Innovative Sleep Monitoring: A Non-Invasive Approach Using Force-Sensing Resistors for Analyzing Sleep Quality and Detecting Sleep-Related Breathing Disorders

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Abstract
This study presents an innovative, non-invasive sleep monitoring system that employs force-sensing resistors (FSRs) embedded in a pillow sheet to analyze sleep quality and detect sleep-related breathing disorders (SDB), offering an alternative to conventional polysomnography (PSG). We employed a comprehensive methodology, integrating FSRs with a wireless network device and dedicated software for real-time, precise data analysis and storage. The FSRs, calibrated to measure biomechanical signals associated with body movement, are integrated with a wireless network device. The experiment involved twenty-seven subjects diagnosed with sleep apnea, and the results were compared with PSG recordings. The intelligent sleep application recorded various sleep metrics, including sleep efficiency (SE), and respiratory rhythm. A regression analysis revealed a strong correlation (R^2 = 0.96) between the SE measured by the PSG device and the pillow-sheet sensor systems, confirming the reliability of the latter. The Bland-Altman plot further supported this consistency. In conclusion, the pillow-sheet embedded with FSR sensors is a promising tool for unobtrusive sleep monitoring and SDB detection. It offers comparable accuracy to PSG, with the added benefits of being user-friendly and non-restrictive, making it suitable for clinical and home settings. The system's ability to provide insights into sleep patterns, detect apnea episodes, and analyze sleep postures presents a significant advancement in sleep research and medicine, with potential applications in personalized sleep health management.

Keywords: Polysomnography, Respiratory Rhythm, Sleep Apnea, Sleep Efficiency, Sleep-Related Breathing Disorders

1. Introduction

Sleeping is essential to our lives because we spend about one-third of our lives in bed. Therefore, sleeping is vital for maintaining our physical [1] and mental health [2]. During sleep, our body recovers energy [3] and repairs damaged cells [4]. In addition, sleep helps to create chemicals in the brain that improve our memory, performance, and learning ability [5]. Therefore, getting enough sleep is crucial for maintaining good health. Adequate sleep is crucial for good health and can benefit mental health, muscle recovery, brain development, cardiac function, body metabolism, learning, memory, and mood [6][7][8][9] and [10]. Sleep-related breathing disorders, such as sleep apnea-hypopnea syndrome (SAHS) [11], can have detrimental effects on an individual's health. SAHS is a type of sleep disorder characterized by repeated episodes of complete or partial cessation of breathing during sleep, which can lead to disrupted sleep patterns and reduced oxygen levels in the body [12]. SAHS affects 9% to 25% of males and 9% to 15% of women [13]. It is a widespread medical problem with a rising prevalence, with the likelihood of occurrence increasing with age and BMI [14] and [15]. SAHS has been linked to various adverse health outcomes, including cardiovascular disease, stroke, and diabetes, making it a significant public health concern that warrants attention.

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Sleep-disordered breathing (SDB) can range from snoring to obstructive sleep apnea (OSA) [16]. Polysomnography (PSG) is the standard test to assess sleep physiology, with sensors monitoring airflow, thoracic movements, and pulse oximetry [17]. However, attaching sensors to the head and body can be inconvenient and interfere with sleep because even little motions on the part of the patient might significantly interfere with the recorded signals, such as heart rate and respiration [18] and [19]. This paper proposes an unobtrusive sleep monitoring method using force-sensing resistors (FSR) embedded in a pillow-sheet prototype [20][21][22][23] and [24]. The FSRs detect changes in resistance with increased force applied to the surface, allowing for the detection of posture and gesture movements during sleep. The resulting data can be used to distinguish between sleep and wakefulness and evaluate symptoms of SDB. The study aims to develop a sleep monitoring system that includes a pillow-sheet embedded sensor array, a wireless sensor network, and a software application for real-time monitoring. The system is intended to determine people's sleeping and waking times based on the frequency of posture and gesture movements. Additionally, the study aims to evaluate the symptoms of SDB (sleep-disordered breathing) using the pillow sheet and compare the sleep disturbance associated with snoring caused by apneas and hypopneas. The study also intends to compare the validity of two algorithms for detecting sleep efficiency and SDB with Pillow-sheet prototypes by comparing them to the PSG device, a standard diagnostic tool for sleep disorders.

In summary, the study has two primary goals: (1) to develop a sleep monitoring system that can track sleep and wake times using a pillow-sheet embedded sensor array, and (2) to evaluate the efficacy of this system in detecting SDB symptoms compared to a PSG device, and to compare the validity of two algorithms for detecting sleep efficiency and SDB with Pillow-sheet prototypes.

2. Methodology

Our research team has created a sleep monitoring system and has expertise in sleep health technology. The development relies on software algorithms that evaluate sleep quality and look for signs of sleep-disordered breathing (SDB) combined with biokinetic sensor technology. The research expands on the concerns listed above by incorporating various important components, such as the data acquisition system, system configuration and input devices, sensor calibration, innovative pillow fabrication, and the experimental phase.

2.1 Data Acquisition System

During the prototype development phase, our team utilized Arduino modules combined with a microcontroller box, which was equipped with memory units and associated circuitry and was built on an open-source computing platform. The microcontroller boards were programmed using the Arduino Integrated Development Environment (IDE). Notably, our system is designed to operate in two different modes: standalone mode and flexible mode with USB connectivity to computers or Raspberry Pi and ZigBee technology platforms, enhancing its integration with the pillow-sheet application.

2.2 System Configuration and Input Device

Our innovative non-invasive sleep monitoring system is composed of three major components designed to work in association, ensuring precise data acquisition and analysis. The hardware architecture consists of the following components (Figure 1):

- FSR Sensors Embedded in the Pillowcase: This component features FSR sensors strategically situated at various positions within the pillowcase, functioning as the primary input devices to capture detailed sleep data.
- A microcontroller box that includes memory and associated circuits as a low-cost wireless acquisition system for transmission and reception, which transmits data from FSR sensors to a PC or display device.
- Dedicated Software for Data Analysis and Storage: This software component is adept at reading and interpreting sleep data, equipped with the capacity to retain historical data.

2.2.1 Pressure-sensing array

The pressure sensor used in this study is based on composite-polymer thick film technology and is a type of piezoelectric polymer. This force-sensitive resistance (FSR) sensor comprises a thin layer of conductive polymer composite (CPC) sandwiched between two metal electrodes. The FSR used in this study has dimensions of 43.69 x 43.69 mm and a thickness ranging from 0.2 to 1.25 mm. It is encased in a fabric envelope that is sewn onto a pillowcase and is used to detect biokinetic movements during sleep.

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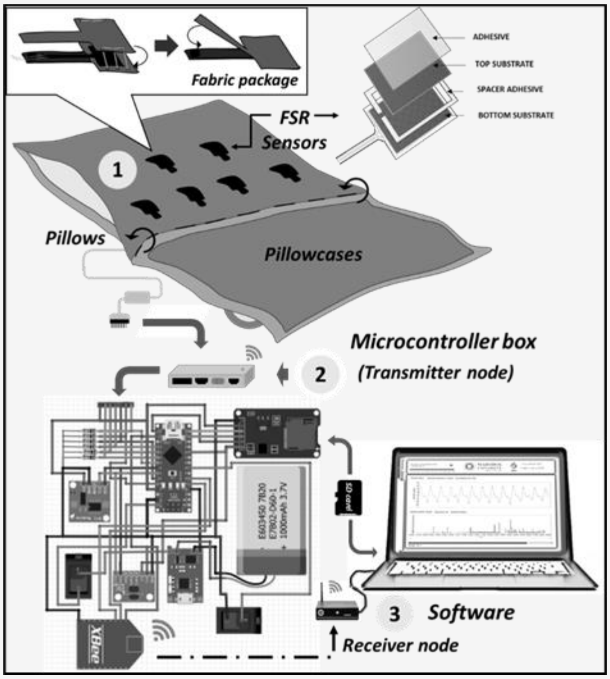

Figure 1: Schematic of hardware architecture and design for a smart sleep system

The FSR signal is processed and measured as a variable analog voltage divider. One of the critical features of an FSR is that it exhibits high resistance when not pressed, and its resistance decreases as more force is applied to it. This resistance change is caused by the compression of the conductive ink or material, which brings the particles within it closer together, allowing electricity to flow more easily.

2.2.2 Wireless network device

ZigBee technology presents an alternative network device for wireless communication between FSR sensors and host computers for real-time monitoring, which has become increasingly relevant for modern health monitoring systems. Despite the existence of other wireless network technologies, ZigBee technology stands out as highly supportive of this concept, offering a two-way wireless communication platform characterized by low latency and low power consumption at lower data rates. This is made possible by its adherence to the IEEE 802.15.4 standard, which defines the physical and medium access control (MAC) layer for the low-power personal area network (PAN). Specifically, we utilized ZigBee modules from Maxstream in this work, which provide 16 personal area network ID (PAN ID) and use a frequency of 2.4 GHz. The power consumption of ZigBee modules is also noteworthy, operating at about 2 mW in the running mode and less than 1 micro-watt in the sleep mode.

2.2.3 Software

Our team created a sleep monitoring software application using the LABVIEW graphical programming language as illustrates in Figure 2. This software serves as a foundational library, providing essential data structures and algorithms for sleep monitoring. It offers a wide range of features, including real-time body movement tracking, graphical data visualization, analysis of sleep-related breathing irregularities, and sleep quality assessment. The program has been designed to be user-friendly and uncomplicated, capable of reading data stored in text files from an SD card to analyze and process information concerning nocturnal responses throughout the night. One of the advantages of this program is its ability to facilitate multiple retrospective data reviews, and it can present the results in graphs and easily understandable figures, enabling users to review and analyze data effectively. The sleep monitoring software application developed by our team utilizes the LABVIEW graphical programming language, as depicted in Figure 2. This software functions as a foundational library, offering essential data structures and algorithms tailored for sleep monitoring purposes. Its extensive array of features encompasses real-time body movement tracking, graphical data visualization, analysis of sleep-related breathing irregularities, and assessment of sleep quality.

Designed with user accessibility in mind, the program possesses an intuitive interface capable of parsing data stored in text files sourced from an SD card, facilitating the analysis and processing of information pertaining to nocturnal responses over the course of the night. Notably, a key advantage of this software lies in its capacity to support multiple retrospective data reviews, with results presented in comprehensible graphs and figures, thereby enabling users to effectively scrutinize and interpret data. To utilize the program for analyzing sleep data from text files, please refer to Figure 2:

1. Click to open the file labeled as number 1 to select a file for reading.
2. Press "Run" at position number 2 and wait until the program completes its operation.
3. Adjust the tab bar at position number 3 to accelerate the processing time.

The software can track respiratory rate and sleep efficiency without physical contact with the skin by utilizing pressure sensors, as shown in Figure 3.

Integrating the measurement hardware and software creates a feasible solution suitable for both clinical and home settings. This integration enables accurate and efficient monitoring of sleep patterns, identifying potential issues that may negatively impact sleep quality. The software component of this solution provides a convenient and effective means of exploring the relationship between respiration rate and sleep quality. The specialist can identify potential issues like stress, anxiety, or respiratory disruptions that could affect a person's quality of sleep by observing the respiration rate. In addition, the software incorporates a sleep-wake analysis system capable of precisely determining sleep-wake cycles by scrutinizing the frequency and threshold magnitude of head and neck movements. By analyzing the movements of the head and neck, the software can distinguish between periods of wakefulness and sleep, providing an accurate picture of a person's sleep patterns.

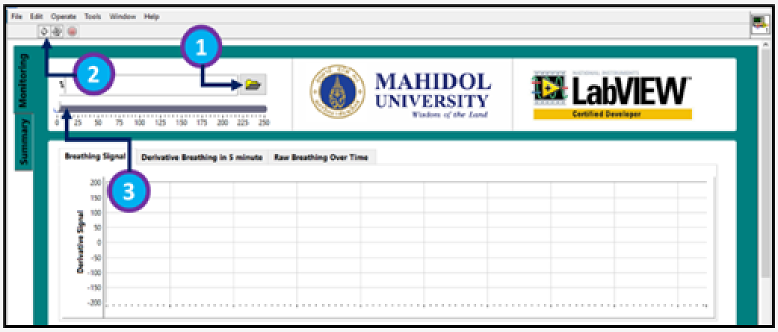

Figure 2: Screenshot of the sleep analysis for analyzing data from text files

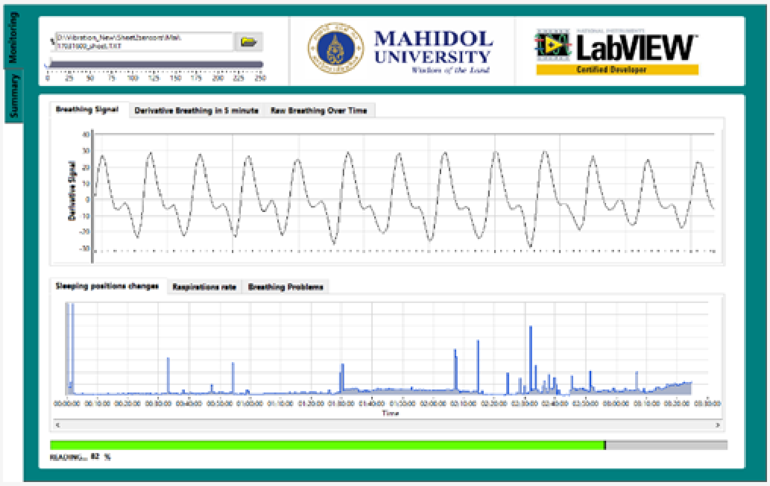

Figure 3: Screenshot of the sleep analysis for analyzing data from text files

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2.3 Sensors' Calibration

In designing a pillowcase, the first step involves selecting a suitable pressure sensor for a prototype to monitor sleep performance and snoring disorders. This section elucidates a comprehensive methodology for calibrating force sensors employed in quantifying biomechanical signals associated with body movement. The force-sensitive resistor (*FSR*) sensor selected for this application can measure forces between 0 and 100 N with a resolution of 1 N. An analog voltage divider obtains a signal output with a fixed reference resistor (R_f) of 10 KΩ. In Arduino microcontrollers, the analog reading ranges from an integer value (Sensor value) between 0 and 1023 (in increments of 1024) and converts to a voltage value between 0 and 5V. Equation 1 shows the sensor value for the voltage output, and the voltage output between the fixed reference resistor (Rf) and the variable FSR (RFSR) is used as the output of the *FSR*, as shown in Equations 2 to 4.

$$V_{out} = S_v \left[\frac{V_{in}}{1023} \right]$$

Equation 1

$$R_{FSR} = \left[\frac{V_{in} R_f}{V_{out}} \right] - R_f$$

Equation 2

$$V_{out} = \left[\frac{V_{in} R_f}{R_f + R_{FSR}} \right]$$

Equation 3

$$G = \frac{1}{R_{FSR}}$$

Equation 4

where:

- V_{out} is the FSR output voltage
- S_v is sensor value
- V_{in} is the input voltage to the FSR
- R_f is a fixed referent resistor
- R_{FSR} is the variable resistance from the FSR

As the applied force to the FSR changes, its resistance value changes proportionally, resulting in a corresponding change in V_{out}. The precise measurement of V_{out} is a critical component in developing and calibrating FSRs, which are utilized in various applications, including robotics, medical devices, and automotive safety systems. Accurate measurement of V_{out} can ensure the optimal performance and reliability of FSRs in various contexts.

Figure 4 depicts the graphical representation visually captures the force-sensitive resistor (FSR) resistance sensor values in conjunction with their respective conductance counterparts, exhibiting an inverse relationship with the resistance exhibited by the FSR sensor. The ensuing results of the force sensor characterization encompass a multifaceted analysis, where the regression line quantifies the sensor's sensitivity while the R-squared coefficient provides insight into its linearity. With a value nearing one, precisely 0.9968, it suggests a near-perfect linear relationship, affirming the reliability of the sensor's readings. The calibration curves delineate the dynamic trend line and the conductance characteristics of the FSR sensors. The conductance relationship is aptly described by a second-degree polynomial given by Equation 5.

$$y = -0.0091x^2 + 0.2236x - 0.0457$$

Equation 5

Such polynomials, especially of higher degrees, are instrumental in capturing complex non-linear relationships, thus providing a more nuanced understanding of the sensor's behavior under varying force applications. In the conducted experiment, there was no necessity for direct weight readings from the FSR features. Instead, the emphasis was on augmenting the repeatability of the current features, aiming for enhanced longevity and consistent performance over time. The present study deemed direct weight readings from the FSR features unnecessary. Instead, our primary objective was to enhance the repeatability of the current features to ensure prolonged operational longevity.

2.4 Smart Pillow Fabrication

The present study describes the development of a smart pillowcase capable of detecting breathing patterns using a fabric pouch that holds the sensors inside the pillowcase. The sensor demonstrates the capacity to discern respiratory patterns by analyzing variations in pressure distribution across the pillow's surface, attributed to the lifting and lowering of the chest during breathing cycles, which movement is consistent with the movement of the head. The FSR sensors are responsible for collecting data on the user's sleep patterns, including potential metrics like the frequency of movements or changes in pressure points throughout the night. As depicted in Figure 5, the pressure signal increased during respiratory inspiration and decreased during respiratory expiration.

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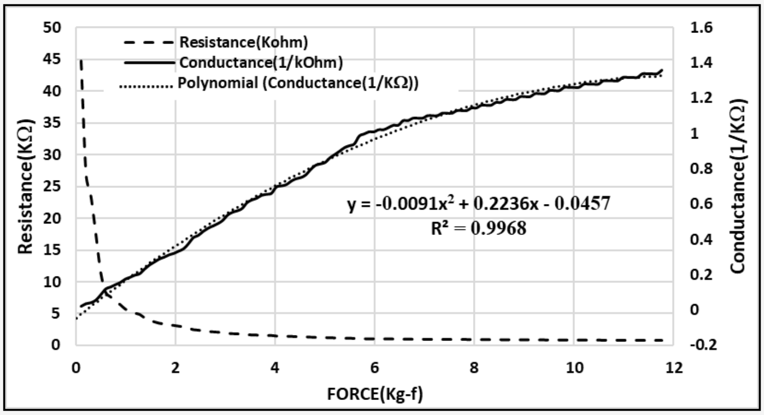

Figure 4: The relationship between the force-resistance and force-conductance curves of the FSR406

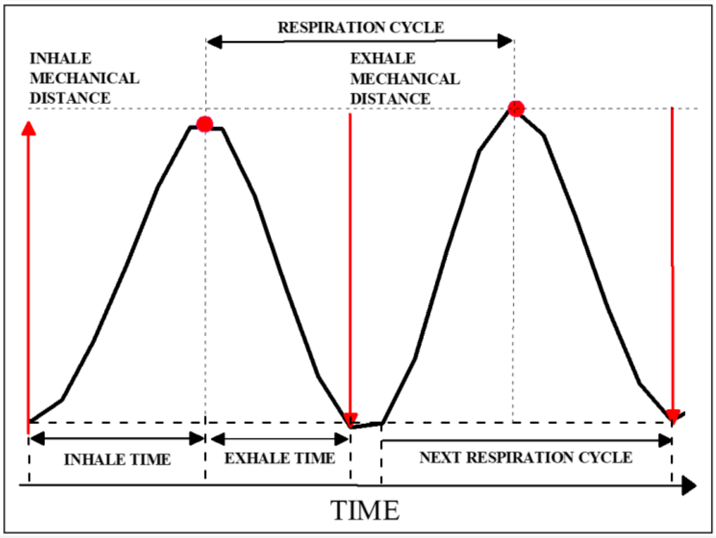

Figure 5: An example of a respiratory cycle and pattern in coordination with head movement during sleep

Each detected respiration cycle was segmented into an inspiration period, corresponding to the inhalation phase, and an expiration period, corresponding to the exhalation phase. This innovative approach to detecting breathing cycles may have potential applications in sleep research and medicine.

2.5 Experiment

The subject selection process was collaboratively orchestrated with a renowned medical sleep center, ensuring a comprehensive representation of all obstructive sleep apnea (OSA) categories and central sleep apnea (CSA) within the test cohort. In a preliminary case-control study, we conducted tests on twenty-seven subjects who had already been diagnosed with sleep apnea. The electronic recordings indicated the beginning and end of the in-bed session as "Lights Out" and "Lights On," respectively. Overnight polysomnographic (PSG) recordings were meticulously conducted. These studies were carried out concurrently with polysomnography assessments at an accredited sleep laboratory. The research protocol, bearing the identification number ID 02-56-59 (No. MURA2013/140), has received the requisite approval from the Ethical Clearance Committee on Human Rights at the Faculty of Medicine, Ramathibodi Hospital, Mahidol University, as substantiated by documentary evidence. The respiratory scoring adhered to the American Academy of Sleep Medicine guidelines' 2012 adult rules, version 2.0. The data gleaned from the polysomnographic (PSG) tests are evaluated and interpreted by seasoned physicians and technical experts. Concurrently, the intelligent sleep test results undergo automated analysis facilitated by smart sleep software systems.

A specialized mathematical framework was employed to compare the differences in sleep efficiency (%SE) between a typical polysomnography unit and a pillow-sheet sensor system. Sleep efficiency is crucial for assessing sleep quality. An alternative formula for %SE is defined in Equation 6 [25][26] and [27].

$$\%SE = \frac{TST}{TRT} \times 100$$

Equation 6

Where *TST* is total sleep time, which is calculated using Equation 7.

$$TST = TRT - TWT - TMT$$

Equation 7

TRT is determined from the sum of TST, TWT, and TMT, as expressed in Equation 8.

$$TRT = TST + TWT + TMT$$

Equation 8

Equation 8 can serve as an alternative method for deriving TRT, wherein it infers the combined durations of sleeping, waking, and moving, rather than being directly measured.

3. Results and Discussion

The advanced sleep platforms incorporate a force sensor and a controller module, enabling the platform to interpret and transmit signals to the LABVIEW software. This system possesses the capability to detect and measure head and body movements. Moreover, it actively extracts user behavioral patterns and biokinetic signals from the captured data, facilitating real-time monitoring. The intelligent sleep application aims to provide users with insights into their sleep patterns and associated lifestyle habits. The intelligent sleep monitoring system monitored many of our sleep-related features in one night. Specifically, the software can record numerous indicators for sleep monitoring, as shown in Figure 6, including time in bed or total recording time, sleep time, sleep efficiency, total awake time, number of posture changes, sleep latency, and overnight respiratory rhythm.

The purpose of this study was to evaluate and compare sleep metrics (sleep efficiency, non-REM sleep, and REM sleep) obtained from pillow-sheet sensor systems to PSG, the gold standard for sleep monitoring. Figure 7 compares data from a Split Night Polysomnography (PSG) with the frequency of body movement measured by pillow-sheet sensor systems. According to the PSG data, the patient spent 32.4% of his sleep time in stage N1, which is higher than average, indicating likely sleep fragmentation or less restorative sleep. Stage N2 accounted for only 7.4% of total sleep time, which is lower than average. N2 sleep is necessary because it serves as a transitional stage to deeper sleep stages. In contrast, stage N3 accounted for 43.9% of total sleep time, indicating a significant amount of deep, restorative sleep. REM sleep accounted for 16.3% of total sleep duration. The intermediate wake (W), REM (R) sleep, light sleep (N2), and deep sleep (N3) stages were determined by visually evaluating brain activity compared with the data from the pillow-sheet system, which consists of raw signals and the frequency of body movement.

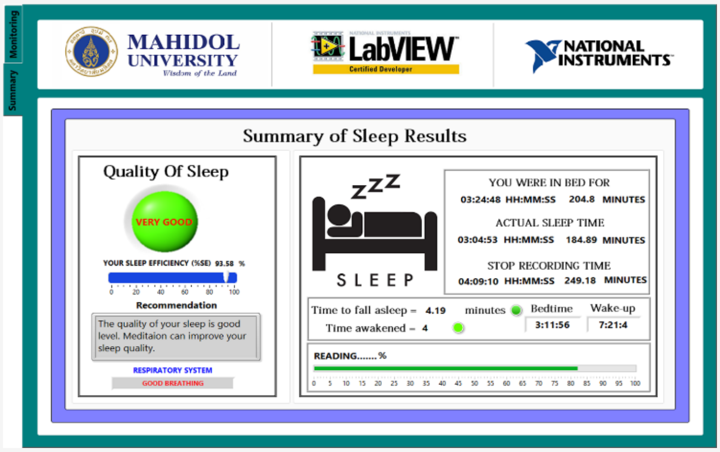

Figure 6: Screenshot of the smart sleep application for monitoring and treating sleep-related breathing disorders

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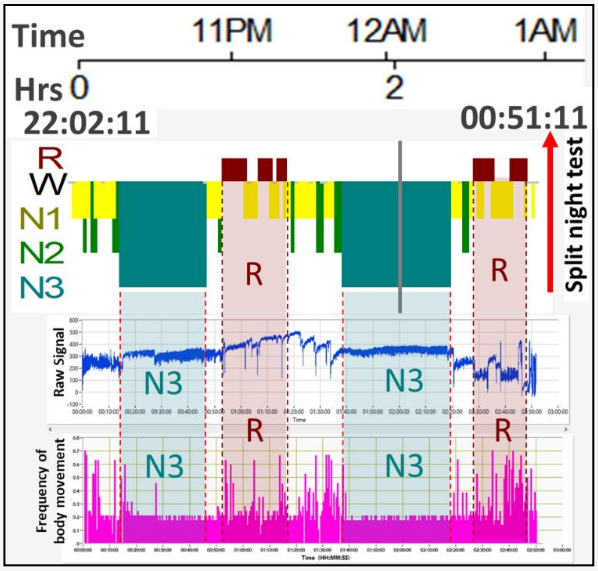

Figure 7: Split-night record for a participant

In the statistical evaluation of Sleep Efficiency (%SE) among patients, distinct patterns emerged when assessed through two different modalities: the traditional Polysomnography (PSG) and the innovative Pillow-Sheet sensor systems. The PSG device, a staple in sleep studies, yielded a mean %SE of 87.47%, with a standard deviation of 8.33, indicating a consistent yet varied range of sleep efficiency scores among the evaluated subjects.

On the other hand, the Pillow-Sheet sensor systems, known for their non-invasive and user-friendly nature, demonstrated compelling compatibility with the PSG's findings. The mean %SE recorded was 87.31%, with a lower standard deviation of 7.16. This data underscores the system's precision and consistency in gauging sleep efficiency, with reduced variability in the recorded data.

To define and explain the relationship between Sleep Efficiency (%SE) as measured by the standard PSG equipment and the innovative Pillow-Sheet sensor systems, a careful regression analysis was carried out, utilizing a robust dataset containing %SE measurements from both systems. The linear relationship was evaluated and quantified, providing useful insights into the correlation and predictive power of the two measurement modalities. The coefficient of determination (R2) was calculated to be 0.96, indicating that the PSG device readings explain roughly 96% of the variability in the %SE observed by the Pillow-Sheet sensor devices. The slope of 0.84 in the regression equation signifies a strong positive linear relationship. For every unit increase in %SE as measured by the PSG device, we can anticipate a corresponding increase of 0.84 units in the %SE measured by the Pillow-Sheet sensor systems, with a baseline intercept of 14.00.

The regression analysis (Figure 8) illuminates a significant and robust linear relationship between the %SE readings of the PSG device and Pillow-Sheet sensor systems. The high R^2 value is indicative of the latter's reliability and its precision in echoing the readings of the traditional PSG device.

The Bland-Altman plot (Figure 9) provides a comprehensive comparison between the PSG device and the Pillow-Sheet sensor systems in measuring sleep efficiency (%SE). The plot illustrates the agreement between these two methods, offering insights into their consistency and reliability. The mean difference between the two systems is 0.16. The majority of data points fall within the upper (3.99) and lower (-3.66) limits of agreement (LOA), highlighting this consistency and providing empirical confirmation of the congruence between the systems. Through both visual and quantitative presentations of the data, this graphical representation aligns with the findings of the regression analysis.

Figure 10 presents a comparative study on sleep apnea detection between traditional Polysomnography (PSG) equipment and innovative pillow-sheet sensor systems. Key parameters, including SpO2 levels, airflow, and abdominal movements, were meticulously analyzed to assess the efficacy and precision of both systems in detecting and recording apnea and hypopnea events during sleep. A significant decline in oxygen saturation, as indicated by SpO2 levels, signified occurrences of apnea, serving as a reliable indicator for sleep disruptions.

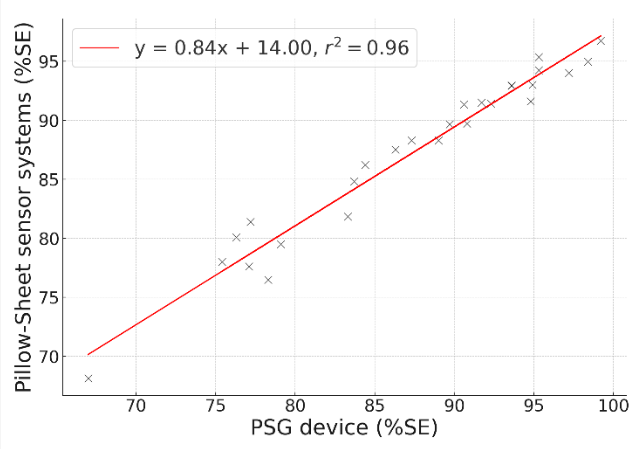

Figure 8: Regression analysis of sleep efficiency (%SE) between PSG device and pillow-sheet sensor systems

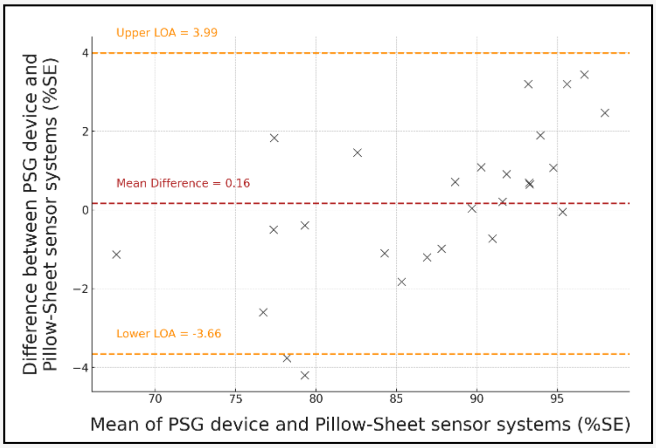

Figure 9: Bland-Altman analysis comparing sleep efficiency (%SE) measurements obtained from PSG devices and pillow-sheet sensor systems

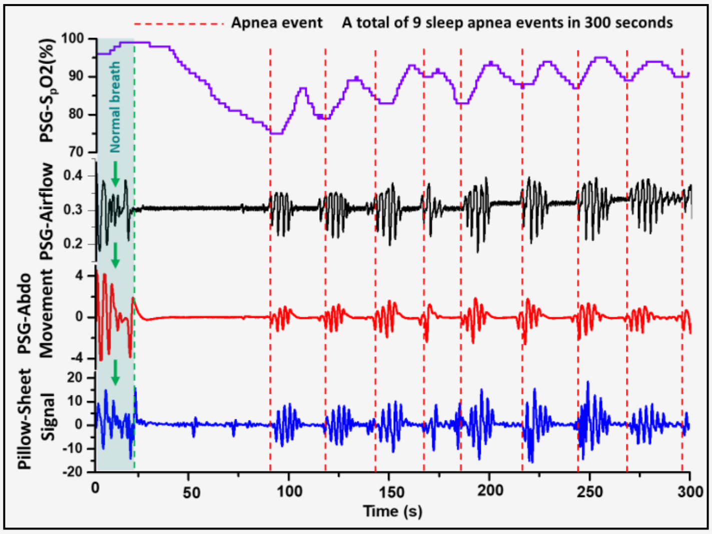

Figure 10: Comparison of apnea-hypopnea events from experimental records, including outputs of SpO2 (%), airflow (thermistor), and abdominal movement (the rip belts) monitored by the PSG device, against outputs from pillow-sheet sensor systems based on time-domain response

In comparative terms, the pillow-sheet sensor system exhibits notable excellence. The amplitude of the respiratory signals it captures closely resembles those recorded by the gold-standard PSG equipment, particularly when compared with airflow and abdominal movement. This consistency in data fidelity underscores the potential of the FSR sensor as a reliable tool in the nuanced field of sleep apnea diagnosis.

4. Conclusion

In summary, the pillow-sheet embedded with FSR sensors significantly advances sleep research and medicine. It offers comparable accuracy to PSG and introduces the benefits of being user-friendly and non-restrictive. The system's ability to provide insights into sleep patterns, detect apnea episodes, and analyze sleep postures underscores its potential applications in personalized sleep health management. The strong correlation between the data from the traditional PSG and the innovative pillow-sheet sensor system underscores the reliability and potential of this new technology in revolutionizing sleep monitoring and the diagnosis of sleep-related breathing disorders. Integrating technology, comfort, and precision in this system paves the way for a new era of sleep study, where patients can be monitored unobtrusively, leading to more accurate and natural sleep data being recorded, which is instrumental in diagnosing and managing sleep disorders effectively.

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