Unobtrusive Sleep Posture Detection for Elder-Care in Smart Home

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Abstract. Quality of sleep is an important attribute of an elder's health state and its assessment is still a huge issue. The sleep posture is a significant feature to evaluate the quality of sleep, and how to detect elder's sleep posture is a key challenge in elder-care community. This paper proposes an unobtrusive sleep postures detection solution and introduces pressure sensor matrix to monitor the elder's sleep posture in bed. Based on the proposed sleep detection system, the processing methods of experimental data and the classification approaches for sleep posture detection are also discussed.

1 Introduction

Sleep is essential to people's physical health and emotional well-being, and most people will spend one-third of lives in bed. But, in fact, complaints of sleep difficulty are common among the elder. In an aging study of over 9000 subjects aged 65 and older, more than 50% of older adults reported frequent trouble falling asleep, difficult waking or waking too early, or needing to nap and not feeling rested [1].

Sleep disorders are under-recognized public health problems that have a cumulative effect on elders' physical and mental health, and usually put the older adult at greater risk for decreased physical functioning, problems with memory, increased risk of falls and mortality. Meanwhile, sleep disorders in the elder almost involve abnormal behaviors in the bed, which are also an important marker associated with health-related diseases, including congestive heart failure, cancer, nocturia, shortness of breath due to chronic obstructive pulmonary disease, neurological deficits related to cerebrovascular accidents, and Parkinson's disease [2].

As the proportion of aged people in the population increases, a simple and minimally invasive detecting the sleep behaviors in the bed should be developed to maintain the elders' health. Unfortunately, there are no convenient, unobtrusive and accurate ways to obtain elder's body behaviors during sleep outside of a clinic.

This paper will meet the challenge from monitoring the elder's sleep behaviors using a novel and unobtrusive approach. Body movement is generally considered to be an important index in the analysis of sleep behavior shifts in sleep physiology [3].

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The term ‘body movements’ can be described by body postures changing to/from a lying position, to turn from side to side, and to reposition the body while in bed. In the literature to analyze the distribution of behaviors during sleep [4], body movements were classified as minor movements (actogram signal or head leads artifact), major movements (actogram signal plus head leads artifact). Major movements usually are 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. So, given a time interval, the body movement can been detected by the sleep posture. In this paper, we will concentrate on the three typical normal sleep postures, including left-lateral sleep (LLS), right-lateral sleep (RLS) and supine sleep (SS), and these postures will be detected by a matrix of pellicle pressure sensors deployed in the bed. By detecting the sleep postures, the authors try to recognize the elder’s sleep behaviors in bed in a non-invasive means.

The key contributions in this paper include: i) Introducing pressure sensors into sleep detection; ii) Presenting the detailed design of sleep detection system; and iii) Proposing a sleep postures detection approaches based on pressure 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 sleep detection system with pellicle pressure sensors; section 4 presents the experimental method for sleep posture detection; section 5 proposes the experiments analysis and performance evaluation; finally section 6 presents the conclusion of this paper.

2 Related Work

Many sleep sensing approaches have been proposed for assessment of body behaviors in bed, in this section, we will describe some of the representative work on continuous sensing of body behaviors (movements) in bed.

The assessment of sleep-related motor disturbances is traditionally performed by overnight polysomnograph (PSG) to continuously record oractigraphy[5]. Although polysomnography, which includes EEG measurement, is a widely used and reliable method, the technique is rather complicated and both subject and examiner are seriously restricted [6]. With actigraphy, activity monitors are attached to a person’s wrist or lower extremity [7] to assess nocturnal activity. It is commonly used for long-term assessment and medical and behavior therapy in conditions such as insomnia and periodic limb movements during sleep (PLMS) [8]. Most of the actigraph models used in sleep studies can determine sleep and wake periods from the level of activity of the patient, but their algorithms only provide accurate sleep/wake periods if the patient provides bedtimes and get up times.

Besides, accelerometers and RFID can also be used to assess movement in bed [9], but they also place a burden on the subject because the patient has to wear them all the time.

Another important approach in this field is to assess sleep behaviors in bed in a continuous and unobtrusive way by instrumenting the bed itself. Tamura et al. [10] proposed a bed temperature measurement system for detection of body movement. The system detects torso and leg movements by placing arrays of 15 thermistors under the waist and under the legs. The system only reports the frequency of movements and time in bed, and does not classify the type of movement. Several authors [11] have employed the static charge sensitive bed (SCSB) for monitoring of motor activity. The SCSB is composed of two metal plates with a wooden plate in the middle that must be placed under a special foam plastic mattress, which will be difficult to bulid. Van der Loos also proposed a sensing system called SleepSmart, composed of a mattress pad with 54 force sensitive resistors and 54 resistive temperature devices, to estimate body center of mass and index of restlessness [12]. The system does not report the frequency and type of movements, and this large-size equipment is difficult to set up and can only be used in specific laboratories. Other sensing techniques, such as optical fibers and conductive fibers have also been used for monitoring body movement in bed. Tamura proposed a body movement monitoring system using optical fibers [13]. Kimura designed an unobtrusive vital signs detection system, which uses conductive fiber sensors to detect body position, respiration, and heart rate [14]. Technologically, the fiber sensors can be incorporated in a conventional bed sheet, but obviously it will be costly and not applicable for home use. The use of load cells is another approach to detect body movements in bed [15], in which load cells is placed at each corner of a bed. The detection of movements is based on short-term analysis of the mean-square differences of the load cell signals, and not applicable for specific sleep postures detecting.

As mentioned above, the previous solutions are not applicable for sleep detection in home in a non-invasive way, and this paper proposes an unobtrusive sleep posture detection system for elder-care, which is relatively cheap and easy to deploy in a common bed without any special alteration.

3 System Development

In this section, we will discuss our sleep detection system (SDS) in two aspects. On the one hand, we will address the framework and main components of SDS; on the other hand, we will also describe the FFS Matrix deployment.

3.1 The Framework of SDS

To date, we have implemented SDS in the first step, and the goal of SDS is to develop a low-cost, multi-sensor, modular, unobtrusive sleep sensing platform that accurately infer the sleep posture, discover the sleep pattern and provide personalized suggestions in future. The framework of SDS can be seen in Fig.1, and there are four levels in it, including physical sense level, data acquisition level, posture detection level, and service provision level.

Physical Sense: The level consists of a matrix of 32 pressure sensors and a Driving Power Unit (DPU) to sense the body pressure. In SDS, we chose a novel type of pressure sensor named FlexiForce. The Flexiforce sensor (FFS) is ultra-thin, low-cost and flexible. FFS is resistive-based technology and will produce an analog signal. FFS acts as a variable resistor in an electrical circuit. When the sensor is unloaded, its resistance is very high (greater than 5 Meg-ohm); when a force is applied to the sensor, the resistance decreases. To trigger the FFS-Matrix, we applied a direct-current low-voltage driving power unit (DPU). For ensuring the scalability of FFS, we customized a multi-channel port for DPU, and it can support 80 FFSs.

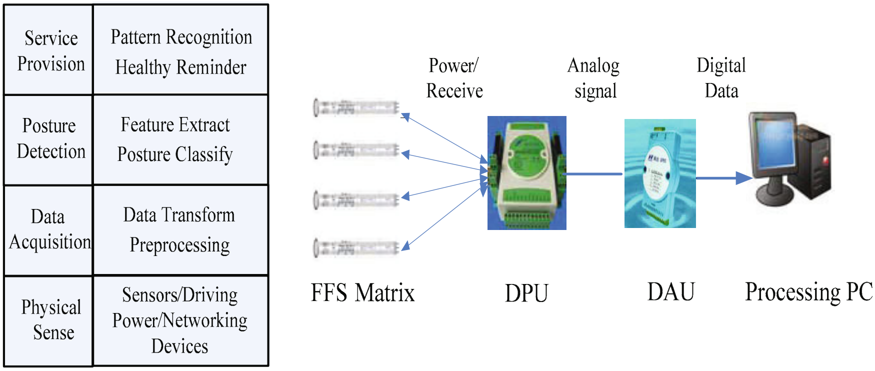

Fig. 1. The framework and main components of SDS

Data Acquisition: This level includes a Data Acquisition Unit (DAU) to process the analog signal. As seen in Fig. 1, DPU power the FFS-Matrix and transmits the analog signals as current, and then the DAU receives and transform these signals into digital data. Concurrently, DAU will also connect with the Processing PC with the Standard MODBUS RTU protocol, and its output is a digitized data that is correlated to the applied pressure but is not an absolute measure of pressure.

Posture Detection: This level is modularized software residing in the Processing PC, including three parts: the receiving module is a soft port to receive real-time digitized data from the DAU; the forwarding module is to input the data into MySQL database for permanent storage and also feed the raw data into posture detection module, which is finally to preprocess the received data and analysis the elder's sleep posture using classification algorithms.

Service Provision: Based on the sleep postures and their duration, we can infer the elderly user's sleep pattern, and evaluate the quality of sleep. On the one hand, the important healthy information will be fed back to the elder and his caregiver; on the other hand, the preferred sleep posture is usually recommended according to the elder's own disease [17], for example, an elder with coronary heart disease is generally suggested a right-lateral sleep posture, thus SDS will also provide necessary reminder to the elder when the sleep pattern is improper for his health. This part is under developing and we will report our progress in future.

3.2 Sensors Deployment

Besides the framework of SDS, we must meet the challenge of sensors deployment. Based on the investigation, we choose FFS to monitor the elder's sleep pressure in bed, which is 203mm long, 14 mm wide, and 0.208 mm thick, with 3 male square pins.

As seen in Fig.2, there is an "active sensing area" at the end of the sensor, which is a 9.53mm diameter circle. The application of a force to the active sensing area of the sensor results in a change in the resistance of the sensing element in inverse proportion to the force applied. FFS is constructed of two layers of substrate, such as a polyester film [16]. Meanwhile, known from common sense that the elder's body posture is mainly relied on his trunk, hence the FFS Matrix was deployed as seen in Fig.2, and there are two arrays to monitor the body pressure of back and hip separately. To ensure the accuracy, these two FFS arrays are fixed onto a flexible and rigid pad, and which occupies 2M by 0.75M, with sensor elements spaced 10 CM apart. The pad is placed on the bed under the coverlet and on the top of normal mattress, without any special installation requirement. Please note, this is the first step of our implementation, and the normal width of this material is 0.75M (we have booked a customized king-size pad from the vendor). Moreover, the 10CM-distance between the FFSs is from our trial experiments, which is proper arrangement for detecting an adult's pressure. We will try more experiments and adjust the distance if the solution applied to child-care.

Since FFS is ultra-thin and non-invasive, the elder will not feel any uncomfortable for FFS Matrix and can be easy to accept the unobtrusive monitoring manner. Furthermore, we developed a 48-channel hub-like port to assemble so many wires connecting sensors, which is placed under the bed together with DPU and DAU.

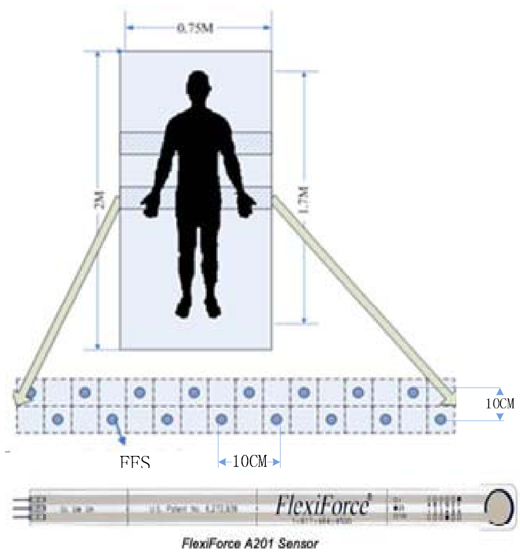

Fig. 2. The deployment of FFS Matrix

4 Data Collection

In this section, we will introduce the approach of collecting data from pressure sensors. In order to verify the usability of SDS, we selected ten students (8 men, 2 women; ages 21 to 26 years) with no mobility problems participated in the study, and especially their body forms are very diverse. Table 1 shows the height, weight, and the mean pressure of each subject. From Fig.3, we can get the first expression of SDS's characteristics, and the approximate curve fitting shows that the mean pressure is nearly proportional to the weight, which is comply with the principle of the FFS, and we would confirm it by a larger data set in future.

Table 1. Height,Weight and Mean Pressure of Subjects

Subject ID	Height (CM)	Weight (KG)	Mean Pressure
1	170	80	293
2	162	53	232
3	174	60	273
4	160	44	221
5	182	70	280
6	165	60	241
7	168	56	242
8	175	59	224

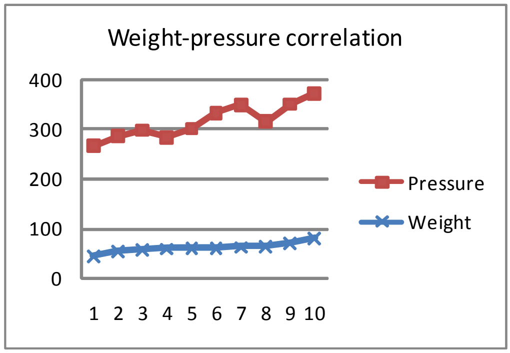

Fig. 3. Qualitative correlation between weight and pressure

The sensors' data were collected from the experiments as follows: every subject slept on the SDS for 15 times in turn, and randomly lied in the left-lateral sleep, right-lateral sleep and supine sleep for 5 times separately. Please note, the subjects' positions and respective gestures for sleep were not restricted, that is, they lied in the bed as they preferred. Although there should be more postures in real world, this paper is to report the primary work of our solution, and we will do more experiments to verify the system in near future. After the experiments, 150 groups of raw data were obtained, and as mentioned in 3.1, the data was sent to the MySQL database and the posture analysis module simultaneously.

5 Posture Detecting and Performance Evaluation

To analyze the experimental data and detect the sleep posture, we implement two classification methods to predict the sleep posture of a new observation based on the training sleep posture data set. The first one is Naïve Bayes. Since Naive Bayes classifier, which is a simple probabilistic classifier based on applying Bayes' theorem with attribute independence assumption has worked quite well in many complex real-world situations, it is implemented on our data set. Meanwhile, since the sleep data set is a high-dimension data set, the different importance of dimensions may impact the result significantly. For this reason, we import the Random Forest method, which has advantage in estimating weight of dimensions and is suitable for high-dimension data set.

Two evaluated validations are involved into the analysis of the experimental results, 10-fold cross-validation and leave-one-out cross validation. In the 10-fold cross-validation, the sleep data set is randomly partitioned into 10 subsamples. In the 10 subsamples, one subsample is retained as the testing data, and the remaining 9 subsamples are used as training data. This cross-validation process is then repeated 10 times with each of the 10 subsamples used once as the test data. The predict accuracies of 10-fold cross-validation in the following tables are the average result of 10 tests from the folds. As the name suggests, leave-one-out involves using a single observation of the sleep data set as the test data, and the remaining observations as the training data. This is repeated such that each observation in the sample is used once as the validation data. The predict accuracy is the average predict result of 150 times tests.

As mentioned in section 4, the data set contains 150 observations belonging to 3 kinds of sleep postures, which are left-lateral sleep, right-lateral sleep and supine sleep. Before the data analysis, we have tried some typical pre-processes on the data set, for example, discretize, normalization, but the classification accuracy of the data set is decreased. Therefore, the classification methods are implemented on the raw data set. The results of two classification methods and two validation processes are list in the table below.

Table 2. Predict Accuracy with Two Cross-Validations

	10-fold		Leave-one-out	
	Naïve Bayes	Rand om	Naïve Bayes	Rand om
LLS	0.620 0	0.8600	0.6000	0.8800
S	0.660 0	0.8600	0.6800	0.8800
RLS	0.760 0	0.8600	0.7800	0.8600
Averag	0.680 0	**0.8600**	0.6867	**0.8733**

Comparing with 10-fold cross-validation, the leave-one-out cross-validation has more training observations than 10-fold, so the predict accuracy of leave-one-out validation is slightly higher than 10-fold. The Table 2 also shows the Naïve Bayes and Random Forest method both have a little improvement of predict accuracy on the leave-one-out validation test contrasting with the 10-fold.

We analyze the result in the leave-one-out validation. The Table 2 indicates that when we use the Random Forest as the classification method, it provides us almost 90% accuracy to predict the sleep postures, while the Naïve Bayes attains the accuracy about 69%. The Random Forest method performs over Naïve Bayes method in classifying this high-dimension data set. The table 2 also indicates that the Random Forest method is a stable method. Three sleep postures have similar predict accuracies. While in the Naïve Bayes method, left-lateral sleep has the lowest predict accuracy 60%, while the highest predict accuracy is the right-lateral sleep 78%. Compared the results of these two methods, the Random Forest method has higher predict accuracy and attains more stable results than the Naïve Bayes method in our sleeping postures data set.

6 Conclusions and Future Work

This paper proposed an unobtrusive sleep postures detection system based on a kind of ultra-thin pressure sensor matrix. We presented the design of sensors deployment and the implementation of the sleep detection system. Moreover, based on the experiments, we discussed the data analysis and evaluation of the system and the result proved that the proposed solution is a promising way to monitor the elder's sleep posture. In the near future, we will detect more postures to testify the system, and investigate the elder's sleep pattern and complex body movements based on the sleep postures and corresponding duration, and also invite some older adults to evaluate the real benefice of the system.

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