A Sleep Monitoring Application for u-lifecare Using Accelerometer Sensor of Smartphone

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Abstract. Ubiquitous lifecare (u-lifecare) is regarded as a seamless technology that can provide services to the patients as well as facilitate the healthy people to maintain an active lifestyle. In this paper, we develop a sleep monitoring application to assists the healthy people for managing their sleep. It provides an unobtrusive and proactive way for the self-management. We utilize the embedded accelerometer sensor of the smartphone as a client node to collect the sleeping data logs. Our proposed model is server-driven approach and process the data over the server machine. We classify the body movements and compute the useful sleep analytics. It facilitates the users to keep the record of daily sleep and assists to change their unhealthy sleeping habits that are identified by our computed sleep analytics such as bed time, wake up, fell asleep, body movements, frequent body movements at different stages of the night, sleep efficiency and time spent in the bed. Furthermore, we also provide our pilot study results to demonstrate the applicability with the real-world service scenarios.

Keywords: Sleep Monitoring, Accelerometer Sensor, Smartphone, u-lifecare.

1 Introduction

Ubiquitous lifecare (u-lifecare) is a proactive approach to adopt healthy lifestyle in our daily routines. For instance, daily exercise, diet, sleep and social relationships are the wellbeing indicators. A progressive health effects can be observed if they are well managed. Among these sleep in one of the most important health attribute as almost one-third of the human lifetime is spent by sleeping [1]. Insufficient sleep or poor quality has direct impact on person mood, decision capabilities, mental and physical health conditions. Furthermore, serious complexities in sleep may cause the chronic disease such as cardiovascular problems, depression and stress.

The ways to monitor the sleep are polysomnography [2], actigraphy [3] and maintaining sleep diary [4]. Polysomnography is a reliable method due to heterogeneous invasive sensors to monitor the quality of sleep and adopted in the hospital environments. However, it is an intrusive and uncomfortable way to monitor

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the sleep. Actigraphy is another way to monitor the sleep but less intrusive as compared to polysomnography. Still subjects need to wear the accelerometer embedded watch/bracelets during the sleep. Sleep diary is an easy and simple way to monitor the sleep but it is difficult to remember every night situation and needs sometime to manage it regularly. The adoption of any sleep monitoring solution depends on the sleep complications, severity level and symptoms.

Current generation smartphones are an alternative solution to wearable sensors due to their many diverse and powerful embedded sensors. The smartphone includes accelerometer, magnetometer, gyroscope, proximity, ambient light, GPS and cameras. Furthermore, it is one of the best choices for u-lifecare applications due to its unobtrusive characteristics, high storage capacity and computation, low energy consumption and programmable capabilities. In order to practice healthy sleeping pattern in daily routines, we proposed a sleep monitoring application based on the accelerometer sensor of smartphone. It can help the ordinary people to monitor the sleep in a proactive way that may avoid the sleep complications. For self-management, our application provide the visualization of the body movement patterns and useful analytics to assess the efficiency of sleep. We detect the body movement patterns through Support Vector Machine (SVM) and compute the important sleep analytics that may help to adopt active lifestyle.

Although, sleep monitoring is complex study in case of sleep disorders and other complications related to sleep. The scope of our study is to consider the healthy people in a u-lifecare context and ultimately integrate sleep monitoring application with our under developed u-lifecare research project [5]. We will provide the recommendations over sleep analysis such as music therapy, physical activities and control the physical objects to improve the quality of life and make the u-lifecare vision true.

We structure our paper as follow: Section 2 provides information about some of the existing approaches for sleep monitoring. Section 3 presents our proposed smartphone-based approach. In Section 4, we illustrate the experimental results followed by discussion. And finally the conclusion and future work are drawn in Section 5.

2 Related Work

Several research studies have been presented and a large number of sleep monitoring applications are available in the market. Adriana et al. [6] detected the body movements in bed using unobtrusive load cell sensors. They identified the movement when forces sensed by the load cells under the bed legs. Basically, they calculate the energy in each load cell signal over short segments to capture the variations caused by the body movements. The evaluated their system over the dataset collected in the laboratory. This solution is not possible to adopt in daily routines because extra hardware (i.e., load cell sensor) is required to build the system.

In the market, developers also developed other handy solutions to monitor the sleep like Wakemate [7]. It is a sleep monitoring system, which consists of wearable accelerometer band and communicate with the smartphone over the Bluetooth. Smartphone act as a server to receive the accelerometer signals and process them to monitor the sleep. It is able to record the body movements and provide intelligent alarm services to wake up the subject within the 20 minutes window prior to the desired alarm time. One of the first smartphone-based applications is sleep cycle [8] to monitor the sleep and predict the optimal wake up points. They utilized the embedded accelerometer of smartphone for sleep monitoring and process the signals using a proprietary algorithm.

Similarly, some other applications [9] [10] [11] with same functionalities are also available on the app store but details are still not available how they process the sensory data. A technical detail to process smartphone accelerometer data is still vacant to make this vision a reality. In this study, we provide the technical details to process the accelerometer data as well as pilot study implementation results.

3 The Proposed Approach

The proposed approach consists of a smartphone application as a client node to record the accelerometer data and server machine to process the logs for computing the body movements with sleep analytics. The architecture of proposed approach is shown in Fig. 1 and details of sub-components are as follow:

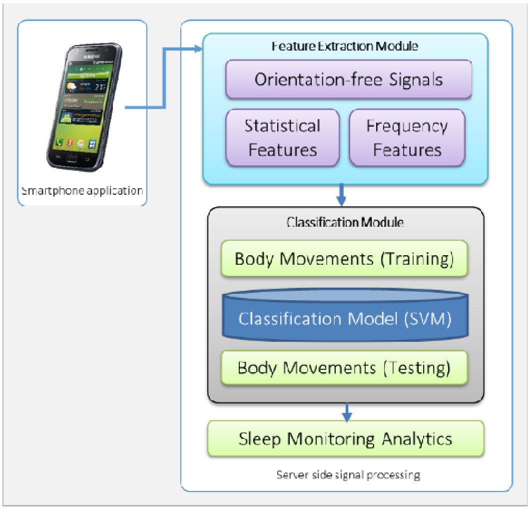


Fig. 1. The architecture of the proposed approach

3.1 Smartphone Application

An Android based smartphone application is developed to log the sensory data. It activate the accelerometer sensor and record the three dimensional data inside storage of the smartphone. In our study, we analyzed and recorded the data at 50 Hz, which is a suitable sampling rate for detecting the body movements over a window of fifteen seconds. The application is server-driven and allows the phone to transfer the data over the Wi-Fi/4G for further processing. Consequently, it resolves the limited data logging issues and allows easy access to sleep data by users themselves as well as, if necessary, physicians or researcher community.

3.2 Server Side Signal Processing

It is composed of *(a) Feature Extraction:* It is highly domain specific method to transfer the raw signals into meaningful region. Firstly, we solve the orientation issue of accelerometer data suggested by Mizell [12] and then extract the following time and frequency domain features.

$$\mu = \frac{1}{n}\sum_{i=1}^{n} x_i^2 \tag{1}$$

$$E = \frac{1}{n}\sum_{i=1}^{n} |FFT_i|^2 \tag{2}$$

In eq. 1, the mean (μ) is a statistical time domain feature to measure the central tendency of varying quantity over the defined fifteen seconds window. Similarly, in eq. 2, the energy feature is calculated by applying the Fast Fourier Transformation (FFT) to find the quantitative characteristics of the data over a defined time period. After it, extracted feature are passed to the classification sub-component. *(b) Classification Module:* We classify the body movements or stationary states through theoretically rich statistical method Support Vector Machine (SVM). In our case, body movements are the small number of available samples as compared to stationary states during sleep that makes the learning process difficult for other classification algorithms. For this reason we select SVM and its slow training issues are resolved through SMO for efficient performance [13]. For the binary linear classification problem (i.e., body movement or stationary in our problem domain) SVM requires the following optimization model including the error-tolerant margin.

$$Minimize\ \frac{1}{2}w^T w + C\sum_{i=1}^{n} \xi_i \tag{1}$$

$$Subject\ to: y_i(w^T x_i + b) \geq 1 - \xi_i, \quad and \quad \xi_i \geq 0 \tag{2}$$

Where "w" is a weight vector and "b" is bias. "C" is the error penalty and "ξ_i" are slack variables, measuring the degree of misclassification of the sample "x_i". The maximum margin is obtained by minimizing the first term of objective function, while the minimum total error of all training examples is assured by minimizing the second term. The above optimization model can be simplified by using the Lagrangrian multiplier techniques and kernel functions:

$$Maximize\ (w.r.t\ \alpha) \sum_{i=1}^{n} \alpha_i - \frac{1}{2} \sum_{i=0}^{n} \sum_{j=1}^{n} \alpha_i\, y_i \alpha_j y_j K(x_i, x_j) \quad (3)$$

$$Subject\ to: \sum_{i=1}^{n} \alpha_i y_i = 0, \quad 0 \leq \alpha_i \leq\ C \quad (4).$$

Where "K" is the kernel function that satisfies $K(x_i, x_j) = \Phi^T(x_i)\Phi(x_j)$. We used generic polynomial kernels function and is defined by:

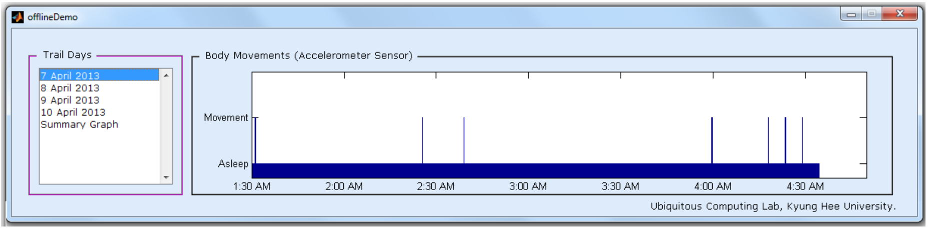
$$K(x_i, x_j) =\ x_i^T x_j \quad (5)$$

After training, we store the trained model over the server for further classification of unseen sleep data. *(c) Sleep Monitoring Analytics:* After recognizing the body movements, we also keep the record of bed time, wake up time and calculate the fell asleep, frequent body movements patterns, sleep efficiency and time spent in the bed. These are the important parameters to understand the individual sleep and irregularities can be found by computed analytics.

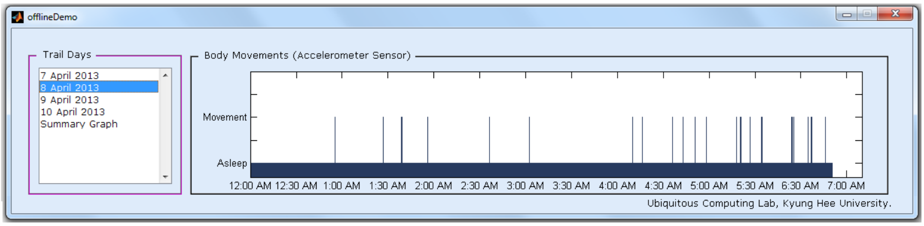
4 Experiments and Discussion

For our pilot study, seven healthy adults (five male and two female) between 25 to 33 years old participated in this study for two weeks. The participants are also requested to complete their sleep diary as a reference. Data is collected using two different scenarios, bed with spring mattresses and plain mattress on the floor, to assess the generalization of proposed approach. We perform the experiments in which subject start the application and keep the mobile phone near the pillow during sleep. Accelerometer sensor of the smartphone is activated and logs the raw signals during the whole night. In the morning, the application is stopped by the subject. Before sending data to the server, first time it requires the user credentials and server authentication to transfer the logged data.

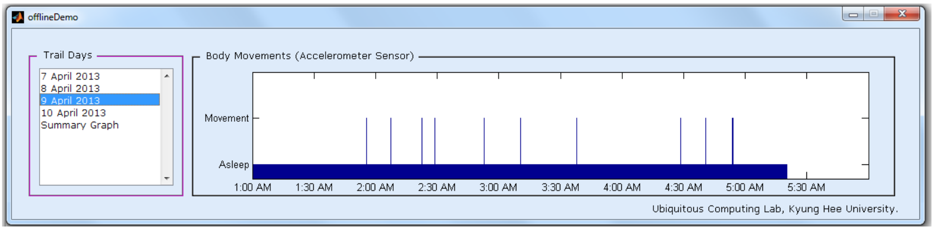
In order to get the training data for classification, four subjects are request to performed five trails of body movement in a natural and comfortable way. The data is collected and transferred to the server through our developed application. We extract the features from accelerometer data and trained the classification module over the server for further analysis of sleep. Time scale for inferencing is set to a one minute epoch that is sufficient to distinguish the stationary state or body movement. For discussion, we are presenting one subject sleep monitoring trail results of working days over one week span in Fig. 2.



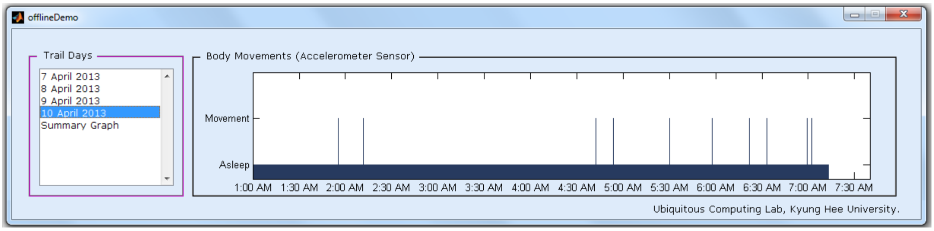
(a) Detected body movements of the subject during the night of 7th April



(b) Detected body movements of the subject during the night of 8th April



(c) Detected body movements of the subject during the night of 9th April



(d) Detected body movements of the subject during the night of 10th April

Fig. 2. Movement and asleep pattern during the four night trial

Fig. 2, shows the trail days with the body movements and asleep states graph for each day. In order to get useful information, we compute the following sleep analytics (as shown in Table 1) that may help the subject to adopt a healthy lifestyle in a proactive way.

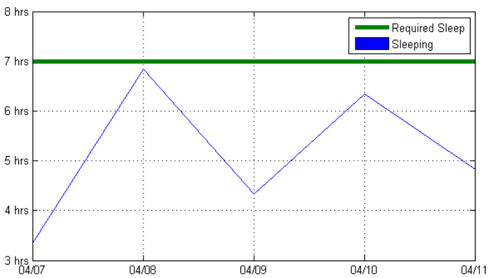
Table 1. Sleep analytics of working day over one week of span

Sleep Analytics	**04/07/2013**	**04/08/2013**	**04/09/2013**	**04/10/2013**
Bed time	1:30 a.m.	12:00 a.m.	1:00 a.m.	1:00 a.m.
Wake up	4:50 a.m.	6:50 a.m.	5:20 a.m.	7:20 a.m.
Fell asleep	5 min	< 5 min	< 5 min	<5 min
Body movements	6 times	21 times	10 times	10 times
Frequent movements	Morning	Morning	All Night	Morning
Sleep efficiency	80%	84%	88%	92%
In bed time	3hr 20 min	6hr 50 min	4hr 20 min	6hr 20 min

In Table 1, we can infer the irregularity pattern for going to sleep by observation of bed time analytics. It has an important impact on the mood and freshness level on the person daily life routines. For instance, according to the subject sleep diary, after the day 10th April sleep, feels more fresh and active as compared to the last night sleep. It is due to sufficient sleep, on time going to bed and average body movements during the whole night. In our study, we analyze that too much body movements also cause the low quality of sleep and has direct impact on the person's mood. Sometime people feel some problem to fell asleep once they are in the bed. Fell asleep statistic may help to know the duration of it and may correlate with the coffee intake or any other activity before going to bed. The number of body movement and the frequent body movements at the part of the night (i.e., start, midnight, and morning) can tell us about the movement pattern and helpful to find disturbance if it is observed too much. In Figure 4(b), subjects frequent body movements are observed after 4:30 a.m. According to subject report, the room temperature is too cold last night. This kind of analysis may facilitate the automation of other dependent technologies like adjust the room temperature when such kind of situation happens. Furthermore, we also calculate the sleep efficiency according to Michael [14] by the following equation.

$$Sleep\ Efficieny = \frac{(Total\ Sleep\ Time - Awakened\ Time)}{Total\ Sleep\ Time} \tag{5}$$

We also computing the summary graphs and analytics to provide a quick review over the monitored sleep. Fig. 3 shows the weekly summary graph and analytics of four night sleep.



Summary graph analytics
• Average sleep (working days): 5hrs 20mints
• Average sleep efficiency: 86.8%
• Sleep debt: 9hrs 20 mints
• Irregularity pattern is observed going to bed routine

Fig. 3. Summary graph and analytics of four night sleep

5 Conclusion and Future Work

In this study, we designed and developed the sleep monitoring application in a client-server environment. Where smartphone act as a client node to collect the acceleration data during sleep and server process the raw signals. Our method classify the body movements and asleep states by SVM algorithm. We compute the sleep analytics like bed time, wake up, fell asleep, body movements, frequent body movements at different stages of the night, sleep efficiency and time spent in the bed. Our application facilitates the healthy individuals to monitor their sleep and provide a proactive platform for self-management. Currently, our application evolve server side processing and limited to the sleep analytics only. We have plan to implement the proposed model inside the smartphone, commercialize it and provide recommendations for self-management of sleep.

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