Stream Data Analysis of Body Sensors for Sleep Posture Monitoring: An Automatic Labelling Approach

Poyuan Jeng
Department of Electrical and Computing Engineering
National Chiao Tung University
Hsinchu, Taiwan
Email: pyjeng.eed03g@nctu.edu.tw

Li-Chun Wang
Department of Electrical and Computing Engineering
National Chiao Tung University
Hsinchu, Taiwan
Email: lichun@g2.nctu.edu.tw

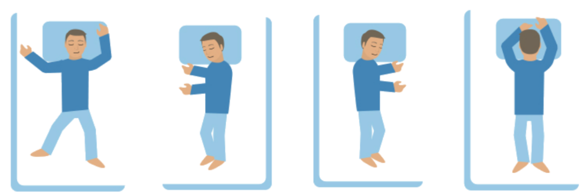
***Abstract*—Sleeping is one of the most important activities in our daily lives. However, very few people really understand their sleeping habits, which affect sleep-related diseases such as sleep apnea, back problems or even snoring. Most current techniques that monitor, predict and quantify sleep postures are limited to use in hospitals and/or need the intervention of caregivers. In this paper, we describe a system to automatically monitor, predict and quantify sleep postures that may be self-applied by the general public even in a non-hospital environment such as at a persons home. A Random Forest approach is adopted during training to predict and quantify sleep postures. After going through training procedures, a person needs only one sensor placed on the wrist to recognize the persons sleep postures. Our preliminary experiments using a set of testing data show about 90 percent accuracy, indicating that this design has a promising future to accurately analyze, predict and quantify human sleep postures.**

***keywords*—sleep posture; accelerometer; body sensor network; stream data.**

I. Introduction

Bad sleep postures affect our health and even cause injuries. For example, sleep apnea is a disorder, which causes multiple pauses in breathing during sleep. Different sleep postures will affect the apnea index [1, 2], i.e., the severity of sleep apnea. It is found that the apnea index of a back sleepers is more than twice as high as that of a side sleeper [2]. As another example, a prolonged same sleep position may result in pressure ulcers, which is particularly serious for the elderly or diabetic patients. One simple pressure ulcer prevention approach is to have caregivers move patients bodies to avoid patients lying in the same posture for more than two hours. However, the need for caregivers intervention is not only high cost, but it is often limited to nursing homes and hospitals.

Hence, inexpensive, self-appliable and automatic sleep posture monitoring technologies will play a key role in health care and eldercare. In the literature, many research works on the monitoring and prediction of sleep postures have been proposed. For example, a depth camera and a video camera were set up for monitoring and predicting sleep positions at the cost of revealing the customers privacy [3]. A pressure mat was placed under the bed to capture the pressure distribution for quantifying sleep postures, but it was proved to be expensive [4]. The aforementioned approaches require a high threshold to implement because the environmental setting is troublesome and the cost of the equipment is high. Thus, the techniques are difficult to extend from the hospitals or nursing homes to personal homes.



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

Fig. 1. Four sleep postures (a)back, (b)left side, (c)right side and (d)stomach [5].

In this paper, we present a sleep posture analysis, prediction and quantification system, which requires only one accelerometer to be worn by the care receivers. Accelerometers are readily available and at least indirectly familiar to most people because they exist in smartphones. During a training stage, two accelerometers are used. The care receivers wear one accelerometer on the chest and the other one on the wrist. Data collected from the wrist accelerometer sensor are processed using a sliding window approach to obtain the features of a bodys motions. Our system then maps these features to current positions based on the chest accelerometer sensor and generates the training data for a predictive model for use in the future. A random forest algorithm is modified and used to predict and analyze the actual sleep postures. After the training stage, our system during actual use by a care receiver can recognize four sleep postures: supine, stomach, right side and left side[5], as shown in Figure 1. Our preliminary experiments show an 88 percent overall accuracy, indicating that the design has a promising future to accurately analyze, predict and quantify human sleep postures.

978-1-5090-4909-7/17/$31.00 ©2017 IEEE

II. Related Works

Some research works for sleep quality measurement have been reported in detecting sleep events, such as snoring and body movement [6, 7]. However, sleep posture detection techniques for improving health care have been seen rarely. In our literature review, we categorize the existing research regarding sleeping posture monitoring into two classes, contact body and non-contact body type. In the contact body class, the equipment deployed to monitor care reception has contact with a care receiver's body; in the non-contact body class, the equipment does not contact the receivers body. In this section, we will introduce the equipment and the usage of the equipment in each class.

A. Non-contact body class

In the non-contact class, using non-contact body type equipment for sleep posture monitoring could increase the comfort level of a care receiver during his sleep. However, at least one downside to this approach is that the monitoring of postures will be easily confused by other objects, such as blankets and clothes. Also, the deployment of the monitoring equipment will affect the results by their positions and angles.

Most of the research in this class adopts a surveillance camera-based approach for monitoring. The monitoring systems usually use image recognition-based methods to monitor sleeping postures. These systems use camera-like equipment for the data collection from a care receiver. The data is processed into features, and then input to a model, which was trained to get the posture. For example, in [3], the authors use Kinect's depth sensor to capture the 3D image of a subject while he is sleeping. There are two techniques to estimate the five basic sleeping postures, which are Back, Left side, Right side, Stomach and Sitting on bed.

There are also research works using monitoring equipment other than camera-based equipment. The authors in [8] deployed pairs of Wi-Fi transceivers and captured the channel state information to monitor the respiration and movements of a subject during his sleep.

B. Contact body class

In this class, we further categorize the works into two subclasses, non-wearable and wearable.

1) Non-wearable sub-class: The non-wearable approach for monitoring sleep posture is using a pressure mat as the monitoring equipment. Dozens of pressure sensor are embedded in a pressure mat so that a pressure mat can detect the distribution of the subjects weight on the mat. The weight distribution of a person on a bed can be detected by placing a pressure mat between the person and the bed. By analyzing the pressure distribution, the sleep posture of care receiver can be obtained. In [4], the authors used fifty-five features, which are calculated from the pressure distribution, and four classification methods to train the sleep posture estimation model.

2) Wearable sub-class: In [9], the authors placed an accelerometer on the care receiver's chest and collected data from the sensor. During the sleep of a care receiver, his actual postures were recorded by a camera. The authors then applied a linear discriminant algorithm using the collected data to train a model for posture recognition. Then, the model was applied to real-time sleep postures monitoring. There are also commercial products for sleep posture monitoring[11]. The products exploit a disposable accelerometer, which can be worn on the chest to monitor sleep postures.

Normally, the wearable sub-class is not a comfortable approach for the care receiver because the sensors worn on the body might restrict their activities. However, the inconvenience could be reduces by changing the placement of the sensors. In [10], they placed a tilt sensor on the subject's wrist, and record the sleep posture and the data of sensor. Needless to say, it is more comfortable to wear a sensor on your wrist than on the chest. After collecting data for ten nights, they analyzed the data. The result shows there are certain relationships between the body postures and the tilt of a sensor.

We believe our sensor-based sleep posture monitoring methods are able to combine the benefits of low deployment cost, high accuracy and, by placing sensors at the right place, the patient will be much more comfortable. In our literature survey, we did not find a research that uses a machine learning technique to solve the sleep posture monitoring problem from wrist activities nor the calibration and training technique that we propose.

III. System Description

A. System Architecture

The system consists of two Bluetooth low energy (BLE) monitoring devices, an Android smartphone and a server. A smartphone is used as an Internet gateway to collect and send sensor data to a server for sleep posture monitoring. Figure 2 shows that for the training stage, two sensors are used, but in the actual real-time estimation stage, only one sensor is necessary.

We adopted an acceleration sensor known as Koala, which is a Bluetooth low energy (BLE) device to detect and record physical motions. Koala could detect the acceleration in the range -2G to 2G in X, Y and Z direction. By using the BLE technology, Koala can function for more than five hours at a sampling rate of 100 Hz. In our system, the sampling rate can be set lower to make the Koala function even longer.

In our system, two Koala sensors are required for collecting data. The Koalas sensors are worn on different parts of the patient's body. One is strapped to the chest, and the other is strapped around the left wrist.

B. Proposed Method

The operation procedures of the proposed sleep posture monitor system consist of two stages: training and monitoring. In the training stage, the sensed data from the two accelerometers are gathered simultaneously and processed to learn the posture model of each individual. These two sensors

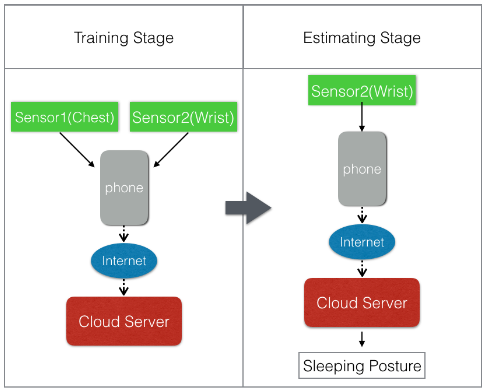


Fig. 2. The operation procedures of the proposed sleep posture monitoring system.

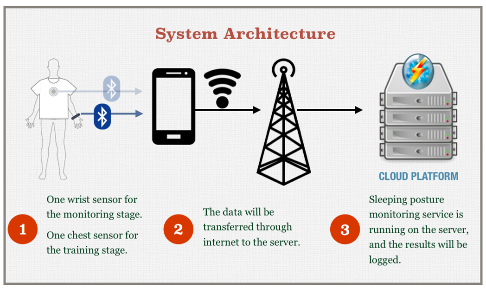


Fig. 3. System architecture.

are placed on chest and wrist, which are called chest sensor and wrist sensor hereafter. We discard the data which was collected before both sensors were connected to the phone. In the monitoring stage, we monitor a subjects real-time postures based on the learned posture model from the training stage. The sensed data gathered from the chest and wrist sensors are processed by different methods, which are discussed next.

1) Chest Sensor: It is assumed that the orientation of the sensor can represent the body position when a sensor is tightly tied on the chest. The criterion for distinguishing body positions is the angle and direction between gravity and the chest sensor.

2) Wrist Sensor: When receiving the raw data of the wrist sensor, the monitoring system starts extracting the features of the subjects sleep data based on a sliding window protocol with a receiver window size of the bandwidth times one second. The feature extraction method is adapted from[12],and the features are the means of acceleration on the three orthogonal direction of the sensor.

3) Learning Algorithm: A random forest learning algorithm is used to train the sleep posture model for the proposed monitoring system [13]. Random forest algorithm is an ensemble learning method, consisting of many decision trees each trained by a random subset of the entire training data. Each tree brings in the data then outputs a class as a result when the algorithm is used as a classifier. Among the different output results of decision trees, the one with the most votes will be the final output of the entire forest.

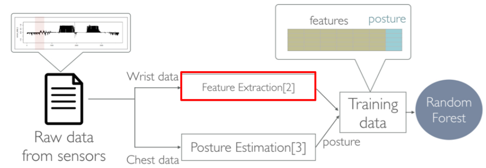


Fig. 4. Model training process for sleep postures prediction.

Fig. 5. Required hardware for a customer to use the sleep posture monitoring system.

From the chest sensor data, the target classes of sleep postures are learned. 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. Fig. 4 shows the training process of sleep postures.

IV. Experimental Results

A. Experiment settings

We implemented the proposed system by using an Android phone and Koala sensors, as shown in Fig.5.

- Training dataset: The model training dataset was collected from both chest and wrist sensors. The dataset for each person is obtained based on the following two scenarios:
  - Lying with the aforementioned four sleep postures and sitting on the bed for 3 minutes.
  - Changing two sleep postures for 10 times.

Note that the number of decision trees for random forest learning algorithm in our experiment is set to 10.

B. Results

The accuracy of the trained model was evaluated by another experiment using different testing data. Table I shows the accuracy for 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.

V. Conclusions

In this paper, a cost-effective and user-friendly sleep posture monitor system is proposed. We demonstrate that data from using one accelerator sensor placed on a patients wrist, together with a random forest learning algorithm, can achieve

TABLE I
ACCURACY OF SLEEP POSTURE PREDICTIONS USING THE PROPOSED SYSTEM

Actual Class \ Predict Class	Stand	Back	Right Side	Left Side	Stomach	Accuracy
Stand	36	0	4	0	0	0.90
Back	1	17	0	0	0	0.94
Right Side	1	0	12	0	1	0.92
Left Side	0	0	0	28	2	0.93
Stomach	1	3	2	0	23	0.79

over 90% accuracy in sleep posture recognition. The proposed one-sensor sleep posture monitor system is much more cost-effective than the existing products using camera monitoring or pressure mat sensing. More importantly, our research is the first to show that the placement of the wrist accelerometer is a feasible solution for sleep posture monitoring. In summary, we proved that the proposed system can analyze, predict and quantify human sleep postures, which also provides important insights into the design of body sensor systems in the future.

REFERENCES

[1] A. M. Neill, S. M. Angus, D. Sajkov, and R. D. McEvoy, Effects of sleep posture on upper airway stability in patients with obstructive sleep apnea., Am J Respir Crit Care Med, vol. 155, no. 1, pp. 199204, Jan. 1997.

[2] R. D. Cartwright, "Effect of sleep position on sleep apnea severity," Sleep, vol. 7, no. 2, pp. 110-114, 1984.

[3] V. Metsis, D. Kosmopoulos, V. Athitsos, and F. Makedon, "Non-invasive Analysis of Sleep Patterns via Multimodal Sensor Input," Personal Ubiquitous Comput., vol. 18, no. 1, pp. 19-26, Jan. 2014.

[4] A. Mineharu, N. Kuwahara, and K. Morimoto, "A study of automatic classification of sleeping position by a pressure-sensitive sensor," in 2015 International Conference on Informatics, Electronics Vision (ICIEV), 2015, pp. 1-5.

[5] http://www.bpillow.com/the-merits-and-demerits-of-your-sleeping-posture/

[6] Y. Ren, C. Wang, J. Yang and Y. Chen, "Fine-grained sleep monitoring: Hearing your breathing with smartphones," 2015 IEEE Conference on Computer Communications (INFOCOM), Kowloon, 2015, pp. 1194-1202.

[7] T. Hao, G. Xing, and G. Zhou, iSleep: Unobtrusive Sleep Quality Monitoring Using Smartphones, in Proceedings of the 11th ACM Conference on Embedded Networked Sensor Systems, New York, NY, USA, 2013, p. 4:14:14.

[8] X. Liu, J. Cao, S. Tang, and J. Wen, Wi-Sleep: Contactless Sleep Monitoring via WiFi Signals, in 2014 IEEE Real-Time Systems Symposium (RTSS), 2014, pp. 346355.

[9] Z. Zhang and G.-Z. Yang, "Monitoring cardio-respiratory and posture movements during sleep: What can be achieved by a single motion sensor," in 2015 IEEE 12th International Conference on Wearable and Implantable Body Sensor Networks (BSN), 2015, pp. 1-6.

[10] K. V. Laerhoven, M. Borazio, D. Kilian, and B. Schiele, "Sustained logging and discrimination of sleep postures with low-level, wrist-worn sensors," in 12th IEEE International Symposium on Wearable Computers, 2008. ISWC 2008, 2008, pp. 69-76.

[11] http://www.leafhealthcare.com

[12] S. J. Preece*, J. Y. Goulermas, L. P. J. Kenney, and D. Howard, A Comparison of Feature Extraction Methods for the Classification of Dynamic Activities From Accelerometer Data, IEEE Transactions on Biomedical Engineering, vol. 56, no. 3, pp. 871879, Mar. 2009.

[13] L. Breiman, Random Forests, Machine Learning, vol. 45, no. 1, pp. 532, Oct. 2001.