Non-intrusive sleep pattern recognition with ubiquitous sensing in elderly assistive environment

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RESEARCH ARTICLE

Non-intrusive sleep pattern recognition with ubiquitous sensing in elderly assistive environment

Hongbo NI (✉)[1], Shu WU[2], Bessam ABDULRAZAK[3], Daqing ZHANG[4], Xiaojuan MA[5], Xingshe ZHOU[1]

1 School of Computer Science, Northwestern Polytechnic University, Xi'an 710072, China
2 Center for Research on Intelligent Perception and Computing, National Laboratory of Pattern Recognition Institute of Automation, Chinese Academy of Sciences, Beijing 100090, China
3 Department of Computer, University of Sherbrooke, Sherbrooke JIK2R1, Canada
4 Handicom Lab, Institut Telecom SudParis, Evry 91011, France
5 Huawei Noah's Ark Lab, Hong Kong, China

Abstract The quality of sleep may be a reflection of an elderly individual's health state, and sleep pattern is an important measurement. Recognition of sleep pattern by itself is a challenge issue, especially for elderly-care community, due to both privacy concerns and technical limitations. We propose a novel multi-parametric sensing system called sleep pattern recognition system (SPRS). This system, equipped with a combination of various non-invasive sensors, can monitor an elderly user's sleep behavior. It accumulates the detecting data from a pressure sensor matrix and ultra wide band (UWB) tags. Based on these two types of complementary sensing data, SPRS can assess the user's sleep pattern automatically via machine learning algorithms. Compared to existing systems, SPRS operates without disrupting the users' sleep. It can be used in normal households with minimal deployment. Results of tests in our real assistive apartment at the Smart Elder-care Lab are also presented in this paper.

Keywords sleep pattern, elder-care, pressure sensor, UWB tags, Naïve Bayes, Random Forest

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E-mail: nihb@nwpu.edu.cn

1 Introduction

Sleep is one of humans' primary activities, as we spend a third of our life in bed. However, as reported by Ancoli-Israel in Ref. [1], about one-third of people, especially the elderly, have some kind of sleep problems. An aging study with over 9 000 subjects aged 65 and older found that more than 50% of older adults frequently experienced trouble falling asleep, difficulty in waking up or waking up too early, or having to nap from time to time but not feeling rested afterward [2,3]. These sleep disorders have a cumulative effect on the elderly's physical and mental health, and usually put the older adult at a greater risk of falls and even mortality, due to declined physical functionalities and memory.

As the life expectancy of human has increased significantly, the rate at which the population ages is likely to increase over the next three decades [4], and Nearly 180 million people in China were over 60 years of age in 2010, and that figure is expected to double in the next 20 years [5]. Many elderly people prefer to live alone and stay independent, despite their age-related degeneration in various aspects including sleep disorder.

Regular sleep pattern is unique for each sleeper, which consists of a sequence of body movements while sleeping.

For elderly people, changes in sleep pattern, e.g. abnormal increase in motor activities in sleep, may be a strong indicator of certain health problems [6]. Body movements refer to changing body postures to/from a lying position, turning from side to side, and repositioning the body while in bed. According to prior work that analyzed the distribution of behaviors during sleep [7–9], body movements can be divided into minor movements (actogram signal or head leads artifact) and major movements (actogram signal plus head leads artifact). Major movements in particular, are usually associated with changes in body posture, involving the head, arms, torso rotations, any combination of upper and lower limbs, and any combination of limbs and torso rotations. In other words, people's sleep pattern can be largely described by their body postures in sleep.

The objective of this work is to design and develop a convenient, unobtrusive and accurate sleep pattern monitoring system for elderly users, by tracking their body behaviors while sleeping at home. We focus on the five typical postures, namely, left-lateral sleep (LLS), right-lateral sleep (RLS), supine sleep (SS), prone sleep (PS) and getting up (GU). We apply a multi-parametric sensing approach to detect these postures. This approach employs a matrix of pellicle pressure sensors deployed in users' beds and six UWB tags embedded in users' pajamas.

The key contributions of this paper include:

- Introducing multi-parametric sensing into sleep behavior detection;
- Presenting the detailed design of our sleep pattern recognition system (SPRS) with multi-parametric sensors;
- Proposing various sleep pattern recognition approaches based on multi-parametric data.

The rest of this paper is organized as follows: Section 2 summarizes the related work in sleep detection. In Section 3, we describe the design of SPRS and Section 4 proposes the experimental method for sleep posture detection. Section 5 presents a sleep pattern recognition approach based on body postures, and evaluates its performance based on experimental results. Finally, Section 6 concludes this paper.

2 Related work

In this section, we summarize some of the representative work on continuous body movement sensing techniques for sleep monitoring in bed.

Traditionally, people use overnight polysomnograph (PSG) to record oractigraphy and perform assessment of sleep-related motor disturbances [6]. Although widely used and relatively reliable, polysomnography, which includes EEG measurement, is rather complicated with many restrictions on both subjects and examiners [10]. Another commonly used approach, actigraphy, requires activity monitors attached to a person's wrist or lower extremity [11,12] to assess nocturnal activity. It serves for long-term assessment, medical and behavior therapy in conditions such as insomnia and periodic limb movements during sleep (PLMS) [13]. Most of the actigraph models used in sleep studies can identify sleep and wake periods from the level of activity of patients, but only if patients specify their time periods in bed.

Accelerometers and RFID in combination can also detect movement in bed [14,15], and Paolo proposed a position recognition system which was composed of a sensor node placed on the breast of the patient and by fixed off-body motes connected to a server [16]. However these systems require patients to wear them all the time, which is rather inconvenient and may cause social stigma.

To reduce the burden on users and interference with their daily activities, researchers proposed to instrument the bed instead. Hoda developed a night monitoring and support system [17], NOCTURNAL, using bed sensors and passive infra-red (PIR) sensors, and tested the system with two clients. Unfortunately, this type of sensors can only obtain the basic status of the clients, namely in-bed or out-of-bed, but not any details of sleep patterns.

Several researchers have employed the static charge sensitive bed (SCSB) for monitoring motor activities [18]. The SCSB contains two metal plates with a wooden plate in the middle that must be placed under a special, difficult-to-built foam plastic mattress. Researchers have also looked into the force sensitive resistor. For example, Van der Loos proposed a sensing system called SleepSmart. It utilized a mattress pad with 54 force sensitive resistors and 54 resistive temperature devices to estimate the body center of mass and degree of restlessness [19]. Huang and Gaddam also used force sensitive resistors mounted under the mattress and the four legs of the beds separately [20,21]. Zhu et al. proposed an approach for long-term monitoring of respiration rhythm (RR), pulse rate (PR) and body movement (BM) during sleep [22]. These systems failed to distinguish different types of body movements and report their frequencies respectively. Furthermore, these systems contained some large-sized equipments that are difficult to set up and maintain outside of specific laboratories. Other sensing techniques, such as optical fibers and conductive fibers have also been explored. Witt proposed an embedded respiratory movement monitoring system using optical fibers [23]. Tang designed a vital sign's detection system, which used conductive fabric as the capacitive electrode for EEG measurements [24]. Technically, the fiber sensors can be woven into a conventional bed sheet, but practically they are too expensive for home use. Load cells placed at each corner of a bed is another approach studied in prior work [25]. Short-term analysis of the mean-square differences of the load cell signals cannot specify different sleep postures, only detecting the existence of body movements, and not applicable for specific sleep postures detecting.

On the other hand, recent development in wide-band impulse technology opens up space for new position location and object identification methods in a short-range environment. Consisting of low power communication along with unlicensed band, ultra wide band (UWB) is mainly used for localization in indoor navigation and surveillance applications [26–28]. In the domain of medical care, smart healthcare systems that apply UWB sensors have benefited patients in chronic conditions and under long-term health monitoring [29]. However, to our knowledge, little research has studied the use of UWB in sleep detection application.

Compared to previous sleep detection methods that are not applicable for home use, the unobtrusive sleep pattern recognition system (SPRS) for elderly care proposed in this paper adopts multi-parametric sensing technique, and can be easily deployed in an ordinary bed.

3 Description of the developed system

In this section, we present our sleep pattern recognition system (SPRS) in two steps. First, we demonstrate the framework and main components of SPRS; second, we describe the flexiforce sensor (FFS) Matrix and UWB sensors deployment.

3.1 The framework of SPRS

To this end, we have implemented the first phase of SPRS. Our goal is to develop a low-cost, multi-sensor, and unobtrusive sleep sensing platform that can accurately identify user's sleep and pattern, infer the quality of sleep, and provide personalized suggestions. Figure 1 shows the framework of SPRS.

SPRS contains four layers: physical sense layer for sensing the pressure and positioning; data acquisition layer to receive and send out the sensing data, posture detection layer to recognize sleep posture, and service provision layer to provide healthy services.

• Physical sense

This layer consists of a matrix of 32 pressure sensors and 6 UWB tags, which sense the body pressure and position respectively. In SPRS, we employed a novel type of pressure sensor named FlexiForce. The FFS is ultra-thin, low-cost and flexible. It applies the resistive-based technology and produces an analog signal. FFS appears as a variable resistor in an electrical circuit board. When it is unloaded, its resistance is very high (greater than 5 Meg-ohm); when the sensor detects an applied force, its resistance decreases. To trigger the FFS-Matrix, we developed a direct-current low-voltage driving power unit (DPU). We also utilize small UWB tags attached to the body to achieve accurate enough position information for recognition of sleep postures.

Service provision	Pattern recognition healthy reminder
Posture detection	Feature extract posture classify
Data acquisition	Data transform preprocessing
Physical sense	Sensors/driving power/networking devices

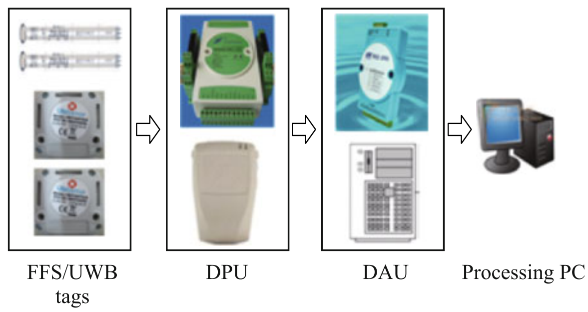

Fig. 1   The framework and main components of SPRS

• Data acquisition

This layer contains a data acquisition unit (DAU) responsible for processing analog signals and four UWB sensors (radio receivers) for calculating the location of UWB-signal transmitters (Tags). As shown in Fig. 1, DPU powers the FFS-Matrix and transmits the analog signals as electric currents. Then DAU receives and transforms these signals into digital data. As DAU connects with the Processing PC via the standard MODBUS RTU protocol, its output, the digitized data, correlates with the applied pressure but is not an absolute measure of pressure.

• Posture detection

This layer is a piece of modularized software running in the Processing PC. It has three components: a receiving module is a soft port that receives real-time digitized data from DAU as well as synchronized data from the UWB sensors; a forwarding module imports the data into a MySQL database for permanent storage and also feeds the raw data into the third component, a posture detection module. This module preprocesses the received data and analyzes users' sleep postures using classification algorithms.

• Service provision

This layer is responsible for inferring elderly users' sleep patterns and evaluating their quality of sleep, based on the sleep postures and duration information obtained from the previous layer. The results generated can serve as an important health indicator for elderly people and their caregivers. In addition, the system can offer recommendations on preferred sleep posture according to each elderly user's health condition [30]. For example, physicians generally suggest patients with coronary heart disease adopt a right-lateral sleep posture, and SPRS can alert the users whenever their sleep pattern is considered improper.

3.2 Sensors deployment

There are several challenges in sensor deployment under our framework of SPRS.

The first challenge is in our choice of FFS to monitor elderly users' sleep pressure in bed. These sensors are 203mm long 14mm wide, and 0.208mm in thickness, with three male square pins.

As shown in the right image in Fig. 2, there is an "active sensing area" at the end of each FFS sensor, which is circle 9.53mm in diameter. The application of a force to the active sensing area results in a change in the resistance of the sensing element, in inverse proportion to the magnitude of force applied. FFS is constructed of two layers of substrate, such as a polyester film[1]. We deployed two separate arrays of FFS sensors across the back and hip area on the bed, in order to monitor the change of pressures in these two body parts. To avoid a shift in position, we mounted the FFS sensors in each array on a 2m-by-0.75m pad. We placed the adjacent sensors 10cm apart from each other, which was considered the most proper arrangement for sensing old adults' body pressure according to our trial experiments. We may adjust this distance for other user populations. We placed the pads on the bed under the coverlet and on top of normal mattress, without any special installation. Note that we customized the measurements of the pads for king-size beds.

Since FFS is ultra-thin, the elderly participants would not experience any discomfort when sleeping on top of the sensor arrays. In other words, the FFS Matrix operates unobtrusively. Furthermore, we developed a 48-channel hub-like port to assemble assorted wires that connect the sensors, and placed it under the bed together with the DPU and DAU units.

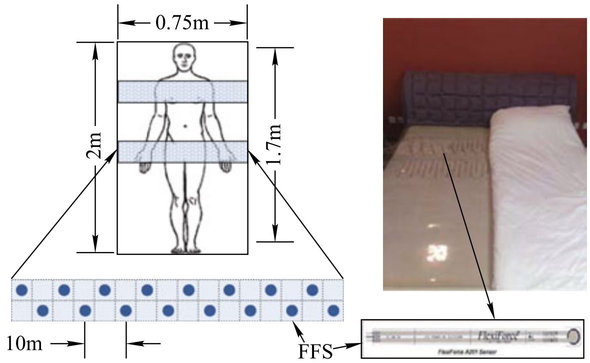

Fig. 2 The deployment of FFS matrix

Second, we innovatively introduced the UWB technology into sleep detection, which have many advantages for applications in elderly care, such as non-invasiveness, low power consumption, non-contact remote operation, biocompatibility, bio-friendliness, etc. [31]. In SPRS, the UWB positioning system adopted Ubisense, and consisted of 4 Ubisensors and 6 active Ubitags embedded in the pajamas on both sides (Fig. 3). Ubitags emit pulses of short duration over a bandwidth between 6–8GHz. Ubisensors captured these unidirectional UWB signals for location computation. In addition, control information is exchanged bi-directionally in the 2.4GHz band between tags and sensors. The UWB tags were so small (38mm × 39mm × 16.5mm, 25g) that we could obtain accurate position information without disturbing the users in sleep.

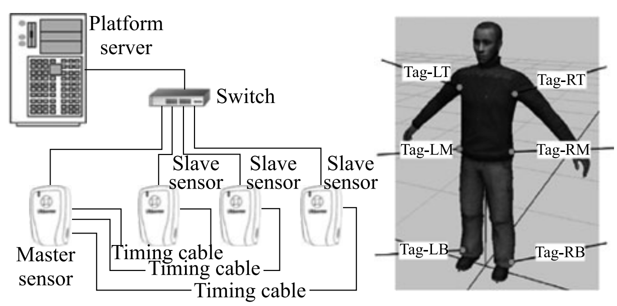

Fig. 3 UWB sensors and tags deployment in the SPRS

1) The website of Tekscan Int., http://www.tekscan.com/flexiforce/flexiforce.html.

Subject ID	Height (cm)	Weibht (kg)	Means (Pressure)
1	160	44	221
2	162	53	232
3	168	56	242
4	175	59	224
5	174	60	273
6	165	60	241
7	170	62	276
8	175	63	235
9	182	70	280
10	170	80	293

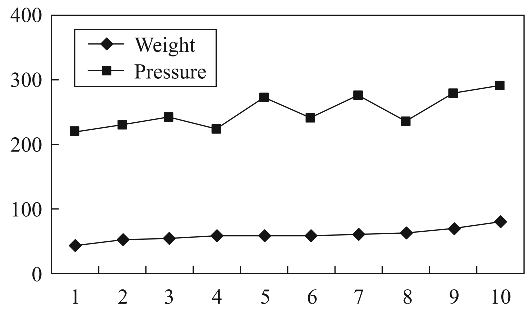

Fig. 4 Correlation between weight and pressure

4 Experiments description

In this section, we introduce our approach to collecting data from pressure sensors. In order to verify the usability of SPRS, we invited 10 subjects (eight males, two females) to participate in the study, whose body forms were very diverse (as seen in Fig. 4).

According to the literature, besides getting up (GU), the typical sleep postures are left-lateral sleep (LLS), right-lateral sleep (RLS) and supine sleep (SS), and prone sleep (PS) which is the most unusual (just 6.5% of the entire population)[2]. So we first collected the sensors' data as follows: every subject lay down on the bed with SPRS deployed the four postures, and got up twice separately during the process. More specially, the subjects' positions and respective gestures for sleep were not restricted, that is, they could lie on the bed however they wanted. Although there are many subclasses of sleep postures in a real world, this paper emphasizes on the four major classes, as a preliminary investigation of the validity of our approach. In the collection process of experimental datasets, we also implemented a camera to record the sleep postures of all subjects. Then in the preparation of the datasets, we label the sleep postures of each subject according to the recorded video, and treat these labels as the ground-truth data.

When a participant slept on SPRS, it forms an event that triggers the Data Acquisition component which then detected and synchronized the body pressure and position information. This event-driven mechanism enables the Data Acquisition component to monitor the transition between postures and update the sensor values in real-time.

The raw data obtained in the experiment, as mentioned in Section 3.1, were then sent to the MySQL database and the posture analysis module simultaneously.

[2] http://maisonbisson.com/blog/post/10182/claim-sleep-position-personality/

5 Result analysis and pattern recognition

In this section, we first discuss the relationship between body weight and the pressure value sensed. Then we will describe the attributes of the sensor data, UWB data and combined data. After introducing the sleep pattern classifiers and evaluation criteria, we present the study results in detail.

5.1 The relationship between weight and pressure

To explore the relationship between a subject's body weight and the pressure detected on the bed, we processed the data as follows. We computed the mean pressure of each participant by taking the average of the values generated from all the FFS sensors, as shown in Eq. (1):

$$\overline{P_i} = \sum_{j=1}^{N} p_j/N, \tag{1}$$

where $\overline{P_i}$ denotes the ith subject's mean pressure, p_j is the jth sensor's data, and N is the total number of pressure sensors.

Figure 4 shows the mean pressure is nearly proportional to the weight, which complies with the principle of the FFS. We will further verify this conclusion with a larger data set in future.

5.2 Data description

Our SPRS generates two kinds of sensing data, i.e. the FFS pressure data on the bed and the UWB positioning data from the pajamas. We observed 269 observations of three subjects and 419 postures produced by the ten subjects in the experiment. These observations are collected in different terms, in the spring term and fall term respectively. The main differences of these two datasets are the number of subjects and the observation number of each subject. In order to examine how the accuracy of posture recognition may change as the number of subjects increases, we compare the results of a smaller data set with 269 observations of three subjects (named Term1) and the results of the data set with 419 observations of ten subjects (named Term2). Furthermore, to investigate the effects of separated data source versus combined data sources on prediction accuracy, we separated the data into SensorData1, SensorData2, UWBData1, UWBData2, CombinedData1 and CombinedData2 as follows:

SensorData1 consisted of FFS sensor data of Term1, and the SensorData2 came from Term2. We classified each posture into one of the five categories: left-lateral sleep (LLS), right-lateral sleep (RLS), supine sleep (SS), prone sleep (PS) and getting up (GU). We pre-processed the data prior to the analysis. We replaced the missing value of an attribute with the mean of this attribute across all sensors, and then discretized the attribute values into 10 bins. Table 1 is a part of SensorData1, where S1 to S30 is the pressure value of 30 FFS sensors. It contains the information of the date and time, the value of sensors and the posture of subject when the sensors were active.

Table 1 Part of sensor data

Date-Time	S.1	S.2	S.3	S.4	…	S.28	S.29	S.30	Posture
100322234011	342	353	218	218	…	258	252	275	SS
100322234023	271	318	218	218	…	258	234	258	SS
100322234031	206	200	401	271	…	363	275	234	LLS
100322234103	206	200	406	265	…	369	275	234	LLS
100322234145	206	200	389	259	…	365	275	234	LLS
100322234357	206	200	395	259	…	258	258	234	PS
100322234406	212	206	395	259	…	228	228	240	RLS
100322234439	206	206	383	247	…	234	240	240	RLS
100322234441	206	206	377	247	…	258	246	240	RLS
100322234445	200	200	389	253	…	234	240	234	GU
…	…	…	…	…	…		…	…	…

We processed the UWB data in a similar way, but their structure is different from that of the FFS data. Table 2 shows samples from the UWB positioning data. The first attribute of the UWB data is the date and time when the positioning data of the corresponding UWB tag was received. The second attribute is the ID of the tags embedded in the pajamas. The last three attributes are the positioning coordinate values (x, y, z) of the UWB tag in the three dimension space. UWB system is much more sensitive than FFS pressure sensors, and can detect a slight change in the position of UWB tags. Pressure sensors usually detect signals every few seconds, while the UWB tags always send data to the receiver several times in one second.

For example, UWB detected nine position changes between the time stamp 15:31:45 and 15:31:50, while the pressure sensors were only triggered once.

Table 2 Part of UWB positioning data

Date-Time	Tag-ID	Coordinate Values (x, y, z)		
13-3-22 15:31:44.187	020-000-060-112	3.155	–1.520	0.443
13-3-22 15:31:44.671	020-000-116-081	3.866	–2.947	0.331
13-3-22 15:31:45.234	020-000-116-145	3.799	–1.889	0.543
13-3-22-15:31:45.765	020-000-117-008	4.010	–2.525	0.537
13-3-22 15:31:46.328	020-000-117-008	4.000	–2.549	0.493
13-3-22 15:31:46.843	020-000-117-026	3.347	–1.950	0.420
13-3-22 15:31:47.406	020-000-117-026	3.275	–1.956	0.486
13-3-22 15:31:47.968	020-000-116-081	3.709	–2.797	0.525
13-3-22 15:31:48.500	020-000-116-081	3.754	–2.816	0.604
13-3-22 15:31:49.31	020-000-116-145	3.749	–1.913	0.523
13-3-22 15:31:49.609	020-000-116-145	3.862	–1.857	0.604

To align FFS and UWB data, we computed the 10%-trimmed coordinate means of each UWB tag during the time interval between two activations of FFS sensors, and use the new numbers to represent a single UWB data point. If UWB receiver did not receive any signal from some of the tags in an one-time interval, it means that no change in the position of these tags was detected. We set the coordinate values of these tags as missing. For example, using the 10%-trimmed positioning means of each tag, the nine UWB observations from 15:31:45 to 15:31:50 are transformed into one vector, which contains:

13-3-22 15:31:45, (3.8033, –1.8863, 0.5567), (…), (3.7315, –2.8065, 0.5645), (…), (3.3110, –1.9530, 0.4530), (4.005, –2.537, 0.5150).

In this time interval, two coordinate values were missing. In the end, according to the time interval of pressure sensor activation, we transferred and assigned the modified UWB data of Term1 to 269 posture observations of three subjects (named UWBData1), and the modified UWB data of Term2 to 410 observations of ten subjects (named UWBData2).

Finally, we created the combined data sets by pulling the UWB positioning data and Sensor pressure data together. We concatenated the attributes of two data sets to compose a new data. The combined data sets had 48 attributes. The first 30 attributes were derived from the Sensor data (all the sensor value of sensor1 and sensor32 were the same, so we remove them), and last 18 attributes came from UWB data. This resulted in two combined data sets, CombinedData1 and CombinedData2. CombinedData1 is composed of SensorData1 and UWBData1, and similarly for CombinedData2 (Table 3). The first column is the time when the pressure data was recorded. The S.1 to S.30 columns are the pressure values of the Sensor 1 to Sensor 30 at the time. The U.1 to U.18 columns are the transformed positioning information of UWB tags. The last column is the sleep posture of this subject.

Table 3 Part of combined data

Date-Time	S.1	S.2	…	S.30	U.1	…	U.18	Posture
100322234011	342	353	…	275	3.716	…	0.574	SS
100322234023	271	318	…	258	3.745	…	0.643	SS
100322234031	206	200	…	234	3.536	…	0.191	LLS
100322234103	206	200	…	234	3.229	…	1.122	LLS
100322234145	206	200	…	234	3.691	…	0.674	LLS
100322234357	206	200	…	234	3.282	…	0.372	PS
…	…	…	…	…	…	…	…	…

5.3 Classifiers and evaluated validations

We adopted some classical machine learning methods to predict the sleep posture of testing observations based classifiers built on the training sleep posture data. These methods are naïve bayes (NB), naïve bayes tree (NBTree), random forest (RF) and radial basis function network (RBFN). They covered the major strategies of classification, i.e., bayes theory, decision tree, bagging and artificial neural network. Given that our pressure sensor and UWB data were high-dimensional with high interdependency among attributes, many classifiers, such as Decision Table and Bayesian Network, are not suitable for the task and thus were not implemented.

Naïve Bayes is a simple and fast probabilistic classifier based on the applying Bayes' theorem with the assumption of attribute independence [32]. Since NB has been shown to work very well in many complex real-world situations, we implemented it for our classification problem. However, the Sensor and UWB data are both highly correlated in theirs attributes, and the combined data also has strong interactions between the sensor and UWB attributes. This is somewhat conflict with the independence assumption of NB, and thus we implemented an improved NB method named Naïve Bayes Tree (NBTree) [33]. It is a hybrid of Naïve Bayes and Decision Tree, which does not work on the assumption of independent attributes.

A radial basis function network (RBFN) [34] is a three-layer artificial neural network using radial basis functions as activation. The output of this network is a linear combination of a set of radial basis functions. Many experiments [35] showed that RBFN is superior over other neural network approaches in accuracy and training time of prediction in pattern recognition tasks. Therefore, we selected RBFN as a representative of neural network approaches.

Since the test data set consists of numerous highly interdependent attributes, we need to examine the relationship among the attributes and different importance of dimensions carefully. Moreover, the lying position of subjects have a strong influence on the predict accuracy of many classifiers, we should use a roubust classifier which is sensitive to sequent pattern of observations. For these two reasons, we applied RF [34], which has advantages in detecting attribute relationship and handling the large data set. It is a robust ensemble classifier consisting of many decision trees and outputs the mode of individual trees.

To examine the ease of overfitting for the four classifiers adopted from different domains, we carried out two validations. In the 10-fold cross-validation, we randomly partitioned the data set into ten subsamples, one of which for testing and the rest for training. We repeated the process 10 times, using a different subsample for testing each time. The predict accuracy of 10-fold cross-validation is the average over 10 iterations. Leave-one-out cross-validation, as its name suggests, uses all but one data points for training, and repeats the process until every single data point has been picked for testing once.

Because of the limitation of length, in the experiments of separated Sensor and UWB data sets, we only analyzed and compared the predict results of NBTree and Random Forest. We applied all of the four methods (NB, NBTree, RBFN, and RF) to the combination data. More specifically, we set the parameters of RBFN and RF as follows. In RBFN, the ridge value for the logistic regression was 1.0E-8, the number of clusters for K-Means was 2 and the minimum standard deviation for the clusters was 0.1. In Random Forest, we generated 10 trees with six random attributes and infinite maximum depths.

5.3.1 Five postures detection on sensor data

In this Section, we analyzed the performance of our algorithms for sleep posture prediction based on the Sensor data. Tables 4 and 5 list the prediction results of the NBTree and the Random Forest classifiers under the two validation methods on SensorData1 and SensorData2. The values in the "Average" row are the weighted average accuracies of five posture predictions (LLS, RLS, SS, PS and GU). The RMSE represents the root mean squared error which measures the difference among prediction accuracies of these five sleep postures.

Compared with 10-fold cross-validation, the leave-one-out cross-validation has more training data and the predict accuracies were slightly higher than that of 10-fold in general. The average values of Table 4 and Table 5 both show that there is some improvement in prediction accuracy when we apply the classifiers with the leave-one-out validation. The prediction accuracy of NBTree decreases greatly from 95% to 80% when the number of subjects increases from three to ten. Under the same condition, the prediction accuracy of Random Forest also declines, but the difference is smaller than that of NBTree.

The results in Table 4 and Table 5 indicate that the Random Forest method is more stable than NBTree. The RMSE values of Random Forest are much smaller than that of Naïve Bayes, which means RF achieved more consistent prediction accuracies across the five sleep postures than NBTree.

Table 4 Prediction accuracy of SensorData1

	10-fold		Leave-one-out	
	NBTree	RF	NBTree	RF
LLS	1.000 0	0.980 4	0.980 4	0.980 4
SS	0.983 5	0.991 7	0.975 2	0.991 7
RLS	0.872 3	1.000 0	1.000 0	1.000 0
PS	0.954 5	0.954 5	0.931 8	0.981 8
GU	0.000 0	1.000 0	0.000 0	1.000 0
Average	0.940 5	**0.985 1**	0.951 7	**0.981 4**
RMSE	0.146 6	**0.019 0**	0.136 4	**0.009 5**

Table 5 Prediction accuracy of SensorData2

	10-fold		Leave-one-out	
	NBTree	RF	NBTree	RF
LLS	0.851 6	0.851 5	0.831 7	0.841 6
SS	0.818 7	0.871 3	0.848 0	0.871 3
RLS	0.659 8	0.835 1	0.701 0	0.845 4
PS	0.886 4	0.931 8	0.909 1	0.954 5
GU	0.166 7	1.000 0	0.166 7	1.000 0
Average	0.785 2	**0.866 3**	0.806 7	**0.868 7**
RMSE	0.248 0	**0.067 8**	0.184 3	**0.071 0**

5.3.2 Five postures detection based on UWB data

Similar to the previous finding, the predict accuracy of NBTree decreases faster than that of Random Forest as the number of subjects increase. NBTree attained fairly good prediction results with three subjects in Table 6, but the average accuracy dropped from 93% to 88% when the dataset extended to ten people (Table 7). On the contrary, RF only suffered 1% accuracy decrease given more subjects. One disadvantage of Random Forest method is that it is prone to over-fit with noisy datasets [31]. This is the reason why the Random Forest method achieved worse results in the leave-one-out evaluation than in the 10-fold evaluation. However, this problem could be alleviated in a real application with many training subjects.

The RMSE of NBTree and Random Forest both increased with the number of subjects, but faster with the former method. It is shown that in UWBData1 the RMSE of NBTree is smaller than that of Random Forest, while in UWBData2 it is the opposite. This suggests that the Random Forest method is more stable than NBTree in predicting different postures based on positioning data with larger number of subjects.

Table 6 Prediction accuracy of UWBData1

	10-fold		Leave-one-out	
	NBTree	RF	NBTree	RF
LLS	0.843 1	0.824 1	0.843 1	0.824 0
SS	0.983 5	0.967 0	0.983 5	0.983 3
RLS	0.872 3	0.957 1	0.872 3	0.936 4
PS	0.954 5	0.955 1	0.954 5	0.909 4
GU	1.000 0	0.833 4	1.000 0	0.833 4
Average	**0.933 1**	**0.933 1**	**0.933 1**	0.929 4
RMSE	**0.153 3**	0.160 6	**0.152 1**	0.162 3

Table 7 Prediction accuracy of UWBData2

	10-fold		Leave-one-out	
	NBTree	RF	NBTree	RF
LLS	0.910 9	0.950 0	0.910 9	0.921 0
SS	0.900 6	0.924 0	0.865 5	0.912 0
RLS	0.814 4	0.918 0	0.866 6	0.918 0
PS	0.840 9	0.886 0	0.863 6	0.955 0
GU	0.833 3	0.500 0	0.833 3	0.500 0
Average	0.875 9	**0.918 9**	0.880 7	**0.914 1**
RMSE	0.186 3	**0.174 7**	0.187 0	**0.174 8**

5.3.3 Postures detection based on combined data

As shown in the previous sections, we achieved good prediction performances with the pressure sensors and UWB tags respectively. To explore the potential of further improvement, we tried to use these two types of data in combination on sleep posture recognition tasks. The results in comparison with individual data type are shown in Figs. 5 and 6.

The Navie Bayes method assigns all attributes with the same weights and assumes that they are independent of one another [31]. However, in our combined data sets, the first 30 attributes and the last 18 attributes, although coming from two different data sources, describe the same behavior of the same subject, and thus are dependent on each other. If all the attributes are treated the same and the relationships among them are not considered, the prediction results of

Naïve Bayes on the combined data sets may be no better than that on each data set alone. On the contrary, taking the interaction among attributes into consideration may improve the performance of NB on combination data.

The prediction accuracy using Naïve Bayes classifiers was the highest on combined data when involving only three subjects (Fig. 5). But UWB data seemed to yield better results than sensor and combined data when scaling up to 10 subjects (Fig. 6). This suggests that the Naïve Bayes method is not reliable on these simply-combined and high-related data sets. The other classifiers not without any independence assumption all got better predictions using the combined data. Taking Random Forest as an example, it can compute the importance of each dimension and infer the relationships among all attributes in determining classification. Such ability allows RF to achieve better prediction on combined data, and even outperformed all the other classification methods (Figs. 5 and 6).

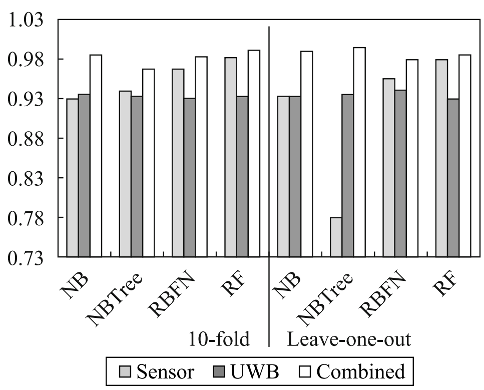

Fig. 5 Prediction accuracy comparison among SensorData1, UWBData1 and CombinedData1

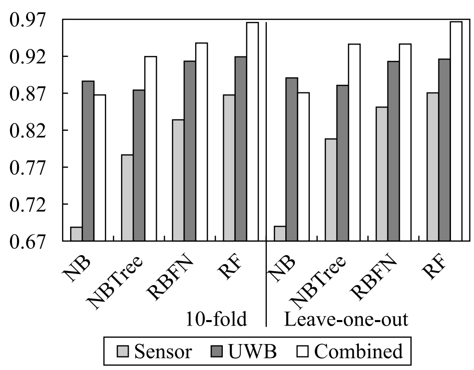

Fig. 6 Prediction accuracy comparison among SensorData2, UWBData2 and CombinedData2

Table 8 summarizes the detailed 10-fold evaluation results on combinedData1 and combinedData2. With combinedData1, the Random Forest method correctly recognized all observations of four postures, and the average accuracy was the highest among all classifiers. RF still outperformed the other methods given combinedData2, and even its slight decrease in accuracy was smallest of all. The classification accuracies of RF on CombinedData1 and CombinedData2 are 0.992 5 and 0.964 2 respectively. These experimental results indicates that the classification accuracies decrease slightly with increasing number of subjects, and performance on combined dataset decreases slightly comparing with the decrease on other classification methods, and also decrease slightly comparing with the decrease on the separate pressure and UWB datasets.

The RMSE value of Random Forest also implied that it is more stable than the other methods when the data came from more people (Fig. 9).

Comparison on RMSE values shows that predictions generated from combined data are generally more stable than that from individual datasets (Figs. 7 and 8). Most classifiers did not sacrifice the stability in exchange for improvement of accuracy.

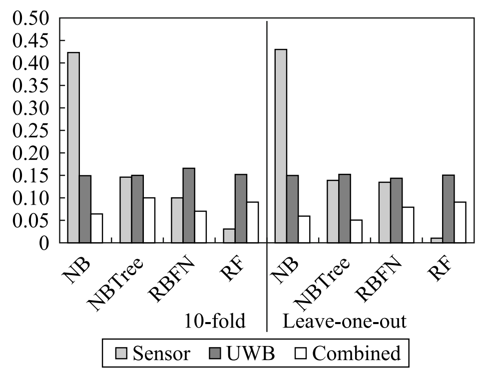

Fig. 7 RMSE of two prediction results on CombinedData1

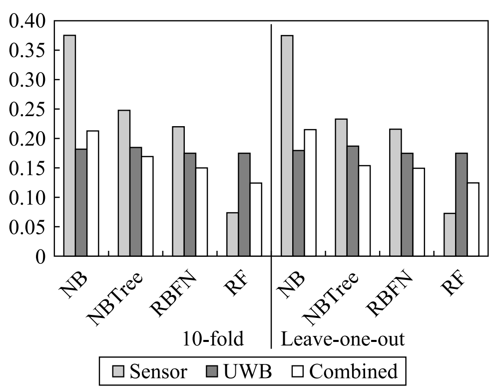

Fig. 8 RMSE of two prediction results on CombinedData2

To determine whether the differences in accuracy are statistically significant, we performed a pair-wise comparison among all methods (Table 9), as well as between the 10-fold and the leave-one-out validations (Table 10). Each cell in

Table 8 Detailed prediction accuracy of CombinedData1 and CombinedData2

	CombinedData1				CombinedData2			
	NB	NBTree	RBFN	RF	NB	NBTree	RBFN	RF
LLS	**0.983 5**	**0.983 5**	**0.983 5**	**0.983 5**	**0.748 5**	**0.929 8**	**0.941 5**	**0.959 1**
SS	**1.000 0**	**1.000 0**	**1.000 0**	**1.000 0**	**1.000 0**	**0.931 8**	**0.931 8**	**1.000 0**
RLS	**1.000 0**	**0.978 7**	**1.000 0**	**1.000 0**	**0.927 8**	**0.927 8**	**0.927 8**	**0.958 8**
PS	**1.000 0**	**0.941 2**	**1.000 0**	**1.000 0**	**0.960 4**	**0.901 0**	**0.960 4**	**0.970 3**
GU	**0.666 7**	**0.666 7**	**0.666 7**	**1.000 0**	**0.666 7**	**0.833 3**	**0.666 7**	**0.833 3**
Average	**0.985 1**	**0.970 3**	**0.985 1**	**0.992 6**	**0.866 3**	**0.921 2**	**0.937 9**	**0.964 2**
RMSE	**0.068 7**	**0.101 4**	**0.069 7**	**0.095 4**	**0.208 8**	**0.168 3**	**0.152 6**	**0.129 5**

the tables contains the number of data sets given which the method in the row wins, losses or ties to the method in the corresponding column on all the previous tests. We use a two-tailed T-Test [36] with a significant level of 0.01 to identify the winner in each pair of methods (A, B) on a given dataset. If the accuracy of method A was significantly higher than that of B, A was the winner, and vice versa. If there was no significant performance difference between the two, it was a tie. The pairwise comparison shows that Random Forest has better performances than all the other methods including radial basis function network (RBFN). It defeats every opponent in at least six tests, and only lost at most one round. RBFN is the second best algorithm, NBTree the third, and NB is the worst of all (Table 8).

Table 9 Significant test on different classifiers (Win/Lose/Tie)

	NB	NBTree	RBFN	RF
NB		3/5/4	0/8/4	0/8/4
NBTree	**5**/3/4		1/8/3	0/9/3
RBFN	**8**/0/4	**8**/1/3		1/6/5
RF	**8**/0/4	**9**/0/3	**6**/1/5	

Pairwise comparison showed that the performances of all classifiers in leave-one-out validation were not significantly different that in 10-fold validation in 18 out of 24 rounds of tests (Table 10). This suggests that the over-fitting problem of these classifers on our data sets was not so serious as anticipated.

Table 10 Significant test on two evaluated criterions (Win/Lose/Tie)

	10-fold
Leave-one-out	2/4/**18**

In addition, we examined the changes in predict accuracies when the number of subjects increased from three to ten (Fig. 9). Results showed that the accuracy of the NB method dropped the most, followed by NBTree and RBFN. The most reliable method was Random Forest, the prediction accuracy of which only dropped 2% when testing on ten subject's data. This suggests that RF is the most suitable classifier for sleep posture classification in practice.

Since some attributes in the data were highly correlated, we further explored if the prediction quality would be improved when only certain attributes were selected for classification. We conducted a simple test on the CombinedData2 with all features ranked and the most effective (top 10) features selected using the method in Ref. [36]. Similar to the previous experiments, we applied the four methods on the new data set with selective attributes and listed the results in Table 11. Results showed that NB performed better on the new selected data set than that on the original data, since the attribute selection process removed most of the dependency. In contrast, the other three methods did not benefit from the process, since they have already implicitly considered the relations across attributes.

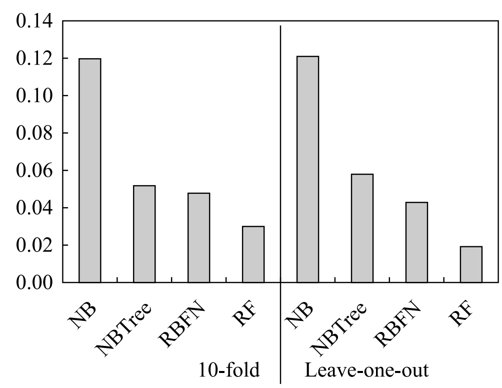

Fig. 9 Decreasion of predict accuracy from three subjects to ten subjects on Combined Data

Table 11 10-fold results on the original CombinedData2 dataset and dataset with attribute ranking and selection

	CombinedData2			
RMSE	NB	NBTree	RBFN	RF
Without Attribute Section	0.866 3	**0.921 2**	**0.937 9**	**0.964 2**
With Attribute Selection	**0.923 6**	0.911 7	0.930 8	0.954 7

5.4 Sleep and turn-over patterns of one subject

In this section, we collected the sleep posture data from one subject and analyzed his sleep posture and turn-over pattern in depth. For each subject, the stream of sleep postures is specific, since the probabilities of sleep posture and the probabilities of turn-over status should be employed for the classification of sleep posture. The analysis in this section can help us in developing a more precious and reliable detection method for sleep posture in future.

We monitored his sleep behaviors in bed and recorded information gathered over the pressure sensors and UWB positioning devices for a week. The data were processed and combined as described in Section 5.2. We used part of the data for training and implemented the random forest method to predict the subject's sleep posture. The prediction was fairly reliable as previous experiment with three subjects, and has achieved 99% accuracy. We further extracted the duration of each sleep posture from time series information, analyzed the distribution of various sleep postures, and calculated the probability of different turn-over behaviors.

The distributions of duration of different sleep postures are demonstrated in Fig. 10. It indicates that RLS and SS are the most frequent sleep postures of the subject, followed by LLS. The PS is the rarest of all.

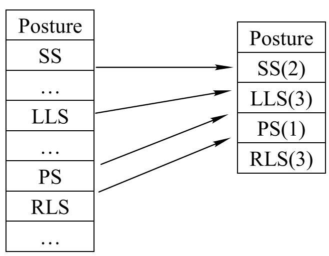

Fig. 10 Time length distribution of different postures

Theoretically, there are eight different kinds of different turn-over. In order to obtain their distribution, we removed the time stamps and only kept the order information of the postures. In other words, the data was simplified into an ordered stream of different sleep postures. One continuous posture was only counted once regardless of its length. . The time series of sleep posture of Table 6 was compressed in a way shown in the following Fig. 11.

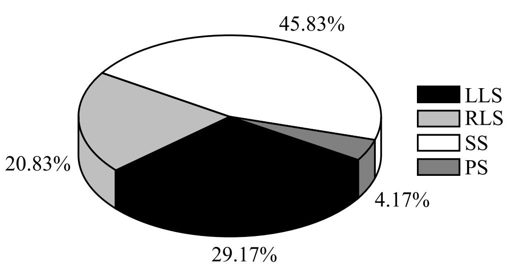

Fig. 11 Summarization of the different postures

Since the get-up behavior was not taken into consideration, we obtained four turn-over statuses from the table above, that is SS->LLS, LLS->PS and PS->RLS. We extracted all turn-over behaviors from the week-long observation data, and computed their probability of occurrence (Fig. 12).

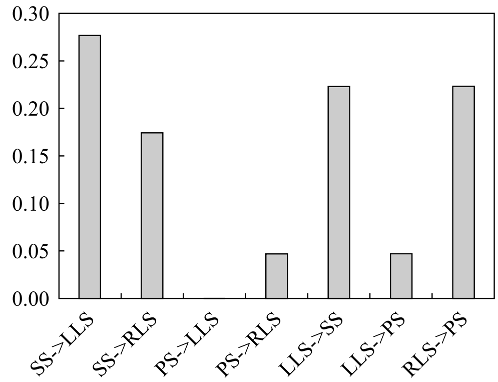

Fig. 12 The probabilities of eight kinds of turn-over

Results showed that the SS->LLS was the most common turn-over behavior for the subject LLS->SS and RLS->SS the second, followed by SS->RLS. The PS->RLS and LLS->PS seldom occurred when the subject was asleep, and the PS->LLS and RLS->PS were never observed. For instance, if a subject was in the prone sleep posture, then the probability of left-lateral sleep in the next time is very low. On the other hand, when the previous posture of this subject is prone, the probability of right-lateral sleep should be very high in the next time.

Such analysis denotes the normal sleep pattern of the corresponding subject. With this information, we can further analyze his/her dynamic sleep posture to improve the classification accuracy of sleep postures further and detect abnormal sleep behavior of the subject in the future.

5.5 Discussion

In this part, based on the real data obtained by the pressure sensors and UWB tags, we adopted some classical machine learning methods to predict the sleep pattern of testing observations based classifiers built on the training sleep posture data. These methods are naïve bayes (NB), naïve bayes tree (NBTree), random forest (RF) and radial basis function network (RBFN). As seen in the various experiments and comparative methods, on the one hand, we can achieve more precise prediction accuracy with combined data than the single data (pressure or UWB); on the other hand, we can believe the most reliable method was Random Forest, e.g., the prediction accuracy of which only dropped 2% when testing on ten subject's data. This suggests that RF is the most suitable classifier for sleep pattern classification in practice.

6 Conclusions and future work

This paper proposed an unobtrusive sleep pattern recognition system using a multi-parametric sensing technique with ultra-thin pressure sensor matrix and UWB tags. This system has multiple advantages over existing approaches. First, it does not place any burden on the target users, i.e., elderly people at sleep (as does PSG). Second, it captures the movements of the entire body, rather than focusing on one specific body part (i.e., actigraphy). Third, the system detects not only the body movement is detected, but also a complete set of motion-related parameters, including detailed information on sleep patterns.

Evaluating on empirical data, we proved that the proposed solution is a viable way to monitor the elderly users' sleep postures and recognize their sleep pattern. In the future, we will detect more specific postures for more accurate sleep pattern recognition. We also plan to work on detection of abnormal sleep behavior, and carry out a field study with actual elderly users at home.

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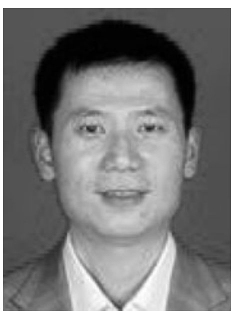

Hongbo Ni is an associate professor from the School of Computer Science, Northwestern Polytechnical University, China. He received his BS and PhD from Northwestern Polytechnical University, and worked as a research fellow in the Department of Information Systems, Sherbrooke University, Canada from 2009 to 2010. He has published more than 40 academic papers, served as publicity/session chair and program member for a number of conferences. His research interests include pervasive computing, embedded computing and system.

Shu Wu received his BS from Hunan University, China in 2004, and his MS from Xiamen University, China in 2007, both in computer science. He received his PhD from Department of Computer Science, University of Sherbrooke, Canada. He has joined Center for Research on Intelligent Perception and Computing at National Laboratory of Pattern Recognition, Institute of Automation, Chinese Academy of Sciences, where he works as an Assistant Professor. His research interests include data mining, information retrieval and recommendation systems.

Bessam Abdulrazak is an associate professor in the Department of Information Systems, Sherbrooke University, Canada. He received his PhD from national telecommunication university in Paris, France. He has published more than 100 academic papers, and served as general chair for a number of conferences. His research interests include Human-Computer Interaction, pervasive computing.

Daqing Zhang is a professor from Institut Mines-Telecom of Telecom SudParis, France. He obtained his PhD from University of Rome "La Sapienza", Italy in 1996. He is the associate editor of four journals including ACM Transactions on Intelligent Systems and Technology, Journal of Ambient Intelligence and Humanized Computing, etc. He also served in the technical committee for conferences such as UbiComp, Pervasive, PerCom, etc. His research interests include ubiquitous computing, context-aware computing, big data analytics, and social computing.

Xiaojuan Ma is a Researcher at Huawei Noah's Ark Lab. Prior to that, she was a Computing Innovation Post-doc Fellow in Human-Computer Interaction Institute, Carnegie Mellon University, USA. She received her bachelor's degree from Tsinghua University, China, and PhD from Princeton University, USA, and worked as a research fellow in the Department of Information Systems, National University of Singapore, Singapore in 2010. Dr. Ma's background is in Human-Computer Interaction. She is particularly interested in multimedia-augmented communication in both human-human and human-robot interactions, design, visual/auditory perception, and (computational) linguistics.

Xingshe Zhou is a professor from the School of Computer Science, Northwestern Polytechnical University, China. He is the director of Shaanxi Key Laboratory of Embedded System Technology, China. He has published more than 100 academic papers, and served as general chair or program chair for a number of conferences. His research interests include embedded computing, distributed real-time computing, and pervasive computing.