Scopus
Search Sources SciVal RI

Download Print Save to PDF Save to list Create bibliography

International Journal of Data Science and Analytics • 2023

Document type
Article
Source type
Journal
ISSN
2364415X
DOI
10.1007/s41060-023-00461-1
View more

Cloud-based non-invasive cognitive breath monitoring system for patients in health-care system

Soni, Mukesh[a] ; Shabaz, Mohammad[b] ; Maaliw, Renato R.[c] ; Keshta, Ismail[d] ; Altaee, Rasool[e] ; Das, Sanju[f]
Save all to author list

[a] Department of CSE, University Centre for Research & Development, Chandigarh University, Punjab, Mohali, 140413, India
[b] Model Institute of Engineering and Technology, J&K, Jammu, India
[c] College of Engineering, Southern Luzon State University, Quezon, Lucban, Philippines
[d] Computer Science and Information Systems Department, College of Applied Sciences, AlMaarefa University, Riyadh, Saudi Arabia
View additional affiliations

Full text options Export

Cited by 0 documents

Inform me when this document is cited in Scopus:

Set citation alert

Related documents

Pilot study of contactless sleep apnea detection based on snore signals with hardware implementation
Li, H. , Lin, X. , Lu, Y.
(2023) Physiological Measurement

Wireless Sensor and Smartphone-based System for Detection of Sleep Apnea
Koley, B. , Mandal, S.
(2022) Proceedings of 2022 6th International Conference on Condition Assessment Techniques in Electrical Systems, CATCON 2022

Multiple Brain Tumor Classification with Dense CNN Architecture Using Brain MRI Images
Özkaraca, O. , Bağrıaçık, O.İ. , Gürüler, H.
(2023) Life

View all related documents based on references

Find more related documents in Scopus based on:

Authors Keywords

Abstract

The health-care industry is seeing a dynamic ease of use of low-cost issue solutions that improve patient care, cut down on problems, increase efficacy, and provide health-care decision-makers access to intelligence information at the point of treatment. During sleep, breathing and apnea are recorded using a non-invasive sleeping breath monitoring system (NSBS), which is suggested in this study. The system gathers information about the movement of the chest and abdomen while sleeping around the pressure-sensitive sensor belt, determines the type of breathing being done, records the presence of apnea, and transmits the information wirelessly via Bluetooth to a mobile device. Real-time waveforms may be drawn and displayed by the mobile app, and the data can subsequently be uploaded to a cloud platform by the mobile device. To enable user sleep nursing monitoring, the PC terminal downloads data from the cloud to create the waveform and show the respiratory status record when the user is sleeping. Getting the pressure signal produced by the body's movement while you sleep is the fundamental tenet of the non-invasive sleep monitoring system. The FSR408 piezoresistive sensor from Interlink is utilized in this design. The sensor is 600-mm long, 16-mm wide, and 1-mm thick. The sensor's maximum range is 10kg, its precision in force resolution is greater than 0.5%, and its reaction time is 1–2ms, which satisfies the requirements for the acquisition of various metrics when a person is asleep. When computing the typical breathing signal, the algorithm's correlation degree similarity is greater than 90%. When an apnea frame is discovered, the resemblance to the usual frame is noticeably decreased, and the lesser the similarity, the longer the apnea period. © 2023, The Author(s), under exclusive licence to Springer Nature Switzerland AG.

SciVal Topics
Metrics

Author keywords

Breathing monitoring; Cloud; De-noising; De-trending; Hardware circuit

International Journal of Data Science and Analytics
https://doi.org/10.1007/s41060-023-00461-1

REGULAR PAPER

Cloud-based non-invasive cognitive breath monitoring system for patients in health-care system

Mukesh Soni[1] · Mohammad Shabaz[2] · Renato R. Maaliw[3] · Ismail Keshta[4] · Rasool Altaee[5] · Sanju Das[6]

Received: 3 August 2023 / Accepted: 12 September 2023
© The Author(s), under exclusive licence to Springer Nature Switzerland AG 2023

Abstract
The health-care industry is seeing a dynamic ease of use of low-cost issue solutions that improve patient care, cut down on problems, increase efficacy, and provide health-care decision-makers access to intelligence information at the point of treatment. During sleep, breathing and apnea are recorded using a non-invasive sleeping breath monitoring system (NSBS), which is suggested in this study. The system gathers information about the movement of the chest and abdomen while sleeping around the pressure-sensitive sensor belt, determines the type of breathing being done, records the presence of apnea, and transmits the information wirelessly via Bluetooth to a mobile device. Real-time waveforms may be drawn and displayed by the mobile app, and the data can subsequently be uploaded to a cloud platform by the mobile device. To enable user sleep nursing monitoring, the PC terminal downloads data from the cloud to create the waveform and show the respiratory status record when the user is sleeping. Getting the pressure signal produced by the body's movement while you sleep is the fundamental tenet of the non-invasive sleep monitoring system. The FSR408 piezoresistive sensor from Interlink is utilized in this design. The sensor is 600-mm long, 16-mm wide, and 1-mm thick. The sensor's maximum range is 10 kg, its precision in force resolution is greater than 0.5%, and its reaction time is 1–2 ms, which satisfies the requirements for the acquisition of various metrics when a person is asleep. When computing the typical breathing signal, the algorithm's correlation degree similarity is greater than 90%. When an apnea frame is discovered, the resemblance to the usual frame is noticeably decreased, and the lesser the similarity, the longer the apnea period.

Keywords Cloud · Breathing monitoring · Nursing · Hardware circuit design · De-noising · De-trending

1 Introduction

Sleep is an extremely important physiological need in human life, but according to a survey, around 38.2% of the population in any country has sleep disorders [1]. Among them, sleep apnea–hypopnea syndrome (SAHS) is a sleep disease that seriously affects people's sleep quality and physical

MS, MS, and RRM wrote the first draft of the research. IK and RA prepared the figures. SD prepared the final draft. All authors have reviewed the manuscript.

✉ Mohammad Shabaz
bhatsab4@gmail.com

Mukesh Soni
Mukesh.research24@gmail.com

Renato R. Maaliw
rmaaliw@slsu.edu.ph

Ismail Keshta
imohamed@mcst.edu.sa

Rasool Altaee
rasool.azeem@uomus.edu.iq

Sanju Das
sanjudasp@gmail.com

1 Department of CSE, University Centre for Research & Development, Chandigarh University, Mohali, Punjab 140413, India

2 Model Institute of Engineering and Technology, Jammu, J&K, India

3 College of Engineering, Southern Luzon State University, Lucban, Quezon, Philippines

4 Computer Science and Information Systems Department, College of Applied Sciences, AlMaarefa University, Riyadh, Saudi Arabia

5 Medical Laboratories Techniques Department, Al-Mustaqbal University College, Hillah, Iraq

6 Department of Computer Science, Assam University, Silchar, India

Published online: 05 October 2023

health and even endangers life [2]. For SAHS, it is more difficult to obtain disease data, the time of symptom onset is random, and the visual manifestation is weak. It is difficult for close relatives or even the patient to determine whether there is a disease condition, and it is cumbersome to conduct hospital observation. Therefore, a series of home-based devices that can monitor over long distances throughout the night provide patients and doctors with information for targeted diagnosis and treatment.

Family caregivers (FC), such as spouses, family, and friends who provide care for the patient, are an important resource for the well-being of terminally ill patients. They do this not just by providing support but also by actively participating in treatment choices and care planning. In the course of an incurable, progressive illness, patients, and their FC must make several difficult choices that will affect their future care and quality of life, such as those regarding life-prolonging therapy, medically assisted nutrition and hydration, transitions in care (such as seeking emergency care), or the location of care and death. From an ethical standpoint, the patient, not the patient's family, proxy, or doctor, decides what therapies are limited or treatments that only temporarily extend life without curing the patient's condition. However, if the patient is no longer capable of making decisions, the family, the proxy health care, or the doctor must decide what treatment the patient will get [4, 5]. Making decisions will be challenging for family members who are dealing with grief, worry, anxiety, and stress as a result of a loved one's terminal illness. If they are unsure about their loved one's wishes for end-of-life care, they cannot be certain that they are making the best choices for the patient.

The "gold standard" for the diagnosis of sleep apnea syndrome is polysomnography (PSG) [3]. The monitoring scheme of sleep apnea syndrome can be roughly divided into two types: invasive and non-invasive. In the invasive monitoring scheme, devices such as ECG electrodes, EEG, and nasal masks are generally used to measure ECG, EEG, and nasal airflow. In the non-invasive monitoring scheme, thoracic and abdominal movements and body position changes are measured by methods such as bio-radar, pressure-sensitive devices, and acceleration sensors. Intrusive monitoring solutions have a more or less physiological impact on patients with sleep disorders. From the perspective of home physiological monitoring, non-invasive monitoring is one of the important development directions [4].

Given that tiredness degrades cognitive and motor function, lowers productivity, and increases the risk of injury, the objective assessment of fatigue is very important in fields such as occupational health and safety. Since they allow for continuous, long-term monitoring of biological signals in unattended settings and have the necessary comfort and non-intrusiveness, wearable devices offer one of the most promising approaches to monitoring tiredness. This is necessary for the creation of precise models for real-time fatigue monitoring.

When sleeping, a person with sleep apnea stops breathing. Sleep apnea comes in three different varieties: central, obstructive, and complicated. Obstructive sleep apnea (OSA) is the most prevalent of them. Understanding the various forms of sleep apnea can assist a person in determining the root of their symptoms and locating the appropriate medical attention. Sleep apnea is associated with inflammation in the body, which raises the risk of several illnesses such as type 2 diabetes, high blood pressure, heart attack, and stroke. OSA can cause the tongue and soft palate to rattle, which can cause snoring. Another effect of it is that a person may awaken feeling as though they are unable to breathe. Even while upper airway blockage prevents central sleep apnea from happening, it still prevents breathing at night.

The reason is neurological. There is no snoring in central sleep apnea because, unlike with OSA, the body does not attempt to breathe. Instead, the person stops breathing as a result of the brain and nerve system not consistently signaling to breathe. One kind of sleep apnea that combines central and OSA is known as complex sleep apnea syndrome. A preliminary sleep investigation may occasionally reveal complicated sleep apnea syndrome. Sometimes, it becomes obvious after trying a standard CPAP machine or other conventional OSA therapies, and the apnea persists. If feasible, ask someone who sleeps in your bed or in your home to assist you in providing a sleep history so that your doctor or other health-care professional may make an assessment based on your symptoms. A sleep center sleep test comprises nightly monitoring of your breathing and other bodily systems as part of an examination.

Another possibility is home sleep testing. Your doctor may just advise lifestyle modifications, such as decreasing weight or quitting smoking, for milder forms of sleep apnea. You may alter how you sleep. If you have nasal allergies, your doctor could suggest allergy medication. If these methods do not help your symptoms or if your apnea is moderate to severe, a variety of alternative therapies are available. Certain gadgets can aid in the opening of a clogged airway. In other circumstances, surgery may be required.

Therefore, the scheme of obtaining data by monitoring the respiratory movement of the chest and abdomen has the advantage of being more friendly to patients. The micro-motion sensitive mattress is a sleep-breathing monitoring device based on a pressure-sensing design [5]. Basic nursing ideas need nurses to have excellent communication skills since doing so can lower the chance of medical mistakes, guarantee improved patient outcomes, and foster patient happiness. While once thought of as just nice, a positive patient experience is now taking center stage. Patient happiness has been incorporated into the notion of quality as the health-care industry transitions from a seller's market to a consumer's market. More urgently, when Medicare pays hospitals, it will take into account patient satisfaction ratings; institutions with higher ratings will be rewarded with incentives. Other insurance providers are quite likely to shortly follow suit. The use of Comfort TalkTM techniques makes use of the mind's inherent capacity to mask pain and lower stress. It is a direct, no-nonsense method for sedating or relaxing patients without using drugs. By studying institutions that have used this strategy, we were able to determine what influences how comfortable health-care providers are in challenging conversations. Individuals looking to enhance their connections with patients might equally benefit from using this information.

Compared with the traditional method of using bio-radar to detect the breathing movement of the chest and abdomen, it has the advantages of low cost and weak impact on the human body, and the mattress solution is suitable for home use monitoring management, its comfort is also suitable for long-term sleep monitoring. The movement of the chest and belly walls is measured using the respiratory inductance plethysmography (RIP) technique, which is a way to assess pulmonary ventilation. Oftentimes, equipment like masks or mouthpieces connected to the airway opening is needed for accurate monitoring of pulmonary ventilation or breathing. For continuous or ambulatory measurements, these devices are generally cumbersome and intrusive, making them inappropriate. A different method of measuring pulmonary ventilation is using RIP devices, which detect respiratory excursions at the body's surface. Reference [6] used regional mattress monitoring to sense the micro-movements of various parts of the body and wavelet analysis technology to accurately obtain beat-by-beat cardiac cycle information. Reference [7] studied the BCG integral signal obtained from the chest shock map and designed a non-invasive detection respiratory effort recognition algorithm based on the shape and amplitude characteristics of the body motion complex wave. Reference [8] obtained high-quality respiration intensity information by combining different sensor signals to achieve a good evaluation of the respiration rate and the respiration signal itself.

Gesture recognition (GR) techniques have been increasingly effective and straightforward in recent years as technology has advanced toward creating more impulsive and immediate interfaces between a system and its users. A tactile sensor system that reduces the human touch signal to a single datum and executes a command by converting a collection of data into text language or initiating a predetermined sequence as a haptic motion has been created as a tool for capturing human motion. The tactile sensor seeks to gather thorough information on a range of actions, from the tip of a finger to significant body movements. Different aspects of the sensor devices are significant for the applications they are intended acceleration for. Additionally, depending on the desired characteristics, different fabrication techniques can be used to create devices of the field effect transistor, capacitive, piezoresistive, and piezoelectric kinds.

The integration of medical infrastructure and data monitoring are examples of cloud-based patient services. For the database program to function, trustworthy medical information must always be made available online. The cloud-based health-care infrastructure consists of a computing interface and several sensors placed on the person's body [9]. Web-based gateways for IoT e-health-care monitoring with wired and wireless services were suggested by the authors. To keep the system affordable and power efficient, wired gateways are utilized in small buildings or rooms, restricting mobility within [10]. By using pressure or volume control to assist (or replace) breathing while wearing a respirator face mask, non-invasive ventilation (NIV) refers to an integrated therapeutic approach based on mechanical ventilators. This ventilatory support enhances pulmonary gas exchange and rests compromised respiratory muscles sufficiently to recover from their fatigued state [11].

Unobtrusive alternatives to in-home sleep monitoring are increasingly popular thanks to developments in the field of sensors and the availability of off-the-shelf devices. For in-home sleep monitoring, several affordable and simple options have been put forth utilizing both wearable and non-wearable technologies. In this paper, we give a thorough review of recent research (2015 and after) in several areas of sleep monitoring, such as sleep stage categorization, sleep posture identification, sleep disorders detection, and vital signs monitoring [12]. A complete night of sleep monitoring is necessary for the diagnosis of several sleep disorders, including sleep apnea, restless legs syndromes (RLS), and periodic limb movement disorder (PLMD). Traditional sleep monitors are unsettling and can cause privacy issues [13].

A breathing issue that happens while you sleep is called sleep apnea (SA) syndrome. Clinical practitioners frequently use polysomnography (PSG) as the gold standard for diagnosing SA syndrome. However, PSG usage is bothersome, obtrusive, and significantly impacts a patient's ability to sleep. For the non-invasive vital sign acquisition during the patient's sleep, a force sensor was used, and the morphological filter was used to adaptively extract the breathing signal. It was shown that the morphological changes that occurred before and during the SA events had a substantial impact on how well the SA events could be distinguished. The SA event was recognized using classifiers by utilizing the differential characteristics of the respiratory signal [14].

A complete stoppage of airflow during sleep is referred to as apnea, whereas decreased airflow or thoracoabdominal movement of 30% or more is referred to as hypopnea when it is accompanied by a 3% or less decrease in blood oxygen saturation levels or alertness. Depending on the underlying cause, apneas and hypopneas can also be divided into three categories: central, obstructive, and mixed. Obstructive sleep apnea (OSA) is thought to affect 10–17% of adult males and 3–9% of women. Men, the elderly, and obese people have higher rates of OSA [5]. Many studies indicate that OSA patients go undetected. Using a previously created computer vision motion-based algorithm, respiratory rate and heart rate estimations are taken from infrared (IR) footage. The approach monitors the variance between a set of chosen feature points over time. Each frame in the approach is split into a grid of squares that are 40 by 40 pixels in size. For a total of 1536 points over the whole image, eight different points (corners or textured areas) are chosen from each grid cell. Over 30-s periods, these points are monitored. The top and bottom 25% of each monitored point's maximum frame-to-frame displacement are eliminated to ensure that tracked motion is meaningful. The estimate of the cardiac and respiratory rates employed the same set of feature points [15].

In this paper, a non-invasive sleeping breath monitoring system (NSBS) is proposed for the collection and capture of breathing and apnea during sleep [16]. The system collects the data of sleep chest and abdomen breathing movement around the pressure-sensitive sensor belt, extracts the breathing rate in real-time, discriminates the breathing type, records the apnea condition, and transmits it to the mobile phone through Bluetooth wireless communication [17]. The mobile app can draw real-time waveforms and display them, and then, the mobile phone can upload the data to the cloud platform. The PC terminal obtains the data from the cloud to draw the waveform and at the same time displays the respiratory status record during sleep, to realize the sleep nursing monitoring of the user.

2 Design of the non-invasive sleep monitoring system

The basic principle of the signal generation of the non-invasive sleep monitoring system is to obtain the pressure signal generated by the body movement during sleep through the pressure sensor strip processed by the enlarged area and use the analog and digital signals to obtain the pressure signal. For maintaining sleep quality, the classification of sleep phases is also crucial. Sleep studies need the arduous visual process of manually classifying the various phases of sleep from raw polysomnography signals. As a result, during the past several years, research has been done to create an autonomous sleep stage grading system based on machine learning techniques. The system is built on a collection of pressure sensors that are positioned on the bed and can measure important metrics to gauge sleep quality. The time spent in bed (TB), body movements (BM), thorax expansion, times spent out of bed (POB), and apnea occurrences may all be recorded with this equipment. We contrast the outcomes of the minimal pressure sensor array with those obtained by conventional polysomnography (PSG). During sleep, breathing is monitored using hetero-core fiber-optic pressure sensors. Due to the variation in core diameter brought on by reliable single-mode transmission, the proposed hetero-core fiber-optic sensor is highly vulnerable to macro-bending. To create pressure sensors with a high sensitivity to both massive pressure changes—such as those brought on by a rollover—and tiny pressure changes brought on by minute body movements, such as breathing during sleep, hetero-core fiber-optic pressure sensors were created [18]. The sensors are set up in a typical bed. All of the manufactured hetero-core fiber-optic pressure sensors are found to have a monotonic response to weight changes in terms of their pressure characteristic performance. In addition, a tiny body movement may be detected even in various body positions, including resting on one's side. Figure 1 shows the schematic diagram of the acquisition system of the respiratory monitoring system.

This design uses the FSR408 piezoresistive sensor from Interlink. The sensor has a length of 600 mm, a width of 16 mm, and a thickness of 1 mm. It is soft and can be bent at any arc. It can be used on the bed to ensure the comfort of the human body. The maximum range of the sensor is 10 kg, the force resolution accuracy is better than 0.5%, and the response time is 1–2 ms, which meets the needs of the acquisition of various parameters when the human body is sleeping. Due to its short width, it is designed on the back of the sensor. A circular thin plastic sheet is attached to the position near the chest cavity, and a square thin plastic sheet is attached to other positions. The front is attached to a soft latex film with the same shape as the plastic sheet, which increases the body's safety. Pressure-sensitive area improved comfort. The overall system block diagram of the non-intrusive sleep monitoring system is shown in Fig. 2, which mainly includes the power supply part, the data acquisition part, and the data processing part.

3 Hardware circuit design

The hardware design of the proposed system includes a sensor circuit, filter circuit, ADC circuit, power circuit module, acceleration sensor module, and MCU circuit.

3.1 Sensor circuit

The resistance value of the FSR408 pressure sensor band has an inverse power relationship with the total pressure it receives, the sensor band is relatively slender, and the pressure distribution is uneven. After repeated experiments in different environments and different test subjects, the value of R1 is selected as 150 Ω. The amplification effect of this

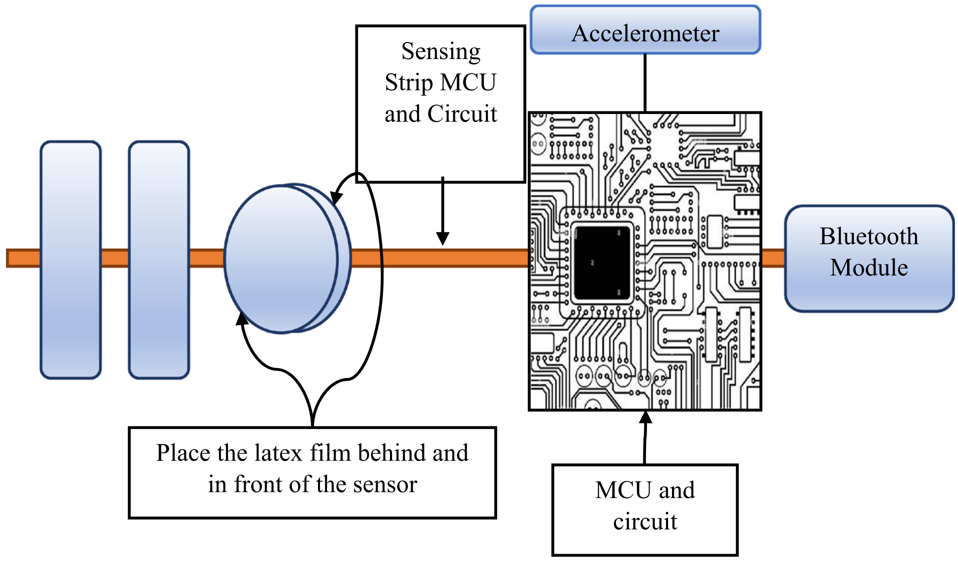

Fig. 1 Schematic diagram of the acquisition system of the respiratory monitoring system

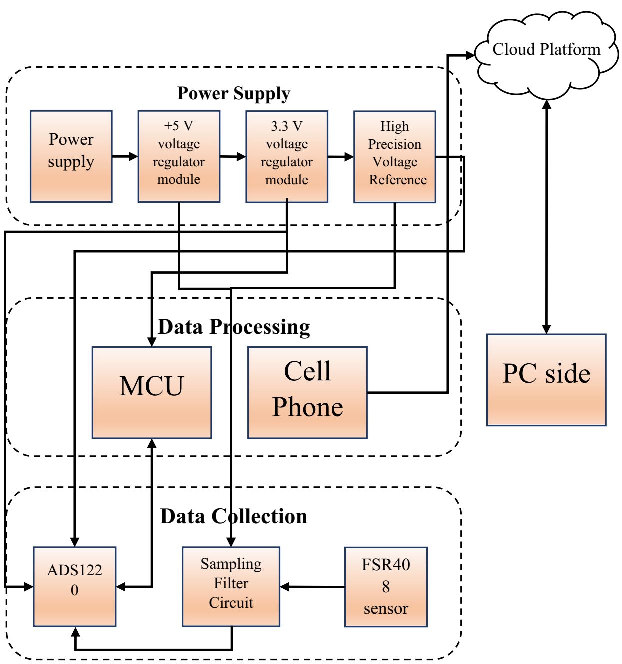

Fig. 2 General block diagram of the monitoring system

resistance value resistor can ensure the voltage within the ADC acquisition range and can amplify the body motion signal as much as possible. The output signal formula is shown in formula (1). Piezoelectric conversion circuits is shown in Fig. 3.

$$V_{\text{out}} = V_{\text{ref}} \left(-\frac{R_1}{R_{\text{FSR408}}} \right) \tag{1}$$

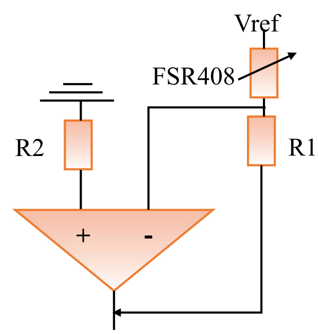

Fig. 3 Pressure-to-voltage circuit

3.2 Filter circuit

In pressure-sensing detection, the specific information transmitted through body motion is a fusion signal including a respiratory component, ballistocardiogram (BCG) component, and noise component. BCG is an indirect method to express the mechanical activity of the heart by detecting the vibration caused by the pumping of blood into the arteries. Medically, it is generally considered that the heart rate is normal at 40–150 per minute, that is, the frequency is 0.6–2.5 Hz. According to experience, the filter circuit design of BCG signal is considered to have the highest frequency component of 20 Hz [19]. According to the Nyquist sampling theorem, the sampling frequency is twice the highest frequency of the signal. After repeated testing and board modification, it is determined that the design uses 50-Hz hardware low-pass filtering and 0.2-Hz hardware high-pass filtering as the circuit passband of the signal, and the model of the shock cardiac signal is reserved for the development of the quadratic algorithm. The high-pass filter is mainly used to filter out the large-amplitude baseline drift and DC components. The baseline drift and DC component will change due to the change in muscle relaxation state and the difference in human body weight. Therefore, the existence of these two makes the threshold value in the data algorithm unable to be determined. Among them, in the unfiltered scheme and the low-pass scheme, due to the relatively large baseline drift, the drawn waveform will be compressed compared with the waveform after bandpass processing, but the amplitude of the single-breath frame still similarity remains.

3.3 ADC circuit

ADS1220 is a precision 24-bit analog-to-digital converter with multi-channel high-speed sampling and programmable gain functions. It communicates with the MCU through SPI protocol. In the design, it is considered that because the human body is in the 50-Hz power frequency radiation environment for a long time, the power frequency components are retained in the body signal, and the circuit board part is easy to mix power frequency interference from the environment and power supply. Therefore, to ensure the integrity of the sampling signal, the sampling frequency of 90 Hz is used, and the ADS1220 module is configured to perform 50-Hz digital notch processing on the signal to eliminate power frequency interference.

3.4 Regulated power supply module

The system uses 7812 and 7912 voltage regulator modules to obtain $\pm$ 12-V voltage to provide a basic power supply for the circuit and uses AMS1117 and REF3133 to obtain a stable 3.3-V power supply and reference source. Among them, ADS1220 and MCU use the 3.3-V power supply provided by AMS1117; the reference voltage of ADS1220, and the sampling circuit is provided by REF3133.

3.5 Accelerometer

A sensor that can measure acceleration is an accelerometer. Masses, dampers, elastic components, sensitive components, and adaptive circuits are typically included. The sensor measures the inertial force acting on the mass block during acceleration and calculates the acceleration value using Newton's second law. Common accelerometer sensors include capacitive, inductive, strain gauge, piezoresistive, piezoelectric, and others, depending on the sensitive parts of the sensor. The accelerometer sensor's operating concept is based on Newton's second law of acceleration, which states that acceleration equals the product of an inertial force and a mass. We only need to take F. Simply balance this force using electromagnetic forces. You can determine the connection between current and F. To calibrate this proportional coefficient, only experiments are required. Of course, the circuit is what does the signal transmission, amplification, and filtering in the middle. The piezoelectric effect is the underlying mechanism behind how most accelerometer sensors operate. The system uses the MPU6050 module as the acceleration sensor to assist the judgment of the main circuit. The MPU6050 communicates with the MCU through the serial port. The main function part is to collect the bed shaking data when the user turns over, record the turning data, and synchronously eliminate the basic signal containing a lot of noise generated by turning over in the pressure-sensitive signal part, and add breathing compensation.

3.6 Combination

The signal-to-noise ratio is frequently poor when employing pressure-sensitive paint under erratic settings for low-speed applications, which may make it difficult to accurately evaluate the collected data. Here, we provide a brand-new unique value decomposed noise-filtering approach. We use the unstable vortex shedding on the side of a square cylinder as a test case to assess the fluctuating pressure field. A potential approach to signal processing in adaptive noise cancellation is adaptive filtering (AF), which can handle a variety of signals in an uncertain statistical environment or a nonstationary environment. It is frequently used to remove artifacts from electroencephalography (EEG), electrocardiography (ECG), impedance cardiography (ICG), and photoplethysmography (PPG) and is typically superior to a fixed filter created using standard techniques. The apnea detection technique employing post-AF tracheal sounds has not yet been tested for accuracy and reliability.

3.7 MCU part

The Internet of Things (IoT) is the wireless linking of everyday things to the Internet, such as automobiles, cash machines, locks for doors, cameras, industrial controls, and municipal traffic systems. Signal processing is helping to increase the number of IoT technologies and applications. Recognizing that the Internet of Things has emerged as possibly the most important new technology since the Internet's inception, academics throughout the world are now turning to signal processing to support and enhance new IoT services and make conventional applications less expensive and more realistic. The Internet of Things (IoT) ecosystem is a massive network of related technologies and parts that technical experts employ to accomplish a particular task. From the perspective of protocol stacks, the physical layer needs advanced signal processing technologies to (1) extract useful information and relatively transfer it to an upper layer and (2) remove unwelcome interference throughout data transmission. The recovery of useful information from the ecosystems

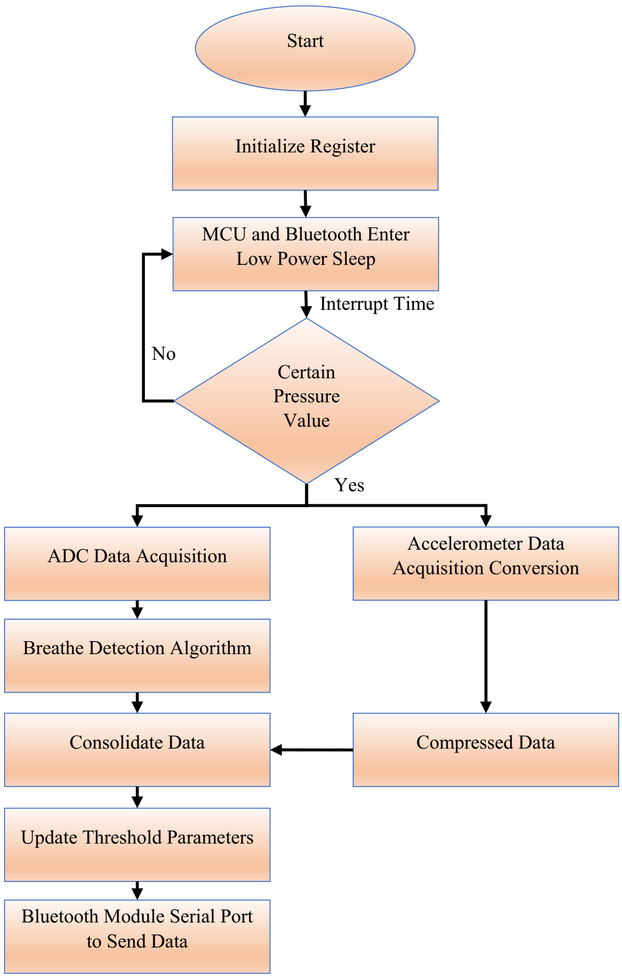

Fig. 4 Flowchart of lower computer program

also necessitates modern data processing. According to the combination of the IoT application environment and signal processing requirements, the system adopts the STM32-F407 microcontroller as the processing core. STM32-F407 has the characteristics of high data operation efficiency and obvious processing advantages and has stable operation and abundant port resources. It can be connected to various block devices in the system to meet the data interaction requirements of the system. It also has an integrated single-cycle DSP instruction. The execution of the algorithm on the lower computer provides a guarantee.

4 Software and respiratory monitoring system

The lower computer program of this system mainly includes data acquisition, respiratory signal discrimination processing, and cloud platform data upload. The flowchart is shown in Fig. 4.

During sleep apnea monitoring, all body motion signals produced by the human body during sleep are long-range and discrete. Due to the limited computing power of the hardware terminal, the feasibility of storing all the data and then processing it with a unified algorithm is low. Therefore, in the system design, the scheme of first single frame interception and then judgment is selected. First, define a respiratory peak as a frame. Since the signal fused in body motion is not only breathing, but other high-frequency signals also exist, the probability of finding the trough is extremely small by using the minimum method directly, so the low-frequency breathing part in the signal must be extracted. Taking into account the MCU efficiency, the design adopts the median filtering scheme [20], and median filtering is widely used in the process of extracting baselines from shock signals. It only needs to perform median extraction of a fixed number of samples according to the sampling rate of discrete data to avoid ECG. For special high-frequency positions such as J peak [21], the low-frequency baseline is extracted as a breath sample.

Because breathing alters the photoplethysmography (PPG) waveform, several studies have tried to get respiratory rate (RR) information from a PPG. However, due to their complexity or computing demands, the majority of these solutions were challenging to apply in real time. A PPG sensor is frequently used by mobile health-care systems to collect many types of health data, including RR, concurrently in a small module. Vital signs, which include blood pressure, body temperature, heart rate (HR), and breathing rate, have long been utilized as the foundational data in health-care systems [22]. Different breathing styles, or modes, call for a somewhat different procedure to enable inspiration and expiration. Eupnea is a type of breathing that takes place while a person is at rest and does not involve conscious cognition. Diaphragmatic breathing is a type of breathing that involves contracting the diaphragm. Air passively exits the lungs when the diaphragm eases. Deep breathing is another name for this style of breathing.

Costal breathing is a breathing technique that needs the intercostal muscles to contract. Air passively exits the lungs when the intercostal muscles loosen. Shallow breathing is another name for this pattern of breathing [23]. Exercise-induced hyperpnea, also known as forced breathing, is a breathing pattern wherein muscular contractions are responsible for both inspiration and expiration. ApneaApp is a smartphone app that uses contactless technology to identify sleep apnea occurrences by tracking the little chest and abdominal movements brought on by breathing. Our device can concurrently recognize and monitor the minute breathing motions of several individuals while operating with the phone held away from the person [24]. By converting the phone into an active sonar system that sends out frequency-modulated sound waves and listens for their reflections, we can do this. We have created algorithms that can recognize different sleep apnea events from the sonar reflections, such as central, obstructive, and hypopnea apneas.

After the breathing baseline is extracted, a single frame of breathing can be intercepted by finding the double-minimum point [25]. However, there may be weak body motion interference judgment during the apnea process. Therefore, after the single frame is intercepted, the algorithm adds the original data to the frame. Integral threshold discrimination and maximum amplitude threshold discrimination ensure that the complete respiratory frame and apnea frame are intercepted. After the interception is completed, the power integral of the original data in the frame is normalized, and finally, the degree of cross-correlation is determined. The cross-correlation formula is shown in formula (2).

$$R_{f,g}(n) = \sum_{k=0}^{N} f^{*}(k) \cdot g(k+n) \tag{2}$$

Among them, $R_{f,g}$ is the correlation value, f is the standard respiratory frame data sequence, g is the currently intercepted respiratory frame data sequence, n is the delay time for obtaining the correlation, and the value of n is less than the sum of the lengths of the two sequences.

Due to the great randomness of the amplitude, frequency, and timing of the breathing signal, the delay time n cannot be determined by logical operations [26]. Therefore, the maximum value of the sequence correlation is obtained as the similarity between the two signals. The calculation formula for the correlation degree is as mentioned in Eq. (3).

$$\xi = \frac{\max\left(R_{f,g}\right)}{\max\left(R_{f,f}\right)} \times 100\% \tag{3}$$

After the correlation determination is completed, if the detected breathing frame is determined to be a normal breathing frame, the integral threshold and the maximum amplitude threshold are updated, so that the judgment data can be adapted according to the individual physiological information of the user. The updated formulas are Eqs. (4) and (5):

$$\mathrm{ThI} = \sum_{k=0}^{N} f(k) \times \varphi_1 + \sum_{k=0}^{N} g(k) \times (1-\varphi_1) \tag{4}$$

$$\mathrm{ThM} = \max(f(k)) \times \varphi_2 + \max(g(k)) \times (1-\varphi_2) \tag{5}$$

Among them, ThI is the integration threshold, ThM is the maximum threshold, and φ_1 and φ_2 are the updated numbers. According to repeated experimental testing and adjustment, the empirical value of φ_1 is predicted to be 0.85, and the empirical value of φ_2 is 0.8. In this system, an acceleration sensor placed on the bed is added to the design. Since the time–frequency components of the body motion signal generated by turning over are complex, it will hinder the judgment of the algorithm. Therefore, the acceleration sensor is used to capture the turning signal and perform signal compensation. The basic flowchart of the algorithm is shown in Fig. 5.

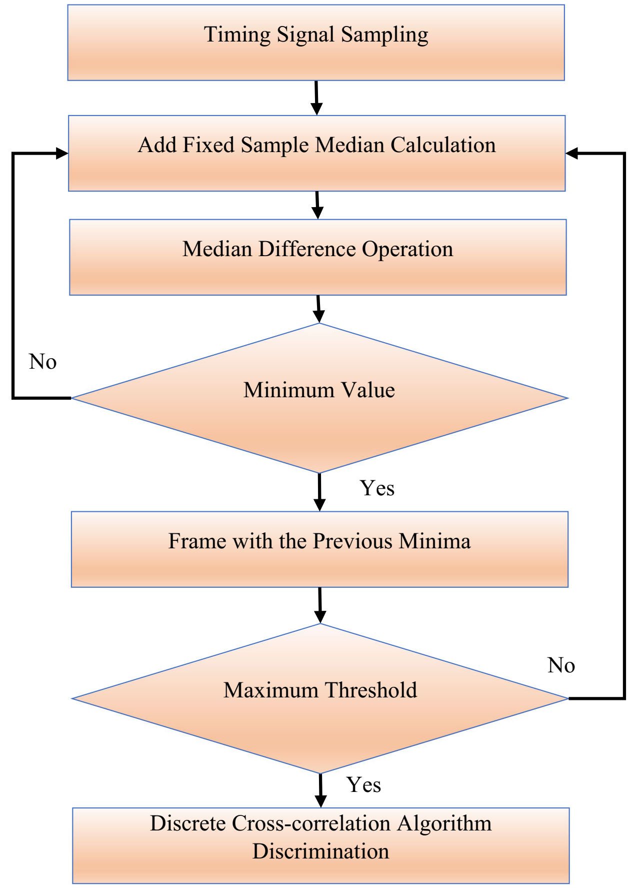

Fig. 5 Algorithm flowchart

In the specific implementation process, the breathing frame interception and the discrimination algorithm part are all completed by STM32F407 for real-time signal analysis. After STM32 passes median filtering and double-threshold judgment, it stores the intercepted respiratory frame data and data volume in the reserved queue and then executes the operation process of the correlation algorithm by DSP instructions, and finally updates the threshold value [27]. Turnover breathing compensation is performed on the mobile phone. When the mobile phone determines the period for turning over, it compensates the number of breaths according to the breathing state of the adjacent period.

5 Experimental verification and analysis

The experiment was done on the mattress, the mattress was flattened, and the sensor strip after area amplification was placed on the projection position of the chest cavity when the human body was lying on the bed. And simulate the

Table 1 Power consumption test results in two modes of the system

Model	Power (W)
Sleep monitoring	0.716 8
Low-power consumption	0.256 0

Table 2 Data for breathing interception (Test object 1)

*n*th breathing frame	Similarity percent (%)
1	78.3
2	86.5
3	84.3
4	89.4
5	56.2
6	77.3
7	84.2
8	53.2
9	86.7
10	85.3

state of apnea after inhalation and the state of apnea after exhalation. Table 1 shows the power consumption value in sleep monitoring mode and bed out mode. A patient with apnea is classified according to their sleeping posture, which can be either right, left, or in the middle, depending on the time of day. Identification of sleeping positions is crucial for apnea detection. The system is constantly set to monitor the sleeping time in numerous areas since the body's state varies throughout sleep. It did this by tracking the patient in three locations, updating every hour, and analyzing how various metrics changed each hour. Oxygen consumption and carbon dioxide generation were monitored in a whole-room indirect calorimeter, and the respiratory quotient (RQ) was calculated at intervals of 1 min. Using CO_2 (Uras 3G) and O_2 (Magnos 4G) analyzers, gas concentrations were calculated based on flow rate and the variations in CO_2 and O_2 concentrations between incoming and departing air. Daily calibrations of the analyzers were performed using calibration gases with known concentrations.

Table 2 and Fig. 6 show the respiratory frame captured by the simulation operation of the apnea detection algorithm and its similarity to the standard frame Degree ξ line chart. Overnight polysomnography in a specialized sleep laboratory is the gold standard for detecting sleep apnea. However, due to the necessity for experienced employees to fully evaluate the recording, these examinations are pricey and have a limited number of beds. More patients might be studied, and a quicker diagnosis made possible by an automated detection system. A collection of human-engineered characteristics is

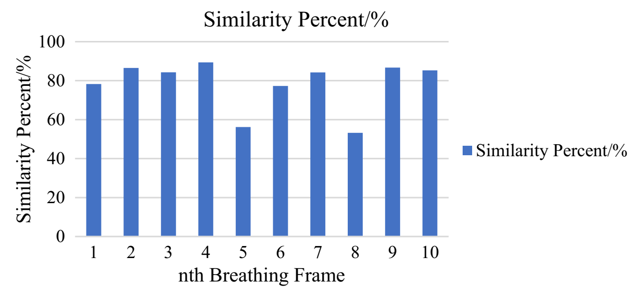

Fig. 6 Similarity between frames of breathing interception (test object 1)

Table 3 Data for breathing interception (test object 2)

*n*th Breathing frame	Similarity percent (%)
1	82.2
2	96.5
3	97.8
4	95.9
5	98.6
6	48.2
7	97.8
8	98.4
9	98.6
10	98.9

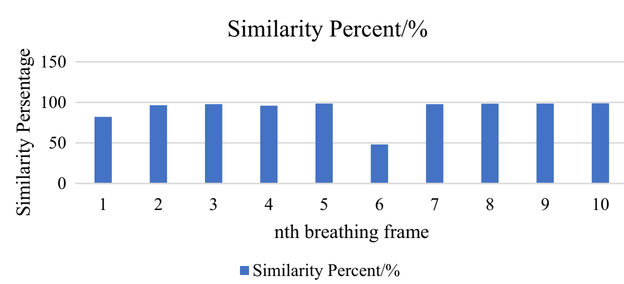

Fig. 7 Similarity between breathing interception frames and frames (test object 2)

used in the majority of automated sleep apnea detection algorithms, which may overlook crucial sleep apnea symptoms.

Table 3 and Fig. 7 show the breathing signal generated by experimenter 2 and its algorithm effect. The inhalation event, which initiates the breathing cycle, is referred to as a breath event. When someone speaks, their inhale reaches a dramatic peak and their exhale has a steady decrease. Throughout a speaking utterance, this quasi-periodic pattern is repeated. These peaks are located using the Automatic Multiscale Peak Detection method (AMPD), which is especially useful for finding peaks in noisy periodic and quasi-periodic signals. To measure the overlap of breath events, breath events from

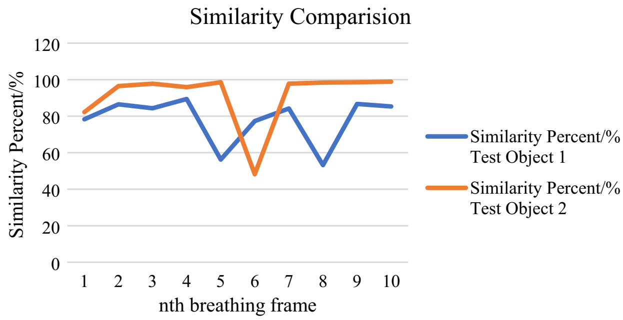

Fig. 8 Similarity comparison with test objects 1 and 2

real and anticipated breathing signals are compared. This improves prediction. The sensitivity of breath events is used to assess this overlap.

In Fig. 7, due to the influence of the system initialization time, only half of the data were entered in the first breathing frame captured by experimenter 2, resulting in a similarity judgment of only 80%. In other data, it can be seen that for different people, the signal amplitude generated by the circuit following body movement is stable, and the high-pass filtering can eliminate the influence of body weight on the signal amplitude. The frame interception scheme uses the judgment result of the adaptive threshold effect to be better and more accurate.

The complete waveform of each breath is accurately isolated. The similarity of the correlation degree algorithm is above 90% when calculating the normal breathing signal. When the apnea frame is detected, the similarity is significantly lower than that of the normal frame, and the longer the apnea time, the lower the similarity.

To verify the accuracy of respiration discrimination, the experiment used an HKH-11C respiration sensor to conduct synchronous respiration monitoring, and two experimenters conducted two 5-min data collections according to the previously described collection methods. Figure 8 shows the similarity comparison with test objects 1 and 2.

A random rollover signal was added to the second test. Record the data and analyze the accuracy. The accuracy formula is shown in formula (6):

$$C = \left(1 - \frac{\sum_{i=1}^{n} |T_i - R_i|}{\sum_{i=1}^{n} R_i}\right) \times 100\% \tag{6}$$

In the formula, T_i represents the average number of measurements per minute of the monitoring system, and R_i represents the average number of measurements per minute of the actual measurement. The data comparison is shown in Table 4. The data show that the system can accurately discriminate the breathing model, and for different experimenters, the correlation values calculated by matching the standard breathing frame are relatively close.

However, in the case of adding body movement, because the algorithm performs empirical compensation on the number of breaths during the body movement time, there is a case of misjudging apnea as a normal breathing wave. Therefore, to further improve the accuracy on this basis, the compensation part of the breathing type should be considered and studied.

6 Conclusion

In this paper, an embedded non-invasive sleep monitoring system is proposed, which adopts FSR408 flexible resistive pressure-sensing strip, which can cooperate with sampling filter circuit for signal acquisition in a non-invasive way; in terms of algorithm, median filtering, differential integration of valley search, dual-threshold determination, and correlation calculation realize the discrimination of sleep apnea; the monitoring data can be transmitted to the mobile phone app through the Bluetooth module and can be uploaded to the cloud server for secondary algorithm processing and analysis. After the system has undergone experimental testing, the data obtained essentially satisfy the criteria for accuracy and meet the needs for sleep monitoring of families, nursing homes, and other scenarios. The collected raw data can still be mined using algorithms, and the Internet of Things interface is reserved for cloud platforms, etc. Additionally, it was discovered throughout the experiment that each researcher had a different preferred sleeping position, and there was a

Table 4 Measured sleep parameters compared to actual

Experimenter/experimental order	Number of breaths/(times/min)		Apnea times/(times/min)	
	Test	Actual	Test	Actual
July 14	11.3	11.5	1.1	1.1
Aug 14	10	10	1.3	1.3
July 17	13.7	16	2.5	2.4
Aug 17	13	14	0.76	1.2
Accuracy (%)	96.6	96.2		

chance that the sensor would not fit the primary force-bearing components, which would lower the quality of the data. When computing the typical breathing signal, the algorithm's correlation degree similarity is greater than 90%. When an apnea frame is discovered, the resemblance to the usual frame is noticeably decreased, and the lesser the similarity, the longer the apnea period. Future studies will be conducted to address this issue and make improvements to the sensor array layout.

Funding This research does not receive any kind of funding in any form.

Data availability Data shall be made available on request.

Declarations

Conflict of interest The authors declare no conflict of interest.

References

1. Penzel, T., Glos, M., Fietze, I., Herberger, S., Pillar, G.: Distinguish Obstructive and central sleep apnea by portable peripheral arterial tonometry. In: 2020 42nd Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC), , pp. 2780–2783, (2020) https://doi.org/10.1109/EMBC44109.2020.9175700
2. Pitkänen, H., et al.: Gamma power of electroencephalogram arousal is modulated by respiratory event type and severity in obstructive sleep apnea. IEEE Trans. Biomed. Eng. **69**(4), 1417–1423 (2022). https://doi.org/10.1109/TBME.2021.3118229
3. Nikkonen, S., et al.: Automatic respiratory event scoring in obstructive sleep apnea using a long short-term memory neural network. IEEE J. Biomed. Health Inform. **25**(8), 2917–2927 (2021). https://doi.org/10.1109/JBHI.2021.3064694
4. Ferrer-Lluis, Y., Castillo-Escario, M., Glos, I.F., Penzel, T., Jané, R.: Sleep apnea & chronic obstructive pulmonary disease: overlap syndrome dynamics in patients from an epidemiological study. In: 2021 43rd Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC), pp. 5574–5577 (2021) https://doi.org/10.1109/EMBC46164.2021.9630515.
5. Nakari, E.K., Tajima, Y., Takadama, K.: Non-contact sleep apnea syndrome detection based on what random forests learned. In: 2020 IEEE 2nd Global Conference on Life Sciences and Technologies (LifeTech), pp. 240–244 (2020) https://doi.org/10.1109/LifeTech48969.2020.1570619209.
6. Hanif, U., et al.: Estimation of apnea-hypopnea index using deep learning on 3-D craniofacial scans. IEEE J. Biomed. Health Inform. **25**(11), 4185–4194 (2021). https://doi.org/10.1109/JBHI.2021.3078127
7. Lazazzera, R., et al.: Detection and classification of sleep apnea and hypopnea using PPG and SpO_2 signals. IEEE Trans. Biomed. Eng. **68**(5), 1496–1506 (2021). https://doi.org/10.1109/TBME.2020.3028041
8. Deviaene, M., et al.: Multilevel interval coded scoring to assess the cardiovascular status of sleep apnea patients using oxygen saturation markers. IEEE Trans. Biomed. Eng. **67**(10), 2839–2848 (2020). https://doi.org/10.1109/TBME.2020.2972126
9. Srinivasan, S., PrasannaBharathi, S., Chamundeeswari, G., Muthu Kannan, P.: Intelligent Healthcare Monitoring System Using Cloud Computing. In: Kumar, R., Mishra, B.K., Pattnaik, P.K. (eds.) Next Generation of Internet of Things. Lecture Notes in Networks and Systems, vol. 201. Springer, Singapore (2021)
10. Shah, S.T.U., Badshah, F., Dad, F., Amin, N., Jan, A.M.: Cloud-assisted IoT-based smart respiratory monitoring system for asthma patients. Appl Intell Technol Healthc (2019). https://doi.org/10.1007/978-3-319-96139-2_8
11. Pocket Guide to COPD Diagnosis, Management, and Prevention, A Guide for Health Care Professionals, 2020 Report. © 2020 Global Initiative for Chronic Obstructive Lung Disease, Inc. (2020)
12. Xiong, Q.: Design and research of non-invasive sleep monitor. 90. (2023) https://doi.org/10.1117/12.2682986.
13. Hu, X., Naya, K., Li, P., Miyazaki, T., Wang, K., Sun, Y.: Non-invasive sleeping posture recognition and body movement detection based on RFID. In: 2018 IEEE International Conference on Internet of Things (iThings) and IEEE Green Computing and Communications (GreenCom) and IEEE Cyber, Physical and Social Computing (CPSCom) and IEEE Smart Data (SmartData), Halifax, NS, Canada, pp. 1817–1820 (2018) https://doi.org/10.1109/Cybermatics_2018.2018.00302.
14. Zhang, H., Zhu, W., Ye, S., Li, S., Yu, B., Pang, Z., Nie, R.: Monitoring of non-invasive vital signs for detection of sleep apnea. J. Mech. Med. Biol. (2021). https://doi.org/10.1142/s0219519421400078
15. Guerrero, G., Le Rolle, V., Loiodice, C., Amblard, A., Pépin, J.-L., Hernández, A.: Modeling patient-specific desaturation patterns in sleep apnea. IEEE Trans. Biomed. Eng. **69**(4), 1502–1511 (2022). https://doi.org/10.1109/TBME.2021.3121170
16. John, K.K., Nundy, B.C., John, D.: SomnNET: an SpO_2 based deep learning network for sleep apnea detection in smartwatches. In: 2021 43rd Annual International Conference of the IEEE Engineering in Medicine & Biology Society (EMBC), pp. 1961–1964 (2021) https://doi.org/10.1109/EMBC46164.2021.9631037.
17. Khan, F., Tarimer, I., Alwageed, H.S., Karadağ, B.C., Fayaz, M., Abdusalomov, A.B., Cho, Y.-I.: Effect of feature selection on the accuracy of music popularity classification using machine learning algorithms. Electronics **11**(21), 3518 (2022). https://doi.org/10.3390/electronics11213518
18. Sebastian, P.A. Cistulli, G.C., Chazal, P.: Identifying the predominant site of upper airway collapse in obstructive sleep apnoea patients using snore signals. In: 2020 42nd Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC), pp. 2728–2731 (2020) https://doi.org/10.1109/EMBC44109.2020.9175626.
19. Nassi, T.E., et al.: Automated scoring of respiratory events in sleep with a single effort belt and deep neural networks. IEEE Trans. Biomed. Eng. **69**(6), 2094–2104 (2022). https://doi.org/10.1109/TBME.2021.3136753
20. Vaquerizo-Villar, F., et al.: Automatic sleep staging in children with sleep apnea using photoplethysmography and convolutional neural networks. In: 2021 43rd Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC), pp. 216–219 (2021) https://doi.org/10.1109/EMBC46164.2021.9629995.
21. Smbatovna, S.K., Alekseevna, M.L.: Recognition of sleep apnea by EEG using nonlinear dynamics methods. In: 2021 Ural Symposium on Biomedical Engineering, Radioelectronics and Information Technology (USBEREIT), pp. 0009-0011 (2021) https://doi.org/10.1109/USBEREIT51232.2021.9455089
22. Joergensen, V.H., Hanif, U., Jennum, P., Mignot, E., Helge, A.W., Sorensen, H.B.D.: Automatic segmentation to cluster patterns of breathing in sleep apnea. In: 43rd Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC), pp. 164–168 (2021) https://doi.org/10.1109/EMBC46164.2021.9629624.
23. Hussain, S.M., Wahid, A., Shah, M.A., Akhunzada, A., Khan, F., Amin, N., Arshad, S., Ali, I.: Seven pillars to achieve

energy efficiency in high-performance computing data centers. In: Recent trends and advances in wireless and IoT-enabled networks, Springer: New York, pp. 93–105 (2019) https://doi.org/10.1007/978-3-319-99966-1_9

24. Freycenon, N., Longo, R., Simon, L.: Estimation of heart rate from tracheal sounds recorded for the sleep apnea syndrome diagnosis. IEEE Trans. Biomed. Eng. **68**(10), 3039–3047 (2021). https://doi.org/10.1109/TBME.2021.3061734
25. Al-kahtani, M.S., Khan, F., Taekeun, W.: Application of internet of things and sensors in healthcare. Sensors **22**(15), 5738 (2022). https://doi.org/10.3390/s22155738
26. Shao, S., Han, G., Wang, T., Song, C., Yao, C., Hou, J.: Obstructive sleep apnea detection scheme based on manually generated features and parallel heterogeneous deep learning model under IoMT. IEEE J Biomed Health Inform (2022). https://doi.org/10.1109/JBHI.2022.3166859
27. Dong, Q., Jiraraksopakun, Y., Bhatranand, A.: Convolutional neural network-based obstructive sleep apnea identification. In: 2021 IEEE 6th International Conference on Computer and Communication Systems (ICCCS), pp. 424–428 (2021) https://doi.org/10.1109/ICCCS52626.2021.9449255.

Publisher's Note Springer Nature remains neutral with regard to jurisdictional claims in published maps and institutional affiliations.

Springer Nature or its licensor (e.g. a society or other partner) holds exclusive rights to this article under a publishing agreement with the author(s) or other rightsholder(s); author self-archiving of the accepted manuscript version of this article is solely governed by the terms of such publishing agreement and applicable law.

FACULTY POSITION RECLASSIFICATION FOR SUCS

(DBM-CHED Joint Circular No. 3, series of 2022)

CERTIFICATION OF PERCENTAGE CONTRIBUTION

(Research Output with Multiple Authors)

Title of Research: Cloud-Based Non-Invasive Cognitive Breath Monitoring System for Patients in Healthcare System
Type of Research Output: Journal Article (Scopus-Indexed, Springer Nature)

Instruction: Supply ALL the names of the authors involved in the publication of Research output and indicate the contribution of each author in percentage. Each author shall sign the conforme column if he/she agrees with the distribution. The conforme should be signed by all the authors in order to be considered. Please prepare separate Certification for each output.

	Name of Authors	Current Affiliations	% Contribution	Conforme *(Sign if you agree with the % distribution)*
1	Mukesh Soni	Chandigarh University	16.67%	
2	Mohammad Shabaz	MIET	16.67%	
3	Renato R. Maaliw III	SLSU	16.67%	
4	Ismail Keshta	AlMaarefa University	16.67%	
5	Rasool Altaee	Al-Mustaqbal University	16.67%	
6	Sanju Das	Assam University	16.67%	
	** Should have a total of 100%*		100.00%	

Prepared by:

Renato R. Maaliw III, DIT
(Name and Signature)
Faculty

Certified by:

Nicanor L. Guinto, Ph.D
(Name and Signature)
Director, Office of Research Services