Design of Smart Wearable System for Sleep Tracking Using SVM and Multi-Sensor Approach


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Abstract - Healthcare has been considered one of the main issues to be spotted and improved in a high manner. Thus, many technology trends are customized to be used in the development of the field of healthcare. One of the fields that highly affects health is sleeping, therefore, the importance of developing a portable and cost-affordable sleep-tracking system has arisen. Getting enough good-quality sleep is essential for living a healthy life. This could be done by monitoring vital signals that affect the quality of sleep such as heart rate, blood oxygen saturation, and positioning. Furthermore, these parameters could be used to detect sleep stages. Detecting sleep stages provides the ability to specify sleep quality and how to get better sleep hygiene. In this paper, a sleep quality monitoring system using commercial off-the-shelf sensors has been developed. The main aims are to make the system cheap, besides being portable, lightweight, and easy to use with better sleep quality and sleep stages accuracies compared to recently published systems. Based on the personalized data collected, the system could identify the sleep onset latency, the wake after sleep onset, the total sleep time, and the pattern based on the step before. Then, users would know about their quality of sleep and sleeping habits, which will be directly reflected in their health and well-being. The obtained results indicate that sleep quality accuracy is 97.5% and sleep stages accuracy is 67.5% which are better than similar systems used with Commercial off the Shelf sensors.

Keywords: Internet of Things, wearable electronics, sleep tracking, vital signs, sleep stages, sleep quality, support vector machine.

1. Introduction

Recently, integration between the Internet of Things (IoT) and healthcare has risen and become essential [1]. One of the fields that affect health in a high manner is sleeping, which is why monitoring it was very demandable. Getting enough sleep with good quality is crucial to live a healthy life. Therefore, quality of sleep could be one of the main issues that should be observed to get a better daily life routine. Studies and research have linked the productivity and concentration of people with getting good sleep hygiene. Furthermore, sleeping connects directly with several functions performed by brains such as concentration, productivity, and cognition. Sleep is considered a brain activity used to release exhaustion [2].

Sleep monitoring could be accessed using a wide range of methods or systems that could be wearable or non-wearable devices. One of the concepts that are tracked is sleep quality and it is the measurement of how well you're sleeping—in other words, whether your sleep is restful or restorative. It differs from sleep satisfaction, which refers to a more subjective judgment of how you feel about the sleep you are getting. The most accurate one is the polysomnography (PSG) laboratory test, shown in Fig. 1. This test depends on collecting several parameters that characterize sleep patterns. These parameters are brain waves, heart rate, blood oxygen saturation, respiration, besides, positioning, and leg and arm movements. They are used aiming to distinguish between sleep stages. Additionally, PSG could distinguish if the user struggles with any sleeping disorder, and the collected data gives neat information that helps form a treatment plan. This system provides high reliability; however, it is not portable and cannot be used in daily monitoring [3].

The second considered system is Fitbit [8], and it is a wrist-worn activity tracker that records everyday activities such as walking, running, swimming, and cycling. A 3-axis accelerometer is used in all Fitbit trackers and watches to detect motion and other movements, with complex algorithms to detect patterns of them. Additionally, it measures heart rate depending on the photoplethysmogram (PPG) signal. The data collected is used to detect the quality of sleep with a specified...
score. Then, the gained information can be viewed via the Fitbit app. Fitbit has an acceptable accuracy in comparison with PSG and could perform better than actigraphy in some cases. It has been found that Fitbit underestimated total sleep time by 6.1 minutes, whereas the actigraphy underestimated it by 31.5 minutes. From another perspective, Fitbit overestimated sleep efficiency by 3.0% and actigraphy by 12.9% [9].

The third system is Oura Ring [10] which is a commercial device based on a smart ring and has the most accurate sleep tracking system in comparison with other commercial systems. This ring has sensors that measure health parameters and collect data that could be translated into information. Then, the data collected is transferred to the company’s customized mobile application called Oura App via Bluetooth. This smart ring gathers readings of acceleration and gyroscope, PPG signal, and body temperature to detect sleep parameters. Oura Ring has high accuracy in determining the four statuses of sleep represented in awake, light sleep, deep sleep, and Rapid Eye Movement (REM) [10], [11].

The fourth considered system is a device that uses COS sensors [2]. This system used an ADXL345 accelerometer for determining movements, MAX30100 with the purpose of monitoring heart rate and SpO2, and MAX9814 microphone amplifier. The system has three steps: 1) the collected data is transferred to the used microcontroller, which is an Arduino, 2) this data is sent to a computer, and 3) the data will be processed using a random forest classifier. These steps are used with the target of determining the quality of sleep. It classified sleep quality as very unpeaceful, unpeaceful, medium, peaceful, or very peaceful. This monitoring system has reached an accuracy of 95% in categorizing the sleep of patients into these classes. However, the system has limitations as it is not a portable system. Furthermore, replacing Arduino with Raspberry Pi would enhance the processing capability of the system without the need for an external computer.

In this paper, the proposed system comes in a similar design to a regular watch which provides portability. Furthermore, it provides an enhancement as it could track sleep stages using COS sensors. We have used a Support Vector Machine (SVM) that leads to better performance and a robust system. The system detects body movements and uses them to detect and calculate sleep parameters such as sleep onset latency (SOL), wake after sleep onset (WASO), total sleep time (TST), and sleep efficiency (SE). The proposed system could figure out when you fall asleep and wake up as well as the interval of sleep. So, based on observing movements, the system could detect sleep disorders such as insomnia.

The remaining parts of this paper are arranged as follows. Section 2 provides the proposed system concepts, functions, and a brief background. Section 3 presents a detailed description of the proposed system. In section 4, the proposed system prototyping results are discussed. Section 5 concludes the paper.

2. The Proposed System Functions

Firstly, we explain the main concept of the proposed system, in addition to, the functionalities of the whole system in this section. After spotting challenges and identifying recent advances in the area of interest, many advancements appeared with feasible features and improvements to be considered. We would start defining these features, how they are calculated, and the mathematical aspects utilized in this demand.

2.1. Sleep Quality

As we have mentioned, sleep quality represents a vital parameter that could affect health in many aspects. Thus, the importance of detecting factors that affect sleep quality has considerably arisen. These factors are represented in having an
irregular sleep schedule, drinking too much caffeine, and being diagnosed with a sleeping disorder such as insomnia or obstructive sleep apnea (OSA) [12].

There are many quantitative measures that are meant to be part of the concept of sleep quality. Examples of these measures are mentioned in [4] as SOL, WASO, TST, and sleep efficiency (SE).

- **SOL**: represents the waking required to make the transition from full wakefulness to sleep.
- **WASO**: symbolizes the intervals of waking during the sleeping period and it could be calculated as:

\[
WASO = \sum_{i=1}^{NA} Awd(i),
\]

where NA represents the number of awakens in the interval between sleep onset (Son) which represents the first time of falling asleep and sleep offset (Soff) which signifies the time of waking up and cannot fall asleep again. Moreover, Awd(i) is the duration of the waking at instance i.

- **TST**: it is the total time of being asleep during the interval of bedtime. We can figure it out as the duration from sleep onset to the awake.

\[
TST = TIB - (SOL + WASO),
\]

where TIB is the bedtime.

- **SE**: it is defined as the amount of time you spend sleeping while in bed. It could be defined as the percentage between total sleep time and bedtime.

\[
SE = \frac{TST}{TIB}.
\]

These parameters and measures are used to target a well understanding of the experience of sleeping which will reflect the quality of sleep.

2.2. Sleep Stages

Some fitness monitoring wearable manufacturers, such as Fitbit, have already integrated a sleep detection capability for wearable devices. However, rather than just identifying whether a person is sleeping, a more in-depth study might be performed to track one’s health while sleeping. With this type of analysis, the focus has shifted from the number of hours of sleep you get to how efficient and restorative that sleep is. The sleep cycle's seamless passage through four different sleep stages is critical to sustaining a healthy body. Table 1 shows the various stages of sleep. This classification is based on an examination of brain activity during sleep and the patterns of nerve signals [13], [14].

Furthermore, the data collected based on heart rate, blood oxygen saturation, and body movement could be an alternate technique to detect these stages. In addition, body temperature is a factor as it got reduced while sleeping. Deeper sleep stages are also distinguished by the reduced amount of oxygen required by the brain, resulting in a lower blood SpO2 level. Additionally, body temperature is decreased during sleep.

![Table 1: Sleep Stages](image)

<table>
<thead>
<tr>
<th>Sleep Stages</th>
<th>Type</th>
<th>Alternative Name</th>
<th>Duration (Minutes)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Stage 1</td>
<td>NREM</td>
<td>N1</td>
<td>1-5</td>
</tr>
<tr>
<td>Stage 2</td>
<td>NREM</td>
<td>N2</td>
<td>10-60</td>
</tr>
<tr>
<td>Stage 3</td>
<td>NREM</td>
<td>Deep Sleep</td>
<td>20-40</td>
</tr>
<tr>
<td>Stage 4</td>
<td>REM</td>
<td>REM Sleep</td>
<td>10-60</td>
</tr>
</tbody>
</table>

2.3. Measuring Heart Rate and Blood Oxygen Level

Heart rate is an important characteristic for sleep tracking for a variety of reasons. This is considered crucial for anything from increasing sports performance to regulating stress levels to tracking heart rate. Otherwise, it is considered a vital parameter in detecting stages of sleep without the need of monitoring brain activity.

An optical light-emitting diode (LED) is used as a light emitter in heart rate sensors, paired with an LED light sensor. The sensor's output is presented in beats per minute (BPM). The operating premise of the heart rate sensor is to measure the time difference between periodic changes in the volume of blood, knowing that oxygenated blood has somewhat more volume than deoxygenated blood. The volume change, which occurs as a result of an increase in blood oxygen levels with each heartbeat, is followed by a change in the fluid's reflection properties and is thus detected indirectly via an optical sensor.
In [15], an IoT-based smart wearable system for remote health monitoring adopted MAX30100 for measuring heart rate and blood oxygen saturation. However, it suffers from many design problems that make it operate improperly. We upgraded MAX30100 with MAX30102. MAX30102 has higher storage, resulting in higher data transfer as it has 32-bit FIFO in comparison with the 16-bit FIFO of MAX30100. It is more sensitive to changes in IR receiver voltage [16].

2.4. Body Movements
The main idea of body movements is to detect any activity as it is a vital parameter with heart rate to distinguish between awake or asleep, then, the detection of sleep stages. Furthermore, it could be an indication of sleeping disorders such as OSA that may cause movement of legs or arms while sleeping [17]. Thus, we used MPU9250 IMU which stands for Inertial Movement Unit, and measures velocity, orientation, and gravitational force. This module depends on combining a 3-axis accelerometer, 3-axis gyroscope, and 3-axis magnetometer and these nine different readings could be used as indications for body movements. These nine different readings identify movements of the wrist.

Firstly, the accelerometer is used for measuring vibration and acceleration. This could be done by measuring the displacement of mass or frequency of a vibrating element. Secondly, the gyroscope is mounted on a frame, and in the case of a rotating frame, it could sense angular velocity. It could be used to detect deviation from the object orientation [18]. The third and last element is the magnetometer, which detects the strength and direction of the magnetic field. This could indicate the orientation [14].

2.5. Body Temperature
Providing a clinical-grade measurement of human body temperature is of substantial importance to the indication of many health deviations. From fever diagnoses to basal body temperature monitoring, the current developments in wearable thermometers have achieved a widespread set of fundamental advantages. Furthermore, it has been monitored that there are slight differences between body temperature in cases of being awake or asleep as it has shown that while sleeping body temperature is falling by one or two degrees. In this demand, they utilized a touchless temperature sensor to detect the temperature by using an infrared thermometer for the detection of temperature.

3. The Proposed System
Figure 2 illustrates the proposed system architecture. The process of building the system can be broken down into five primary stages: the first, or sensing stage, deals with the collecting of important health signals utilizing MAX30102, MLX90614, and MPU9250 sensors. The sensors’ readings are transferred using the I2C communication protocol to a centralized unit in the second stage. This centralized unit represents the third stage, and it is a powerful microprocessor (Raspberry Pi Zero W) that performed the required data processing. In the next stage, we adopted a Support Vector Machine classifier that uses the gained data to be trained to recognize patterns for further data processing. In the following, a detailed description of the custom Printed Circuit Board (PCB), communication with Raspberry Pi, data collection, labeling, pre-processing, and modeling will be described.

Fig. 2: Sleep Tracking System Architecture.
3.1. Custom Printed Circuit Board

The proposed device is implemented on a double-layer PCB. As the need to make it as small as possible to be portable, we customized the dimensions of the PCB to be the same as Pi Zero W of dimension 65mm × 30mm. The used sensors are soldered on the top side to be on the side that faces the hand directly to be accessed to the data collection, while Raspberry Pi is spotted on the bottom side. Furthermore, we have designed and drawn tracks of SCL and SDA on the top layer as shown in Fig. 3.a, whereas tracks of power and ground are on the bottom layer that appeared in Fig. 3.b.

![PCB Design](image)

Fig. 3: PCB Design

3.2. Communication Between Sensors and Raspberry Pi

It is considered the second stage in system architecture. Pi and sensors are connected using the I2C communication protocol. The two connection lines are SCL and SDA. SCL is the line on which clock signals that are generated by the master devices and used to synchronize the data are sent. SDA is the line that carries the actual data sent from master to slave and vice versa. Every sensor has a specific address as shown in Table 2, as each device is allocated to a unique address.

Table 2: I2C addresses of used sensors.

<table>
<thead>
<tr>
<th>Device</th>
<th>Address</th>
</tr>
</thead>
<tbody>
<tr>
<td>MPU9250</td>
<td>0x68</td>
</tr>
<tr>
<td>MAX30102</td>
<td>0x57</td>
</tr>
<tr>
<td>MLX90614</td>
<td>0x5a</td>
</tr>
</tbody>
</table>

3.3. Data Collection

This step is considered the first step in the system architecture. The sensor data collection application is written in Python and uses existing sensor libraries. The application extracts the desired parameters from the registers and saves them as a CSV file for further processing. The collected data is going to pass through data processing aiming to extract information from them. The collected parameters are accelerometer (x, y, and z-axis) measured in gravitational force constant (g), gyroscope (x, y, and z-axis) measured in degrees per second, magnetometer (x, y, and z-axis) measured in metric gauss (G), object temperature (i.e., skin temperature) in Celsius, heart rate pulses in beats per minute (bpm), and blood oxygen saturation (%SPO2).

3.4. Data Summary

The collected data has two classifications. The first one distinguishes between being awake or asleep. The importance of this classification is raised from the need to differentiate between being in bed and when you fall asleep. This is necessary to calculate sleep efficiency. The second classification is to differentiate between sleep stages represented in light sleep, deep sleep, and REM. Furthermore, the characteristics of the collected data are represented by the number of samples, average age, and average hours of sleep as illustrated in Table 3.

Table 3: Data Summary.

<table>
<thead>
<tr>
<th>No. of Participants</th>
<th>Average Age</th>
<th>Average Hours of Sleep</th>
</tr>
</thead>
<tbody>
<tr>
<td>10 Participants</td>
<td>22 years</td>
<td>4 hours</td>
</tr>
</tbody>
</table>

3.5. Data Labeling

In this stage, we needed to use a reference device to label the collected data. Thus, we used Amazfit T-Rex Pro Watch to differentiate between stages [19]. This watch has an optical heart rate sensor, accelerometer, magnetometer, barometer for
measuring air pressure, and ambient light sensors. Most sleep tracker devices have accuracy in detecting stages of sleep that vary between 60% to 65% [10]. However, Amazfit has an overall accuracy of determining sleep 95.2% ± 0.36% in comparison with actigraphy [19]. It could classify data into different stages based on body movement, and heart rate. It is integrated with a mobile application called Zepp to display results. The displayed results show TST by dividing it into stages with the interval of each stage. Then, we labeled data as awake, light sleep (LS), deep sleep (DS), and REM based on reference results.

3.6. Data Pre-processing

After finishing data labeling, we started to divide data into packets based on labeling. Data is collected every second and this is the reason why we divided labeled data into packets and each packet has 100 samples. This number of samples in each packet has been considered with an aim of avoiding fluctuations that may occur while the process of data collection.

3.7. Data Modelling

In this phase, we used an SVM as it provides a robust system and better performance. Moreover, it is better in the demand of the used dataset with a low number of samples because it avoids overfitting. In general, using simpler methods in the smaller dataset is better as it leads to a more generalized model which prevents overfitting.

As the dataset may have many overlapping data, we have moved towards SVM. The idea behind it is to make the best decision boundary that can classify n-dimensional space in a way that makes further categorization for new data points correct. It may have different and several decision boundaries, however, the best decision boundary is called the hyperplane of SVM. SVM chooses the extreme points/vectors that help in creating the hyperplane. The methodology depends on moving data from a relatively low dimension to a higher dimension to be able to classify them. This is done by utilizing kernel functions to find SVM in higher dimensions. Furthermore, we have used a nonlinear classifier as the data are not separated in a linear manner [20].

In the adopted model, we have used a grid search to get the most accurate results and it indicates the best hyperparameters. This is done through hyperparameter tuning as it has several parameters. This process is based on building and evaluating these different combinations of algorithm parameters. Three major parameters need to be tuned to improve model accuracy. These parameters are:

- Kernels: As we have mentioned, data may appear overlapped and this is the reason why we need to move it to a higher dimensional plane, especially in the case of nonlinear separation. The main role of the kernel is to move the low-dimensional data into higher-dimensional data. In our case, we have used a polynomial kernel.
- C: It is considered as the regularization parameter as it is used as the parameter of misclassification or error term. This parameter is used to inform the SVM classifier how much error is accepted. It is used targeting to manage the trade-off between misclassification and decision boundary. Higher values of C mean better classification of data points; however, a higher chance of overfitting may occur.
- Gamma: It specifies how the calculation of the line of separation is influenced. Higher values of gamma reflect a higher influence for nearby points, lower values mean that far points are considered when determining the decision border.

4. Results and Discussion

The proposed system has achieved acceptable accuracy in the two classifications. These results are signified in system accuracy, precision, and F-score mean as presented in Table 4.

<table>
<thead>
<tr>
<th>Parameters</th>
<th>Awake/Asleep Classifier</th>
<th>Sleep Stages Classifier</th>
</tr>
</thead>
<tbody>
<tr>
<td>Accuracy</td>
<td>97.5 %</td>
<td>67.74 %</td>
</tr>
<tr>
<td>Precision</td>
<td>97.57 %</td>
<td>83.87 %</td>
</tr>
<tr>
<td>F-Score (%)</td>
<td>97.38 %</td>
<td>66.88 %</td>
</tr>
</tbody>
</table>

The first classifier is used to differentiate between being awake or asleep. As displayed in the confusion matrix shown in Fig. 4, if the true label is being asleep, the predicted label indicates being asleep. Secondly, being awake in the true label shows that prediction matches the true label with 80% due to the condition of laying down without being asleep which will
be confused with LS. However, the classifier has achieved an accuracy of 97.5%. This could be used to determine intervals of TST and TIB, then, measure sleep efficiency.

The second one is used to detect sleep stages. LS represents a long interval of TST; thus, LS is considered most data of the sample set. Furthermore, REM is only about 20% of total sleep time and heart rate could go up and down during this stage. Thus, it may be predicted LS while its REM. However, it could differentiate between DS and LS in a high manner as the heart rate significantly gets dropped in the stage of DS. Confusion Matrix that visualizes the results is shown in Fig. 5.

As shown in Table 5, the two classifications have acceptable accuracy. Regarding the first classification, the system has achieved an accuracy of 97.5% in separating between being awake or asleep and consecutively, used in calculating sleep quality. The second classifier has achieved an accuracy of 67.74% in detecting sleep stages comparable to Amazfit [19].

Table 5: Comparison between sleep tracking systems.

<table>
<thead>
<tr>
<th>Features</th>
<th>Amazfit [19], 2021</th>
<th>Oura Ring [10], 2021</th>
<th>COS System [2], 2020</th>
<th>Proposed System</th>
</tr>
</thead>
<tbody>
<tr>
<td>Sleep Stages</td>
<td>60% – 65%</td>
<td>79%</td>
<td>–</td>
<td>67.74%</td>
</tr>
<tr>
<td>Sleep Quality</td>
<td>95.2%</td>
<td>–</td>
<td>95%</td>
<td>97.5%</td>
</tr>
</tbody>
</table>

5. Conclusion

In recent years, sleep tracking was recognized as one of the most important applications in health monitoring. In this paper, we proposed a wearable sleep tracking device using COS sensors that could determine sleep quality and sleep stages. We managed to make a device that meets the design requirements of portability, lightweight, small size, and ease of use. The device comes in a similar design to a regular watch, with the addition of multiple sensors and a powerful processing unit.

We used the collected data to build an SVM classifier. Then, we used Amazfit T-Rex Pro as a reference for data labeling. For this purpose, we built two classifiers. The first one is used aiming to differentiate between being asleep or awake and the classifier accuracy was 97.5%. Based on this classification, we could measure sleep efficiency as it is the percentage between TST and TIB. The second classifier is used to distinguish between sleep stages. This classifier has an accuracy of 67.74%, which is acceptable as we depend on COS sensors, besides, the most accurate system in this demand achieves an accuracy of 79% [10]. However, the sleep quality of this system is not provided instead the authors considered the heart rate accuracy and the heart rate variability.

Our future work will concentrate on two directions. Firstly, we could collect data on patients who are diagnosed with insomnia and OSA. This collected data could be used as a reference to estimate if the user is facing any of these problems and based on the answer, it could alarm him and direct readings to his doctor. The second direction will be concentrating on improving system efficiency. Thus, we will need to collect more data on people with different sleeping habits. Moreover, we could use PSG as the reference for labeling which will reflect a higher accuracy.
Acknowledgments

We would like to thank the Egypt-Japan University of Science and Technology for providing all the laboratories and facilities needed to build the prototype of the system. Also, we would like to express our gratitude to ITIDA and ITAC collaborative funding program for the financial support (Project Number: GP2021.R16.12).

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