Sleep monitoring using an infrared thermal array sensor

Conference Paper · March 2019

DOI: 10.1117/12.2515515

2 authors:

Zhangjie Chen
Texas A&M University

Y. Wang
Texas A&M University

Sleep monitoring using an infrared thermal array sensor

Zhangjie Chen , Ya Wang

Zhangjie Chen , Ya Wang, "Sleep monitoring using an infrared thermal array sensor," Proc. SPIE 10970, Sensors and Smart Structures Technologies for Civil, Mechanical, and Aerospace Systems 2019, 109701D (27 March 2019); doi: 10.1117/12.2515515

Event: SPIE Smart Structures + Nondestructive Evaluation, 2019, Denver, Colorado, United States

Sleep Monitoring using an Infrared Thermal Array Sensor

Zhangjie Chen[a], Ya Wang*[a]
[a]J. Mike Walker ’66 Department of mechanical engineering, Taxes A&M University, College Station, TX, USA 77840

ABSTRACT

Recently, sleep evaluation has attracted lots of attention as sleep disorders have become a public health problem that causes cumulative effect on physical and mental health. Poor sleep qualities can lead to adverse effects on performance of basic activities in normal life such as memorization, concertation and learning especially among elderlies. Sleep posture is one of the keys factors that evaluates sleep qualities to prevent medical conditions such as pressure ulcer formation. In this paper, a sleep monitoring system is developed based on an infrared array sensor to detect different sleep postures. Motion and presence detections are performed and achieved an accuracy over 90%. And eleven different postures can be successfully identified with an accuracy above 95% in controlled lab environment. As the infrared array sensor has the unique property of non-contact, non-privacy invasion and passive sensing, it provides an unobtrusive, low cost and convenient method of long-term sleep monitoring.

Keywords: Thermal infrared array, sleep monitoring, posture detection

1. INTRODUCTION

1.1 Background

Recently, the importance of sleep evaluation has largely increased due to the growing concern of sleep disorders. Poor sleep qualities can lead to adverse effects on performance of basic activities in normal life such as memorization, concertation and learning especially among elderlies.

Polysomnography (PSG) is the primary sleep assessment method which involves the recording of numerous parameters such as EEG, ECG, pulse oximetry, and respiration. PSG has been proved to be the golden standard for sleep quality evaluation as it can accurately identify the sleep stages. However, it requires specific equipment and trained personnel which limited its application within clinical use. Thus, it’s not suitable for long-term daily activity monitoring such as elderly people care in nursing homes. Research have also shown that sleep quality is closely related to the sleep length and movements[1]. And sleep posture is a significant feature to evaluate the sleep quality[2]. As sleep posture cannot be detected by using PSG, it has become another major aspect in sleeping monitoring research other than sleep stage detection.

In addition, sleep posture detection is crucial for bedridden patients. Bedridden is referring to a person who is confined to bed or unable to leave bed due to medical orders, illness or psychological misfortune. Bedridden patients are more likely to be suffered from pressure injuries caused by failure in regularly changing the body posture to reduce the risk of developing bed sores. Nursing homes and hospitals usually set repositioning programs to avoid the development of bed-sores in bedridden patients. Nowadays, the accepted care guide for on-bed patients is to have them repositioned or turned every two hours[3]. However, 24/7-hour supervision of bedridden by the caregivers might be quite challenging especially when the caregiver is handling a huge number of bedridden patients. And there is also a possibility for bedridden to fall out of bed when left unsupervised which might cause serious injuries[4]. Given these applications, automatic sleep posture monitoring is desired.

Inertia sensors, pressure sensors and vision sensors are most common sensing approaches among the techniques used for sleep posture detection. A widely adopted sleep movement device is the actigraphy, which is a watch-like device containing accelerometers to measure limb movement[5]. And more than one sensors are usually required for body posture detection[6]. The main drawback of this technique is that multiple sensors need to be attached to the body which can be uncomfortable to the users. Bed pressures sensor is not intrusive, but it requires a specially modified bed and the pressure mat is expensive as it needs to contain lots of sensor nodes[7]. Four different sleep postures can be detected with an

*ya.wang@tamu.edu; phone +1 979-458-8123;

Sensors and Smart Structures Technologies for Civil, Mechanical, and Aerospace Systems 2019, edited by
Jerome P. Lynch, Haiying Huang, Hoon Sohn, Kon-Well Wang, Proc. of SPIE Vol. 10970, 109701D
© 2019 SPIE · CCC code: 0277-786X/19/$18 · doi: 10.1117/12.2515515

accuracy between 83.6% and 95.9% based on the time derivative of mattress surface indentation[8]. A dense pressure sensing device with 64x128 sensor nodes has been used to identify six sleep postures which reaches an accuracy of 88% for fourteen subjects[9]. Smart phone applications have also been developed for sleep monitoring such as sleep duration detection[10] and movement detection[11].

Device-free/remote sensing has become an attractive approach for sleep monitoring. Radio frequency signals such as Wi-Fi can be applied to sleep posture detection while it requires a pair of Wi-Fi devices to be placed at two sides of the bed and only works for limited postures. For instance, A Wi-Fi based approach can only identify four different sleep postures at an accuracy of 98% [12]. Night vision camera is an active infrared camera that can accurately detect the postures [13]. However, concerns can be raised regarding video monitoring systems in terms of an invasion of privacy. Depth camera is a good alternative to cameras to avoid an invasion of privacy while it is costly (above $200) [14]. An microbolometer sensor based thermal camera has an even higher cost and is usually used for research purpose. Passive infrared (PIR) sensors are inexpensive, and widely used motion sensors for occupancy presence detection[15], estimation[16] and localization[17]. They have also been applied for sleep monitoring but can only realize sleep movement detection[18]. A group of different sensors can also be used together to improve the performance in sleep posture detection. A 8x8 infrared array sensor is used to detect lower body positions together with a pressure sensor to reduce the number of sensors, and an accuracy of 88% is achieved for six different postures [19]. Five infrared cameras and one depth camera are integrated to detect more than ten body postures with over 90% accuracy [13]. Researchers have also applied a bed pressure sensor and a tri-axial accelerometer together for sleep quality monitoring, including detecting four sleep postures in a hospitalized environment[20]. Thermopile array is another type of remote thermal sensor based on Seebeck effect. They are low resolution thermal camera with a close cost as regular optical cameras. Thermopile sensors can be used for occupancy sensing in building energy saving[21] and other advanced functions for smart home such as occupancy estimation [22], fall detection[23], occupancy tracking[24] and localization[25]. And due to its unique properties e.g. remote passive thermal sensing, low cost, and non-privacy invasion, thermopile array could be an alternative for sleep monitoring.

In this paper, we focus on sleep posture analysis using a low resolution thermal infrared array sensor. In section 2, the prototype development and experiment setup for sleep monitoring is illustrated, and the prototype is installed near the bed to detect different sleep status of the user. In section 3, different detection algorithms are reported. In section 4, eleven typical on bed postures including ten sleep postures are identified based on the thermal signals received. Motion and presence detection are also performed based on the designed continuous experiment data.

2. PROTOTYPE DEVELOPMENT AND EXPERIMENT SETUP

2.1 Prototype development

In this paper, a thermopile array sensor MLX90640 produced by Melexis N.V. is used. It has a resolution of 32×24 pixel with a Noise Equivalent Temperature Difference (NETD) of 0.1K RMS at 1Hz refresh rate and a field of view of 55°×35°. This sensor can passively generate a temperature profile of a subject during dark environment.

Figure 1(a) shows a sensor breakout built by SparkFun Electronics used in the sensing prototype development. The Teensy 3.6 control board is used to read sensor data through IIC interface and send data to PC through serial port. The sampling frequency is set at 8Hz. The prototype is shown in

Figure 1(b) and a sample of the sensor output plotted in 'jet' color scale is shown in

Figure 1(c).

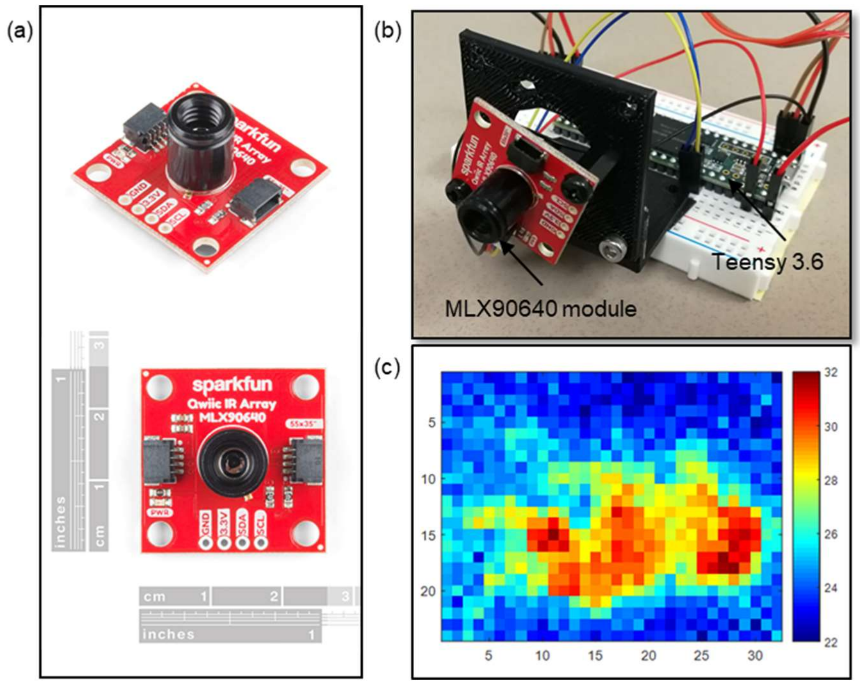

Figure 1 (a) Sensor breakout from SparkFun Electronics[26] (b) Sensing prototype (c) A sample of sensor output in 'jet' color scale recording a foetus posture

2.2 Experiment setup and datasets

The simulated experiments are performed in a controlled lab environment. The sensing prototype is fixed on a tripod next to an airbed. The height between the sensor and the surface of the bed is 1.2m and the sensor has an elevation angle of -65° to cover the whole surface area of the bed as shown in Figure 2.

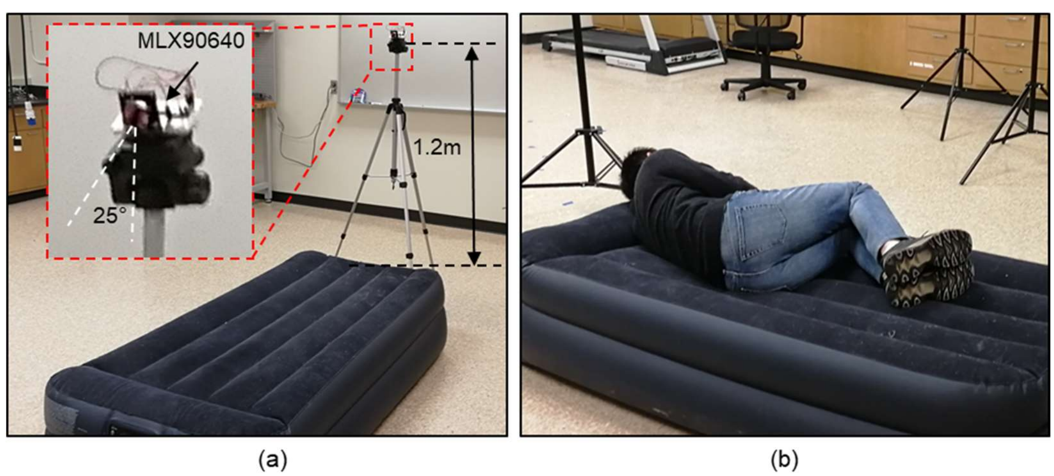

Figure 2 (a) Experimental environment (b)Example of a testing subjects performing left foetus posture

Two different datasets are collected. The first one is used for establishment and evaluation of the sleep posture classification model. We call it the discrete dataset in which each user performs each posture for about ten seconds and data are saved into separated files. The discrete dataset is performed by two testing subjects. Eleven different on-bed postures have been involved including ten different sleeping postures and a 'sitting on bed(ST)' body posture. The sleep postures in the experiments are chosen based on the most popular American sleep postures as shown in Figure 3[27]. Ten sleep postures used in this paper are soldier (SD), left foetus(LF), right foetus(RF), left log(LL), right log(RL), freefaller(FF), starfish(SF), back soldier(BS), left yearner(LY), and right yearner(RY). An example of user performing left foetus posture is shown in Figure 2(b).

Another dataset is the continuous experiment dataset in which users perform multiple postures according to a pre-designed sequence of postures. So, in this dataset, the transaction process between the two postures are recorded which makes it closer to real scenarios. This dataset is used to perform the user motion and presence detection and to verify the performance of posture classification model established based on the discrete dataset. The continuous data set is performed by three human testing subjects and contains only five popular postures (soldier, left foetus, right foetus, freefaller, sitting on bed). The experiments are performed based on the following designed sequences: (Into bed – soldier – sitting on bed – soldier - left foetus - right foetus – freefaller – soldier – exit bed). And each testing subject repeats the sequence twice.

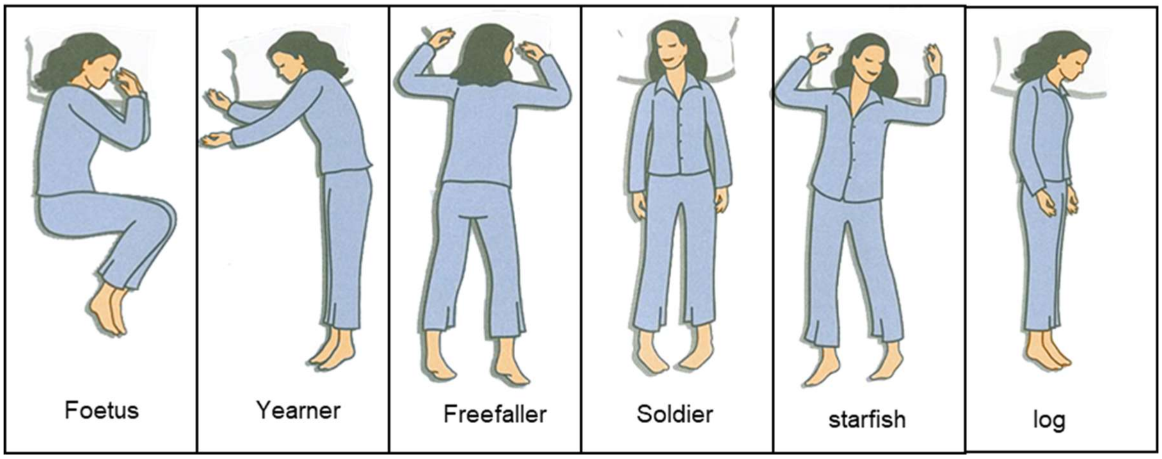

Figure 3 Popular American sleep postures [27]

3. DETECTION ALGORITHM

3.1 Overview

The discrete data is used for development and evaluation of sleep posture detection model. Hand-crafted features are extracted in this work. Five-fold cross validation is used to compare the performance of different classifiers. Then feature selection process is performed to eliminate unnecessary features. The continuous data set can be used for presence, motion and sleep posture detection which are the three major functions of the our sleep monitoring system which consists the whole sleep monitoring system. The sleep posture detection is only performed when the subject keeps stationary. By doing this, the ground truth during the transition (the moving process from one posture to another posture) doesn't need to be determined. The left chart in Figure 4 shows the establishment of sleep posture detection model. And the right chart of Figure 4 shows the overflow of the sleep monitoring system. In this paper, the Python Scikit-Learn library is used to calculate all the classifications.

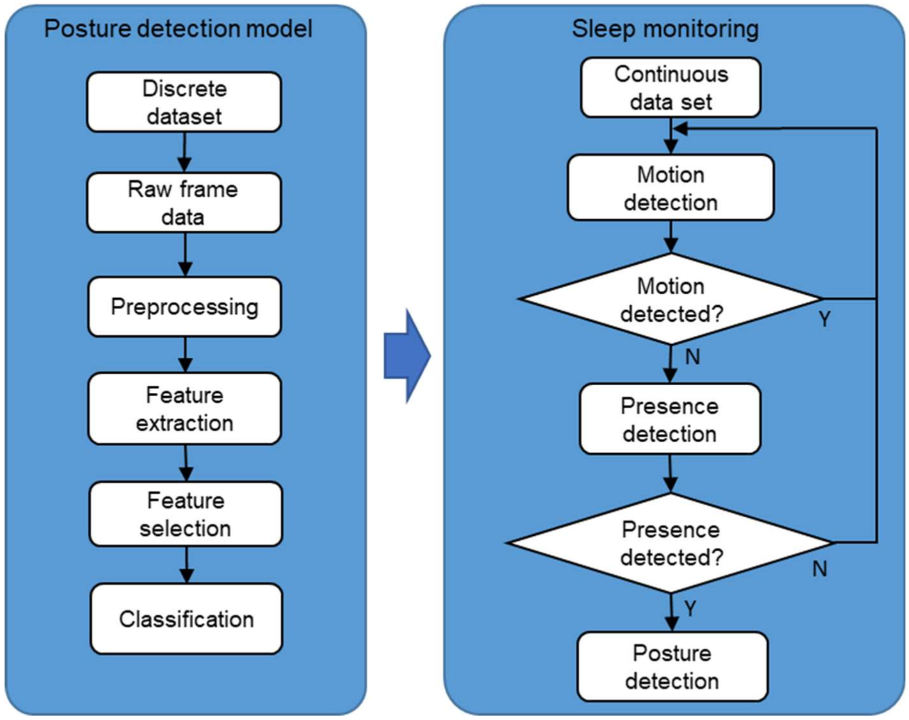

Figure 4 Overview of the detection algorithms

3.2 Presence and Motion detection

As the sleep posture detection is performed when the subject keeps stationary, motion detection needs to be performed first. We use the number of active pixels between two continuous frames to determine the motion status. Three techniques are used to identify the motion period. (1) A threshold to determine peak values (2) A combination of close motion area (3) eliminated short motion area. As the sampling frequency of the sensor is 8Hz, another motion period with a length than 1s (8 frames) is considered as noise. Figure 5 shows an example of these three techniques; the blue line represents the active pixel numbers by time. Two peak areas are marked by the dashed black line and combined to get the area marked by red dashed lines which is considered as a motion period. In addition, short peak period circled by green lines are not considered as motion.

No motion detection means two different situations, either the user is stationary or there is no user on the bed. So, a presence detection is required. For the presence detection, the body part of the image is highlighted first based on a fixed threshold $T_h = 25°C$. And an adaptive T_p threshold is used for presence detection based on the size of the highlighted area. The T_p is updated according to the most recent frame data in which motion is detected.

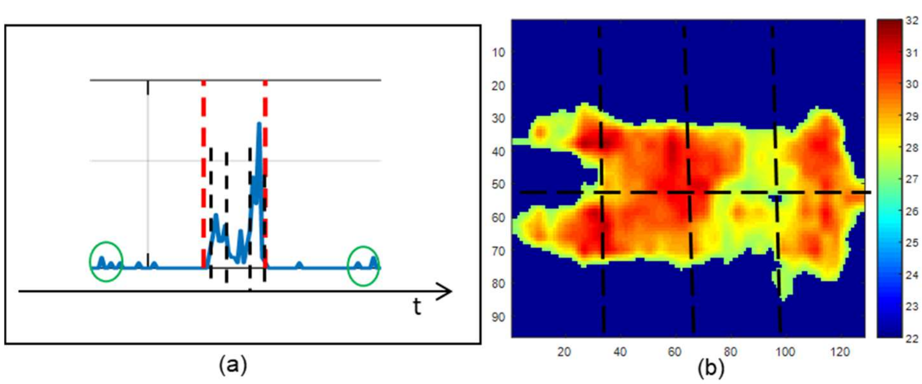

Figure 5 (a) Motion detection (b) Feature extraction

3.3 Feature extraction

Eighteen hand-crafted features are designed for posture classification. Table 1 summarized all the feature used for sleep posture detection. As the frame image is highlighted by a fixed threshold, a histogram can be achieved based on the highlighted part and four related features can be extracted from the histogram. Highlight area can also subdivided into eight equal areas. And the size of each area can be calculated as feature values.

Table 1 Feature used for posture classification

Feature ID	Description	Feature ID	Description
1-5	Thermal histogram value in the range of 25-30	9	Kurtosis of histogram
6	Mean of histogram	10	Area size of pixel with a value larger than the threshold
7	Variance of histogram	11-18	The proportion between the area size of pixel with a value larger than the threshold T_h within eight subdivisions of the image and the whole image (as shown in Figure 5(b)
8	Skewness of histogram		

3.4 Feature selection

Three kinds of feature selection methods are included in this paper. Univariate feature selection, tree-based feature selection and Recursive feature elimination (RFE). Univariate statistical tests for feature selection. It can be used to eliminate some unhelp features to reduce amount of calculation. Here the chi-squared test is performed to evaluate the importance of different features. Tree-based estimators can also be used to compute feature importance which in turn can be used to discard irrelevant features. As RF classifier reaches the highest accuracy, it is used to calculate feature importance. Recursive feature elimination (RFE) with cross-validation (CV) is used to find the best feature combination. RFECV is a kind of wrapper feature selection method which gets the better feature set by comparing the performance from difference feature sets. As it is very time consuming to calculate the performance of all different feature sets, RFE select features by recursively considering smaller and smaller sets of features. And during this process, cross-validation is performed to calculate accuracy for each feature sets selected in the RFE process.

3.5 Classification

Six classification methods are used in this paper, including logistic regression (LR), K-Nearest-Number (KNN), Random Forest (RF), Decision Tree(DT), Support vector machine (SVM) and Gradient Boosting Decision Tree (GBDT). fivefold cross validation is performed to compare the performance of different classifiers.

4. RESULTS ANALYSIS AND DISCUSSION

4.1 Sleep posture detection model selection and evaluation

The posture detection performance based on six classifiers are shown in Table 2. Fivefold cross validation is performed, and the random forest classifier reaches the highest accuracy. In addition, tree based classifiers including random forest can give a feature importance value based on note of trees[28]. So random forest will be used for posture classification and feature selection in the rest of this paper.

Table 2 Performance of different classifier

Classifier	Accuracy	Training time
LR	90.45%	0.043s
KNN	97.01%	0.001s
DT	88.41%	0.008s
RF	98.75%	0.235s
SVM	97.90%	0.218s
GBDT	96.25%	0.713s

Figure 1 shows the feature importance calculated from chi-squared test and RF classifier.

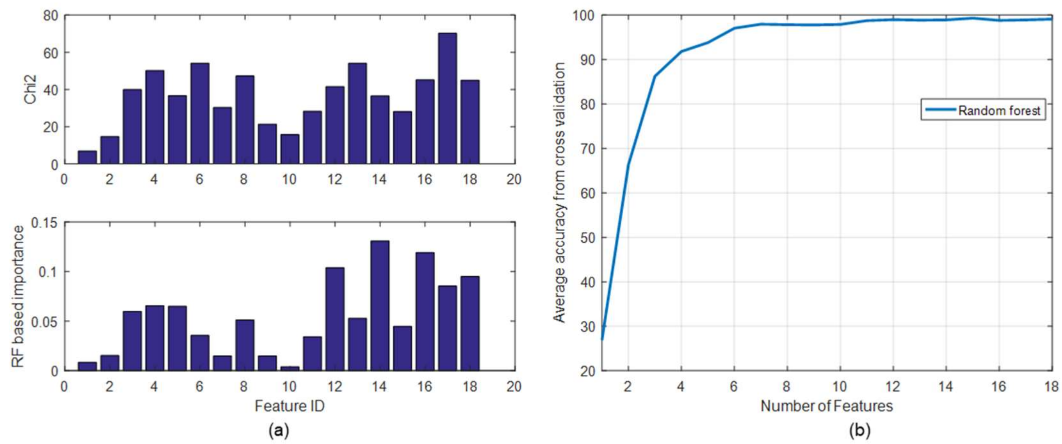

Figure 6 Feature selection (a) chi2 and RF based feature selection (b) RFECV

Figure 6(a) shows the feature importance calculated by using the chi square and the tree-based method. One can find that feature 1,2,7,9,10 have a low feature importance. And from RFECV method, one can get that the Random forest classifier reaches a highest accuracy of 98.9% with 12 features. The relationship between the feature number and the accuracy based on RFECV is shown in Figure 6(b). In addition, the feature space plotting based on the three important features: (14, 17, 18) are shown in Figure 7

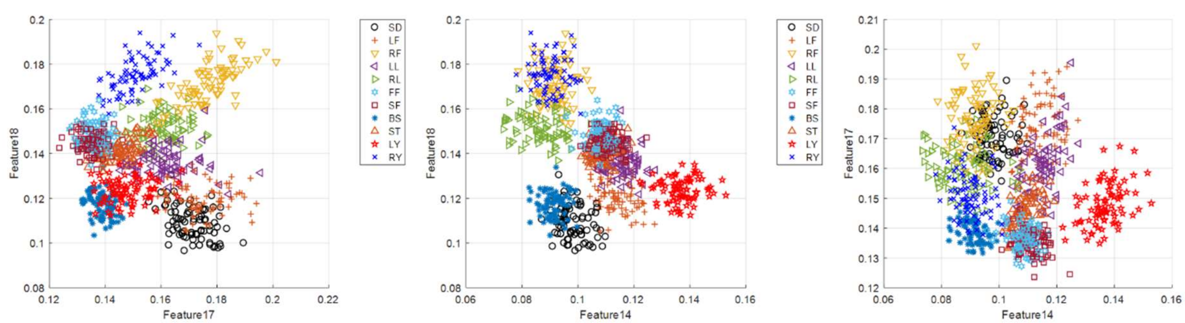

Figure 7 Feature space plotting based on feature ID 14 17 18

4.2 Presence, motion detection and sleep posture detection model verification

Figure 8 shows the motion and presence detection result in which eight motion periods are all correctly identified. And the presence detection also successfully identified the arrival and leaving of the user.

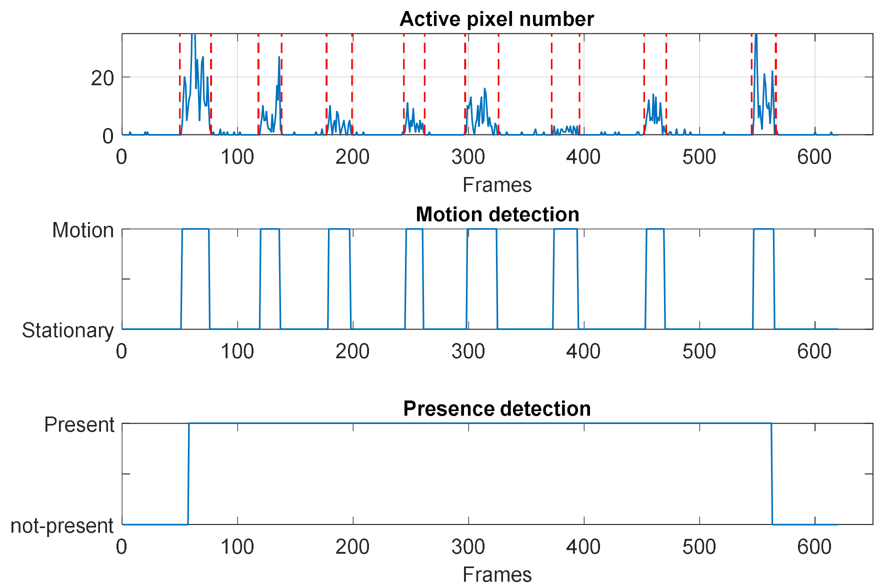

Figure 8 Motion and presence detection result

For model verification, the data of five postures from two human testing subjects are used as the training dataset and the six trails of continuous data from three human testing subjects are used as the testing dataset. By involving the data of a third testing subject who has not been included in the training dataset, the stability of the posture detection model can be verified. The overall accuracy for presence detection, motion detection and posture detection are 93.23%, 89.5% and 96.23% respectively. The details of accuracy for different postures are shown in Table 3. For clarification, the definition of motion detection accuracy is the proportion between the successfully identified motion period and the total motion period. The standard deviation is calculated based on the accuracy of three human subjects.

Table 3 Summary of model performance on continuous experiment data

Type	Average Accuracy	Standard deviation
Presence	93.23%	5.17%
Motion	89.5%	3.61%
Soldier(SD)	98.03%	0.36%
Left foetus(LF)	95.27%	0.94%
Right foetus(RF)	95.66%	0.44%
Free faller(FF)	92.32%	0.92%
Sitting on bed (ST)	85.01%	2.44%

Figure 9(a) shows the confusion matrix based on a single trail of continuous data, and the error bar plotting based on the data in Table 3 is shown in Figure 9(b).

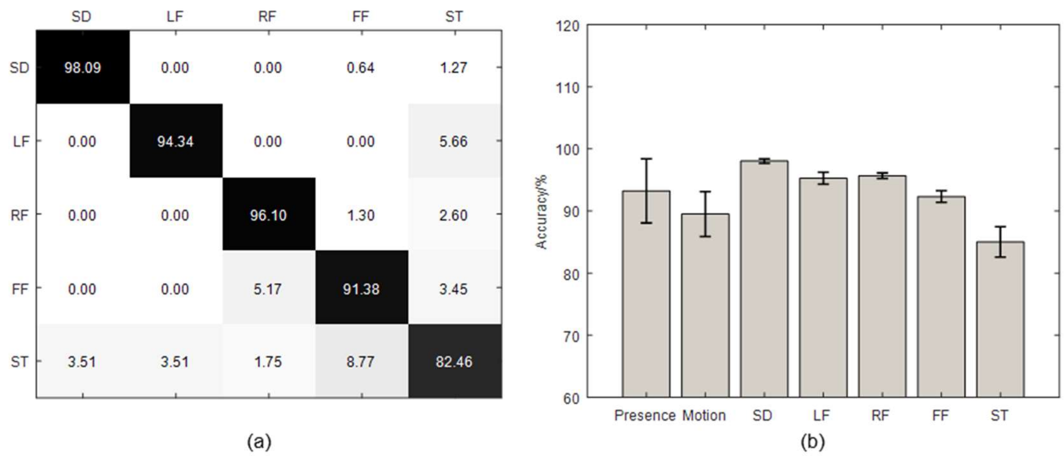

Figure 9 Continuous experiment data (a) Confusion matrix (b) accuracy summary

5. SUMMARY

In this paper, a sleep monitoring system is developed based on a thermal infrared array sensor to detect different sleep postures. The motion detection and presence detection during sleep has been proposed with an accuracy of 90%. And eleven different postures can be successfully identified with an accuracy of 98.75% using the discrete dataset. The experiment using the continuous data set has also reach 96% accuracy for five difference postures. The thermal infrared array sensor has the unique property of non-contact, non-privacy invasion and passive sensing. According to our work, it can provide an unobtrusive, low cost and convenient method of long-term sleep monitoring.

REFERENCES

[1] J. Kaartinen, I. Kuhlman, and P. Peura, "Long-term monitoring of movements in bed and their relation to subjective sleep quality," Sleep and Hypnosis, 5, 145-153 (2003).
[2] J. Razjouyan, H. Lee, S. Parthasarathy *et al.*, "Improving sleep quality assessment using wearable sensors by including information from postural/sleep position changes and body acceleration: a comparison of chest-worn sensors, wrist actigraphy, and polysomnography," Journal of Clinical Sleep Medicine, 13(11), 1301-1310 (2017).
[3] M. J. Peterson, N. Gravenstein, W. K. Schwab *et al.*, "Patient repositioning and pressure ulcer risk-Monitoring interface pressures of at-risk patients," Journal of Rehabilitation Research & Development, 50(4), (2013).
[4] N. A. B. Z. Abidin, M. A. B. As'ari, M. N. Jamaludin *et al.*, "Awakening Event Detection for Fall Prevention Among Bedridden Using Kinect-Like Depth Image."Proc. International Medical Device and Technology Conference(2017)
[5] A. Sadeh, and C. Acebo, "The role of actigraphy in sleep medicine," Sleep medicine reviews, 6(2), 113-124 (2002).
[6] C. Wrzus, A. M. Brandmaier, T. Von Oertzen *et al.*, "A new approach for assessing sleep duration and postures from ambulatory accelerometry," PloS one, 7(10), e48089 (2012).
[7] J. J. Liu, W. Xu, M.-C. Huang *et al.*, "Sleep posture analysis using a dense pressure sensitive bedsheet," Pervasive and Mobile Computing, 10, 34-50 (2014).
[8] V. Verhaert, B. Haex, T. De Wilde *et al.*, "Unobtrusive assessment of motor patterns during sleep based on mattress indentation measurements," IEEE Transactions on Information Technology in Biomedicine, 15(5), 787-794 (2011).
[9] J. J. Liu, W. Xu, M.-C. Huang *et al.*, "A dense pressure sensitive bedsheet design for unobtrusive sleep posture monitoring." Proc. IEEE PerCom, 207-215.(2013)
[10] Z. Chen, M. Lin, F. Chen *et al.*, "Unobtrusive sleep monitoring using smartphones." Proc. ACM PervasiveHealth, 145-152.(2013)

[11] J.-K. Min, A. Doryab, J. Wiese *et al.*, "Toss'n'turn: smartphone as sleep and sleep quality detector." Proc. ACM CHI,477-486(2014).
[12] J. Liu, Y. Chen, Y. Wang *et al.*, "Monitoring Vital Signs and Postures During Sleep Using WiFi Signals," IEEE Internet of Things Journal, 5(3), 2071-2084 (2018).
[13] F. Deng, J. Dong, X. Wang *et al.*, "Design and Implementation of a Noncontact Sleep Monitoring System Using Infrared Cameras and Motion Sensor," IEEE Transactions on Instrumentation and Measurement, 67(7), 1555-1563 (2018).
[14] J. Lee, M. Hong, and S. Ryu, "Sleep monitoring system using kinect sensor," International Journal of Distributed Sensor Networks, 11(10), 875371 (2015).
[15] L. Wu, and Y. Wang, "A Low-Power Electric-Mechanical Driving Approach for True Occupancy Detection Using a Shuttered Passive Infrared Sensor," IEEE Sensors Journal, 19(1), 47-57 (2019).
[16] Y. P. Raykov, E. Ozer, G. Dasika *et al.*, "Predicting room occupancy with a single passive infrared (PIR) sensor through behavior extraction." Proc. ACM UbiComp,1016-1027(2016).
[17] J. Lu, T. Zhang, F. Hu *et al.*, "Preprocessing Design in Pyroelectric Infrared Sensor-Based Human-Tracking System: On Sensor Selection and Calibration," IEEE Transactions on Systems, Man, and Cybernetics: Systems, 47(2), 263-275 (2017).
[18] H . Wang, H. Zheng, J. C. Augusto *et al.*, "Monitoring and analysis of sleep pattern for people with early dementia." Proc. IEEE BIBMW, 405-410(2010).
[19] R.-S. Hsiao, T.-X. Chen, M. A. Bitew *et al.*, "Sleeping posture recognition using fuzzy c-means algorithm," Biomedical engineering online, 17(2), 157 (2018).
[20] Y. Nam, Y. Kim, and J. Lee, "Sleep monitoring based on a tri-axial accelerometer and a pressure sensor," Sensors, 16(5), 750 (2016).
[21] A. Beltran, V. L. Erickson, and A. E. Cerpa, "Thermosense: Occupancy thermal based sensing for hvac control."Proc. ACM BuildSys,1-8(2013).
[22] A. Tyndall, R. Cardell-Oliver, and A. Keating, "Occupancy estimation using a low-pixel count thermal imager," IEEE Sensors Journal, 16(10), 3784-3791 (2016).
[23] Z. Chen, and Y. Wang, "Infrared–ultrasonic sensor fusion for support vector machine–based fall detection," Journal of Intelligent Material Systems and Structures, (2018).
[24] Z. Chen, Y. Wang, and H. Liu, "Unobtrusive Sensor based Occupancy Facing Direction Detection and Tracking using Advanced Machine Learning Algorithms," IEEE Sensors Journal, (2018).
[25] D. Qu, B. Yang, and N. Gu, "Indoor Multiple Human Targets Localization and Tracking using Thermopile Sensor," Infrared Physics & Technology, (2019).
[26] [SparkFun IR Array Breakout - 55 Degree FOV, MLX90640 (Qwiic)].
< https://www.sparkfun.com/products/14844>
[27] [Starfish or Freefall? What Your Sleep Position Can Tell You].< https://bettersleep.org/better-sleep/sleep-positions>
[28] P. M. Granitto, C. Furlanello, F. Biasioli *et al.*, "Recursive feature elimination with random forest for PTR-MS analysis of agroindustrial products," Chemometrics and Intelligent Laboratory Systems, 83(2), 83-90 (2006).