first stage of each conditioning block (Fig. 2a) directly connected by shielded wires to the piezo films. The goal of this stage is impedance adaptation and frequency response shaping. Regarding the frequency response of this stage, considering the capacitance of the piezoelectric sensor, it acts like a high-pass filter, with a lower cut-off frequency 0.32 Hz and a gain of 0.65 V/V. The second stage of the conditioning chain consists of a four-order unity-gain low-pass Sallen-Key filter. This filtering circuit introduces an upper cut-off frequency of 11 Hz for each signal channel. Precision operational amplifiers of these stages were OPA2188 (Texas Instruments, Texas, USA), a low offset voltage/drift and low noise operational amplifier. Bode diagrams of these stages were measured and gains and cut-off frequencies were consistent with theoretical calculation and numerical simulations. After filtering, amplification, and level adapting stages to the microcontroller ADC voltage range ([0, 3,3] V) are required. In the BR channel, an amplifier provides additional voltage gain and level adaptation to the input range of the microcontroller ADC. At the end of this stage, a gain of 32 dB is obtained with respect to the output of the filter stage. On the other hand, the HR channel uses a programmable gain amplifier (PGA) MAX9939 (Analog Devices, MA, USA) that provides gain and offset selected from the available options. The choice to use a PGA is driven by the inherent variability in heartbeat signal intensity among individuals, a factor that does not significantly affect the BR channel. To address this variability, the system employs a customised Android application to automatically select the appropriate gain for each subject during a calibration procedure. The details of the calibration procedure will be subsequently described.

In this system, a ESP32 commercial microcontroller board (Espressif Systems Co., Ltd., Shanghai, China) is used for processing the acquired signals. This model includes an Xtensa 32-bit LX6 microprocessor (Tensilica, Inc., Santa Clara, CA, USA). The selection of the ESP32 module was made due to its compatibility with the Arduino Integrated Development Environment (IDE) (Arduino LLC, Somerville, MA, USA), data processing capability, as well as the wide range of peripherals: Bluetooth connectivity, I^2C, GPIOs, ADC and DAC converters. In the ESP32 the signals from the two different channels are processed to

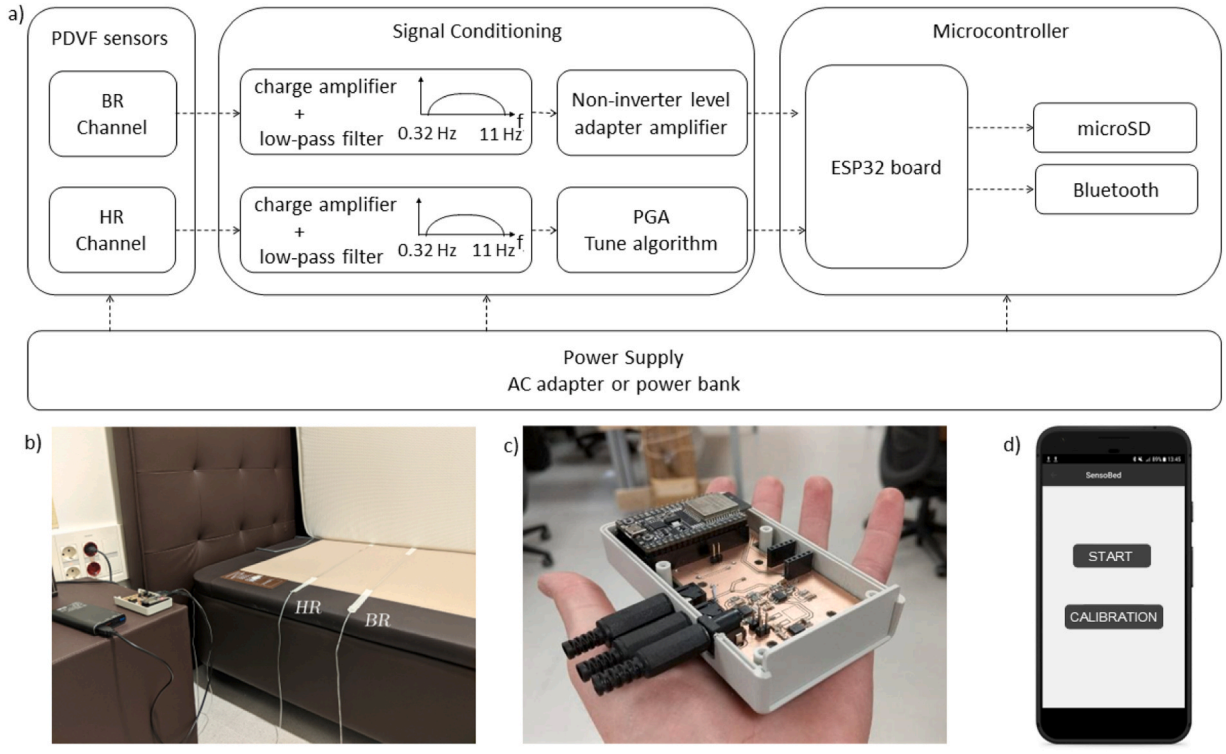

Fig. 2. a) System diagram block. b) *Sleep Monitor Strips* allocated over the bed base (under the mattress). c) Complete developed system. d) Start/Calibration screen for the developed Android application.

extract heart rate, breathing rate and activity of the sleeping subject under study as it will be further detailed. These calculated values are wirelessly sent to a smartphone via a Bluetooth link.

The whole system is powered through a supply system that accepts a power bank or AC/DC adapter whose output voltage cannot exceed 42 V (linear regulator limit). The working supply voltage of the operational amplifiers is ±5 V which is achieved by linearly regulation of the supply voltage and then inverted by means of a voltage inverter circuit configuration of the ADM660 charge-pump voltage converter (Analog Devices, Massachusetts, USA). As it is shown in Fig. 2(c), the complete developed hardware system is included in a two-layer board which has been inset into a 11 cm long, 6.5 cm width and 3 cm height plastic housing.

2.2. Smartphone application

The system is remotely controlled through a purpose-built Android application, offering users the capability to initiate and conclude data acquisition, perform data analysis, and calibrate the equipment, when necessary, particularly for new users. The application has a user-friendly interface that graphically represents the obtained information using a colour code to distinguish the sleep stages information. It was developed using the official Android IDE (Android Studio 4.2.2) and tested for API 28 (Android 9.0), although it is compatible with earlier Android versions. This application employs Bluetooth as communication protocol to connect to the ESP32 through its MAC address. When the two devices (smartphone and system) are paired, the acquisition procedure menu is then available for the user. The user can click in "Start" or "Calibration" (Fig. 2d). Once the measurements have started, data are saved in a SD card, with backup purposes, and from here, at the end of the night registration, the information is sent to a smartphone for further processing. By pressing the "Finish" button, the user ends the communication triggering the analysis of the obtained data. Four different tabs show the processed information: HR, BR and activity subject's registration as well as the analysis of the stages throughout the night. The application also allows users to visualise previous night's records, as the device stores the information in its internal memory.

The performed calibration procedure is based on the PGA, which, as mentioned before, permits to compensate for the person-to-person variability in the heartbeat signal intensity as well as for mattress variations, i.e. different material or thickness. The systems automatically increase the gain of the amplifier every 5 seconds in order to get the highest possible HR signal without compromising the information, i.e., saturating HR signals. The person must stay unmoving and in supine position during the procedure. Thus, when the signal becomes saturated, the system stores the immediately preceding value of the gain as the final parameter. Simultaneously, a sound alert is emitted to notify the user that the calibration procedure has been successfully completed. The PGA MAX9939 allows to configure seven different gain values, thus the range is wide enough to cover subjects' intensity variations in vital signals. This procedure only needs to be carried out once for each participant. PGA parameters are automatically recorded for each subject and ready for future system use. Moreover, HR channel signal is integrated during 5 seconds with the selected gain to be used as reference value for determination of subject activity. As it will be mentioned below, the binary activity indicator will be determined by comparison of the time integrated HR channel signal with this value stored during the calibration procedure. Furthermore, the application is connected to a MQTT (Message Queuing Telemetry Transport) broker, using a publish-subscribe protocol for communication. The smartphone sends the information using WebSocket technology, showing the information obtained for each subject in a custom-made website.

3. Experimental Setup

Twelve healthy participants took part in this study (4 females; 37 ± 16 years old). Biometric figures of the participants were weight 68 ± 8 Kg, and height 172 ± 4 cm. The study adhered to the ethical principles outlined in the Declaration of Helsinki and each participant provided written informed consent. Protocol was approved by the Ethics Committee in Human Research (CEIH) of the University of Granada, Spain (number 2446/CEIH/2021). Participants were required to be free of caffeine and other stimulant substances the day of the sleep assessment. They were also asked to follow their usual sleep-wake routine the day of the assessment and to arrive at the laboratory at least one hour before their usual bedtime. The participants were asked to sleep normally with the only requirement of lying with the head over the pillow in the top area of the mattress, regardless the body position. It is worth noting that the use of a reduced sample size of 12 subjects in this work serves the purpose of proving the feasibility of our system as a proof of concept, rather than performing a product release or a clinical trial. In this sense, our system demonstrates the potential for further development and applications.

Participants slept in specially-designed research rooms. The PSG assessment included EOG, EMG, ECG, and EEG. Leg movements and thoracic and abdominal respiration were evaluated. Scalp electrodes for multi-channel EEG recordings were applied according to the standard 10–20 system of electrode placement in the lateral pathways. Data was scored in 30-second epochs using established criteria by trained scorers. The sleep signals were recorded through SOMTE® and analysed manually by using ProFusion PSG (COMPUMEDICS® Ltd., Victoria, Australia).

Concurrently with the PSG study, the custom-developed system outlined in this work was positioned beneath the mattress (see Fig. 2b), with the case containing the electronics component housed inside the lift-up base. After the calibration step previously described, the participants initiated the data acquisition procedure through the Android application when ready to commence sleep period. This simultaneous deployment allowed for a comparative assessment of the system's performance in comparison with the gold standards.

4. Sleep stage identification

4.1. HR, BR and activity pre-processing and feature extraction

Fig. 3 depicts the digital pre-processing stage and feature extraction, where the hardware for each pre-processing stage is pointed out as well.

Data pre-processing is initially carried out in the ESP32-based measurement system. BCG signals from HR and BR channels are acquired with a sampling rate of 137 Hz. Then, these signals are averaged for high frequency noise filtering with 64 samples, and divided in epochs of 30 s, as recommended by the American Academy of Sleep Medicine (AASM) Manual [35]. From these two BCG signals, three primary features are extracted for each epoch:

- BR derived from the BR channel signal, applying the Fast Fourier Transform (FFT), with quadratic interpolation applied for better FFT peak detection. The resulting frequency is then multiplied by 60 to transform the value into breaths-per-minute (bpm) units.
- HR obtained from the HR channel. Before applying the FFT, each time sample is powered to the sixth, for enhancing signal power and better heart rate detection. Subsequently, FFT is applied and the peak is detected using quadratic interpolation. This frequency is also multiplied by 60 to transform that value into beats-per-minute (bpm) units.
- Activity (ACT), binary vector, is extracted from the HR channel signal. HR signal is time integrated and then compared with the HR signal recorded as reference during the calibration phase described above. If the integrated HR signal is 20 % equal or higher than the reference value, ACT is assigned the value of 1; otherwise, ACT is set to 0. This threshold was selected after a careful comparison with the activity signal provided by the reference PSG.

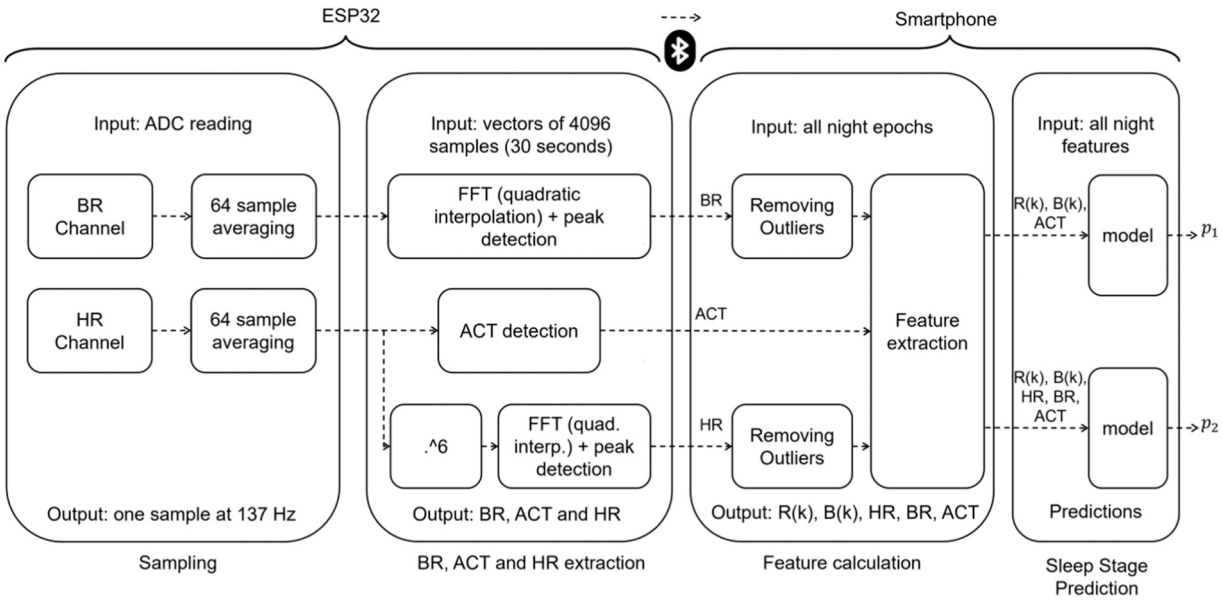

Fig. 3. Digital pre-processing and feature extraction of dataset. Full processing is divided between ESP32 module and Smartphone, starting with the HR and BR channel signals and ending with the sleep stage prediction (p_1 and p_2), depending on the number of features considered.

The ESP32-based system shows a power consumption of 0.41 mW. When powered through an USB connection to a power bank (3.7 V@15000 mAh), the system power lifetime is around 130 hours. It means to register 16 nights of 8 hour each, with a fully charged power bank.

Once the sleep time is finished, the vector containing all epochs along with the primary features (BR, HR, ACT), is transmitted via Bluetooth to the smartphone. In this device, several steps of data pre-processing are undertaken:

1. Artefacts due to subject movements: In the presence of subject activity, noisy BCG signals are usual. Therefore, to avoid BR and HR erroneous data when activity has been detected (ACT=1), both features are substituted by the linear interpolation of their nearest valid data, those with epochs of ACT=0.
2. Removing outliers: to remove the influence of outliers, each BR and HR are compared to their mean values of the first quarter of each sleep register. If the difference is higher or lower than 30 %, those data are considered outliers, and they are replaced by the linear interpolation of the nearest valid data.

According to previous reports, heart and breathing rate variabilities offer valuable insights into sleep stages [9,36]. Specifically, heart rate becomes less rhythmical during REM sleep. For this reason, features related to these variabilities have derived from the primary ones. To quantify heart rate variability, following the formalism of Kurihara and Watanabe [37], let $HR^{former}(k)$ be the heart rate of the former 30 s of the 1 min of discrete time k. Similarly, and $HR^{later}(k)$ the heart rate of the latter 30 s of the discrete time k. The index R(k) to show the REM sleep stages as given in Eq. (1) is obtained through the moving average for the range from $k - q$ to $k + q$, considering $q = 10$,

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

Similarly, we here introduce a new index B(k) defined like R(k) but now considering the breathing rate (Eq. 2):

$$B(k) = \frac{1}{2q+1}\sum_{i=-q}^{q}\left|BR_{k+i}^{former} - BR_{k+i}^{latter}\right| \quad (2)$$

In summary, aiming at keeping a low number of features, the five features included in this work are given in Table 1:

Fig. 4 represents the significance of the five features considered using ANOVA, a test that allows to determine the importance of a feature on the response regarding its variance. It is worth noting that those related to the vital signal variability (B(k) and R(k)) show the higher values, in particular, the new proposed in this work, the B(k) feature. This fact is aligned with previous studies that pointed out this sleep stage behaviour [9,30,36–38]. This is related to the observed lower vital signal variability in the NREM sleep stage compared to wake or REM stages [39]. Therefore, this setup is expected to obtain more sensitivity in the identification of the NREM stage than the rest of stages. This will be discussed in the next section in the light of the obtained results.

4.2. Sleep stage classification by machine learning techniques

To detect the different stages (Wake, REM or NREM sleep stage) based on the above-mentioned features extracted from the HR and BR channels, the Leave One Out Cross Validation (LOOCV) technique was employed for training and testing data. In this technique, one subject's data is left out for testing while the remaining eleven subjects are used to train the selected machine learning classifiers. This iterative process is repeated until each subject has been left out for testing at least once. In this study, two different supervised classifiers were applied to the sleep dataset in accordance with previous reports [27,28,30,40]. Support Vector Machine (SVM) is a non-probabilistic linear classifier, where multiple kernels were tested. K-Nearest-Neighbour (KNN) classifier was also applied, with variations in the number of neighbours and with different distance metrics used for classification. Performance indicators were calculated to evaluate and compare the two different classification models and machine learning techniques in the prediction to assign each epoch to a sleep stage [41].

Table 1
List of features used in the classification process.

Feature	Short description
HR	Heart beats per minute
BR	Breaths per minute
ACT	Activity index
R(k)	Heart rate variability index
B(k)	Breathing rate variability index

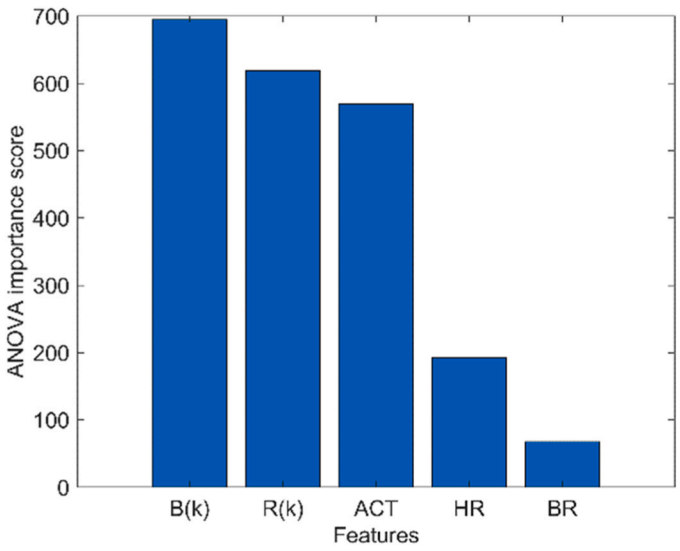

Fig. 4. ANOVA importance score of extracted features shown in Table 1.

5. Results and discussion

Firstly, preliminary and extensive tests showed that the proposed system performance is robust against changes in the subject position (supine, lateral, prone) and for two kinds of mattresses of different thickness. Fig. 5(a) and (b) show an example of the HR and BR channel raw signals, respectively, for half of an epoch just before digitalization. Even visually, both HR and BR features can be easily identified from them. HR can be extracted from the typical BCG signals in Fig. 5(a), and BR from the signal wandering in Fig. 5(b). Fig. 5(c) shows the activity index in a two hours sleep interval, where ACT=1 indicates a detected movement according to our previous definition of activity. Moreover, heart and breathing rates before (blue lines) and after data pre-processing (orange lines) are compared in Fig. 4(d), showing a reduction in the number of outliers and artefacts due to bodily movements. Adequate data smoothing has been achieved after signal pre-processing, preparing them for derived feature extraction: R(k), and B(k).

In Fig. 6 comparisons between HR and BR measured and pre-processed by the proposed system (orange lines) to those acquired by the PSG system (blue lines) are shown. A high agreement can be observed, providing a suitable starting point for further data analysis.

Regarding the dataset, an average of 926 epochs have been processed for each participant, corresponding to approximately 7 hours and 43 minutes of data recording time. According to the information from the PSG, the distribution of sleep stages in the dataset shows that, on average, 66 % of the time was associated with the NREM stage, 23 % for REM, and 11 % for Wake. Thus, the REM/NREM ratio was 35 % which can be considered as normal percentages of healthy subjects [39].

Two classification scenarios have been considered to compare standard (single layer) classification versus hierarchical (two layers/phases) classification of 3 sleep stages: Wake, REM, and NREM.

5.1. Single layer classification

Table 2 presents the performance results of the sleep stage classification process with the obtained dataset. Global results of the two mentioned classifiers are shown along with the hyperparameters (kernelScale for SVM and N, the number of neighbours to consider, for k-NN)

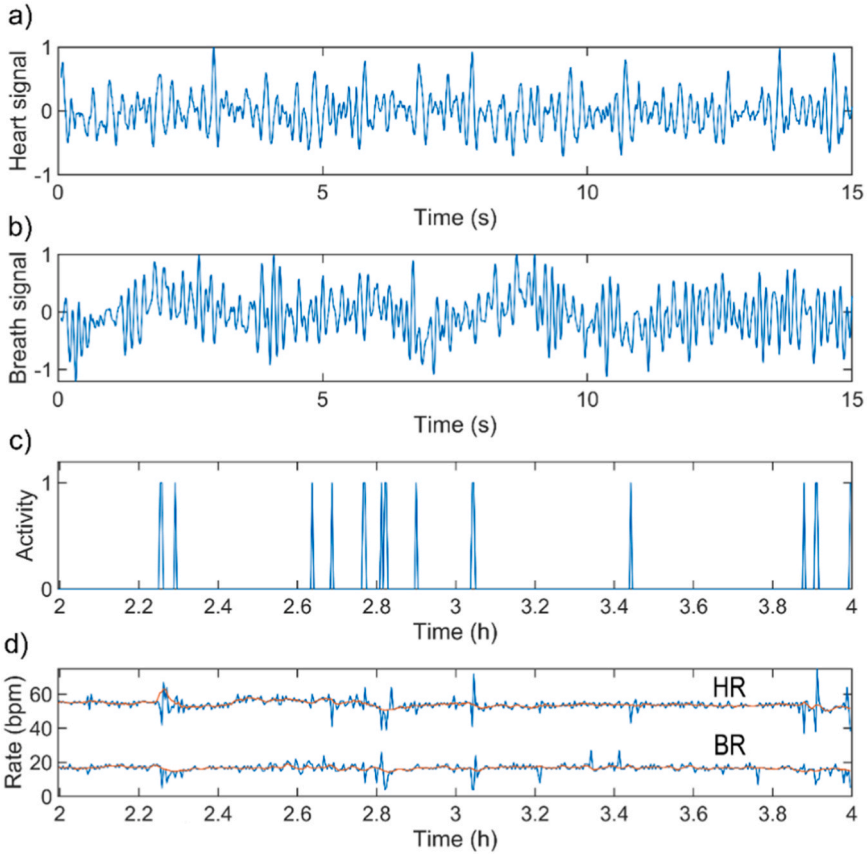

Fig. 5. Signals before digitalization: a) HR channel signal showing typical BCG signal of heart beats, b) BR channel signal where breath information is contained in the signal wandering, and c) example of activity detection in two hours showing ACT=1 when body movement was detected. After digitalization: d) HR and BR before (blue lines) and after (orange lines) the pre-processing during 2 hours.

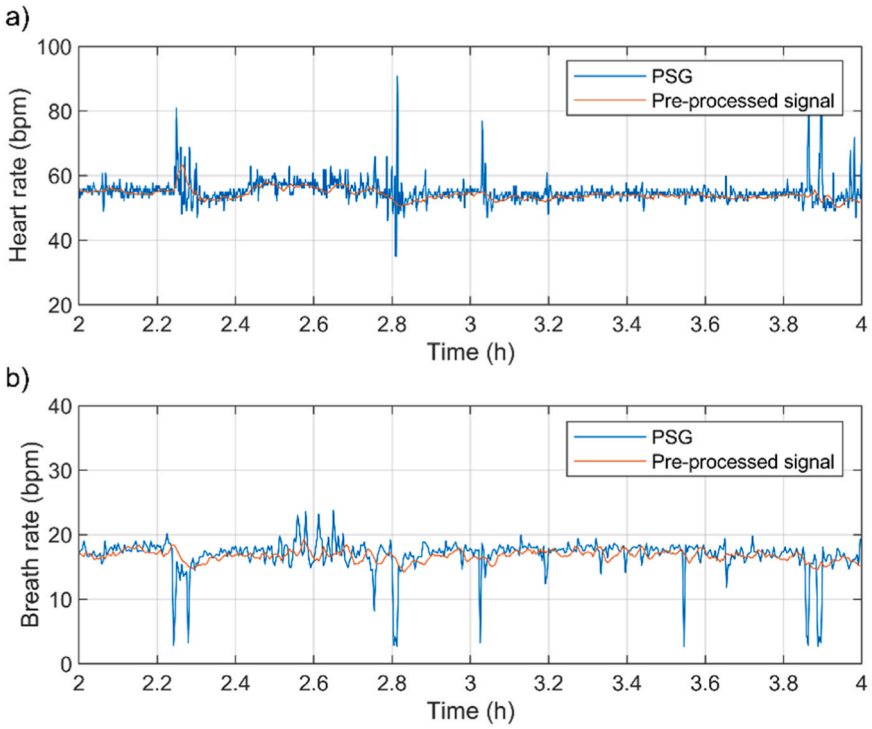

Fig. 6. Comparison of a) heart rate and b) breathing rate in which blue lines account for PSG outcome and orange lines for the proposed system.

Table 2
Comparison of two classifiers and number of features in terms of average precision, recall and accuracy.

Features	Classifier	Hyperparameter	Precision	Recall	Accuracy
HR, BR, ACT, R(k), B(k)	KNN	N = 113	45.9 %	52.8 %	66.9 %
	SVM	kernelScale = 3.5	49.8 %	56.7 %	68.3 %
ACT, R(k), B (k)	KNN	N = 113	47.0 %	58.1 %	69.0 %
	SVM	kernelScale = 3.5	43.5 %	56.7 %	68.8 %

providing the best performance. Moreover, considering the significance map of the features given in Fig. 4, sleep stage identification was performed in two settings: with all the five features, and with the three most important features: ACT, R(k), and B(k). Firstly, it can be derived that depending on the number of features considered, better results are obtained for different classifiers. SVM classifier provides slightly better global accuracy when 5 features are considered, whereas with 3 features, KNN does. Notably, commendable total accuracies near 70 % have been achieved with this portable system considering such a very low number of features. These accuracies are close to those previously reported works in this field [9,30].

A more detailed analysis regarding the classification for each of the three sleep stages is shown in Tables 3 and 4. Confusion matrices of the two analysed scenarios are displayed. Table 3 shows the classification scores with 5 features and SVM classifier, and Table 4 for 3 features and KNN classifier. As expected, and mentioned above, the scores for the

Table 3
Confusion matrix for 5 features and single layer classification with SVM classifier.

SVM	**NREM**	**REM**	**Wake**	Recall
NREM	**535**	47	30	87.4 %
REM	134	**67**	12	31.5 %
Wake	62	9	**31**	30.4 %
Precision	73.2 %	54.5 %	42.5 %	**68.3 %**

Table 4
Confusion matrix for 3 features and single layer classification with KNN classifier.

KNN	**NREM**	**REM**	**Wake**	Recall
NREM	**540**	61	11	88.2 %
REM	126	**83**	14	39.0 %
Wake	73	14	**14**	13.9 %
Precision	73.1 %	52.5 %	48.3 %	**69 %**

NREM sleep stage present excellent figures in terms of recall near 90 %, and precision above 73 %.

5.2. *Hierarchical classification*

A hierarchical classification scheme was also implemented with two phases: 1) Wake vs. Sleep, and 2) within sleep stages, NREM vs. REM. Now, the KNN classifier was applied with three features (ACT, R(k), and B(k)). A notable improvement in average accuracies of 90 % and 77 % was obtained for phase 1 (Wake/Sleep), and phase 2 (NREM/REM) separately. The global accuracy after the two phases was 69 %, as in the single layer classification setting. Since very similar results were obtained, no significant score improvement was achieved in this study using hierarchical models. For this study, the low percentage of Wake signals in the dataset (11 % Wake and 89 % sleep) could be the reason why there was no significant improvement in the first phase classification. Therefore, in comparison with other previously reported works, the presented system exhibits a similar behaviour in terms of accuracy, but considerably reducing the number of used features, thus decrasing computational cost [30].

5.3. *Discussion*

Fig. 7 compares the hypnograms of the PSG with the developed system for one subject. The general sleep structure with 3 sleep cycles is also obtained. Most of the discrepancies arise from distinguishing REM and Wake stages. It is well known that separating Wake and REM stages

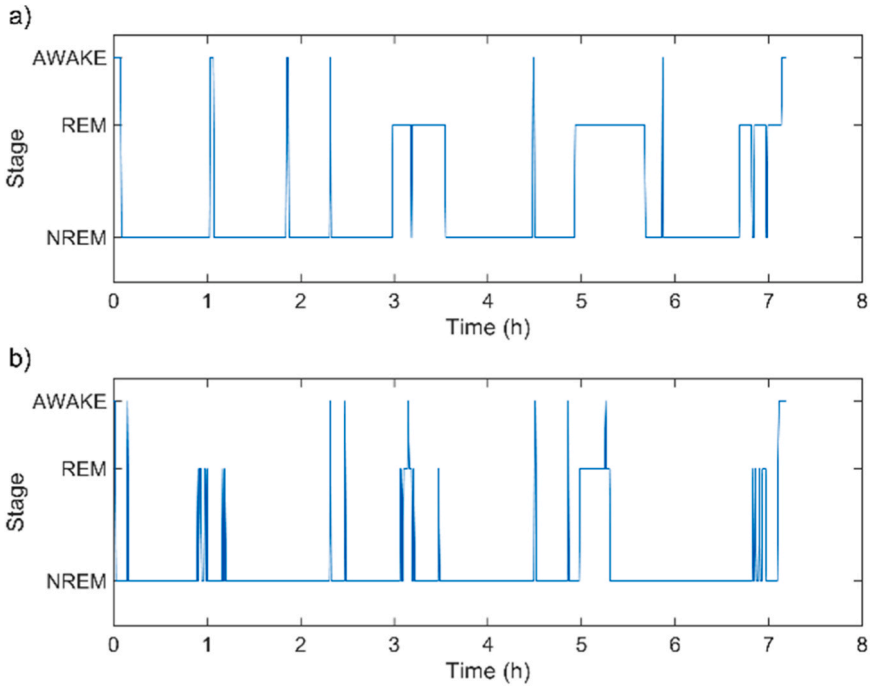

Fig. 7. Hypnogram comparison between a) the gold standard outcome (PSG) and b) the prediction by our system.

is rather difficult for this kind of setups, as proved by previous literature [30]. In fact, if Wake stage is not included in the classification, an accuracy around of 90 % is achieved with this system, improving the metrics given by very similar sensing technology shown in Table 5. Table 5 also displays the high performance achieved with hydraulic bed or pressure sensors but using a high number of features [28,30,33]. We can also infer from Table 5 that this work presents a higher number of subjects under study than the average and a very reduced number of features.

The primary aim of this study was to develop an easily accessible technology for identifying sleep stages outside of the traditional sleep laboratory setting. Signal pre-processing is carried out in the electronic system, while the machine learning algorithms are implemented on the smartphone. The performed modelling of the sleep, based on a very low number of features, is aligned with this goal, thus decreasing the computational cost and associated time-consumption.

By selecting features related to variability of vital signals, we have achieved a suitable system performance for NREM/REM stage identification. This kind of portable, non-invasive, and smartphone-controlled system for on-site sleep stage identification is well-suited for integration into point-of-care monitoring systems, aligning with the Internet-of-Things paradigm. Sensor strips can be effortlessly positioned under any mattress, enhancing the adaptability of our compact design. Self-calibration is also a crucial aspect of IoT systems. Therefore, another remarkable feature of this system is the adaptability to each different mattress and subject through the described calibration procedure. This procedure ensures that analog amplification is automatically adjusted for each setup, providing versatility to the developed system. Moreover, data analysis results can be easily transmitted through standard channels available on current smartphones. Thus, the main novelty of this work is to present a user-friendly platform that combines portable hardware and a smartphone app, serving as a complementary tool for sleep studies, designed as a home appliance.

6. Conclusions

Film strip sensors integrated into the base mattress, coupled with a practical smartphone-based and portable electronic measurement system, present a viable solution for screening sleep quality outside traditional sleep laboratory settings. Through a user-friendly interface and including a calibration step for fitting the system to each individual subject and bed, this non-invasive development has proven effective for sleep evaluation. The incorporation of features related to heart and breathing rate variabilities has showcased significant potential for identifying NREM stages using classifiers commonly used in the literature. This approach achieves an accuracy rate of approximately 70 % for three sleep stages (90 % for NREM/REM), while simultaneously reduces the number of features used in the machine learning algorithms.

Table 5
Comparison of performance among similar non-invasive sleep stage identification systems.

Stages	Nº subjects	BCG Sensor type	Main signals	Nº Features	Signal Processing	Accuracy	Ref.
WAKE/REM/NREM	9	Emfit foil electrodes	Heart beat and movements	4	Hidden Markov Models	79 %	[42]
WAKE/REM/Light/ NREM/Deep REM	20	Load cell/ PDVF film	Heart beat	5	Analytical thresholding	76 %	[43]
WAKE/REM/NREM	7	Pressure	Breathing	32	SVM/KNN	77 %	[30]
WAKE/REM/NREM	5	Hydraulic bed	Heart, breathing, activity	24	SVM/KNN	85 %	[28]
WAKE/REM/NREM	5	Hydraulic bed	Heart, breathing, activity	24	Deep Neural Network	91 %	[33]
WAKE/REM/N1/N2/N3	36	Vibrational bed-legs	Heart signal	5	Logistic regression	78 %	[29]
WAKE/REM/NREM	12	PVDF strips	Heart, breathing, activity	5/3	SVM/KNN	69 %	This work

CRediT authorship contribution statement

Antonio Martínez-Olmos: Software, Investigation, Formal analysis. **Miguel A. Carvajal:** Methodology, Investigation. **Noelia Ruiz-Herrera:** Writing – review & editing, Validation, Software, Investigation, Formal analysis, Data curation. **Antonio J. Pérez-Ávila:** Visualization, Software, Investigation, Formal analysis, Data curation. **Alberto J. Palma:** Writing – original draft, Supervision, Resources, Methodology, Funding acquisition, Conceptualization. **Luis Fermín Capitán-Vallvey:** Writing – review & editing, Supervision, Methodology, Funding acquisition, Conceptualization. **Nuria López-Ruiz:** Writing – original draft, Visualization, Supervision, Software, Methodology, Investigation, Formal analysis, Data curation.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data Availability

Data will be made available on request.

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