Wearable SpO_2 and Sleep Posture Monitoring System for Obstructive Sleep Apnea Patients

Rita Brugarolas[1], Jose M. Valero-Sarmiento[1], Andrew Brna[2]
[1]Department of Electrical and Computer Engineering, [2]UNC & NC State Joint Department of Biomedical Engineering
North Carolina State University, Raleigh, NC 27697-7911, USA

***Abstract*— Obstructive Sleep Apnea (OSA) affects 20% of adults in the world and is caused by a collapse of the soft tissue surrounding the upper airway, obstructing airflow. The vast majority of mild and moderate OSA patients are positional patients, which means that these patients show most of their breathing abnormalities while sleeping in supine position. For these patients positional therapy may be a simple and effective treatment solution. In this study we present a training system for positional patients to alert them when a SpO_2 desaturation is occurring, or when they spend a long period of time sleeping in supine position. The alert is given to the patient initially as a smooth vibration in their wrist band, but if the condition persists, a buzzer is used for auditory indication. The system uses an accelerometer on the chest or abdomen to determine the sleeping posture and a commercial finger clip pulse oximeter to monitor heart rate and SpO_2.**

Keywords—accelerometer; machine learning; pulse oximetry, Bluetooth low energy;

I. INTRODUCTION

Obstructive Sleep Apnea (OSA) is a form of respiratory dysfunction that affects 20% of adults in the world [1]. It is caused by a collapse of the soft tissue surrounding the upper airway, which obstructs airflow. To prevent asphyxiation, the patient must arouse to increase respiratory effort, shifting from a deeper to a lighter stage of sleep. These cycles of collapse-obstruction-arousal can happen hundreds of times over the course of a single night and have multiple long-term negative effects on the patient's health. Patients are at increased risk of hypertension/cardiovascular disease, cerebrovascular disease/stroke, and metabolic syndrome/diabetes. Many patients have excessive daytime sleepiness and impaired cognitive function. If untreated, the average life span of a patient with obstructive sleep apnea is estimated to be 20 years shorter than the average life span of the general population [2]. However, with proper diagnosis and treatment, many of these risks can be reduced, giving the patient more fulfilling wakening hours and overall better health.

The vast majority of mild and moderate OSA patients are positional patients (between 65% and 87%) which means that these patients show most of their breathing abnormalities while sleeping in supine position, and positional therapy may be a simple and effective solution for them [3]. In the recent years several accelerometer based products such as *Nightbalance®* appeared in the market for sleep positional training.

Polysomnography is the standard procedure to diagnose OSA. The Apnea Hypopnea Index (AHI), which is defined as the total number of apneas and hypopneas over an hour of sleep, is used to define the severity of the disease. The American Academy of Sleep Medicine (AASM) defines an apnea event as the complete obstruction for more than 10 seconds and a hypopnea event as the partial obstruction for more than 10 seconds with greater than 30% reduction in airflow and greater than 3% oxygen desaturation or arousal [4]. Centers for Medicare & Medicaid Services utilize 4% oxygen desaturation for defining an apnea event [5].

In this study we present a training system for positional patients to alert them when a SpO_2 desaturation is occurring or when they spend a long period of time sleeping in supine position. The alert is given to the patient as a smooth vibration in their wrist band and if the condition persists a buzzer is used for auditory indication.

The system uses an accelerometer on the chest or abdomen to determine the sleeping posture and a commercial-off-the-shelf (COST) finger clip pulse oximeter to monitor heart rate and SpO_2.

The contributions of this study can be summarized as follows:

- Chest patch consisting of a Texas Instruments system-on-chip (SoC) (CC2540) to collect accelerometer data and transmit it to the computational node using Bluetooth low energy (BLE).
- Developed machine learning classifier, in particular, decision tree classifiers, for the detection of sleep postures (prone, supine, right and left) in real time using the Statistic Toolbox in MATLAB.
- Developed software to collect SpO_2 and heart rate from a wireless COTS pulse oximeter (Contec CMS 50D plus) using MATLAB.
- Algorithmic implementation of an apnea event detector following the AASM definition.
- Wearable alert system consisting of a wristband with a DC vibration motor to provide haptic cues and a buzzer in the chest patch for auditory alerts.

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II. Wireless Sensing System

A. Hardware

The chest patch consists of a Texas Instruments system-on-chip (CC2540), a 3-axis microelectromechanical system (MEMS) based accelerometer (CMA3000) (Murata Electronics Oy, 2012) connected to it through serial-peripheral-interface (SPI) and a piezo audio transducer. This SoC includes a BLE low power radio frequency transceiver to enable the transmission of the sensor data to the computational node, in this case a PC running MATLAB. The 3-axis of the accelerometer are sampled at 10 Hz and the data is transmitted after each measurement is taken using the notification mechanism of BLE. The complete system is powered from a 3 V coin cell battery with a 225 mAh capacity. The current drawn by the system during operation was indirectly measured by recording the voltage drop on a 10 Ω resistor connected in series to the power supply. The current while the BLE transmitter was active was 0.186 mA and 4μA during sleep mode (extracted from datasheet). Accelerometer data is transmitted every 100 ms and for each transmission the system is active for 21.5 ms and in sleep mode the remaining 78.5 ms. With this measurements the energy consumption was calculated to be 127.9 μJ, which indicates that the system could run for 219 days with the coin cell battery. In the computational node the accelerometer data is fed to a machine learning decision tree classifier developed in MATLAB using the Statistics Toolbox. The algorithm makes a prediction for each incoming measurement generating 10 predictions per second. The display on screen is updated every second showing the most frequent prediction of the last second of data. These predictions are used to 1) send a BLE command to the chest patch to activate the buzzer alert 2) activate a control signal using a data acquisition card (National Instruments NI USB 6008) to activate the vibration alert. An NMOS transistor with the gait terminal connected to the control line and drain and source connected to the supply voltage and the motor respectively are used. Ideally we would have a separate BLE transceiver in the wrist band to receive the activation signal instead of the data acquisition card. Fig. 1 shows the chest patch (c) and the wrist band (g).

The system is programed to increase the intensity of the alerts if the patient is not following the recommendations to change posture and the breathing abnormalities persist. Initially the patient receives vibration alerts of increased duration followed by auditory alerts of increased frequency and followed by the combination of the two alerts. The flow diagram showing the system functionality is shown in Fig. 2. The duration in supine position for which each alert should be given and the duration of the alerts have been arbitrarily set, but they would be tuned for each subject based on preference and their OSA severity. In addition, if the patient persists in supine position for a duration longer than Time5 the system will not provide any alerts during a snooze time period and then resume the alerts. In order to set appropriate values the system should be tested on a larger cohort of patients.

III. Sleep Posture Prediction

Accelerometer data has two components: the static acceleration and the dynamic acceleration. The static acceleration corresponds to the projection of gravity over each axis and the dynamic acceleration is associated with the vibration and actual motion of the sensor. During sleeping we expect the static component of the acceleration to be dominant during the majority of the time, seeing dynamic acceleration during posture transitions.

Fig. 3 shows accelerometer data recorded from the chest of a subject during different postures. In contrast to actigraphs such as *Fitbit*® that are worn on the wrist, our system monitors the trunk orientation rather than extremity movement. Machine learning algorithms are a very powerful tools to identify patterns in the accelerometer data for the different sleeping postures. For this particular situation we developed a decision tree classifier using the Statistics Toolbox in MATLAB.

Decision tree classifiers belong to the supervised machine learning algorithms category, so they require a dataset with known postures in order to build a model that captures these patterns in the data. This is known as a training dataset and consists of a set of accelerometer measurements recorded while the subject is performing all the postures of interest. For each measurement a label associated with the posture is provided. This example data is then used to build the classifier. The classifier only needs to be built the first time the system is used and after that it can be executed in real time for every new incoming accelerometer measurement.

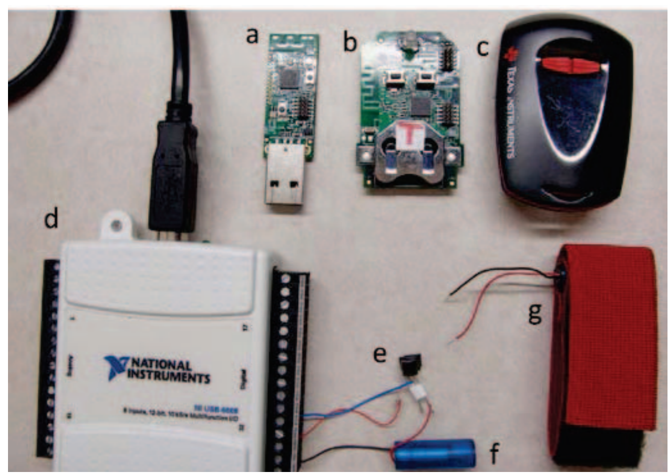

Fig 1. a) USB dongle for the computer to establish the BLE connection. b) CC2540 Mini DK including the 3-axis accelerometer and buzzer. c) Package for the circuit board to be attached to patient chest or abdominal region. d) NI USB 6008 data acquisition card to send control signals to motor from MATLAB. e) N-MOS transistor with the gait terminal connected to control line and drain and source connected to Vdd and motor respectively. f) Vibration motor. g) Vibration motor embedded on wrist band

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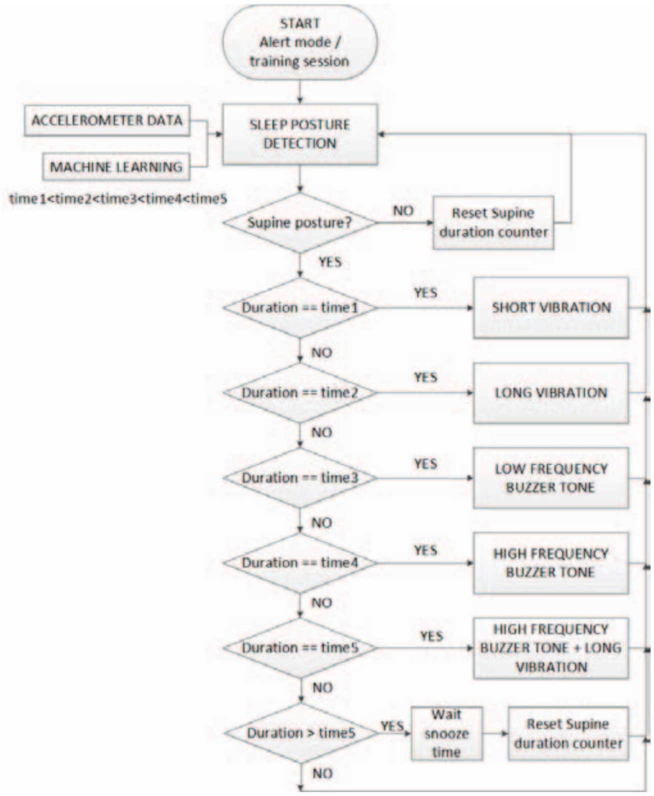

Fig 2. Diagram flow of the alert/training system showing triggering conditions for motor vibration and sound frequency beeping alerts

The code to produce a training dataset is similar to that used to record live positional data; Appendix section 1.3 contains detailed instructions on how to modify the provided code to produce the posture classifier model. Since the algorithm is built with data recorded from the patient it will adapt to their body size and type and for best posture prediction accuracy the device should be worn always at the same location.

The algorithm was tested with an awake and healthy subject performing at least two repetitions of each posture (prone, supine, right and left side and sitting). Table I shows the distribution of instances (accelerometer samples) of each posture and the classification results. The instance-based classification accuracy is measured in sensitivity (SE) and specificity (SP). SE is the ratio of correct posture classification, or True Positives (TP) over the number of TP and False Negatives (FN). SP is the ratio of TP over the number of TP and False Positives (FP). Table I shows that for every posture sensitivity and specificity were above 99%. While analyzing the algorithm results it was observed that all FP and FN occurred at transitions between two postures.

The algorithm generates a posture prediction for every incoming sample and in order to reduce the effect of noise in the data the most common prediction over a one second time window is what is provided to the user. Using this smoothing approach the overall posture classification accuracy was a 100% indicating all postures where correctly detected.

TABLE I. POSTURE PREDICTION ACCURACIES

Posture	Number of Instances	TP	FP	FN	SE	SP
Sit	174	174	0	0	100	100
Supine	1300	1299	3	1	99.92	99.77
Left side	730	727	1	3	99.59	99.86
Right side	761	761	0	0	100	100
Prone	579	579	0	0	100	100
TOTAL	3544					

Fig. 4 shows a zoom-in section of two accelerometer axis showing the chest oscillation associated to the expansion and contraction of the lungs during inspiration expiration. We did not include this source of information to trigger the alert mechanisms but would be interesting in further development as a way of indirectly measuring air movement.

IV. WIRELESS PULSE OXIMETER

Pulse oximeters estimate oxygen saturation of arterial blood transcutaneously by means of two LEDs of different wavelength. They provide an empirical estimate (the pulse oximeter measurement, SpO_2) that was demonstrated to have an adequate correlation with the actual oxygen saturation of the arterial blood, SaO_2, which is measured by means of the analysis of arterial blood samples [6]. These devices have also demonstrated a favorable response to rapid fluctuations of SpO_2 proving their ability to accurately monitor this physiological signal and its changes [7].

Most commercially available devices are intended to be used in a standalone fashion, either as a single finger clip with on-board display and computational capabilities, or as reusable (or disposable) finger clip sensors connected through wires to a central device where the calculations for obtaining the final reading are performed. Some of the high-end devices of this category usually have some kind of serial connection that can be used to interface with a computer and make use of some piece of software to plot the recorded data, analyze it and keep track of your sleep quality. We selected the Contec CMS 50D Plus pulse oximeter, a device with an USB port that can be used to connect it directly to a computer through a USB cable, or to plug an accessory (see Fig. 5) that creates a BLE wireless connection between the pulse oximeter and a computer. This feature makes our system more convenient for the patient as we would remove the limitations of using a cable, which should have been connected during the whole night while the patient sleeps, making the device and, hence, our system, very uncomfortable.

Another key feature of the CMS 50D Plus is related to the software that is available for interacting with the device. There are two different programs that come with the standard package, one is called SPO_2 Assistant Review and allows to download all the data recorded on the 24 hour flash memory that is installed on the pulse oximeter and analyze the readings; the second one is called SPO_2 Assistant Realtime and plots the live data coming directly from the device.

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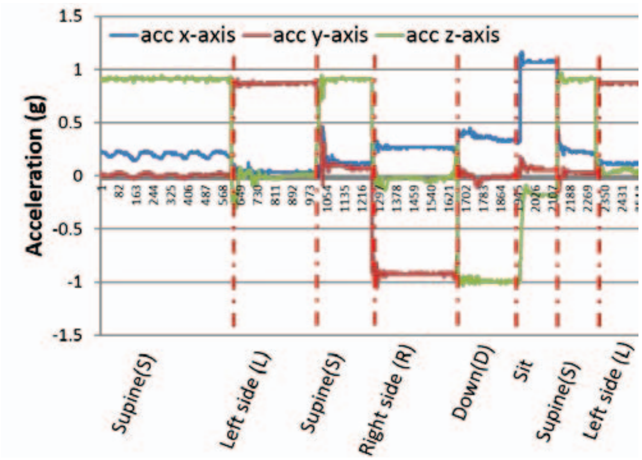

Fig. 3. Sample accelerometer data for different sleeping postures

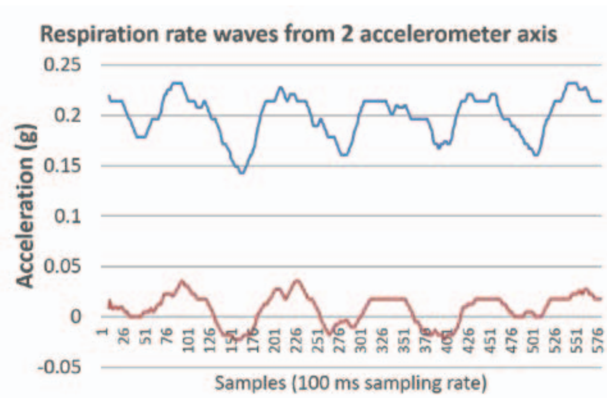

Fig. 4. Zoom-in of accelerometer data during supine posture showing respiratory oscillations caused by the expansion and contraction of the chest.

Fig 5. (Top Left) CMS 50D Plus. (Top Right) CMS Wireless Option. (Bottom) CMS 50D Plus with wireless accessory

In order to control the pulse oximeter and get the data, we created three different MATLAB functions to run at the computational node: one for starting the serial communication, another one for obtaining the raw data from the fingertip device and performing the required calculations to extract the actual readings for pulse and oxygen saturation, and finally, a third one for closing the serial port. The code for each of these functions is included in the Appendix section 1.1.

V. Detection of apnea events

We based our apnea detection method on the apnea event definition by the AASM as the complete obstruction for more than 10 seconds, and a hypopnea event as the partial obstruction for more than 10 seconds with greater than 30% reduction in airflow and greater than 3% oxygen desaturation or arousal. This definition requires storage of historical measurements and the definition of a threshold based on patient baseline. The detection algorithm was also implemented in MATLAB

Each SpO_2 was retrieved from the pulse oximeter and compared to a "value threshold". The value threshold itself was made by subtracting 5 from the target subject's resting $\%SpO_2$ level, which was determined visually and manually added to the code at run-time. Since the pulse oximeter used often hovered among similar values during subjects' resting breathing during initial testing, a 5% reduction was used in place of the definition's 3%. This would reduce the impact of data points affected by measurement noise, ultimately lowering the chance of a false positive reading.

After comparison, the resulting True/False "flag" was stored in a 1-dimensional vector variable, where 1 represented a value equal to or less than the value threshold, and 0 represented a greater value. To ensure only the latest 10 seconds were being observed, the entire contents of the vector were shifted by one space each time a new flag was created, ejecting the oldest flag and inserting the newest flag. The actual size of the flag vector did not change at any point. Additionally, while the AASM defines an apnea event to be at least 10 seconds in duration, recent research points to possible diagnosis with shorter periods of time [8], so to save memory our flag vector examined the most recent 5 seconds instead of 10.

Once a full 5 seconds-worth of data was collected and the vector was filled with actual, measured data, the final algorithm checked for apnea events. To determine an apnea event, the algorithm first summed the values in the flag vector and compared it against the total number of elements in the vector. This gave the percentage of the detection period that was below the detection threshold. This calculated percentage was compared against a "percentage threshold." The percentage threshold, set to 80% by trial-and-error, emulated a low-pass filter, reducing the impact of single-point outliers and short-term trends on detection. If the calculated percentage was greater than or equal to the percentage threshold, the program reported an apnea event occurrence. This process was repeated each time a new data point was collected from the pulse oximeter.

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To validate the detection algorithm, SpO_2 data was collected from a healthy, prone test subject for just over 200 seconds and compared against an artificially high value threshold. It was found that the pulse oximeter used would show an increase in blood SpO_2 if the subject hyperventilated for a number of seconds. By using a higher value threshold and having the subject hyperventilate to briefly raise his SpO_2 by 3-4% on command, the difference between SpO_2 values and the value threshold could be manipulated to simulate apnea events. Because the test subject's baseline SpO_2 was observed to hover between 94-95%, a value threshold of 95% was used for the validation test. Under these conditions, it was expected that the algorithm would register apnea events as the subject breathed normally, and apnea events would not be registered for a time after the subject hyperventilated.

Figure 6 gives the results of the validation test, and it demonstrates that the algorithm does appropriately detect apnea events in accordance with the design parameters above. The three plots in Fig. 6 are the measured $\%SpO_2$ level (with value threshold indicator), the sub-threshold flag, and the event detection state, respectively. Location (a) shows that the algorithm would return an apnea event when measured SpO_2 dropped to or below the value threshold for an extended duration (8.2 s). Conversely, location (b) shows that the algorithm would ignore drops shorter than the percentage threshold (80% of a 5 second examination window, or 4 seconds), although the sub-threshold state of the measured data is still recorded. This highlights the discriminatory capacity of the algorithm. Lastly, locations (c) and (d) further confirm that the percentage threshold component of the algorithm functioned appropriately. Location (c) shows that 4 seconds of sub-threshold confirmations resulted in an apnea event detection, even though 5 seconds of data was being examined, and location (d) shows that once the subject's SpO_2 rose above the value threshold for a period corresponding to the percent threshold, the apnea event was no longer noted.

While the algorithm was shown to work according to the original design criteria, additional changes would need to be made to make the system more robust. For example, if a patient stops breathing completely, thus dropping their blood SpO_2 values for a time, or removes the pulse oximeter while the algorithm is running, an erroneous apnea event would be returned. Future iterations of the detection algorithm would benefit from using additional inputs such as timing of chest oscillations to better identify true apnea events. Additionally, the algorithm only uses a single, hard-coded SpO_2 value to produce the value threshold. If resting SpO_2 values change over the course of the night for adults as they have been seen to with children [9], it could be beneficial for the algorithm to adjust the value threshold over time.

VI. User Interface

A Graphical User Interface (GUI) was developed with MATLAB's GUIDE tool to display the heart rate and SpO_2 data received from the wireless pulse oximeter in real time. Fig. 7 shows the general appearance of the finished interface with a set of artificial test data. When the conditions for an event as described above are met the *Apnea Event* indicator in the GUI turns red. Ideally, the *Apnea Event* indicator would

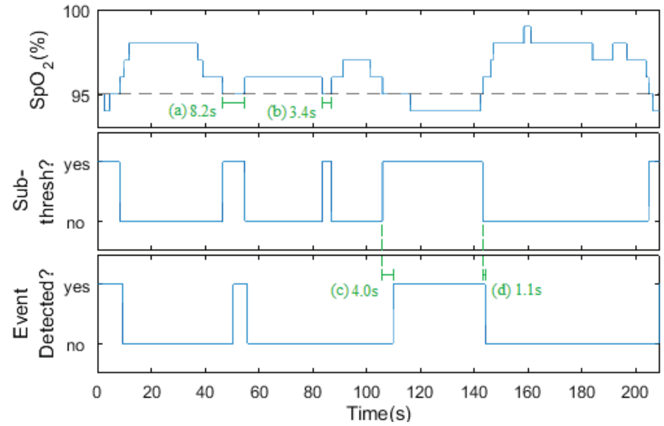

Fig 6. Apnea Event Detection Algorithm Validation Test with live subject

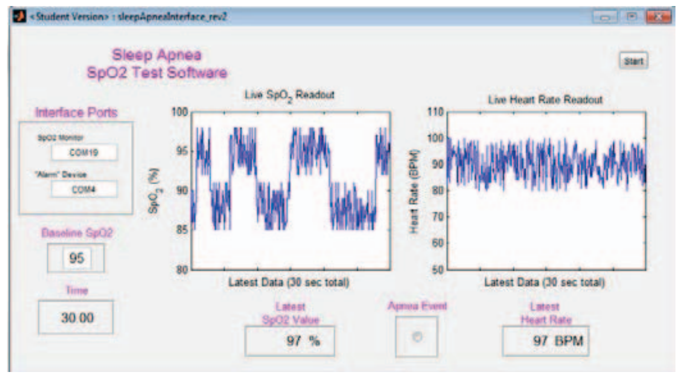

Fig. 7. Graphical user interface showing SpO_2 and HR sample values

start the sequence of haptic and auditory alerts for the patient. In the current implementation the alert system is triggered by postural information only but code could be easily modified to respond to SpO_2 desaturation conditions as well. In addition to real time display, data is stored in files so it is available for the patient and for off-line analysis. To allow home-users to install the software without having to purchase or manage an expensive MATLAB license, the GUI was compiled to a stand-alone executable using the MATLAB Compiler tool. The executable form of the code could then be distributed for use royalty-free. Appendix 1.2 contains code for the algorithm detection of apnea events and the Graphical User Interface.

VII. Discussion and Conclusions

The work described in this article comprises the physical and algorithmic building blocks of a wearable training system for positional patients to alert them when a SpO_2 desaturation is occurring or they spend a long period of time sleeping in supine posture.

The wearable system consists of a chest patch to collect accelerometer data and transmit it to the computational node using BLE, and a wristband with a DC vibration motor to provide haptic cues. A buzzer in the chest patch provides auditory alerts.

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Software to collect SpO_2 and heart rate from a wireless COTS pulse oximeter (Contec CMS 50D plus) using MATLAB has been developed and could be useful in projects where the goal is to use that information instead of developing a pulse oximeter device. We found that most ccommercially available devices are intended to be used in a standalone fashion, either as a single finger clip with on-board display and computational capabilities or as reusable (or disposable) finger clip sensors connected through wires to a central device where the calculations for obtaining the final reading are performed.

In addition we describe how to build and use machine learning classifiers, in particular, decision tree classifiers, for the detection of sleep postures in real time using the Statistic Toolbox in MATLAB. These techniques can be applied to the detection of a different set of postures or activities.

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APPENDIX - see Media files.

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