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Energy-aware Activity Classification using Wearable Sensor Networks

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Abstract

This paper presents implementation details, system characterization, and the performance of a wearable sensor network that was designed for human activity analysis. Specific machine learning mechanisms are implemented for recognizing a target set of activities with both out-of-body and on-body processing arrangements. Impacts of energy consumption by the on-body sensors are analyzed in terms of activity detection accuracy for out-of-body processing. Impacts of limited processing abilities for the on-body scenario are also characterized in terms of detection accuracy, by varying the background processing load in the sensor units. Impacts of varying number of sensors in terms of activity classification accuracy are also evaluated. Through a rigorous systems study, it is shown that an efficient human activity analytics system can be designed and operated even under energy and processing constraints of tiny on-body wearable sensors.

Keywords

Wearable Sensor Network; Activity Analytics; Machine Learning; Neural Network; On-body Processing

1. Introduction

Recent advances in low-cost and energy-efficient sensing and networking technology are opening up new possibilities for wearable medical diagnostics[1][2]. A number of tiny sensors, strategically placed on the human body, can create a network that can monitor physical activities and vital signs, and provide real-time feedback analytics to medical service providers. Many patient diagnostic procedures can benefit from such continuous health monitoring for optimal management of prevention of chronic conditions and supervised illness recovery.

Motivation

Regular participation in physical activities provides many important health benefits, including reduced risk of coronary heart disease, hypertension, type II diabetes, obesity, several types of cancers, and loss of bone mass[3]. Most of the evidence linking physical

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activity to health benefits has been based on self-reported data, which often provides an index of all four components of activity (frequency, duration, intensity, and type). Such self-reports do not reliably indicate the fine granularity (i.e., breakdown for specific activities) information which can substantially enhance the assessment accuracy of metabolic energy expenditures due to physical activity. A wearable activity identification system can provide quantifiable fine-grain activity information from day-to-day life, enabling remote assessment and epidemiologic/clinical research in an automated manner. Such a system can also enable real-time remote monitoring of soldiers, elderly population, and athletes during sporting events.

In this paper we report the results from a systems level study of a wearable sensor network applied for human activity analytics. A wearable sensor system with networked machine learning for activity identification was developed. Based on six data streams containing acceleration reading from three sensors, the system was trained for identifying 14 activities (i.e. lying down, sitting reclined, sitting up straight, standing, walking briskly and slowly, jogging, climbing stairs, riding a bike briskly and slowly, sweeping, jumping jacks, squatting, and bicep curls). Important design issues, including sensing, processing, data collection, energy efficiency, and application level accuracy are studied in the paper individually as well as in terms of their interdependencies in various operating conditions.

Objectives

The objectives of this study are to: a) develop a wearable system that is capable of collecting and streaming acceleration samples out of on-body sensors over a wireless link, b) develop machine learning mechanisms for recognizing a target set of activities, c) analyze the impacts of varying number of on-body sensors on activity detection accuracy, d) characterize sensor energy consumption, identification accuracy, and their trade-offs, and e) characterize the impacts of processing constraint on the sensors and its impact of activity detection accuracy.

2. Related Works

Human activity recognition research has appeared in the literature primarily from an out-of-body analysis standpoint. The work in [4] collects annotated acceleration data from 20 subjects, and then different classifiers were deployed to analyze the data. It was shown that a decision tree classifier provides the best accuracy. Influences of the positions of sensors on detection accuracy are also analyzed. It is shown that the sensor on thigh provides the highest accuracy when only one sensor is used, and sensors on thigh and wrist work best when two are used.

The paper in [5] conducted posture recognition experiments on two different subjects. Although high accuracy of over 90% was achieved when one person’s data is used in both training and testing sets, significant amount of accuracy loss was observed when the system is trained by one person’s data while tested on the other’s. The approach in [6] evaluates performance of different features and classifiers based on 5 typical activities. The approach in [7] analyzes the importance of different sensors in differentiating different activity subsets, and it is proved that one sensor combination may perform well for some activities but may not for all.

The approach in [8] implemented a real-time out-of-body decision tree algorithm that provided high accuracy using subject-dependent training. In the system Titan [9], which is also used in [10], when a task is inserted the Network Manager would inspect the capabilities of the sensor nodes, and insert it into a node accordingly.

In contrast to those work in the literature, our approach in this paper is to develop a systems study that, in addition to developing activity analytics classifiers, characterizes energy and processing constraints of the on-body sensor units. Additionally, the analysis of the impacts of sensor network size on activity detection accuracy is of great value for future research on activity detection using fewer sensors. The impacts of energy consumption by the sensors on out-of-body activity detection accuracy are analyzed by varying the acceleration sampling rate, and its subsequent energy overhead due to data reporting requirement over radio links. Subsequently, on-body activity detection accuracy in the presence of processing load constraints is characterized by modeling and stochastically varying the background processing loads on sensors.

3. System Architecture

Each wearable sensor is a small *6cm × 3.2cm × 1.5cm* package, weighing approximately *20 grams*. As shown in Fig. 1, the package contains a sensor subsystem (MTS310 from MemSic Inc.) and a processor and radio subsystem (Mica2 motes), running TinyOS operating system. Batteries weigh approximately *13 grams* and are attached separately. For each sensor package, two 600mAh *AAAA* batteries are able to support the system for more than 30 hours.

A sensor package is worn with an elastic band so that once worn, the sensor orientation does not change with respect to the body segments. Three sensor packages are worn on ankle, thigh, and wrist of the same side of the body. Fig. 1 shows the picture of a thigh-worn sensor package. Once activated, each sensor package continuously samples its acceleration (*-2g to +2g*) in two axes at 10Hz and sends them to a nearby (within *50 meters*) laptop using a 900MHz wireless link via an access point. According to [11], majority of the spectral energy for daily activities is between 0.3Hz and 3.5Hz. Therefore, the 10Hz sampling rate is able to capture daily activities and provide satisfactory accuracy. Activity analytics are performed either on-body in the sensors, or out-of-body in the laptop, and the software are written in C so that it can migrate over various platforms using different wireless protocols, such as Bluetooth or Wi-Fi. As shown in the diagram, the sensor nodes form an ad hoc sensor network with dynamic reconfigurable mesh topology.

Activity analytics are categorized into two processing modes, namely on-body and out-of-body. For out-of-body, all sensor data are wirelessly collected to an out-of-body machine for analysis. In on-body scenarios, analysis is performed at the sensor nodes, either at a single node or at multiple nodes for improved load distribution. Section 4 uses the out-of-body scheme, while performance of on-body scenarios is analyzed in Section 5.

4. Experiments

3.1. Data Collection

Two phases of data collection were conducted. Acceleration data was collected from 10 and 30 subjects during the Phase-I and Phase-II of the study respectively. Half of the subjects were male and the other half were female in each phase. Details of the subject set are shown in Table 1. Subjects in each session performed all 14 activities, namely, lying down, sitting reclined, sitting up straight, standing, walking briskly and slowly, jogging, climbing stairs, riding a bike briskly and slowly, sweeping, jumping jacks, squatting, and bicep curls.

In Phase-I, each subject performed 4 sessions. During each session, a subject was asked to wear the networked sensor system and to perform each of the 14 activities for 2 minutes. In Phase-II, each subject was asked to perform one 14-activity session, 5 minutes for each activity. Because some activities are too laborious, such as jumping jacks and stair climbing, they were split into multiple sessions with shorter durations. But the total duration for each activity was kept to 5 minutes. The acceleration sampling rate was 10Hz for each of the sensors.

3.2. Feature Extraction

Mean, entropy, and standard deviation of acceleration, computed over overlapping time windows, are used as the machine learning features for activity detection. The features are computed for each of the six streams on windows of 42 consecutive samples, representing 4.2 seconds at 10Hz sampling rate. 50% overlapped sliding windows are used. A 4.2s window size was chosen based on previous studies [4][8] with good identification performance using window size spanning 2 to 5 seconds with 50% overlapping.

Entropy can be expressed in the form of standard deviation when the distribution of the random variable is known in some cases [12]. However the performance of entropy and standard deviation as machine learning features capturing the intensity of activity may not be the same, since the relation between entropy and standard deviation is not linear and the distribution of acceleration data in our case is unknown.

3.3. Classifier

Features extracted from each sensor are directly injected into a classifier. Different machine learning algorithms, including, Neural Networks, Decision Tree (J48), Naïve Bayes, Nearest Neighbor and Support Vector Machine (SVM) are applied. The Machine Learning Toolkit Weka [13] is used for implementing the classifiers.

3.4. Results

A number of classifiers including Nearest Neighbor, Support Vector Machine (SVM), Neural network, Decision Tree (J48), and Naïve Bayes were evaluated. Classifiers were trained and tested in such a way that data from 30 out of 40 subjects were used for training, and data from the remaining 10 subjects were applied for testing purpose. The subjects were divided into 4 groups, and the above procedure was repeated 4 times – once for each group.

Average accuracy across all four groups is Table 2 shows the accuracy of different classifiers.

5. Discussion

4.1. Impacts of sensor network size

All the results presented so far correspond to a 3-node sensor network as depicted in Section II. In this section we present detection accuracy results when fewer sensors were used in the system. Training and testing sets are still organized in the same way as in the previous experiments. Table 3 shows the detection accuracy for different sensor combinations. Observe that the Ankle-and-Wrist combination provides a 96.20% accuracy which is only slightly lower than the 96.95% accuracy obtained when all three sensors were used (see Table 2). However, when only one sensor is used the loss of accuracy is noticeable and much more than that when two sensors are used.

The reason for the accuracy drop when few sensors are removed from the system is that the movement of certain body parts during some activities cannot be detected with confidence. For instance, when the sensor on the wrist is removed, bicep curls is not detectable anymore, since the only difference between standing and bicep curls is the arm lifting. Similarly, when only one sensor on the ankle is used, the difference between standing and sitting up straight becomes undetectable.

Fig. 2 summarizes the detection accuracies with varying number of sensors used in different combinations. *W*, *A*, and *T* refer to the sensors on wrist, ankle, and thigh respectively. All 14 target activities are categorized into four overlapping groups, namely, static activities (lying down, sitting reclined, sitting up straight, standing), dynamic (walking briskly and slowly, jogging, climbing stairs, riding a bike briskly and slowly, sweeping, jumping jacks, squatting, and bicep curls), everyday activities (walking briskly and slowly, sweeping, climbing stairs), and exercise related activities (bicep curls, riding a bike briskly and slowly, jogging, jumping jacks, walking briskly, squatting). The following observations can be made. The three sensor scenario (A&T&W) provides the best detection accuracy of over 95% for each of the activity groups. While when sensor on the thigh is removed, the detection accuracy for dynamic, everyday and exercise activity sets decreases 1-2%. However, the detection accuracy for static activity set increases around 1% in this scenario, because sensor data on the thigh does not provide additional discrimination power but blurs the boundary of static activities. Specifically, the thigh sensor stays either vertically in the case of standing or horizontally when sitting up straight, sitting reclined and lying down, so that these activities can be differentiated using data from the other two sensors with even higher accuracy. Similarly, when the sensor on the ankle is removed, the accuracy drops no more than 3% for dynamic, everyday and exercise activity sets, but significant decline can be observed in the case of static activities, because difference between sitting up straight and sitting reclined becomes invisible. Comparing with the cases when sensor on the ankle or thigh is removed, lowest accuracy is derived when the sensor on the wrist is disabled, since the other two sensors on the ankle and thigh just reflect the movement or position of the leg. Furthermore, as we can imagine, when only one sensor is left in the system, more significant drops in detection accuracy can be anticipated. In this case, the sensor on the ankle can achieve the best accuracy, while the one on the thigh performs marginally worse. However, when only the sensor on the wrist is kept, the lowest accuracy is observed, indicating the movement on the leg is more informative than that on the upper limb.

4.2. Energy-accuracy trade-off

Energy efficiency of the networked sensor system and its implications on activity recognition accuracy is studied in this section. Fig. 3 reports accuracy, when the acceleration sampling rates of the wearable sensors are changed. As expected, with lower sampling rates (i.e. higher intervals) the overall accuracy degrades for all three classifiers in a linear manner.

In order to establish the connection between sensor sampling rate and its impacts on energy, experiments were performed for measuring the run-time current consumption by the on-body sensors. Fig. 4 depicts the sensor power consumption traces for acceleration sampling intervals at 100ms and 200ms. Each gray ellipse in the graphs indicates the surge of consumption due to a radio packet transmission. With higher sampling rates (e.g. lower intervals), more such surges occur due to more frequent packet transmissions, thus causing higher overall power consumption.

As observed in Fig. 4, since a given power budget for the on-body sensors bounds the maximum rate at which acceleration can be sampled (and radio packets can be sent), it also dictates the resulting activity detection accuracy.

Maximum detection accuracy for off-body activity analysis for a given per-sensor power budget is shown in Fig. 5. The reported accuracy represents average over three different classifiers, namely, Neural Network, Decision tree (J48) and Naïve Bayes. As expected, better detection accuracy can be achieved via higher power consumption at the sensor nodes.

6. Networked on-body analytics

In the scheme of on-body detection, one of the on-body sensors, chosen dynamically, is designated as the master node for data processing. As shown in Fig. 6, two of the three on-body sensors designated as the slave units sample their own acceleration data and extract features (i.e. mean and standard deviation) before sending them to the designated master. The master sensor also collects its own acceleration and computes the corresponding features. Once sufficient amount (i.e. 4.2s worth) of feature data is available at the master unit, it executes a previously trained decision tree classifier to recognize the current activity and then periodically sends the detected activity to an access point, when available in range. Decision tree was chosen for its lower computational complexity.

Given that the processor on the on-body sensors are generally cycle-limited, and the activity analytics is expected to share the CPU with other applications [9], the amount of total processing load is expected to impact the activity detection accuracy in the on-body processing mode.

While executing the decision tree based classifier (which was trained off-body), a synthetic background load generating process was executed. The background load comprised of periodic multiplication of two *4×4* unsigned 32-bit integer matrices. It was observed that each matrix multiplication takes approximately 1.5ms. Multiplications are carried out with exponentially distributed periodicity and duration, for which the mean is changed for varying the effective background load. Background load is expressed in percentage as the mean execution time of each multiplication operation over the mean interval between two consecutive multiplications.

The effects of background load are depicted in Fig. 7:a. Experimental analysis revealed that the loss of detection accuracy is primarily due to sampling irregularities and sample losses caused by the background process. The detection process uses a 100ms periodic timer for sampling acceleration data. It turns out that increased background load can: 1) insert large timing jitter for the sampling timer, and 2) subsequently reduce the effective number of samples within each 4.2s entropy computation window. Therefore, the assumption in [9] that a modularized criteria could decide if a task can fit in is not valid.

These effects, which cause the loss of detection accuracy, are shown in Fig. 7:b. The sample interval variation in Fig. 7:b reports effect-1 above. And the sample loss rate represents effect-2. Deterioration of both these quantities with higher background load explains the loss of accuracy. Note that the impacts of background load are significantly more pronounced for the dynamic activities, which is why Fig. 7 reports only the dynamic case. Since the static detection solely relies on mean of acceleration, sample loss and irregularities does not affect the accuracy.

The effects illustrated above are caused by the non-preemptive nature of TinyOS' scheduling strategy. The accelerometer sampling cannot be executed when the CPU is occupied by a background task till its completion. Because of the low processing speed of ATmega128L processor in our system, such effects of non-preemptive TinyOS are amplified. For higher speed processors, similar effects in non-preemptive operating systems such as V×Works or embedded Linux [14] can still be expected, although in a milder fashion.

7. Summary and Ongoing Work

This paper reported the implementation details, system characterization and performance of a wearable sensor network that is capable of monitoring human activities. Impacts of the sensor network size, energy budget on detection accuracy are analyzed. Background CPU load incurred by other applications is also proven to affect detection accuracy. Ongoing work on this topic includes: 1) developing a middleware framework for autonomous process migration for switching between on-body and off-body processing modes based on available energy and processing resources, and 2) including more activities into the activity set and developing an algorithm for detecting daily activities.

Acknowledgments

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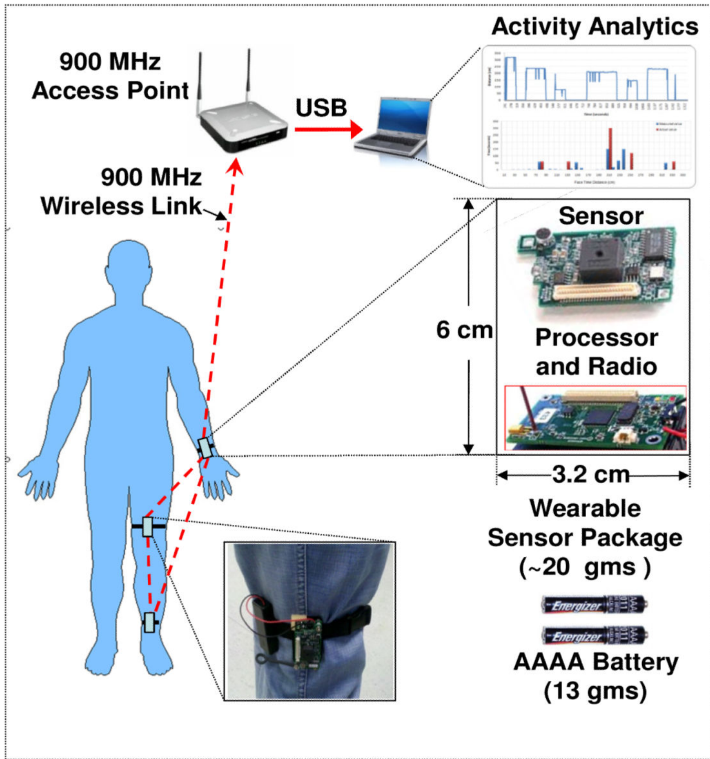

Fig. 1.
Wearable sensor network for activity analysis

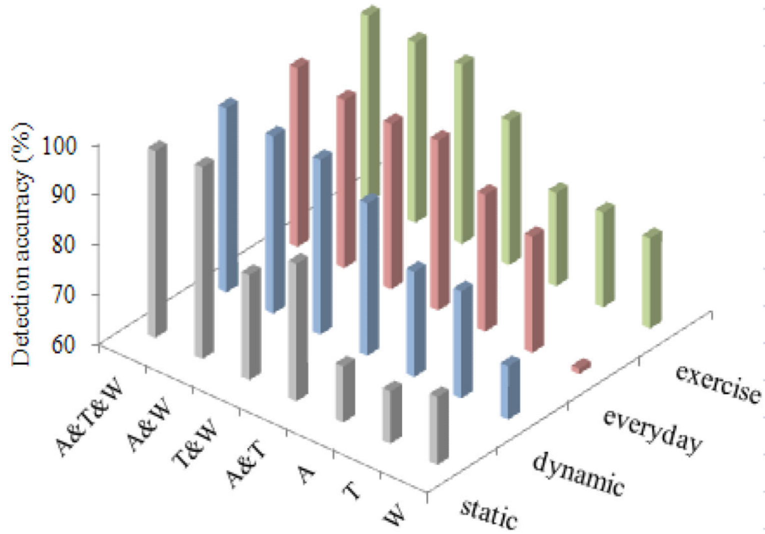

Fig. 2.
Detection accuracy of sensor combinations over activity sets

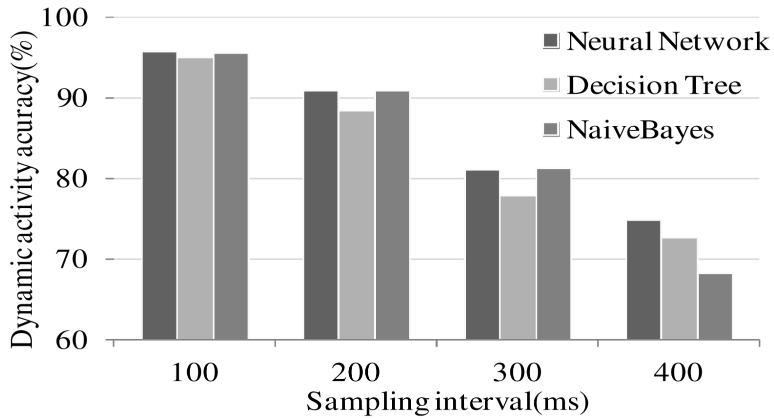

Fig. 3.
Classification accuracy vs. sampling interval

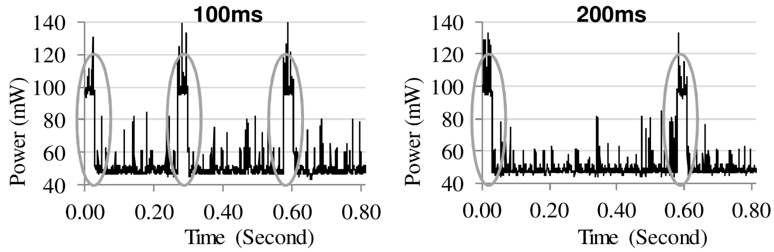

Fig. 4.
Power consumption traces for different sampling rates

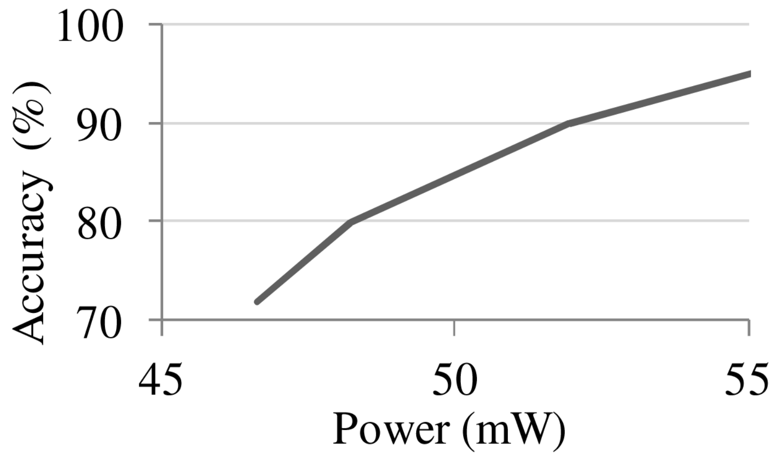

Fig. 5.
Activity recognition as function of power consumption

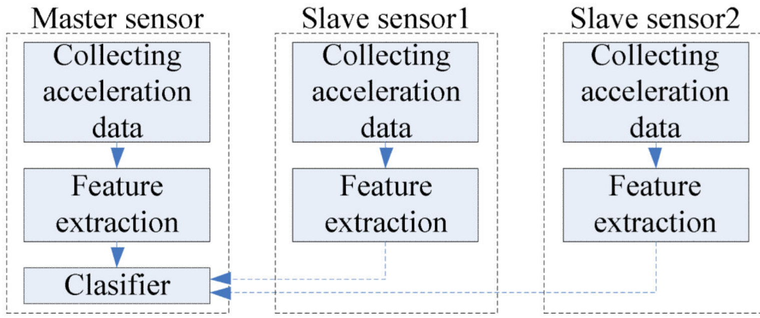

Fig. 6.
On-body processing model

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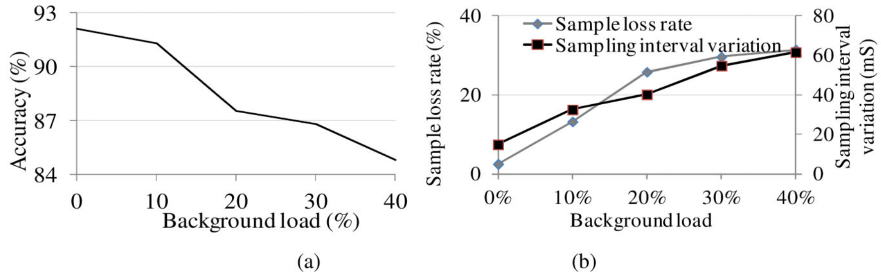

Fig. 7.

Loss of detection accuracy due to limited processing cycles

Table 1

Age, height, and weight statistics of the study subjects

	Age(Year)	Height(cm)	Weight(kg)
Mean	24.52	171.05	70.22
Standard deviation	4.99	10.04	15.29
Max	37	189.95	121.4
Min	19	149	54

Table 2

Recognition accuracy of single-layer classifier system

Classifier	Accuracy using entropy+mean (%)	Accuracy using standard deviation+mean (%)
Neural Network	95.01	95.61
Decision Trees	93.42	93.49
Naïve Bayes	96.18	95.31
SVM	96.95	96.80
Nearest Neighbor	96.27	95.92

Table 3

Detection accuracy using two sensors

	Accuracy(%)
Ankle & Thigh	89.60
Ankle & Wrist	96.20
Thigh & Wrist	91.00
Ankle	78.30
Thigh	78.33
Wrist	71.50