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Real-Time Sensor- and Camera-based Logging of Sleep Postures

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***Abstract*—This paper presents a process of feature selection, and classification algorithm evaluation for a continuous sleep monitoring system, using a tri-axial accelerometer attached to the subject's chest. Two feature selection algorithms, i.e., Relief-F and support vector machine recursive feature elimination (SVM-RFE), and seven classification algorithms, i.e., Bayesian network, naïve Bayesian network, support vector machine, pruned decision tree, instance-based learning with one neighbor, instance-based learning with three neighbors, and multi-layer perceptron, were investigated. By using four features according to the rank obtained from Relief-F, and a multi-layer perceptron classifier, an average accuracy of 85.68 percent has been achieved. Based on the selected model, a real-time logging system of sleeping images triggered by a sleep posture change detected using a wireless sensor node has been developed.**

Keywords—posture recognition; tri-axial accelerometer; sleep monitoring; feature selection

I. INTRODUCTION

It is well-known that the quality of sleep has a relevant impact on mood and performance of an individual [1]. Poor sleep quality can lead to other health issues, such as diabetes [2], dementia [3], and decrease in accuracy of emotional memory recognition [4]. Sleep monitoring could play an important role in preventing health issues, detecting symptoms, and evaluating the quality of sleep. Two groups of users who will benefit from a sleep monitoring system are those with sleep apnea and those with pressure ulcers.

Sleep apnea, which is a potentially serious sleep disorder, could be diagnosed by sleep monitoring [5]. There are various biological changes monitored during sleep such as heart rhythm, blood pressure, respiration rate, eye movements, electrical activities in the brain, electrical activities produced by skeletal muscles, and body positions. Those biological changes are monitored by various signals such as electroencephalogram (EEG), electrooculogram (EOG), electrocardiogram (ECG), electromyogram (EMG), pressure on patient's bed, and acceleration of attached device [6]. Commonly used sensors in sleep monitoring include accelerometers, ECG sensors, pulse oximeters, pressure sensors, and cameras.

Pressure ulcers, or bedsores, are injuries that often occur in people who have problems repositioning their bodies. The cause of bedsores is prolonged pressure on bony prominences, which cut off blood circulation to skin tissues. Lack of blood flow to skin tissues for more than a few hours will lead to tissue death and an ulcer or a sore [7]. As we are entering the aging society era, there exist more and more elderly and bedridden patients who require a special care. For bedridden patients, it is recommended for caretakers to reposition the patient's body every 2 hours [8, 9].

Traditional polysomnography (PSG), or sleep study, conducted at a hospital deploys various sensors to monitor biological changes that occur during sleep. However, numerous sensors utilized in PSG, plus hospital environment, might obstruct patients from revealing their true sleep behavior, which could result in an ineffective diagnoses. Recent technological advances in miniaturized bio-sensing devices, smart textiles, microelectronics, wearable computing, and wireless communication, have enabled the development of wearable and home monitoring systems that can provide users with continuous monitoring anywhere and anytime [6, 10, 11].

Various research studies related to sleep posture monitoring have been conducted. Huang et al [12] proposed a multimodal approach to sleeping posture classification. The proposed system was capable of classifying nine common sleeping postures. The system utilized a pressure sensor array and a video camera. Lee et al [13] proposed the use of ECG signals for estimating four lying body positions on the bed. A twelve-channel ECG sensor was placed on the bed using a conductive textile sheet as the electrodes. Adami et al [14] presented an approach of using load cells under the bed to analyze in-bed and out-of-bed events, and to estimate bedtime and wake up time. The system was capable of classifying three sleep positions. Wai et al [15] proposed a pressure-sensing-bed-based system for sleeping pattern observation. The system was capable of classifying nine directional lying postures. Liu et al [16] proposed a dense pressure sensitive bedsheet utilizing high resolution textile pressure sensors for sleep posture monitoring. Based on pressure image analysis, six lying postures can be classified. Ostadabbas et al [17] proposed an approach for monitoring sleep postures and body limbs for bedsore prevention based on a low resolution pressure sensor mat. The

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system was capable of classifying three lying postures. Kishimoto et al [18] proposed an approach for sleep posture estimation using a wearable tri-axial accelerometer attached on the subject's chest. The algorithm was capable of classifying four lying postures plus sitting.

In our previous study [11], a method for sleep posture monitoring using a tri-axial accelerometer attached to subject's chest was proposed. The method utilized a sensing device without wireless capability. The raw acceleration signals along the x, y, and z axes were used as features. Supervised clustering was used to find the acceleration means of each activity and instance-based learning with one neighbor (IB1) was used for classification. Five activities, namely, sitting, lying backward, lying on the left, lying forward, and lying on the right were classified. All data analysis was performed offline and the results were compared against that of a commercial Actigraph system utilized in a PSG laboratory at King Chulalongkorn Memorial Hospital. An average accuracy of 95.87% was archived. In this study, we further improve the data analysis method with feature extraction and different combination of feature selection and classification algorithms. A sensing device with wireless capability has been utilized. Two additional activities, namely, standing and walking, have been introduced. The selected model was then used to develop a real-time sleep monitoring system in which both the sensory signals and snapshots of sleeping images can be logged for further analysis of sleeping profile.

This paper is organized as follows. Section II describes setup for data collection. Section III describes the feature selection algorithms used in this study. Section IV presents the proposed data analysis technique. Section V presents the experimental results. Section VI demonstrates the real-time sleep monitoring system. Section VII draws the conclusions.

II. Data Collection

Body Sensor Network (BSN) toolkit, developed by Imperial College London, is a low-power, flexible, and compact context aware sensing device [19, 20]. The BSN node used in this experiment consists of a programmable microcontroller board, a tri-axial accelerometer, a radio transceiver (TI CC2420), and a rechargeable battery. The device was attached on a strap and placed in the front, below the subject's chest. Fig. 1 depicts the BSN node and the device coordinate system. The use of a compact wearable device such as BSN empowered continuous sleep monitoring at home, which allowed patients to be monitored in their natural state.

The data collection involved twenty subjects, 10 males and 10 females, aged between 22-47 years, with an average of 34.8 years. Each subject was asked to wear a BSN node [19] equipped with a tri-axial accelerometer while performing different activities, namely, sitting (C1), lying backward (C2), lying on the left (C3), lying forward (C4), lying on the right (C5), standing (C6), and walking (C7) (as depicted in Fig. 2). A sampling rate of 50 Hz was used.

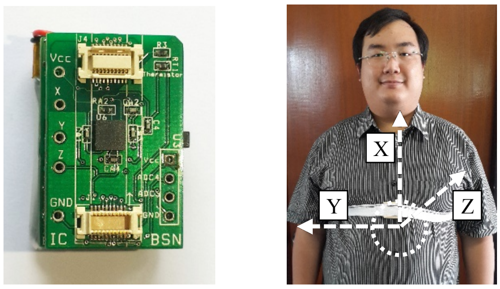


Fig. 1. A BSN node (left) and its coordinate system wrt. subject's body (right)

Fig. 2. A subject while performing seven activities (C1 - C7).

III. Feature Selection

Feature selection is a process of choosing a relevant subset of features for model construction. Since the number of features used in classification algorithms can affect both classification accuracy and time complexity [21-23], feature selection is used in many research studies to reduce number of irrelevant features [24-27]. In [28], Li, et al. investigated the use of several feature selection algorithms, on the hydrocarbon reservoir prediction performance, in the domain of petroleum exploration and production in China. The results show that Relief-F and SVM-RFE can improve prediction performance more than other methods.

Relief [21] is a ranker-based feature selection algorithm which uses a statistical method and avoids heuristic search. It is noise-tolerant and unaffected by feature interaction. It ranks individual features according to a feature relevance score, $W[A]$, that approximates the difference between probabilities conditioned on the nearest instance from a different class (near-miss) and the nearest instance from the same class (near-hit):

$$W[A] = P(\mathrm{A}|\mathrm{nearmiss}) - P(\mathrm{A}|\mathrm{nearhit}) \qquad (1)$$

Relief-F [29] is an extended version of Relief. While the Relief-F still finds one near-hit H from a randomly selected instance, R, instead of finding one near-miss M from a different class, it finds one near-miss $M(C)$ for each different class, and averages their contributions for updating $W[A]$, i.e.,

$$W[A] = W[A] - \frac{\Delta(A,R,H)}{m} + \sum_{C \neq class(R)} \frac{[P(C) \times \Delta(A,R,M(C))]}{m} \qquad (2)$$

where m is the number of instances used for approximating the probabilities. The algorithm will also be repeated m times. Relief-F has been proved to be more effective and was widely utilized in many areas such as gene selection for cancer classification [30, 31], gene selection for tumor classification [31, 32], and feature selection for the characterization of ultrasonic images of placenta [33].

Support Vector Machine Recursive Feature Elimination (SVM-RFE) [24] is another widely-used feature selection algorithm. It uses weight magnitude of Support Vector Machines (SVM) as the ranking criterion and eliminates subsets of features with smallest ranking criterion in a recursive manner. The algorithm first trains an SVM on the training set of instance-labeled pairs (x_i, y_i), for i = 1, 2, 3, …, l, in order to find Lagrange multipliers vector, α. The training problem of minimizing α_k of a subset of surviving features s in the training set can be written as,

$$\text{Minimize:} J = \frac{1}{2}\sum_{hk} y_h y_k \alpha_h \alpha_k (x_h \cdot x_k + \lambda\delta_{hk}) - \sum_k \alpha_k$$

$$\text{subject to: } 0 \leq \alpha_k \leq C \text{ and } \sum_k \alpha_k y_k = 0 \quad (3)$$

Then the algorithm computes the weight vector of dimensional length (s) by:

$$w = \sum_k \alpha_k y_k x_k \quad (4)$$

The ranking criteria is computed by:

$$C_i = (w_i)^2, \text{for all i} \quad (5)$$

Finally, the algorithm finds the feature with lowest ranking criterion, eliminates the feature from the surviving list s, and updates the ranked list. SVM-RFE was utilized in many application domains such as gene selection for cancer classification [24, 34], feature selection of material corrosion data [35], and feature selection for detecting scalp spectral dynamics of interest on EEG signals [36].

IV. Data Analysis

During the data pre-processing step, noise reduction was first performed by replacing the outlier signal samples with the previous signal values, followed by median filtering with a fixed window of size five samples. To avoid the effect of class bias, the number of samples in each class were adjusted to be the same by truncating samples in each class equal to the class with fewest number of samples. Fifteen features, as described in Table I**Error! Reference source not found.**, were then calculated along the x-, y-, and z- axes of the acceleration signals using a fixed window of size 50 samples (1 second), and a shifting window of size 25 samples (0.5 second).

Two ranker-based feature selection algorithms, Relief-F and SVM-RFE, were used in this experiment. They both gave a rank for each individual feature. The smaller rank number indicated the better feature. Based on Weka 3 Toolkit [37], seven classification algorithms as used in [25] were evaluated, i.e.,

- Bayesian network (BN) [38] with conditional probability tables estimated using simple estimator, and structure learned from the data distribution using the K2 search algorithm and Bayesian Score.
- Naïve Bayesian network (Naïve BN) [39]
- SVM [40] trained using sequential minimal optimization algorithm with polynomial kernel as support vector.
- Pruned decision tree (J48) [41]
- Instance-based learning with one neighbor (IB1) [42]
- Instance-based learning with three neighbors (IB3)
- Multi-layered perceptron (NN) [43] trained using back propagation.

Table I. Feature Description

F1 – F3	Mean of the acceleration values along the x-, y-, and z- axes, respectively
F4 – F6	Standard deviation of the acceleration values along the x-, y-, and z- axes, respectively
F7 – F9	Minimum of the acceleration values along the x-, y-, and z- axes, respectively
F10 – F 12	Maximum of the acceleration values along the x-, y-, and z- axes, respectively
F13 – F15	Difference between maximum and minimum of the acceleration values along the x-, y-, and z- axes, respectively

V. Experimental Results

The feature selection results obtained from Relief-F and SVM-RFE are shown in Table II. Based on five-fold cross-validation, the seven classification algorithms described in Section IV were applied on varying numbers of features following the feature rank obtained from Relief-F and SVM-RFE. The overall accuracy values achieved by different classification algorithms using feature sets ranked by Relief-F and SVM-RFE are shown in Fig. 3 and Fig. 4, respectively.

The aim of this experiment is to determine a small subset of features which is sufficient for constructing an effective classification model to be used in a real-time sleep monitoring system. Although different feature orders are returned by Relief-F and SVM-RFE, both feature selection algorithms selected F1, F2 and F3 as the top three best features. This shows that acceleration mean is the most important feature for the classification problem as most activities in the dataset are static activities. From Fig. 3 and Fig. 4 using four features seems to be appropriate as high accuracy can be achieved. The fourth feature selected by Relief-F and SVM-RFE are the minimum value of y-axis (F8) and the standard deviation along x-axes (F4), respectively.

With four features, the candidate classifiers are NN with the feature rank from Relief-F and a naïve BN using the feature rank from SVM-RFE. The accuracy values of 85.68% and 85.55% are achieved by these two models, respectively. In terms of classification time, the NN classifier requires only 67 milliseconds, while the naive BN requires 350 milliseconds. Even though the training time of NN is relatively high compared to other algorithms (114,088 milliseconds compared to 156 milliseconds of naïve BN), model construction is a one-time process, classification time is more important in the long run and thus the model was chosen for further implementation.

TABLE II FEATURE RANK RESULTS FROM RELIEF-F AND SVM-RFE FEATURE SELECTION ALGORITHMS

Feature Selection Algorithm	Feature Rank														
	1	*2*	*3*	*4*	*5*	*6*	*7*	*8*	*9*	*10*	*11*	*12*	*13*	*14*	*15*
Relief-F	F2	F3	F1	F8	F7	F11	F9	F12	F10	F5	F14	F4	F13	F6	F15
SVM-RFE	F3	F2	F1	F4	F5	F7	F11	F9	F8	F14	F6	F15	F12	F13	F10

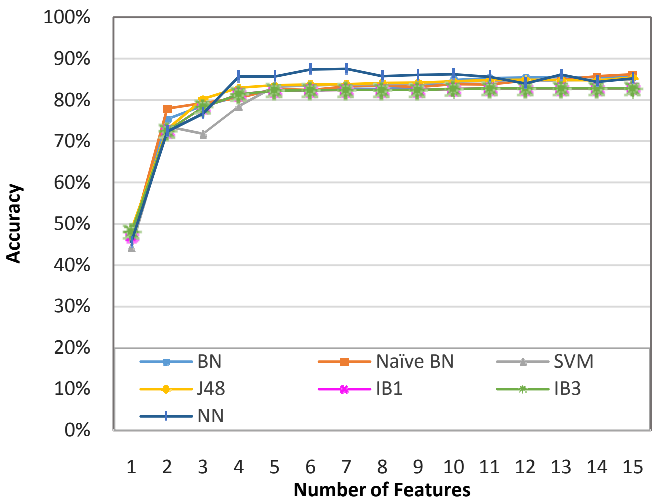


Fig. 3. The graphs show the overall accuracy of different classifiers when applied on datasets with varying numbers of features according the feature rank obtained from Relief-F.

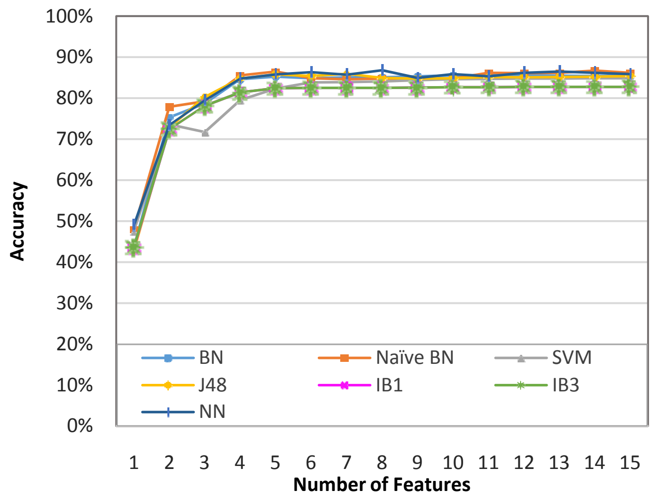
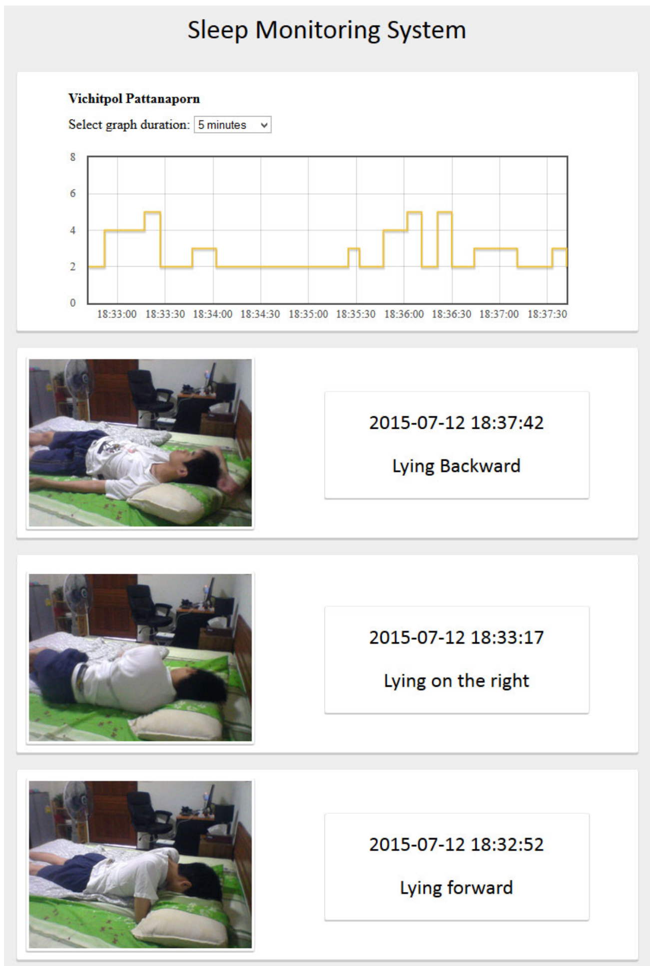


Fig. 4. The graphs show the overall accuracy of different classifiers when applied on datasets with varying numbers of features according to the feature rank obtained from SVM-RFE.

VI. A REAL-TIME SLEEP MONITORING SYSTEM

A client application written in Java has been developed in order to receive and process acceleration signals acquired using a BSN node. The system utilizes a NN classifier with 4 features consisting of F1, F2, F3, and F8 for model construction. It records the time that a user changes his/her activity in the database in order to generate an activity profile. In addition, while the user is lying down, the application will take snapshots of the user when the lying position is changed. The information is useful for physicians to diagnose various sleep problems.

On the server side, a web-based real-time sleep monitoring system has been developed. The web application consists of several pages, such as basic user information, summarized information of user's records (e.g., total hours of recorded activities), details of predicted activities (including sleep positions), a summary of sleep hours categorized by sleep positions. Snapshots of sleep positions during one night is shown in Fig. 5.



however, with four features selected using Relief-F, the multi-layered perceptron yielded a high accuracy of 85.68% with minimal classification time. A real-time sleep monitoring system was developed as a web application that keep a log of classified activities received from a Java client application. It is capable of logging and displaying graphs of user activities, and taking snapshots of user sleep positions. The developed system provides an ability for caretakers to analyze sleeping behavior and sleeping postures of users in an efficient manner. This could provide a foundation for further studies such as sleeping behavioral profile, sleep and sleeping postures monitoring and bedsore prevention. Additional sensing devices and improved classification algorithms can be integrated to improve the functionalities and performance of the system. So that pictures can be taken in the dark, an infrared camera can be used instead. This would also further enhance the system in terms of user privacy.

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