Review

Non-invasive systems for sleep monitoring: Respiratory rate and sleep posture classification

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ABSTRACT

Sleep plays an essential role in human health. Monitoring sleep has increasingly become an important tool for gaining deeper insights into sleep behavior and detecting related health issues. Polysomnography (PSG) in clinical settings is the gold standard for sleep analysis; however, it is expensive and challenging to implement over long periods. As a result, home-based sleep monitoring methods, particularly non-invasive sensor-based systems, are gaining significant attention. This paper focuses on reviewing recent studies related to non-invasive sleep monitoring systems, including both wearable and non-wearable methods. These systems are designed to continuously measure and monitor users' breathing patterns while also detecting and classifying their sleep postures. Additionally, the paper explores future directions for developing respiratory monitoring and sleep posture classification systems that can operate flexibly across different environments, including settings outside professional medical facilities.

Keywords: Accelerometer; Respiratory rate; Sleep position; CNN.

1. INTRODUCTION

Sleep is an essential factor in human daily life. Poor sleep quality or insufficient sleep can lead to a decline in physical health and may cause cognitive and psychological issues. People who do not get enough sleep are more susceptible to various chronic diseases such as obesity, diabetes, and hypertension [1]. Spiege et al. [2] found that insufficient sleep can increase the risk of obesity and diabetes. Borsini et al. [3] confirmed that sleep apnea is a significant risk factor for hypertension. Lack of sleep is also one of the leading causes of road accidents and decreased work productivity [4, 5]. Due to the importance of sleep, this field has gained significant attention in the research community. Studies [6, 7] have been conducted to analyze and understand sleep quality and behavior. It has become a distinct branch of medicine and has attracted considerable interest in recent years [6, 7].

Various techniques can be used to monitor sleep [8]. The traditional approach to analyzing and understanding sleep quality involves clinical methods [9]. Clinical methods utilize specialized hardware and controlled environments under the supervision of experts. Patients are required to stay at monitoring facilities to obtain the most accurate data. This approach is highly technical and costly. Today, smart medical technologies provide widely accessible solutions for sleep monitoring at a relatively lower cost and with greater ease of use [10, 11]. Innovations in smart sensor technology have led to the development of various wearable or bed-integrated sensors. These sensors can effectively monitor sleep by collecting relevant data. These solutions enable home-based sleep monitoring without requiring professional technicians.

This paper focuses on analyzing and evaluating studies related to non-invasive methods for sleep monitoring, aiming to provide an overview of technological advancements in this field. Specifically, the paper examines sleep monitoring systems based on respiratory measurement and sleep posture classification. Additionally, potential research gaps are identified, and future research directions are proposed.

The remainder of the paper is organized as follows. Section 2 presents non-invasive approaches to sleep monitoring. Section 3 introduces the proposed model and its applications. Section 4 provides concluding remarks.

2. NON-INVASIVE METHODS FOR SLEEP MONITORING

Non-invasive sleep monitoring is a crucial research area that enables the assessment of sleep quality without direct physical contact with the body [8]. Shinjae et al. [12] published a review paper summarizing recent advancements in home sleep monitoring technology. Their study primarily focused on commercial devices, categorizing them into four main groups: brain signal-based systems, biological signal-based systems, motion-based systems, and bed sensor-based systems. Additionally, the study discussed the potential applications of consumer devices in sleep monitoring. The authors highlighted limitations in current research and concluded that while the number of mobile devices supporting sleep tracking is increasing, standardization is needed to ensure consistency and reliability.

In another study, Surantha et al. [13] conducted a survey on Internet of Things (IoT)-based sleep monitoring solutions, with a focus on evaluating sleep quality. The authors discussed several common sleep disorders and clinical methods for sleep monitoring while proposing an IoT architecture model to improve sleep tracking and quality assessment.

Additionally, Ibanez et al. [14] focused on sleep questionnaires and sleep diaries, two widely used self-reporting methods in this field. Their survey assessed the accuracy and validity of these methods and provided key analyses regarding their effectiveness in research and clinical practice.

Matar et al. [15] conducted a comprehensive review of non-invasive sleep monitoring methods, focusing on sleep stages, sleep disorders, and tracking techniques while classifying studies based on physiological signals such as breathing, heart rate, and body movements. Sadek et al. [16] reviewed non-invasive technologies, including wearable and non-wearable devices, but primarily emphasized consumer devices rather than in-depth research. Fallmann et al. [17] categorized sleep monitoring methods into clinical and home-based approaches, highlighting computational analysis algorithms for sleep stage classification, movement tracking, and disorder detection, while also addressing the challenges associated with these techniques.

Based on the reviewed studies, it is evident that non-invasive sleep monitoring is an evolving field with various approaches. Among these, two key factors for effective sleep assessment are respiratory measurement and sleep posture classification. Breathing patterns can reflect sleep quality and help detect signs of respiratory disorders such as sleep apnea, while sleep posture plays a crucial role in identifying sleep-related issues such as back pain, improper positions, or snoring.

2.1. Respiratory measurement systems

According to the study by Liu et al. (2019) [18], in clinical practice, respiratory rate (RR) is defined as the number of breaths measured per minute, commonly reported in bpm. RR is considered a vital sign, and abnormalities in breathing rate can serve as early indicators of severe clinical conditions. Disorders in the respiratory or circulatory system, leading to hypoxia or increased carbon dioxide levels, can be detected through RR monitoring [18]. The study indicated that abnormal respiratory rates could predict critical conditions such as the risk of readmission to the intensive care unit (ICU), chronic heart failure, pneumonia, pulmonary embolism, and drug overdose [18].

RR is assessed as a more sensitive indicator than blood pressure and heart rate in identifying high-risk patients for severe cardiopulmonary complications [2]. This is because relative changes in RR tend to be significantly larger, making it easier to distinguish between stable and high-risk patients [19]. Abnormal RR values (<6 bpm or >24 bpm) are among the most accurate predictors of mortality, whereas high heart rate or increased blood pressure do not exhibit a similar correlation. Even a slight deviation of just 4 bpm from normal breathing can serve as an early warning sign for severe events such as cardiac arrest due to brain hypoxia [19]. Notably, abnormal respiration is considered the most common precursor to cardiac arrest [19].

However, hypoxia or carbon dioxide buildup does not always lead to an increased respiratory rate and airflow [19]. Certain medications, such as opioid painkillers and anesthetics, can suppress respiratory reflexes, impairing the body's physiological response to hypoxia or elevated carbon dioxide levels. In such cases, RR monitoring becomes particularly crucial for ensuring safe and effective anesthesia, as slow breathing often indicates a decline in consciousness—a typical consequence of anesthetic use [19]. Due to its ability to detect early signs of patient deterioration, RR has been integrated into various early warning systems to enhance monitoring effectiveness and enable timely medical intervention.

Although RR is a critical indicator of severe clinical conditions, its measurement is still predominantly performed manually, leading to low accuracy or even being overlooked. Respiratory rate monitoring conducted by nursing staff may be unreliable [20], especially in busy medical environments where other physiological parameters, such as heart rate and blood pressure, are prioritized due to their ease of automatic measurement using simple electronic devices. As a result, RR is not consistently monitored, even in patients with respiratory issues, due to the lack of reliable automated respiratory monitoring systems.

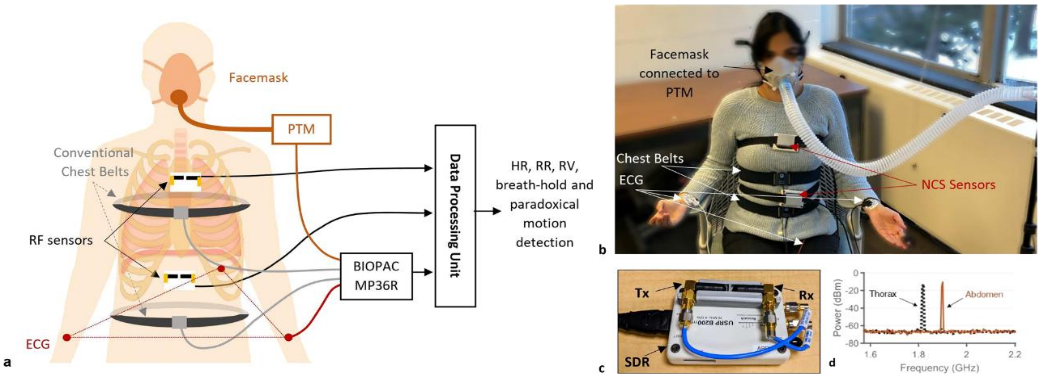

Figure 1. *Illustration of a contact-based respiratory measurement system [19].*

Currently, RR can be measured using various methods such as spirometry, capnometry, and pneumography [21]. K. H. Chon et al. [21] introduced a method to estimate respiratory rate from PPG signals using Variable-Frequency Complex Demodulation (VFCDM). Compared to CWT and AR models, VFCDM showed higher accuracy, greater consistency, and faster computation, successfully estimating breathing rates between 12–36 breaths per minute, including higher rates not well addressed by earlier methods. D. Bian et al. [22] proposed an end-to-end deep learning method based on the ResNet architecture to estimate respiratory rate (RR) from photoplethysmogram (PPG) signals. To address data limitations common in deep learning, the authors generated a synthetic PPG dataset, which improved model performance by 34%. Trained and validated on two public datasets (n=95), the model achieved a mean absolute error of 2.5 ± 0.6 breaths per minute, using 5-fold cross-validation. However, these methods often require complex and expensive equipment, which may interfere with natural breathing, making them difficult to implement in scenarios such as mobile monitoring, stress testing, or sleep studies [22]. Therefore, the demand for developing automatic, reliable, and convenient respiratory monitoring devices has become increasingly urgent to ensure more effective RR tracking. Figure 1 illustrates a contact-based respiratory measurement system [19].

In recent years, automatic RR monitoring systems have been developed, bringing significant benefits [22]. These systems can provide early predictions of critical clinical events such as cardiac arrest or the risk of admission to the intensive care unit (ICU). Notably, continuous RR monitoring helps detect abnormalities associated with mortality risk or severe diseases up to 24 hours in advance, with a sensitivity and specificity of 95%. This underscores the importance of integrating technology into respiratory monitoring to enhance healthcare quality and enable timely interventions in critical situations. Figure 2 illustrates a non-contact respiratory measurement system [20].

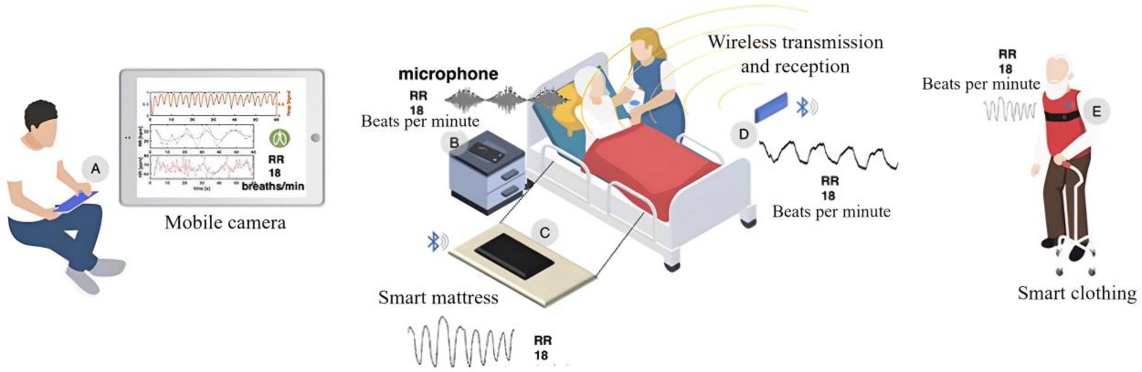

Figure 2. *Illustration of a non-contact respiratory measurement system [20].*

Contact methods, such as spirometry, capnometry, and pneumography, typically offer higher accuracy as they directly collect data from the user's respiratory system [21]. Additionally, these devices tend to be less expensive and can be flexibly used in various environments without spatial measurement limitations. However, the main disadvantage of these methods is the inconvenience and discomfort for the user, particularly when devices need to be worn or attached for extended periods, which can affect patient experience and compliance. In contrast, non-contact measurement methods offer significant advantages in terms of comfort, as users do not need to attach devices directly to their bodies [22]. Technologies like infrared sensors, radar, or image analysis help monitor respiratory rate remotely without disrupting the monitored person's activities. However, the accuracy of these methods is still limited, as they are susceptible to environmental factors such as light, user position, or unrelated movements. Additionally, most non-contact systems require the user to lie or sit within a fixed monitoring area, which limits their applicability in mobile situations or diverse environments. The cost of these systems is also higher compared to contact methods, reducing their feasibility for widespread deployment.

In the past decade, machine learning (ML) techniques have been widely applied to estimate respiratory rate. Lee et al. [23] developed the EGBA algorithm based on PPG signals to improve accuracy in estimating respiratory rate by using multi-stage features. However, combining multiple feature extraction methods can lead to biases and reduce the reliability of respiratory rate estimation [24-26]. To address this issue, appropriate features need to be selected for automatic input into ML.

Liu et al. [27] developed an enhanced generative LSTM model for respiratory rate estimation, while Kumar et al. [28] proposed an LSTM-based method utilizing PPG and ECG signals. Additionally, several studies have applied sensors such as accelerometers and capacitive sensors to measure respiratory rate.

In the field of wearable devices, Hernandez et al. [29] developed BioWatch, a wrist-worn device capable of simultaneously estimating heart rate and respiratory rate in various postures. However, this device estimates respiratory rate indirectly through heart rate signals and may cause discomfort with frequent use. Building on this research, Shen et al. [30] proposed a smart shirt integrating accelerometers, ECG, and impedance sensors to measure respiratory rate more accurately using algorithms such as Bayesian Inference and the Kalman Filter. More recently, in 2020, Havriushenko et al. [31] applied deep learning models, including LSTM and CNN, to extract features from smartwatch-collected signals, enabling precise and automated respiratory rate prediction.

2.2. Sleep posture detection and classification systems

Many serious health issues can occur suddenly during sleep, such as stroke, heart failure, cardiac arrest, or sleep apnea syndrome [20]. However, if respiratory rate is monitored during sleep, these conditions can be detected early, and timely warnings can be issued [20]. Additionally, research has shown that sleep posture is closely related to sleep quality, influencing phenomena such as nightmares, sleep apnea syndrome, and snoring [21]. Some studies have also indicated that improper sleep posture can lead to severe consequences, including an increased risk of mortality, particularly in cases of sudden infant death syndrome (SIDS) [21]. Furthermore, sleep posture affects breathing patterns and can help ensure proper respiration while minimizing the risk of sleep-related health issues [22].

Human sleep postures vary and can generally be classified into four main positions: left-side lying, right-side lying, prone (face-down), and supine (face-up), as illustrated in figure 3. Additionally, the figure includes a separate state of wakefulness, distinguishing between sleep postures and an awake condition.

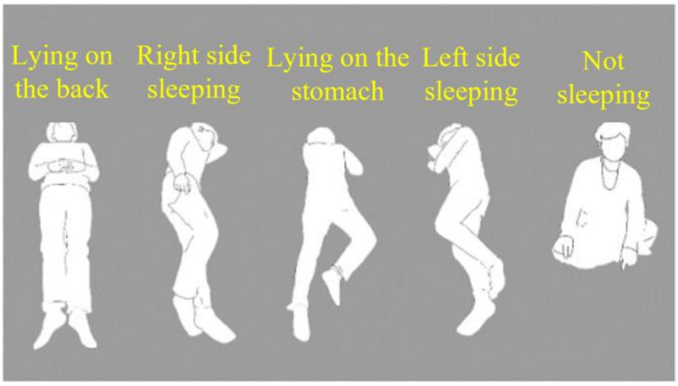

Figure 3. *Illustration of sleep postures and the wakeful position.*

Detecting sleep posture is not a simple task, as it requires continuous observation throughout the sleep process. Therefore, automatic sleep posture detection systems have been developed to accurately record users' sleep positions without the need for manual supervision. These systems play a crucial role in sleep research and in diagnosing posture-related sleep disorders.

Studies on sleep posture classification have applied various methods, including both non-contact systems and wearable devices for data collection and analysis. Non-contact systems typically use cameras or wireless signals such as radar and Wi-Fi to capture information about sleep posture [31]. The collected data is then preprocessed and fed into machine learning models for posture classification. However, camera-based methods face limitations in low-light conditions at night, reducing classification accuracy. Meanwhile, wireless signal-based systems can be affected by objects obstructing the signal, leading to data loss. Additionally, a common drawback of these methods is that users must remain within the device's coverage area to ensure reliable signal acquisition.

To overcome these limitations, wearable-based methods have been developed to collect data directly from the human body. The research team of Xing et al. [32] utilized hemodynamic and respiratory signals from a wearable device to determine sleep posture based on body vibration characteristics. Other studies have applied pressure sensors embedded in bed to classify sleep postures [33-35]. However, this method encounters challenges in distinguishing between signals from the monitored person and signals from other objects on the bed, reducing the model's accuracy.

Additionally, other studies have utilized wrist-worn sensors [36, 37], which enhance the ability to detect posture while lying in bed. However, discrepancies between body posture and wrist movement sometimes result in errors in sleep posture recognition. To improve accuracy, methods using accelerometer sensors [38-40] have been applied to classify body posture more precisely. In the study by [41], an accelerometer sensor was placed on the neck to detect sleep posture, combined with a machine learning model to improve accuracy. The signals obtained from the accelerometer exhibit clear differences between various postures, allowing the use of simple classification algorithms to accurately recognize users' sleep positions. Figure 4 illustrates the signals collected from the accelerometer sensor.

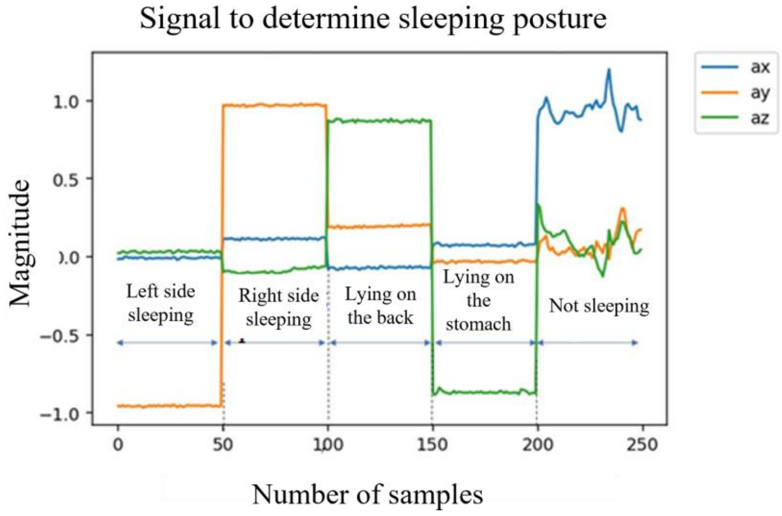

Figure 4. Illustration of accelerometer data for different sleep postures [41].

3. PROPOSED MODEL

3.1. System overview

The proposed system aims to address the fragmented nature of current sleep monitoring solutions by providing a unified platform that can concurrently estimate respiratory rate and classify sleep posture. Existing systems typically focus on only one of these two critical indicators, often requiring users to wear multiple devices to obtain comprehensive information about their sleep. This fragmentation not only introduces inconvenience but also poses a barrier to continuous monitoring in real-world settings. In contrast, our system integrates both functionalities into a single wearable device, enhancing usability, reducing setup complexity, and ensuring better coherence between respiratory and postural data. The overall architecture comprises three main components: (1) a wearable data acquisition unit that captures motion and respiratory-related signals, (2) a signal processing and machine learning module that extracts relevant features and performs prediction tasks, and (3) a wireless communication and user interface component that delivers feedback in real-time and supports historical data analysis. These modules work in unison to deliver a robust, compact, and scalable sleep monitoring solution suitable for both personal health applications and clinical research environments.

3.2. Sensing hardware and placement

At the heart of the system lies a compact wearable device equipped with an inertial measurement unit (IMU), which includes a three-axis accelerometer and a three-axis gyroscope. This IMU is capable of continuously capturing both linear and rotational motion, making it ideal for monitoring the subtle changes associated with breathing as well as larger shifts in body orientation during sleep. The device is designed to be lightweight and comfortable, enabling long-term use throughout the night without causing discomfort or interfering with natural sleep behavior. It is strategically placed on the chest or upper abdomen, locations that exhibit the most significant thoracic movement during respiration. This placement ensures that the accelerometer can accurately detect the rhythmic vertical displacements of the chest wall, while the gyroscope can capture rotational dynamics that correspond to posture changes. The integration of multiple sensing modalities within a single device allows for comprehensive monitoring using a minimal hardware footprint, thereby improving user compliance and reducing system cost.

3.3. Signal acquisition and preprocessing

The raw data collected by the IMU is sampled at a frequency of 50 to 100 Hz, providing high temporal resolution suitable for both respiratory analysis and posture detection. To prepare the raw sensor data for analysis, it is first segmented into overlapping time windows—typically 5 to 10 seconds in length—to facilitate feature extraction and model input formatting. Each window undergoes a series of preprocessing steps designed to enhance signal quality and improve robustness against noise and motion artifacts. A low-pass Butterworth filter is applied to eliminate high-frequency noise components that may arise from abrupt body movements or environmental interference. Following filtering, normalization techniques are used to correct for baseline drift and ensure consistency across different subjects and sessions. The preprocessed signals are then subjected to feature extraction, which includes the calculation of time-domain features such as signal amplitude, standard deviation, and peak-to-peak values, as well as frequency-domain features like spectral power and dominant frequency components. These features serve as the foundational input for the machine learning models tasked with estimating respiratory rate and identifying sleep posture.

3.4. Respiratory rate estimation

Respiratory rate estimation is achieved through the use of a supervised machine learning model—specifically, Random Forest Regression (RFR). RFR is chosen due to its strong performance in modeling nonlinear relationships between input features and output variables, making it well-suited for interpreting physiological signals that exhibit complex, non-stationary behavior. The model takes as input a set of features derived from the vertical (z-axis) component of the accelerometer signal, which reflects the amplitude of thoracic movements during breathing cycles. By training on labeled data, the model learns to map these features to accurate estimates of breaths per minute (BPM). The use of multiple decision trees in RFR helps to minimize overfitting and increases generalization across different individuals and sleeping conditions. Furthermore, the ensemble nature of the model allows it to handle noise or partial data more gracefully, which is especially valuable in overnight monitoring scenarios where users may shift positions or adjust their bedding. This component enables the system to deliver real-time, reliable respiratory rate monitoring without the need for cumbersome chest straps or nasal sensors.

3.5. Sleep posture classification

The sleep posture classification component is implemented using a hybrid deep learning architecture that combines Convolutional Neural Networks (CNNs) and Gated Recurrent Units

(GRUs). This design leverages the respective strengths of CNNs in capturing spatial patterns and GRUs in modeling temporal dependencies, resulting in a powerful tool for identifying and tracking sleep postures throughout the night. Initially, CNN layers process the multi-channel IMU signal to extract localized features that represent the distribution and dynamics of movement across the accelerometer and gyroscope axes. These features are sensitive to posture-specific characteristics, such as the tilt and orientation of the torso. The output of the CNN is then fed into a GRU layer, which retains temporal context across consecutive time windows, enabling the model to distinguish between sustained postural states and transient movements. To stabilize training and enhance convergence speed, batch normalization is applied after each convolutional layer. The final dense layer uses a softmax activation function to classify each time segment into one of several predefined postures, including supine (lying on the back), prone (lying on the stomach), left lateral, and right lateral. The model is trained on annotated datasets collected from controlled environments, with ground truth labels assigned based on video observation. This ensures a high level of classification accuracy and robustness across a variety of sleep behaviors.

3.6. Wireless communication and user interface

Once the system has processed and interpreted the sensor data, the results—including estimated respiratory rate and current sleep posture—are transmitted wirelessly to an external monitoring device. The system supports both Bluetooth Low Energy (BLE) and Wi-Fi communication protocols, allowing it to balance power efficiency and data transmission speed based on the application context. BLE is typically used for personal sleep tracking applications where energy conservation is paramount, while Wi-Fi is preferred in clinical or telemedicine settings that require real-time, high-bandwidth data transfer. On the user-facing side, a mobile or desktop application provides an intuitive graphical interface for visualizing data in real-time. Users can view their respiratory rate trends, sleep posture history, and receive alerts when abnormal patterns—such as prolonged periods in a single posture or irregular breathing—are detected. In a healthcare setting, the system can be configured to automatically notify clinicians of concerning events, such as signs of sleep apnea or frequent position shifts indicative of discomfort or pain. This integration of real-time analysis with user-friendly visualization and remote connectivity transforms the system into a powerful tool for proactive health management and clinical decision support.

4. DISCUSSION

Numerous previous studies have explored different categories of non-invasive sleep monitoring systems. Shinjae et al. [12] categorized these into brain signal-based, biological signal-based, motion-based, and bed sensor-based systems. However, most of the reviewed devices only focused on specific aspects of sleep and often required external or multiple devices, leading to limited convenience and lower compliance in long-term usage. Furthermore, the authors emphasized the lack of standardization in commercial sleep tracking devices, which results in inconsistent data quality and comparability. In contrast, our proposed system offers an integrated approach capable of capturing both respiration and posture-related data through a single wearable sensor, while employing machine learning to enhance reliability and interpretability.

Motion-based systems, particularly those utilizing inertial sensors, have shown promise due to their affordability and ease of use. Studies by Surantha et al. [13] and Matar et al. [15] pointed out the importance of IoT integration and real-time analysis in improving sleep tracking quality. While these frameworks are theoretically robust, many existing systems lack full implementation or only focus on environmental factors and high-level sleep quality indicators. Our system overcomes this limitation by implementing detailed physiological signal processing through CNN-GRU models and Random Forest Regression, enabling real-time classification of sleep posture and estimation of respiratory rate with high granularity. Additionally, the inclusion of BLE/Wi-Fi communication and a dedicated user interface supports a complete IoT solution suitable for deployment in both home and clinical settings.

Traditional respiratory monitoring methods, such as spirometry, capnometry, and pneumography [21], provide accurate results but are often contact-based and require bulky equipment. These are unsuitable for continuous, comfortable sleep monitoring, especially at home. As highlighted by Liu et al. [18] and Fallmann et al. [17], although respiratory rate (RR) is a critical predictor for severe conditions—including cardiac arrest, pulmonary embolism, or drug overdose—current hospital practices often rely on manual RR measurement, which is error-prone and inconsistently performed [20]. Our system addresses this challenge by offering continuous, automated RR monitoring in a non-intrusive format. Unlike camera-based or radar-based non-contact systems [22], which suffer from environmental interferences and spatial constraints, our wearable device provides consistent signal quality regardless of lighting conditions or room layout.

From a machine learning perspective, recent studies have shown increasing use of deep learning models such as LSTM, CNN, and hybrid networks to estimate RR from PPG or ECG signals [27–31]. However, many of these solutions require additional sensors or complex setups, which compromise user comfort. In contrast, our system leverages IMU data only simplifying the hardware design while still achieving high prediction accuracy through feature-rich preprocessing and the application of robust models like Random Forest Regression. Moreover, while devices like BioWatch [29] and smart clothing [30] offer novel form factors, they may cause discomfort or are difficult to scale due to their dependence on multiple sensing modalities. Our solution achieves a balance between comfort, portability, and performance by relying solely on a chest-worn IMU.

Regarding sleep posture detection, existing solutions often utilize either camera-based systems [31], which are limited by lighting and privacy concerns, or pressure sensor-based beds [33–35], which may confuse the user's signals with those of surrounding objects. Wrist-worn sensors have also been studied [36, 37], but they do not always reflect the actual orientation of the body. Our system improves upon these limitations by placing the IMU on the chest—a location that provides strong and consistent signals related to both respiration and posture. As shown in studies such as [41], chest-based accelerometers yield distinct signal patterns for different postures, enabling high classification accuracy even with relatively simple algorithms. In our case, we further enhance performance using a CNN-GRU hybrid model that captures both spatial and temporal features of the data, surpassing the limitations of conventional methods.

Overall, the proposed model addresses multiple challenges identified in prior literature. It eliminates the need for multiple sensing devices, avoids the environmental constraints of non-contact systems, and bypasses the discomfort of multi-sensor wearables. Additionally, it provides meaningful feedback to users and clinicians alike through a user-friendly interface, supports real-time monitoring, and enables early detection of respiratory abnormalities and sleep-related issues. Nonetheless, the system still faces certain limitations, such as the need for initial calibration to accommodate body variability, and potential issues with data quality in cases of excessive movement. Future work may involve expanding the training dataset across more diverse populations, integrating additional physiological parameters, and validating the model in real-world clinical settings to further enhance its robustness and applicability.

5. CONCLUSIONS

This paper has provided an overview of non-invasive sleep monitoring systems, focusing on respiratory measurement and sleep posture classification. The surveyed studies include both wearable and non-wearable approaches. The advantages and limitations of each method have been clearly outlined. One of the current limitations is that respiratory measurement and sleep posture classification systems still operate independently, causing inconvenience and reducing the effectiveness of sleep monitoring. A potential solution is to integrate both respiratory measurement and sleep posture tracking into a single monitoring system to improve efficiency. Additionally, incorporating machine learning, deep learning, and artificial intelligence models can improve system accuracy and flexibility, making it a powerful tool for clinical research and applications in remote healthcare.

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TÓM TẮT

Các hệ thống không xâm lấn trong theo dõi giấc ngủ: Đo nhịp thở và phân loại tư thế ngủ

Giấc ngủ đóng vai trò quan trọng đối với sức khỏe con người. Việc theo dõi giấc ngủ ngày càng trở thành một công cụ quan trọng giúp hiểu rõ hơn về hành vi giấc ngủ và phát hiện các vấn đề sức khỏe liên quan. Phương pháp đa ký giấc ngủ (PSG) trong môi trường lâm sàng là tiêu chuẩn vàng để phân tích giấc ngủ, nhưng lại có chi phí cao và khó triển khai trong thời gian dài. Do đó, các phương pháp theo dõi giấc ngủ tại nhà, đặc biệt là các hệ thống không xâm lấn dựa trên cảm biến, đang thu hút sự quan tâm lớn. Bài báo này tập trung vào việc khảo sát các nghiên cứu gần đây liên quan đến hệ thống theo dõi giấc ngủ sử dụng phương pháp không xâm lấn và bao gồm cả phương pháp sử dụng thiết bị đeo và không đeo. Các hệ thống này được thiết kế để đo lường và giám sát liên tục nhịp thở của người dùng, đồng thời phát hiện và phân loại các tư thế ngủ của người dùng. Bài báo cũng nghiên cứu về hướng đi trong tương lai để phát triển hệ thống đo nhịp thở và phân loại tư thế ngủ khả năng hoạt động linh hoạt trong nhiều môi trường khác nhau, bao gồm cả bên ngoài các cơ sở y tế chuyên nghiệp.

Từ khoá: Cảm biến gia tốc; Nhịp thở; Tư thế ngủ; CNN.