Article

A Wrist Sensor Sleep Posture Monitoring System: An Automatic Labeling Approach

Po-Yuan Jeng [1], Li-Chun Wang [1], Chaur-Jong Hu [2] and Dean Wu [2]

[1] Department of Electrical and Computing Engineering, National Chiao Tung University, Hsinchu, 30010, Taiwan

[2] Department of Neurology, Taipei Medical University Shuang Ho Hospital, New Taipei City, 23561, Taiwan

* Correspondence: lichun@cc.nctu.edu.tw

Abstract: Sleep postures monitoring systems in the hospital aim at transforming sensing signals into quantitative data to characterize the sleep behaviors of the patient. However, a home-care sleep posture monitoring system needs to be user friendly. In this paper, we present iSleePost - a user-friendly home-care intelligent sleep posture monitoring system. We address the labor-intensive labeling issue of traditional machine learning approaches in the training phase. Our proposed mobile health (mHealth) system leverages the communications and computation capabilities of mobile phones for provisioning a continuous sleep posture monitoring service. Our experiments show that iSleePost can achieve 90 percent accuracy in recognizing sleep postures. More importantly, iSleePost demonstrates that an easily-wear wrist sensor can accurately quantify sleep postures.

Keywords: IoT; wearable device; machine learning; streaming data; sleep posture.

---

1. Introduction

Sleep is one of the most important daily activities. A night of poor quality sleep can make a person feel fatigue on the next day. Long-term sleep disorders will even induce a range of health problems [1]. It has been reported that sleep duration is a risk factor of cardiovascular disease [2]. Recent studies also reveal the relation between poor sleep quality and diabetes [3], hypertension [4] and depression [5]. Besides sleep duration, sleep habits are another indicator of sleep quality[8,26]. Sleep postures are the habit which can cause some health problems. For example, obstructive sleep apnea (OSA) can cause breath pauses during sleep. Various research works have been reported to prevent OSA through complicated system design [9,10]. In fact, this can be achieved by a simple sleep posture monitoring method [11,12]. Sleep study has attracted a lot of attention.

Hence, sleep research centers have become an important institution in hospitals. Taipei Medical University, Shuang Ho Hospital established the first Sleep Research Center in Taiwan. Unlike patients of other traditional diseases, the patients of this center sleep overnight in a sleep monitoring room (as shown in Figure 1). During overnight sleep, multiple sensors are attached to the patient to collect biological data, including electroencephalography (EEG), electrocardiography (ECG), blood pressure, sleep postures, and so on.

Preprints (www.preprints.org) | NOT PEER-REVIEWED | Posted: 3 July 2019 doi:10.20944/preprints201907.0060.v1

Figure 1. Sleep monitoring room in the sleep center. The patients suffer from sleep disease are closely monitored in this room during sleep.

Most current sleep monitoring devices are complex and inconvenient. They also disturb the patient's sleep quality. One important monitoring device of a current sleep monitoring system is actually attached to the patient's chest as shown in Figure 2. This chest device has an inertial measurement sensor for monitoring patients' movements. The sensed data from this device are recorded and further analyzed to estimate sleep postures and sleep quality. This chest-worn device needs to be attached to the patient's chest, resulting in considerable sleep disturbance. Moreover, a patient definitely feels more comfortable to sleep in his/her own home than in the center of a hospital. As a result, a more comfortable monitoring device is a desirable feature for the sleep disorder treatment business.

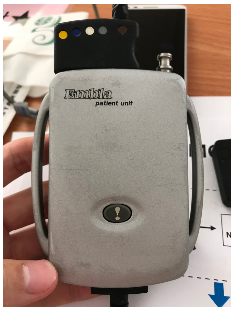

Figure 2. The attached device on the patient's chest for monitoring body movement. The dimension of the device makes it a major disturbance during sleep.

To this end, we have developed a novel wrist-worn sleep posture monitoring system. Current commercial wristband products, such as MI Band, Garmin Smart watch and Apple Watch, can not recognize sleep postures. Although some studies are focusing on sleep posture monitoring, their data are generated from labor intensive labeling, which is not quite practical.

In this paper, we propose a wrist-worn sleep posture quantification system, called iSleePost. During the training phase, iSleePost uses two accelerometers. The care recipient wears one accelerometer on his/her chest for automatic label collection. The other one is worn on the wrist for collecting motion data. Based on a sliding window approach, iSleePost processes the wrist-sensor data to obtain the features of a body's motions. iSleePost maps these features to current positions based on the chest accelerometer sensor. We built iSleePost testbed with physical accelerometers, phone and server to test the feasibility of the proposed idea. Our experimental results demonstrated that iSleePost can recognize four sleep postures: supine, stomach, right side and left side[27], as shown in Figure 3. Two machine learning algorithms are applied for sleep posture prediction in our experiments. Our results show that iSleePost can achieve 90 percent overall accuracy in sleep posture prediction. The design concept of iSleePost sheds the light of quantifying human sleep postures in the future.

Preprints (www.preprints.org) | NOT PEER-REVIEWED | Posted: 3 July 2019 doi:10.20944/preprints201907.0060.v1

(a) (b) (c) (d)

Figure 3. Four common sleep postures for iSleepPost to recognize. (a)prone, (b)left side, (c)right side and (d)supine [27].

The rest of this paper is organized as follows. The related works are discussed in Section 2. The system model is described in Section 3. Our data processing framework is presented in Section 4. The learning algorithms for iSleepPost system are discussed in Section 5. Numerical results on collected data are reported in Section 6. The future applications are discussed in Section 7. Finally, we give our concluding remarks in Section 8.

2. Related Works

In this section, we give a brief survey of the existing sleep posture monitoring research, which can be categorized into two kinds: contact-body class and non-contact body class. In the contact-body class, the equipment deployed to monitor care recipient has contact with a care recipient's body. In the non-contact body class, the equipment does not contact the recipient's body. The monitoring equipment used in each work is briefly introduced. Moreover, the data processing framework of the works and their results are described and summarized.

2.1. Non-contact body class

In the non-contact class, the sleep posture monitoring system using the non-contact body device can improve the comfort level of the care recipient during sleep. However, one disadvantage of this method is that the monitoring of the postures is easily confused with other objects, such as blankets or clothes. In addition, the recognition result of non-contact body devices will be affected by the position and angle of the monitoring equipment. Therefore, such systems are usually not portable and require sophisticated deployment processes.

Most of the research in this category adopts a surveillance camera to monitor care recipients. A video camera or image recording device is set up to continuously record image of care recipients. An image taken from the camera is processed in real time using an image recognition-based algorithm to obtain a sleep posture [17]. Besides, vision-based approaches, depth cameras were adopted for monitoring sleep postures. In [18,19], depth camera were used to capture the a 3D image of sleep. By analyzing the depth data, the system can recognize multiple sleep postures.

Research effort through non-camera-based equipment was proposed to monitor human activities. Wi-Fi is one of the most popular signals for activity monitoring [7]. The authors of [6] deployed a pair of Wi-Fi transceivers and capture the channel state information to monitor the respiration and movements of sleeping subjects. Such a system requires considerable effort in deployment. The position and angle of the equipment need to follow strict instructions to avoid interference. In addition, due to changes in the environment, a complete model training process is required after deployment. As a result, the aforementioned difficulties make them almost impossible to use at home.

2.2. Contact body class

The contact body class is a more direct approach to monitor sleep postures. Thus, most current sleep posture monitoring systems belong to this category. To clearly introduce these works, we further categorize them into two sub-categories: non-wearable and wearable. On one hand, a non-wearable subclass, such as a pressure mattress type sleep posture monitoring system, is characterized in that

Preprints (www.preprints.org) | NOT PEER-REVIEWED | Posted: 3 July 2019 doi:10.20944/preprints201907.0060.v1

the care recipient does not have to wear any equipment. On the other hand, wearable sub-class is characterized by the fact that the care recipients need to wear a monitoring device.

2.2.1. Non-wearable sub-class

The non-wearable approach for monitoring sleep posture uses a pressure mat as the monitoring equipment. A pressure mat is a mattress or mattress topping which has dozens of pressure sensors embedded beneath so that the distribution of the subject's weight on the mat can be measured. A lot of research adopted pressure mat as their primary monitoring equipment for sleep posture recognition. In [20], the authors extracted 55 types of features from the raw data, which are collected from pressure mat, and then applied 4 classification algorithms for sleep posture estimation. In [21], the authors developed a sleep posture recognition algorithm by using limbs' characteristics. Furthermore, [22] adopted hydraulic sensors to substitute pressure sensors for improving the convenience of the sleep monitoring system. [23] adopted a single piezoelectric sensor to measure the ballistocardiogram signas, and further to estimate sleep postures. Last but not least, [24] combined pressure mat and infrared array sensors to obtain sleep postures.

2.2.2. Wearable sub-class

In this sub-class, care recipients need to wear a monitoring device on their bodies. Obviously, this approach can provide more accurate results than other methods. However, one of the disadvantages of this method is that wearing the device can affect the quality of sleep of the subject. In [16], the authors placed an accelerometer on the chest of the care recipient and collected data from the sensor. During the sleep of a care recipient, his/her actual postures are recorded by the camera. The authors applied a linear discriminant algorithm to train a posture recognition model. The model is then applied to real-time sleep posture monitoring. A commercial product for sleep posture monitoring with chest sensor device is actually on the market now [15]. This product exploits a disposable accelerometer, which can be worn on the chest to monitor sleep postures.

In general, the wearable sub-class is not a comfortable approach for the care recipient because sensors worn on the body may limit their activities and cause problems. However, the inconvenience can be reduced by changing the location of the sensor. In [28], they placed a tilt sensor on the subject's wrist, and recorded the sleep posture and the data of sensor. Needless to say, wearing a sensor on his/her wrist is more comfortable than wearing it on the chest. After collecting the data for ten nights, they analyzed the data. The result shows there exist a certain relationship between the body postures and the sensor tilt.

Despite the increasing popularity of sleep research, it is rarely seen that a healthy sleep posture monitoring system can simultaneously achieve the goals of high accuracy, low deployment cost, and high sleep quality. More importantly, most current methods require a labor-intensive data collection process. In this paper, we propose an innovative sleep posture monitoring system based on a wrist-worn device, which has the advantages of low deployment cost, high precision, and user-friendly sensor placement design.

3. System Architecture

Figure 4 shows the architecture of our considered sleep posture monitoring system. Now we describe the hardware components and the communication methods between these components.

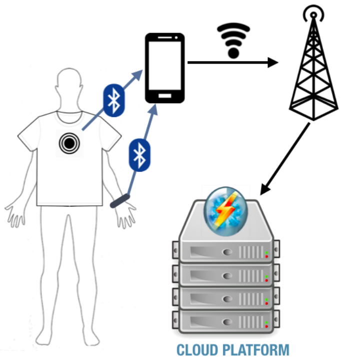

Figure 4. The system architecture of iSleePost, consisting of two wearable accelerometer sensors with BLE chip, a smartphone, and a personal computer connected to the Internet.

3.1. Hardware

The hardware of our proposed system can be divided into three layers: sensing layer, data collecting layer, and cloud layer. Devices with different computing capabilities are adopted to meet the needs of each layers.

3.1.1. Sensing layer

In the sensing layer, two inertial sensors are applied for sensing the motions of different body parts. These sensors should be small and light enough to reduce the disturbance. Also, they should be energy efficient, thereby reducing the frequency of battery replacement. In order to meet these requirements, we adopt Koala as the sensing device for this layer [29]. Koala is an inertial sensor which has been successfully applied for body motion monitoring, such as gait detection [30]. Koala is capable to detect and record physical motions, ranged from -2 G to 2 G in X, Y and Z directions. Moreover, a Bluetooth low energy (BLE) chip is attached on Koala to transmit the data with low energy consumption. The specification of Koala reports that their sampling rate is tunable, which can be set to a low frequency for long operation time.

3.1.2. Data collecting layer

The role of data collection layer is to collect and preprocess the raw data from the sensing layer and then send them to the designated server through the Internet. This layer plays an important role in our system. It transform the amount of raw data into a smaller feature data, which relieves the communications load on the Internet. Also, the device of this layer should be portable to be used at home. Hence, smartphones are the perfect candidate for the data collection layer.

3.1.3. Cloud layer

On the other end of the Internet, we need to deploy a powerful device to train models and predict sleep postures for a group of care recipient. We used a personal computer equipped with Intel i7 processor as the server in the cloud layer in our experimental system.

3.2. Communications

Most of the devices in our system are wirelessly connected for making the system portable. Depending on the capability of devices, different communication methods are considered. To reduce the energy consumption of data transmission between the sensing layer and the data collecting layer, Bluetooth Low Energy (BLE) protocol is adopted and implemented in our system. BLE is a newly announced standard for reducing energy consumption in data exchange between Bluetooth devices. As for the communication between the data collecting layer and the cloud layer, the transmitted data can be sent to the Internet via either Wi-Fi or cellular network from smartphones. Hence, the developed sleep monitoring system can be operated in many environments.

In conclusion, the hardware components of the propsoed iSleepPost system include two wearable accelerometer sensor device with Bluetooth communication function, a smart phone, and a personal computer connected to the Internet.

4. Data Processing Framework

We designed a two-phase framework for sleep posture monitoring. The first is a training phase, one sensor is attached to the chest and the other sensor is strapped to the wrist. After the sleep posture model finishes learning, the monitoring phase is initiated, and only the wrist sensor is needed. The changes in architecture between two phases are shown in Figure 5.

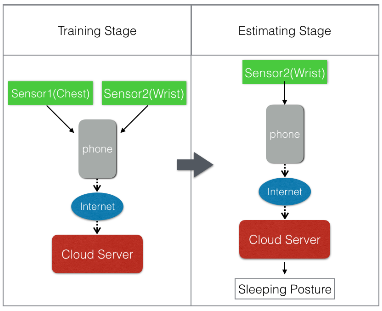

Figure 5. The two operation phases for iSleePost monitoring system: 1) Training phase, 2) monitoring phase. In the training phase, both chest and wrist sensors are required. In the monitoring phase, only wrist sensor is required.

We have designed data pipelines to process the raw sensor data in a timely fashion. We will introduce the data pipelines and the deployment of elements in this section. The overview of data processing framework is shown in Figure 6. The flow chart in the figure shows the processing pipelines. The boxes represent the processing elements and their goals. Above the flow chart are the devices on which the elements are implemented. The processing elements are distributed across the system to reduce network traffic. The arrows indicate the directions of data flows in the framework. At the beginning of the flow are two data collecting sensors. These two sensors are placed on the chest and wrist, which are called chest sensor and wrist sensor hereafter. The sensed data of the chest and wrist sensors are processed in two different ways and presented by the upper half and the lower half in the flow chart.

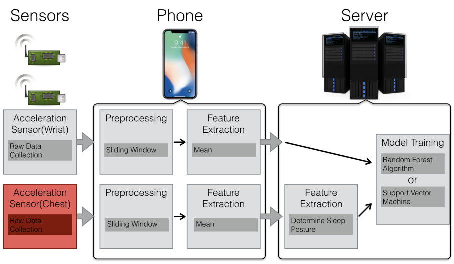

Figure 6. Overview of the data processing framework. The flow chart represents the pipelines of processing data. The device icons above the flow chart shows the device in which the processing elements takes place.

The chest sensor data flow is only in used when the system is in training phase. During the training phase, the sensor data from two accelerometers are gathered simultaneously and processed to learn the posture model. The actual posture can be estimated based on the chest sensor data, while the wrist sensor data can provide the features of wrist positions. In the monitoring phase, we estimate the

Preprints (www.preprints.org) | NOT PEER-REVIEWED | Posted: 3 July 2019 doi:10.20944/preprints201907.0060.v1

postures in real-time based on the learned posture model and the features of the wrist sensor data. In this case, the data flow from the chest sensor will not be used.

The sensed data gathered from the chest and wrist sensors are processed by different methods, which are discussed next.

4.1. Chest Sensor

The orientation of a tightly tied chest sensor can represent the body position, which is the standard method for obtaining sleep posture in hospitals nowadays. Hence, the chest sensor data are used as the ground truth to train and assess the system. The detail of processing chest sensor data is presented in the followings and the flow chart is shown in Figure 8.

$$\theta = arctan(y, x) \tag{1}$$

$$\begin{pmatrix} x' \\ y' \end{pmatrix} = \begin{pmatrix} \cos\theta & \sin\theta \\ -\sin\theta & \cos\theta \end{pmatrix} \begin{pmatrix} x \\ y \end{pmatrix} \tag{2}$$

- Step 1: Calibration
  The system will first collect the raw inertial data to calibrate the axes of the sensor. The care recipient is requested to stand or sit straight to identify the angles of the chest sensor. A rotation matrix will be calculated according to (1) and (2) for transforming the data into a base which the X axis is perpendicular to the ground and the Y axis is parallel to the ground. After that, all the data from chest sensor will be rotated based on the rotation matrix. The effect of the calibration step is shown in Figure 7.
- Step 2.1: Noise Removal
  The noise will be removed by the following cleaning process in the system. The process calculates the variance of data within a sliding window, and then set it as a threshold. The data which contain values less than the threshold are removed for noise cleaning.
- Step 2.2: Feature extraction
  After the noise is removed, the system calculates the mean of the rest of the data within the sliding window to obtain features of each axes.
- Step 3: Differentiate Standing or Lying Position
  The dominating axis is decided by comparing the magnitude of the feature of each axis. If Y or Z is the dominating axis, it indicates that a care recipient is in the lying position.
- Step 4: Recognize Sleep Posture
  According to the positive or the negative of the three axes. Sleep postures are estimated based on the values of Y axis and Z axis, as shown in Table 1.

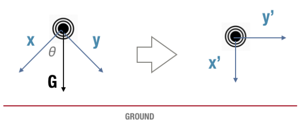

Figure 7. The effect of the rotation matrix. The sensor data will be calibrated into a new X axis which is perpendicular to the ground and a new Y axis which is parallel to the ground.

 doi:10.20944/preprints201907.0060.v1

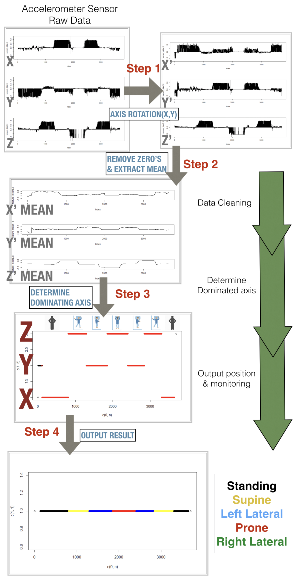

Figure 8. The full data processing flow for chest sensor data. The data in each steps are visualized for a better understanding of our preocess.

Table 1. Decision manner.

Dominating Axis	+/-	Body Posture
Y	Positive	Left Lateral
	Negative	Right Lateral
Z	Positive	Prone
	Negative	Supine

4.2. Wrist Sensor

The processing of wrist sensor data aims at obtaining the characteristic of wrist movement. The proposed sleep posture monitoring system will segment the data by sliding window. Then calculate the mean of wrist sensor data in each window, which is also called the feature data of wrist position in this paper.

The collected raw data from wrist sensor are recorded in the form of $\{timestamp, value1, value2, value3\}$, where the timestamp is in milliseconds and the value is floating point. The three values represent the detected acceleration in three axis, which are X, Y and Z axis. We denote these values with $x_{t,j}$, where t is the timestamps and $j \in \{x, y, z\}$ denotes the axis. We let $\mathbf{x}_t = \{x_{t,x}, x_{t,y}, x_{t,z}\}$ to denote a raw data record. Therefore, the entire raw data $\mathbf{D}$ can be represented as:

$$\mathbf{D} = \{\mathbf{x}_{t_1}, \mathbf{x}_{t_2}, \mathbf{x}_{t_3} ... \mathbf{x}_T\},$$

where T denotes the last timestamp in the whole dataset $\mathbf{D}$. Then, we group the raw data into $N = \lfloor T/windowsize \rfloor$ frames, a frame of data is denoted by

$$\mathbf{f}^i = \{\mathbf{x}_t\}, windowsize \times (i-1) \leq t < windowsize \times i,$$

where $i \in [1, N]$ is the frame index. In other words, a frame is a collection of raw data in the time duration- $windowsize$, and the frames are parts of the whole dataset. The $windowsize$ was set to 1,000 in our system.

After segmenting the raw data into blocks, we need to obtain the features of each block, namely, to obtain the characteristic of wrist movement, and learn the model for predicting sleep postures. We denote the mean of the *j-th* axis of *i-th* frame as μ_j^i , where

$$\mu_j^i = \frac{1}{n_i}\sum x_{t,j}, \quad \forall x_{t,j} \in f^i.$$

The feature set S for learning the model is $\{\mu_x, \quad \mu_y, \quad \mu_z\}$, which are the means of each axis. We denote the feature set as $X^i = \{\mu_x^i, \quad \mu_y^i, \quad \mu_z^i\}$, which is the combination of feature from each axis. Then, we form the feature data matrix $\mathbf{X}$ by concatenating all the frame features. Thus, the feature data is present as:

$$\mathbf{X} = \begin{bmatrix} X^1 \\ X^2 \\ \vdots \\ X^N \end{bmatrix}.$$

Let Y^i be the posture label of the feature data X^i, where $Y^i \in \{Stand, Supine, Right\ Lateral, Left\ Lateral, Prone\}$. The sleep posture labels are referred to as the *target labels* or *classes*. The labels can form a label column:

$$\mathbf{Y} = \begin{bmatrix} Y^1 \\ Y^2 \\ \vdots \\ Y^N \end{bmatrix}.$$

Finally, the feature data and the corresponding target labels are obtained for model learning.

5. Learning Algorithms

From the chest sensor data, the target classes of sleep postures are obtained. The features of the model training are extracted from the wrist sensor data. Combining the target class and the extracted features, we can form the training data of the learning algorithm for identifying sleep postures. Figure 9 shows the training process of sleep postures. In this paper, two classification algorithms are tested for posture monitoring: Support Vector Machine and Random Forest. Both algorithms will be briefly introduced in this section, and then evaluated in the experiment section.

5.1. Random Forest (RF)

The random forest algorithm is used to train the sleep posture model for the proposed monitoring system [31]. Random forest is an ensemble learning method, consisting of many decision tree classifiers. Each decision trees is trained by a randomly selected subset of the training data, which equals the random sampling method with replacement. When constructing the decision tree in RF, the split criterion is decided based on a random selected feature set S. The randomness in the training process can decrease the variance of a RF model. When it comes to the monitoring phase, the features are fed to each decision tree in the forest, and each tree will return a predictive result. The result which is returned by a majority of decision trees represents the predictive result if the entire forest.

The selection of training sets in RF is random, so the accuracy of the trained model varies. In our experiment, we test the RF model multiple times to obtain the range of the accuracy.

5.2. Support Vector Machine (SVM)

SVM is a classifier that classifies data by separating two classes with a hyperplane. The classifier tends to maximize the margin between different classes. The feature space of the data will be mapped

Preprints (www.preprints.org) | NOT PEER-REVIEWED | Posted: 3 July 2019 doi:10.20944/preprints201907.0060.v1

into a higher dimension so that the data could be linearly separated. In both training and testing phase, a similarity function is needed for determining the similarity between data. The similarity function can be implemented by kernel functions. The kernel function should be selected depending on the insight of data.

Because SVM is a binary classifier, it can only classify two classes. However, the multiple classes classification of SVM can be achieved by the one-against-one (OAO) and one-against-all (OAA) approaches[32]. We adopt the OAA for model training. The OAA method will build $|Y^i|$ SVM models. The training process considers the feature data as the first class if they belong to the Y^h-*th* class. The new class label for the *i-th* feature data is denoted by $\hat{Y}^i$. The considered method is defined as

$$\hat{Y}^i = \begin{cases} 1, & if\ Y^i = Y^h \\ -1, & otherwise \end{cases} \tag{3}$$

The main idea for training a linear SVM is finding a hyperplane which can create the largest margin between two classes. We first set the normal vector of the hyperplane as **W** and the offset of the hyperplane as b, Thus, the constrains for each classes are formulated as follows:

$$\begin{aligned} lCr\mathbf{W} \cdot X^i + b &\geq +1 - \xi_i \quad \forall : \hat{Y}^i = +1 \\ \mathbf{W} \cdot X^i + b &\leq -1 + \xi_i \quad \forall : \hat{Y}^i = -1 \\ \xi_i &\geq 0 \quad \forall i. \end{aligned} \tag{4}$$

The formula enforce the hyperplane to separate the two classes and to have at least 1 unit margin to the data. The term ξ_i relax the margin constrain , which allows a few data to have shorter distance to the hyperplane. We can find the hyperplane that maximize the margin of two classes and separate out most of the data by solving the Lagrangian dual problem

$$\begin{aligned} rCl \quad & \mathbf{SVM^{OAA}}: \\ & \max_{\lambda} L_D = \sum_{i=1}^{N} \lambda_i - \frac{1}{2} \sum_{i=1}^{N} \sum_{j=1}^{N} \lambda_i \lambda_j \hat{Y}^i \hat{Y}^j K(X^i, X^j) \\ & \sum_{i=1}^{N} \lambda_i \hat{Y}^i = 0 \\ & 0 \leq \lambda_i \leq C, \forall i \end{aligned} \tag{5}$$

where ˘ $= \{\lambda_1 \quad \lambda_2 \quad \cdots \quad \lambda_N\}$ and C is a penalty constant. $K(X^i, X^j)$ is a kernel function. We use the radial basis function in our system

$$K(X^i, X^j) = e^{-\gamma \left\| X^i - X^j \right\|_2^2}, \gamma \geq 0 \tag{6}$$

where γ is a parameter in RBF kernel function. The optimization problem in (5) can be solved by sequential minimal optimization [33]. Finally, the remaining work is to establish the decision rules for classifying multiple class data. In an OAA-SVM model which is built for class Y^h, the predictive result is decided by the sign of the output of formula. For instance, if we have non-labeled data Z, the classification process is shown in 7.

$$\begin{aligned} lC(Z) &= sign\{(\sum_{i=1}^{N} \lambda_i y_i K(X^i, Z)) + b\} \\ class(Z) &= \begin{cases} Y^h & , if\ C(Z) = "+" \\ other & , if\ C(Z) = "-" \end{cases} \end{aligned} \tag{7}$$

Preprints (www.preprints.org) | NOT PEER-REVIEWED | Posted: 3 July 2019 doi:10.20944/preprints201907.0060.v1

However, there are $|Y^i|$ SVM models build in the system, and each model only considers one class. Therefore, the classifying result will be made by the voting results of each model. A vector of size $|Y^i|$ is constructed and initialized for counting votes. The test data Z are input into every model. If the result from the Y^i model is Y^i, the vote for Y^i will be increased by one; otherwise, the votes for all other class will be increased by one. After the voting is done, the class with the majority of votes will be the output result.

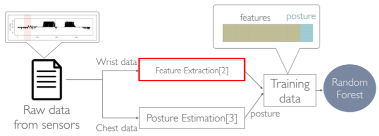

Figure 9. Model training process in the system. The training data and the label data are collected by the smartphone, and then sent to the server for training personal model for posture prediction.

6. Experimental Results

6.1. *Experiment Settings*

We implemented the proposed system by using an Android phone and Koala sensors, as shown in Figure 10. The server is implemented by Python, and with the package Scikit-learn [34]. The datasets used for evaluating the system are introduced in the following:

Figure 10. Required hardware in the sleep posture monitoring system. One the left is an Android smartphone, on the right are two wearable sensors.

- Training Dataset (Labeled Data 1): The model training dataset is collected from both chest and wrist sensors. The dataset of each person is obtained from the following two scenarios:
  - Lying with the aforementioned four sleep postures and sitting on the bed for 3 minutes.
  - Changing two sleep postures 10 times.
- Testing Dataset (Labeled Data 2): The testing dataset is collected in an independent two minutes trial. All postures are done by the subject. Also, the ground truth is recorded during the trail. In other words, both sensors are worn during the collecting phase of testing data.

6.2. *Results*

By comparing the estimated postures of the model and the ground truth recorded from the chest data, the result can be obtained and reported with confusion matrix (CM). Multiple classification models are selected and tested. We discuss the key observations in the following section.

6.2.1. Sleep Posture Monitoring With SVM

The SVM with linear kernel and the OAA approach was adopted. Figure 11 shows the CM of the result. The vertical axis presents the true label of the data, and the horizontal axis presents the estimated label of the data. The accuracy with respect to postures is shown in Figure 12, the accuracy for the prone posture is much lower than the others. This is because the linear SVM cannot establish

Preprints (www.preprints.org) | NOT PEER-REVIEWED | Posted: 3 July 2019 doi:10.20944/preprints201907.0060.v1

an arbitrary decision boundary in data. In other words, the data of prone posture cannot be linearly separated from others.

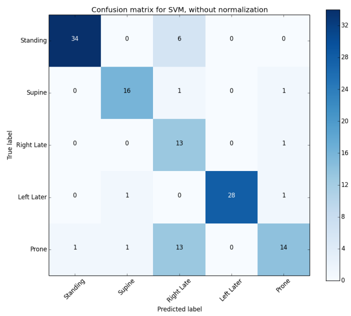

Figure 11. CM for the SVM. with linear kernel. overall accuracy: 0.80

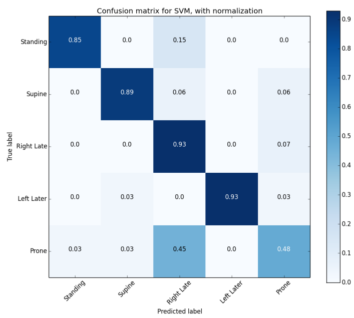

Figure 12. CM with normalized for the SVM. linear kernel.

6.2.2. Sleep Posture Monitoring With RF

A parameter of training random forest model is the number of decision trees, which specifies how many decision tree will be constructed in the model. To decide this number, we split the training dataset (Labeled data 1) into two parts: one for training the model with a specific number of trees, and the other for validating the accuracy of this setting. The proportion for splitting the data we adopted is two thirds for training and one third for validation. Our system trains the models with tree number from one to fifty, and pick the one with the best accuracy to be the posture classifying model. This procedure can prevent the trained model from overfitting. Table 13 shows the accuracy result of four sleep postures as well as for an upright (standing) position. One can observe that the accuracy is over 90% except for the stomach sleep posture. A further experiment is performed to test how the randomness in RF affects the accuracy. We had done the training and testing phases for a hundred trials, and then analyze the collected results from each trial. The accuracy for each posture are shown by a box diagram in Fig 15. Note that the overall accuracy of RF varies in one hundred trials. In this experiment, RF outperforms SVM significantly.

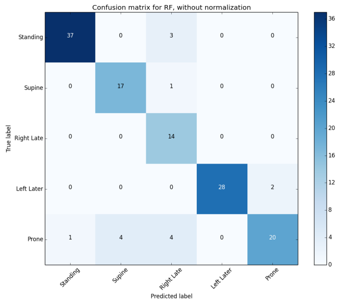

Figure 13. CM for the RF. tree_number = 10. overall accuracy: 0.88

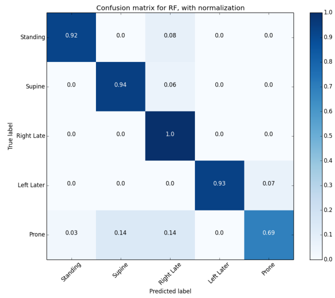

Figure 14. CM with normalized for the RF. tree_number = 10.

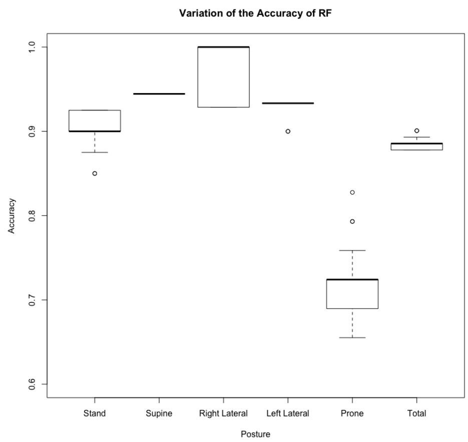

Figure 15. Statistic Result for RF model. The boxes represent the 25 percentile and the 75 percentile. The bold horizontal lines represent the mean. And, the dots represent the outliers.

7. Future Applications

Because the proposed system overcomes the disadvantages of the traditional monitoring systems, we can improve many parts of the current monitoring system, or easily been integrated into an ubiquitous healthcare service system [35]. Moreover, we list some promising applications which will occur in the near future on the followings:

7.1. Precision Medicine

Our system can assist the dosage adjustment of medicines that have sleep-related side effects. For example, the overdosing of Parkinson's disease medicine may make the patient's body rigid during sleep. In practice, the dosage of the prescribed medicine is often adjusted by considering the severity of patient's side effect. However, the events that happen during sleep are hard to be perceived by the

 doi:10.20944/preprints201907.0060.v1

patients themselves. Our sleep posture monitoring system can record all sleep conditions and assist the physicians to prescribe the correct dosage.

7.2. Home Long-term Sleep Monitoring

Our system is easy to be deployed at home, and the sleep condition is recorded every day. Some of the symptoms may not happen every day. Thus, it takes long time to identify these symptoms. Also, we can detect whether the sleep behavior is changed. This might be an indication of sickness. Our system is suitable for these scenarios because of being designed for long-term usage.

7.3. Risky Position Alarm

An alarm function can be easily integrated with our monitoring system to prevent sleep-related diseases. The duration of sleep postures are presented by our system in real-time. Therefore, the alarm system only needs physicians or caregivers to set the condition when patients need to be alarmed.

8. Conclusions

In this paper, a cost-effective and user-friendly sleep posture monitor system is proposed. We design a process to automatically recognize the body posture in the training phase. This process can avoid labor-intensive tasks in labeling the postures of the training phase. In the monitoring phase, our system can recognize the posture by analyzing data collected from one sensor on the wrist, and perform accurately. We test two different types of learning algorithms with our system, and achieve over 90% accuracy with random forest algorithm, and 80% accuracy with SVM algorithm, respectively. The proposed one-sensor sleep posture monitor system is more cost-effective than the existing products using camera monitoring or pressure mat sensing devices. In this paper, we are the first to show the wrist accelerometer can be a feasible sensing device for sleep posture monitoring. We demonstrate that the proposed system can analyze and predict human sleep postures, which can provide important insights into the design of body sensor systems in the future.

References

1. Parish, J. M. Sleep-Related Problems in Common Medical Conditions. Chest 2009, 135 (2), 563-572. https://doi.org/10.1378/chest.08-0934.
2. Nagai, M.; Hoshide, S.; Kario, K. Sleep Duration as a Risk Factor for Cardiovascular Disease- a Review of the Recent Literature. Curr. Cardiol. Rev. 2010, 6 (1), 54-61. https://doi.org/10.2174/157340310790231635.
3. Zhu, B.-Q.; Li, X.-M.; Wang, D.; Yu, X.-F. Sleep Quality and Its Impact on Glycaemic Control in Patients with Type 2 Diabetes Mellitus. International Journal of Nursing Sciences 2014, 1 (3), 260-265. https://doi.org/10.1016/j.ijnss.2014.05.020.
4. Liu, R.-Q.; Qian, Z.; Trevathan, E.; Chang, J.-J.; Zelicoff, A.; Hao, Y.-T.; Lin, S.; Dong, G.-H. Poor Sleep Quality Associated with High Risk of Hypertension and Elevated Blood Pressure in China: Results from a Large Population-Based Study. Hypertens. Res. 2016, 39 (1), 54-59. https://doi.org/10.1038/hr.2015.98.
5. Augner, C. Associations of Subjective Sleep Quality with Depression Score, Anxiety, Physical Symptoms and Sleep Onset Latency in Students. Cent. Eur. J. Public Health 2011, 19 (2), 115-117.
6. Liu, X.; Cao, J.; Tang, S.; Wen, J. Wi-Sleep: Contactless Sleep Monitoring via WiFi Signals. IEEE Real-Time Systems Symposium, Rome, Italy, 2-5 Dec 2014; IEEE Computer Society: Washington, DC, USA, 2014; pp 346-355. https://doi.org/10.1109/RTSS.2014.30.
7. Wu, F.; Solmaz, G. We Hear Your Activities through Wi-Fi Signals. In 2016 IEEE 3rd World Forum on Internet of Things (WF-IoT); 2016; pp 251–256. https://doi.org/10.1109/WF-IoT.2016.7845478.
8. Ren, Y.; Wang, C.; Yang, J.; Chen, Y. Fine-Grained Sleep Monitoring: Hearing Your Breathing with Smartphones. IEEE Conference on Computer Communications (INFOCOM), Kowloon, Hong Kong, 26 April-1 May 2015; IEEE Computer Society: Washington, DC, USA, 2015; pp 1194-1202. https://doi.org/10.1109/INFOCOM.2015.7218494.

9. Le, T.Q.; Cheng, C.; Sangasoongsong, A.; Wongdhamma, W.; Bukkapatnam, S.T.S. Wireless Wearable Multisensory Suite and Real-Time Prediction of Obstructive Sleep Apnea Episodes. IEEE J Transl Eng Health Med 2013, 1, 2700109. https://doi.org/10.1109/JTEHM.2013.2273354.
10. Yang, X.; Fan, D.; Ren, A.; Zhao, N.; Zhang, Z.; Hu, F.; Wang, W.; Ur Rehman, M.; Tian, J. Sleep Apnea Syndrome Sensing at C-Band. IEEE J Transl Eng Health Med 2018, 6, 2701008. https://doi.org/10.1109/JTEHM.2018.2879085.
11. Neill, A. M.; Angus, S. M.; Sajkov, D.; McEvoy, R. D. Effects of Sleep Posture on Upper Airway Stability in Patients with Obstructive Sleep Apnea. Am. J. Respir. Crit. Care Med. 1997, 155 (1), 199-204. https://doi.org/10.1164/ajrccm.155.1.9001312.
12. Jeng, P.; Wang, L. An Accurate, Low-Cost, Easy-to-Use Sleep Posture Monitoring System. International Conference on Applied System Innovation (ICASI), Sapporo, Japan, 13-17 May 2017; IEEE Computer Society: Washington, DC, USA, 2017; pp 903-905. https://doi.org/10.1109/ICASI.2017.7988585.
13. Black, J. Pressure Ulcer Prevention and Management: A Dire Need for Good Science. Ann. Intern. Med. 2015, 162 (5), 387-388. https://doi.org/10.7326/M15-0190.
14. Vanderwee, K.; Grypdonck, M. H. F.; De Bacquer, D.; Defloor, T. Effectiveness of Turning with Unequal Time Intervals on the Incidence of Pressure Ulcer Lesions. J. Adv. Nurs. 2007, 57 (1), 59-68. https://doi.org/10.1111/j.1365-2648.2006.04060.x.
15. Leaf Healthcare. Available online: http://www.leafhealthcare.com (accessed on 29 Jun 2019)
16. Zhang, Z.; Yang, G. Monitoring Cardio-Respiratory and Posture Movements during Sleep: What Can Be Achieved by a Single Motion Sensor. IEEE International Conference on Wearable and Implantable Body Sensor Networks (BSN), Cambridge, MA, USA, 9-12 Jun 2015; IEEE Computer Society: Washington, DC, USA, 2015; pp 1-6. https://doi.org/10.1109/BSN.2015.7299409.
17. Li, M. H.; Yadollahi, A.; Taati, B. Noncontact Vision-Based Cardiopulmonary Monitoring in Different Sleeping Positions. IEEE J Biomed Health Inform 2017, 21 (5), 1367-1375. https://doi.org/10.1109/JBHI.2016.2567298.
18. Metsis, V.; Kosmopoulos, D.; Athitsos, V.; Makedon, F. Non-Invasive Analysis of Sleep Patterns via Multimodal Sensor Input. Pers. Ubiquit. Comput. 2014, 18 (1), 19-26. https://doi.org/10.1007/s00779-012-0623-1.
19. Aifeng Ren; Binbin Dong; Xiangyu Lv; Tianqiao Zhu; Fangming Hu; Xiaodong Yang. A Non-Contact Sleep Posture Sensing Strategy Considering Three Dimensional Human Body Models. IEEE International Conference on Computer and Communications (ICCC), Chengdu, China, 14-17 Oct 2016; IEEE Computer Society: Washington, DC, USA, 2016; pp 414-417. https://doi.org/10.1109/CompComm.2016.7924734.
20. Mineharu, A.; Kuwahara, N.; Morimoto, K. A Study of Automatic Classification of Sleeping Position by a Pressure-Sensitive Sensor. International Conference on Informatics, Electronics Vision (ICIEV), Fukuoka, Japan, 15-18 Jun 2015; pp 1-5. https://doi.org/10.1109/ICIEV.2015.7334059.
21. Sun, Q.; Gonzalez, E.; Sun, Y. On Bed Posture Recognition with Pressure Sensor Array System. IEEE SENSORS; 2016; pp 1-3. https://doi.org/10.1109/ICSENS.2016.7808623.
22. Enayati, M.; Skubic, M.; Keller, J. M.; Popescu, M.; Farahani, N. Z. Sleep Posture Classification Using Bed Sensor Data and Neural Networks. Conf. Proc. IEEE Eng. Med. Biol. Soc. 2018, 2018, 461-465. https://doi.org/10.1109/EMBC.2018.8512436.
23. Liu, M.; Ye, S. A Novel Body Posture Recognition System on Bed. IEEE International Conference on Signal and Image Processing (ICSIP); IEEE Computer Society: Washington, DC, USA, 2018; pp 38-42. https://doi.org/10.1109/SIPROCESS.2018.8600465.
24. Hsiao, R.-S.; Chen, T.-X.; Bitew, M. A.; Kao, C.-H.; Li, T.-Y. Sleeping Posture Recognition Using Fuzzy c-Means Algorithm. Biomed. Eng. Online 2018, 17 (Suppl 2), 157. https://doi.org/10.1186/s12938-018-0584-3.
25. Liu, J. J.; Xu, W.; Huang, M.; Alshurafa, N.; Sarrafzadeh, M.; Raut, N.; Yadegar, B. A Dense Pressure Sensitive Bedsheet Design for Unobtrusive Sleep Posture Monitoring. IEEE International Conference on Pervasive Computing and Communications (PerCom), San Diego, CA, USA, 18-22 March 2013; IEEE Computer Society: Washington, DC, USA, 2013; pp 207-215. https://doi.org/10.1109/PerCom.2013.6526734.
26. Hao, T.; Xing, G.; Zhou, G. iSleep: Unobtrusive Sleep Quality Monitoring Using Smartphones. In Proceedings of the 11th ACM Conference on Embedded Networked Sensor Systems, Roma, Italy, November 11-15, 2013; ACM: New York, NY, USA, 2013; pp 4:1-4:14. https://doi.org/10.1145/2517351.2517359.

27. The Merits And Demerits Of Your Sleeping Posture. Available online: http://www.bpillow.com/the-merits-and-demerits-of-your-sleeping-posture/ (Accessed on 29 Jun 2019)
28. Van Laerhoven, K.; Borazio, M.; Kilian, D.; Schiele, B. Sustained Logging and Discrimination of Sleep Postures with Low-Level, Wrist-Worn Sensors. IEEE International Symposium on Wearable Computers; IEEE Computer Society: Washington, DC, USA, 2008; pp 69-76. https://doi.org/10.1109/ISWC.2008.4911588.
29. Huang, Y.; Yi, C.; Peng, W.; Lin, H.; Huang, C. A Study on Multiple Wearable Sensors for Activity Recognition. IEEE Conference on Dependable and Secure Computing, Taipei, Taiwan, 7-10 Aug 2017; IEEE Computer Society: Washington, DC, USA, 2017; pp 449-452. https://doi.org/10.1109/DESEC.2017.8073827.
30. Guan-Wei, H.; Min-Hsuan, L.; Yu-Tai, C. Methods for Person Recognition and Abnormal Gait Detection Using Tri-Axial Accelerometer and Gyroscope. International Conference on Computational Science and Computational Intelligence (CSCI), Las Vegas, NV, USA, 14-16 Dec. 2017; IEEE Computer Society: Washington, DC, USA, 2017; pp 1691–1694. https://doi.org/10.1109/CSCI.2017.294.
31. Breiman, L. Random Forests. Mach. Learn. 2001, 45 (1), 5-32. https://doi.org/10.1023/A:1010933404324.
32. Hsu, C.-W.; Lin, C.-J. A Comparison of Methods for Multiclass Support Vector Machines. IEEE Trans. Neural Netw. 2002, 13 (2), 415-425. https://doi.org/10.1109/72.991427.
33. Platt, J. Sequential Minimal Optimization: A Fast Algorithm for Training Support Vector Machines. Microsoft Research 1998.
34. Pedregosa, F.; Varoquaux, G.; Gramfort, A.; Michel, V.; Thirion, B.; Grisel, O.; Blondel, M.; Müller, A.; Nothman, J.; Louppe, G.; et al. Scikit-Learn: Machine Learning in Python. arXiv [cs.LG], 2012.
35. Lo, C.-C.; Chen, C.-H.; Cheng, D.-Y.; Kung, H.-Y. Ubiquitous Healthcare Service System with Context-Awareness Capability: Design and Implementation. Expert Syst. Appl. 2011, 38 (4), 4416–4436. https://doi.org/10.1016/j.eswa.2010.09.111.