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Non-invasive Sleeping Posture Recognition And Body Movement Detection Based On RFID

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***Abstract*—Some sleep disorders, such as sleep apnea, restless legs syndromes (RLS), and periodic limb movement disorder (PLMD), require a full-night sleep monitoring for diagnosis. Conventional sleep monitoring devices are disturbing and often raise privacy concerns. In this paper, we propose a sleep monitoring system by embedding RFID tags into bed cloth and realize two main functions: sleeping posture recognition and body movement detection. We apply a finite impulse response low pass filter to get smooth signal wave and use a CNN algorithm to identify the sleeping postures of person objects. Meanwhile, the movements and their durations can also be detected by using k-means algorithm. Finally, we conduct experiments to evaluate the both two functions in a real world scenario.**

I. Introduction

Sleep plays an important part in our daily life because the quality of our sleep is relevant to our health. Abnormal sleep may be a sign of some sleep disorders, such as restless legs syndromes (RLS) and periodic limb movement disorder (PLMD) [1]. RLS is characterized by the movement of limbs with uncomfortable feelings, especially during the rest periods, such as sleeping [2]. During the sleep, RLS and PLMD are often defined in terms of duration, interval, and number between two adjacent movements. RLS is usually diagnosed by medical history and PLMD is generally diagnosed by polysomnography (PSG) or movement recording which require a full-night sleep monitoring.

Traditional vision-based sleep monitoring system is e-quipped with cameras, electrocardiograms (ECGs), and respiratory belts [3], which is disturbing and often raises privacy concerns. Takashi *et al.* [4] have proposed an automatic sleep monitoring system by using in-ear sensors, which is capable of minimising both patients inconvenience and the involvement of a medical specialist. However, it cannot detect the body movement and is still invasive or limited to medical facilities. At present, many researches are devoted to establish flexible system to help patients make diagnosis by monitoring the full-night sleep. Liu *et al.* [5] have introduced a sleep monitoring system based on WiFi signals. By collecting WiFi signals in bedrooms, the proposed system can track a person's breath and detect the sleeping postures in different situations. Li *et al.* [6] have developed WiFi-based sleep monitoring system with motion detection module to identify whether the targets is moving. However, these WiFi-base systems can only detect the breath and sleeping postures and cannot detect the body movement. Lin *et al.* [7] have implemented a IoT-based wireless sleep monitoring system for facilitating the long-term breath tracing at home. The system still allowed a person wear multiple monitoring devices. Recently, smartphones are utilized for sleep monitoring to detect several sleeping events such as body movement, cough and snore. Ren *et al.* [8] have presented a fine-grained sleep monitoring system to detect the breathing rate by leveraging smartphone earphone which is placed close to the user. Although smartphone sensors are not attached on a person's body, but the system is limited by the battery capacity.

Compared to existing sleep monitoring systems, radio frequency identification (RFID) sensing technology is benefited from light, low cost, and small tags, which are suitable for non-intrusive sleep monitoring [9]. Hoque *et al.* [10] have used Wireless Identification and Sensing Platform (WISP) to develop a sleep monitoring system. The WISP tags are attached to the bed mattress to detect the sleeping posture and body movement when a person is lying on the bed. But the system is unable to detect the breath rate. Occhiuzzi *et al.* [2] have investigated the RFID technology to monitor the body movements in some common sleep disorders. But the RFID tags are attached on the legs and can only estimate the movement of legs.

Different from the above work that usually require special devices attached to human body (i.e. probes, head belt, and wrist band), in this paper, a sleep monitoring system targeting on sleeping posture recognition and body movement detection is proposed. Our sleeping monitoring system is completely contactless and does not raise privacy concerns. First, a monitoring environment that the tags are attached on the blanket and the antenna is attached on the ceiling above the bed is established. Then, the RSSI collected by the antenna is analyzed to track the position of a person who lying on the bed. Meanwhile, collected data is regarded as the frame data in each moment and a CNN algorithm is used to identify the sleeping posture and a k-means algorithm is to detect the uncommon body movement. At last, both two functions are evaluated under a practical scenario and the experimental results show that our sleep monitoring system can perform accurate detection.

In the rest of this paper, our methodology is presented in Section II. Section III shows the results of the experiment of breath monitoring and Section IV reviews the related work about RFID technology. Section V concludes this paper.

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II. METHODOLOGY

In this section, we establish a sleep monitoring system which is composed of sleep posture recognition and body movement detection. Fig.1 shows the system components.

A. Overview

In the real world scenario, we put a number of RFID tags attached on the blanket and the antenna is placed on the ceiling directly above the bed. The distance between antenna and tags is kept in 2 meters. When a person is lying on the bed and putting the blanket to cover the body, the readings of these RFID tags can reveal some useful information about human activities, such as breathing. In our previous work, we can use the readings to monitor breath with a high accuracy [11]. In this work, we can still exploit some other complex activities, such as sleep posture and body movement.

B. Sleep Posture Recognition

For our sleep posture recognition system, we attached 64 tags to the blanket on a bed. We placed the tags in a 8*8 matrix and put the blanket cover over a person who lies on the bed in different postures: face up, face down, look left, and look right, as shown in Fig.2. For each posture, we recorded data for a certain time. Then, we can get an array of data (8*8) and each element of the array is an RSSI value at each time slot. Therefore, each array data can be treated as a (8*8) image and the pixel values is represented as the corresponding RSSI value. When the person is changing his posture on the bed, the corresponding RSSI values also changes and the array data in each moment can be represented as a frame. Before analyzing the collected data for recognition, we should also de-noise the raw data for further data processing. We use a finite impulse response (FIR) low pass filter for further data processing. After obtained the de-noised data, we have collected a number of groups of RSSI values for five postures. Then, we divided the raw data into two groups: teaching data and testing data. Finally, we use a convolutional neural network (CNN) algorithm as the recognition algorithm in our experiment. The CNN model includes input layer, output layer, convolutional layer, and pooling layers. The input data as an image processed by convolution and pooling operation and goes through fully connected layers. Theoretically, our classifier can be trained by using standard back-propagation. The cost function is defined as $C(W,b) = \frac{1}{2}||h_{w,b}(x) - \alpha||^2$, where W denotes the collections of all weights in the network, b denotes all the biases, and α is the desired output. From the quadratic cost function, it can be seen that $C(W,b)$ is non-negative. The suitable weights and biases will be found to make $C(W,b) \approx 0$. In order to get the set of weights and biases to minimize $C(W,b)$, we proposed to use the stochastic gradient descent (SGD) method, i.e., C varies as

$$\triangle\, C \approx \frac{\delta C}{\delta W} \triangle\, W + \frac{\delta C}{\delta b} \triangle\, b \tag{1}$$

Note that

$$\triangle\, C = \nabla C \bullet (\triangle\, W, \triangle\, b) \tag{2}$$

where ∇C is the gradient vector and $\nabla C \approx (\frac{\delta C}{\delta W}, \frac{\delta C}{\delta b})^T$. Denote η as the learning rate, which is a small and positive parameter. Thus,

$$(\triangle\, w, \triangle\, b) = -\eta \nabla C = -\eta (\frac{\delta C}{\delta w}, \frac{\delta C}{\delta b})^T, \tag{3}$$

$$\triangle\, C = -\eta ||\nabla C||^2 = -\eta ||(\frac{\delta C}{\delta w}, \frac{\delta C}{\delta b})^T||^2 \leq 0 \tag{4}$$

Therefore, C always decreases with respect to w and b. By separating W and b, the following two equations can be derived as

$$w_{k+1} = w_k - \eta \frac{\delta C}{\delta w_k}, b_{k+1} = b_k - \eta \frac{\delta C}{\delta b_k} \tag{5}$$

C. Body Movement Detection

From the experiment of sleeping posture detection, when a person lies on the bed in a posture or when no one lies on the bed, the RSSI readings are keep within a particular interval. If the person changes to a new posture or makes significant movements in the same posture, the RSSI readings will have a significant change compared to the particular value. Fig. 3 shows the changes of readings during such a move.

The movement events are extracted by the proposed algorithm from the changes of RSSI readings is as follows: For each tag on the blanket, we defined the interval of RSSI readings [-a, b], During the monitoring, we choose the timestamps if the RSSI readings exceed the defined intervals. Then, we calculate the differences between the recent RSSI readings and interval boundary in each time slot. If the movement during a time slot is not more than a predefined threshold, we consider these movements do not affect the sleep quality.

In order to detect the body movement, we also use a clustering algorithm to cluster the time slots when significant movements happened. In this case, we apply the k-means clustering algorithm to detect the movement event. First, we use the threshold which is set as 3 to filter out the time windows where the body movement level is high. Then, we use the clustering algorithm to combine the discrete abnormal time slots into a period of restlessness. Finally, we can get a set of discrete body movement events.

III. RESULTS

In this section, we implement our sleep monitoring system by using COTS RFID systems, including an antenna ,a reader, and 64 tags. The transmission power is set to 30dBm.

A. Sleep Posture Recognition

First, we developed a CNN with the number of convolutional and pooling layers ranging from 1 to 5. Then, we use 400 groups of teaching data to train the five layer neural network. Finally, we use 100 groups of testing data with different postures to calculate the recognition rates. After we get a trained BP neural network, a person lie on the bed in four postures again and we record the RSSI readings for 60 seconds for each position. Then, the new data is classified based on previous trained model. Moreover, in order to test whether someone is lying on the bed, we also collected

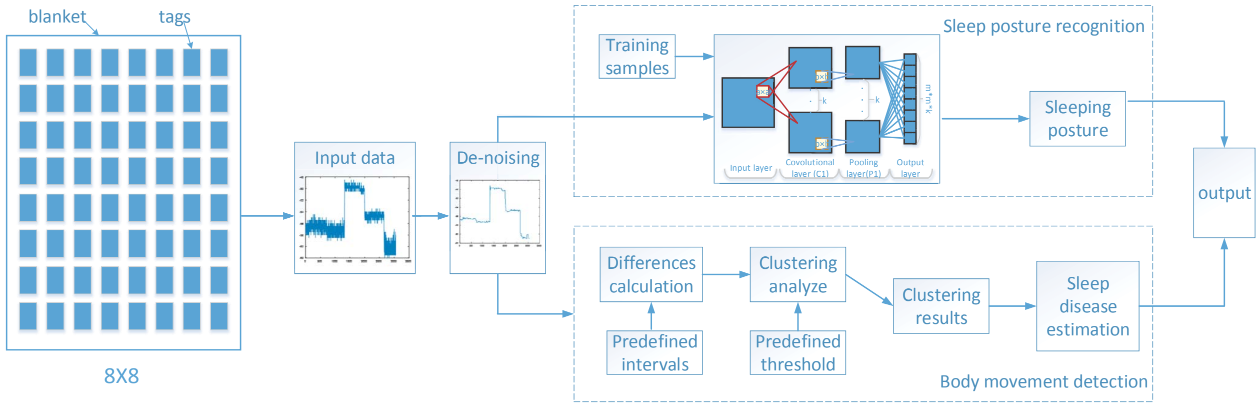

Fig. 1: Sleeping monitoring system.

TABLE I: Sleep posture recognition

		Recognition Rate					
Convolution and pooling layers		1	2	3	4	5	Aver.
Testing data	Nobody	88.7%	87.9%	81.9%	86.9%	90.0%	87.08%
	Face up	71.9%	88.5%	84.0%	85.3%	89.4%	83.82%
	Look right	87.7%	88.3%	86.6%	86.2%	85.0%	86.76%
	Face down	90.3%	85.7%	100.0%	87.0%	82.2%	88.98%
	Look left	86.6%	84.6%	86.1%	86.3%	70.0%	82.72%
	Aver.	85.04%	87.00%	89.64%	86.34%	83.72%	86.284%

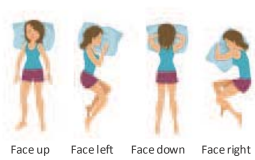

Fig. 2: Four sleeping postures.

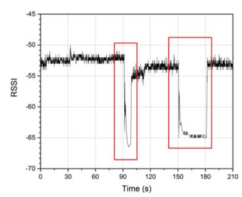

Fig. 3: body movement during the monitoring.

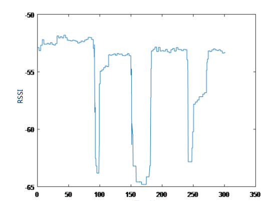

Fig. 4: The de-noised signals of person a.

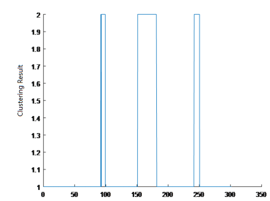

Fig. 5: The clustering results of person a.

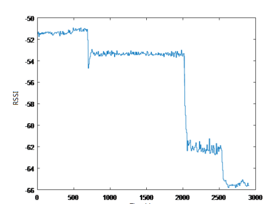

Fig. 6: The de-noised signals of person b.

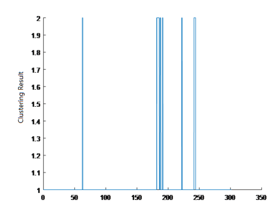

Fig. 7: The clustering results of person b.

data that the bed is empty. Therefore, all collected data is labeled for five categories. The results of our experiments is summarized in Table 1.

According to the experiment results, the average recognition rate is 86.284% and the recognition rate of all the postures ranges from 70% to 100%, because the recognition rate is sensitive to the initial values of network. Moreover, when the number of hidden layers increases, there is not a significant improvement of recognition rate in each posture. When the number of hidden layers is set to 3, we obtain the maximum average recognition rate. When the number of hidden layers exceeds 3, the average recognition rate begin to fail. It could be overfitting to the limited input data when the number of hidden layers is excessive.

B. Body Movement Detection

In this section, Figs. 4-9 show the collected data and the related analysis results of different three people. Each person was lying on the bed for 5 minutes and allowed to shake his arms or legs quickly in each minute. Specifically, when the first minute arrives, the person is allowed to shake his left arm for only 2-3 seconds. Then, the following movements are shaking his right arm, shaking his left leg, and shaking his right leg. For each person, we recorded his RSSI readings and conduct the body movement analysis to get the clustering result. The de-noised signals of 3 persons show that the RSSI readings of one tag cannot show all the four movement. It

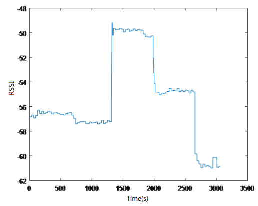

Fig. 8: The de-noised signals of person c.

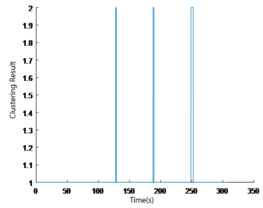

Fig. 9: The clustering results of person c.

is because the four movements are happened in different parts of body, when a part of body moves, the readings of some tags which are not close to this part may not change. It also can be seen that the RSSI readings cannot be kept in a certain interval during the experiment because the tags are attached on the blanket. The moving limbs can move the blanket. When the limbs do not move, the part of blanket cannot return to its previous position. Comparing the de-noised signals and clustering results, it can be seen that all the discrete movement events showed in the de-noised signals can be successfully detected by our system.

IV. Related works

RFID is a kind of non-contacting automatic recognition technology. The radio frequency signals are used to identify targets without manual intervention. Therefore, it can be applied into various environments, such as transportation [12], logistics [13], retail industry [14], and health care system [15]. The application of RFID technology in health care system has been existed for many years. It is usually used to track inventory, identify patients, and manage personnel [16]. However, security and privacy issues also follow [17]. Therefore, the contactless identification technology is getting more attention. Hou et al. [18] have proposed a non-invasive breath monitoring system to monitor breathing with high accuracy even with the presence of multiple users. In this system ,the RFID tags are embedded into yarns which can be used for making RFID clothing. When the person is wearing such clothing, he will not be intrusive by these light thin tags. However, the tags are still attached on the body. In [10], the authors put the WISP tags on the mattress which are not contacted with the body directly, In this way, the readings of tags are not sensitive to slight movements, such as breathing. In this paper, we concentrate on the proposed system to implement both privacy protection and multi-function monitoring.

V. Conclusion

In this paper, a sleep monitoring system with the functions of sleeping posture recognition and body movement detection by means of RFID technology is designed. A finite impulse response low pass filter is applied to get the smooth breathing signals. Moreover, CNN algorithm is adopted to identify the sleeping posture when the person is lying on the bed. Meanwhile, k-means clustering algorithm is used to compute movement events. In this paper, our experiments are limited to the material of blankets. In addition, to get the final clustering result, the intervals and threshold should be manually defined in advance. Our future goal is to design an appropriate to deal with these issues.

VI. Acknowledgement

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