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A System for Activity Recognition Using Multi-Sensor Fusion

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Abstract— **This paper proposes a system for activity recognition using multi-sensor fusion. In this system, four sensors are attached to the waist, chest, thigh, and side of the body. In the study we present two solutions for factors that affect the activity recognition accuracy: the calibration drift and the sensor orientation changing. The datasets used to evaluate this system were collected from 8 subjects who were asked to perform 8 scripted normal activities of daily living (ADL), three times each. The Naïve Bayes classifier using multi-sensor fusion is adopted and achieves 70.88%-97.66% recognition accuracies for 1-4 sensors.**

I. INTRODUCTION

Over the past decades, wearable technology has gained the interest of researchers and clinicians [1]. There have been a number of applications using wearable systems such as monitoring patients with chronic disease and detecting emergency situations for elderly persons [2]. In these applications activity recognition is a requirement of the monitoring system. Inertial sensors such as accelerometers and gyroscopes are appropriate and widely used for activity recognition.

There has been a lot of work in human activity recognition using a single sensor attached to different parts of the body. Karantonis et al. [3] proposed an activity recognition system using a single waist mounted accelerometer to discriminate activities of daily living (ADL) with threshold-based techniques. In many cases, there was a lot of noise sources that affected the recognition accuracy in wearable systems, such as motion artifacts and communication error. Therefore, multi-sensor fusion is adopted to maximize the information content and reduce both systematic and random error.

Sensor calibration and alignment are two major factors affecting the performance of wearable systems [4]. The vast majority of research in this area assumes well defined, fixed sensor locations, and no calibration parameters drift occurs in the experiment. In this paper, we propose two algorithms which can be used to calibrate the signal dynamically and eliminate the affect of a varying sensor orientation.

A number of research studies have proposed classifier algorithms for activity recognition. Yang et al. implemented a neural network classifier for off-line activity recognition [5]. However, implementing such a complex algorithm in wearable systems is a big challenge due to the computational limitation of an embedded-system. The alternative Naïve Bayes classification is a simple probabilistic classifier, assuming strong independence of attributes, and it is suited for the real-time and embedded classification of activity.

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This paper is organized as follows: In section II, the system is presented. The algorithms for in-use calibration and the elimination of sensor orientation changing are addressed. The Naïve Bayes classifier using multi-sensor fusion is investigated. In section III, we analyze the datasets of ADL collected from eight subjects,simultaneously recorded from four sensors, and investigate the recognition accuracies.

II. METHODOLOGY

A. System Architecture

In this study, we adopted the Shimmer wireless sensor platform [6] to collect the movement information. Shimmer is a small sensor platform well suited for wearable applications, which includes a tri-axial accelerometer, a MSP430 microprocessor and a Bluetooth module. It is suitable for the monitoring of human movement and establishing body sensor networks. Four sensors were attached to each subject at the chest, waist, thigh and side of the body. Data was recorded from the sensor arrangement via Bluetooth. Fig. 1 shows the deployment of the system.

B. In-use Calibration

Generally, accelerometers must calibrated before use. In this paper, we define this method as the predefined calibration. In the research, the calibration of the tri-axial accelerometer was performed using the method proposed by Ferraris et al. [7]. However, we assumed that the drift of each axis was linear. Therefore, the complexity of the computation for the calibration drift was obviously reduced.

C. Sensor Orientation

The activity recognition using accelerometers can be affected by sensor orientation changing. One accelerometer sensor can deliver different reports about a movement due to the change of the orientation. A number of researches assume that the sensors are well fixed at a certain position.

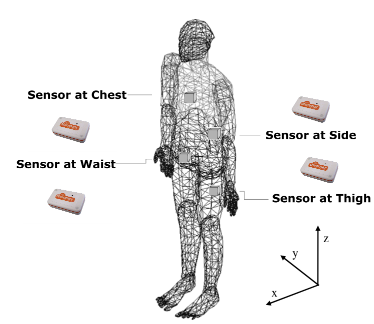

Fig. 1: The System Architecture.

However, the problem still occurs due to the slight difference in sensor orientation when fixing the sensor at the beginning of experiments. In Fig. 2, three subjects with the sensors attached to the waist were asked to perform the following activities: standing, sitting, lying and walking. The signals of sensor attachment change distinctly between different subjects due to the slight change of the orientation.

In this paper, an estimate of the constant gravity vector is adopted to solve the above problem. In the static activity such as standing, the gravity vector is steady. It can be used to estimate the vertical component, and the magnitude of the horizontal component is also obtained [8].

In Fig. 3, there are two relevant coordinate systems. One is the body reference coordinate system relative to the gravity, and the other is the device coordinate system based on the sensor orientation. In the body reference coordinate system, we define the initial gravity direction as the vertical component (however, when the subject is lying, the initial gravity direction changes to the horizontal direction.), and define the initial horizontal direction as the horizontal component. In this paper, we proposed an algorithm to transform the accelerometer signals from the device coordinate system which is sensitive to the orientation to the body reference coordinate system which is steady. During testing, subjects were asked to stand still for at least 1s, and then performed the required activities. Therefore, the gravity vector represented using the device coordinate system is given by (1),

$$v_g = (v_x, v_y, v_z); \tag{1}$$

and the real-time acceleration is denoted as (2).

$$A = (a_x, a_y, a_z); \tag{2}$$

Then, using the vector dot product, we can compute the projection P of A upon the initial vertical axis V_g as described by (3).

$$P = (\frac{A \cdot V_g}{V_g \cdot V_g})V_g \tag{3}$$

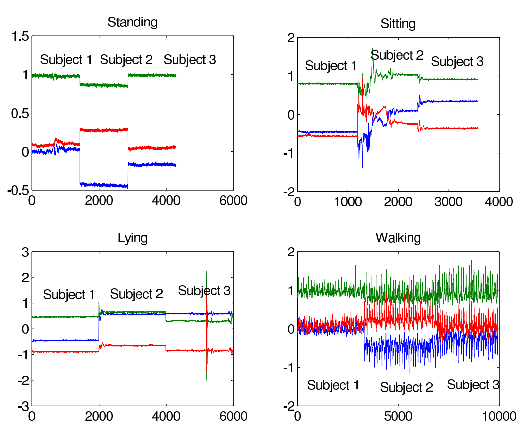

Fig. 2: The signals of different subjects performing the same activity.

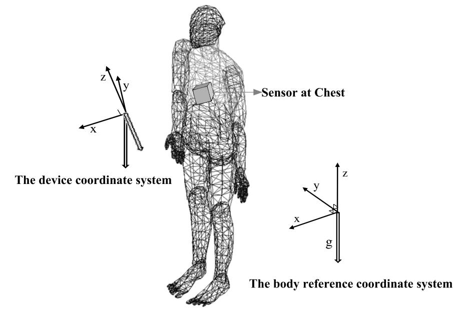

Fig. 3: The comparison of the body reference coordinate system and the device coordinate system.

In other words, P is the vertical component of the acceleration vector A. $|P|$ is the magnitude of the vertical component, and (4) can be used to indicated the direction of the vertical component relative to the initial vertical direction.

$$\cos(\alpha) = \frac{P \cdot V_g}{|P| \times |V_g|} \tag{4}$$

Next, since A is the sum of its vertical and horizontal components, we can compute the horizontal component of the acceleration signal by vector subtraction as denoted by (5).

$$H = A - P \tag{5}$$

However, as opposed to the vertical case, the orientation of H relative to the global coordinate system is hard to detect. Accordingly, we simply compute the magnitude of the horizontal component of the real-time acceleration as $|H|$. The signals transformed to the body reference coordinate system from the above experiments are illustrated in Fig. 4.

In Fig. 4, the transformed signals which were collected from different subjects performing the same activities showed that the vertical and horizontal information is steady despite the change of the sensor orientation.

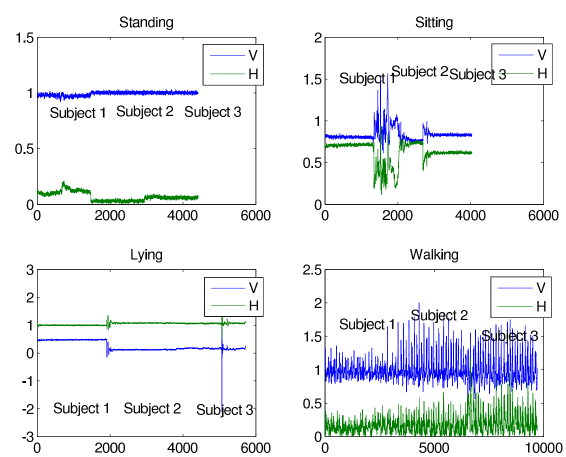

Fig. 4: The signal using the body reference coordinate system.

D. Feature Selection

Before the raw data goes through the classifier, they must be pre-processed using a windowing technique and feature selection to increase the classification accuracy. In this paper, a fixed and not overlapped window size approach was adopted to segment the signals. The fixed window size approach is easy to implement, and thus is ideally suited for real-time applications in embedded system. The sampling rate of the accelerometer is $200Hz$, and the window size is $0.5s$, which means that there are 100 samples in each window.

Raw data seperated into small windows are used to generate the features. Time-domain features were selected in this research, which require less time consumption compared with FFT or Wavelet analysis. The Mean and the Standard Deviation are common time-domain features for activity recognition. In this paper, the Mean is used to identify the static activities, and the Standard Deviation is adopted to identify the dynamic activities in combination with the Mean feature.

E. Naïve Bayes Classifier

Currently, most activity classifiers are designed for off-line recognition. Techniques of spatiotemporal analysis such as hidden markov models (HMM) used in [9] show good classification rates for everyday activities. However, running resource intensive algorithms on an embedded sensor system is a challenging task. Therefore, Naïve Bayes classification is adopted as the classifier considering its high recognition accuracy and ease of implementation.

The Naïve Bayes classifier is a simple probabilistic classifier assuming strong independence within attributes of an instance as (6).

$$\begin{aligned} & argmax_c P(C = c|H_1, H2, \cdots, H_n) \\ & = argmax_c \frac{1}{Z} P(C) \prod_{i=1}^{n} P(H_i|C) \end{aligned} \tag{6}$$

Z is a scaling factor, which depends only on all the hypotheses, C is the classification set, and $P(c)$ is called the class prior probability. Assume acceleration data from the sensors have a Gaussian distribution whose mean and variance depend on class set. In the training stage, all the related mean and variance are calculated and the model is built. During testing, given a particular raw data, the activity with maximum probability based on (6) is identified. The process is shown in Fig. 5.

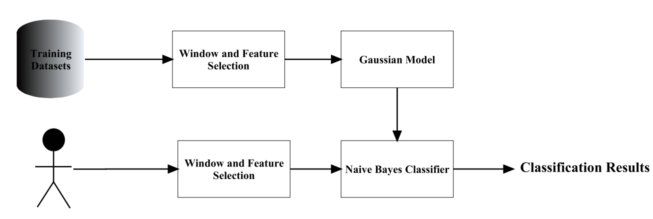

Fig. 5: The process of Naïve Bayes classification.

Moreover, the Naïve Bayes classifier is suitable for multi-sensor fusion. Considering the assumption that all the hypotheses are independent with each other, multi-sensor fusion can be represented by the multiplication of the probabilities of each sensor. For instance, the probability of sitting using four sensors is shown in (7).

$$\begin{aligned} & P(Sitting|S_{chest}, S_{waist}, S_{side}, S_{thigh}) = \\ & \frac{P(Sitting) \times P(chest|Sitting)}{P(S_{chest}, S_{waist}, S_{side}, S_{thigh})} \\ & \times \frac{P(waist|Sitting) \times P(side|Sitting)}{P(S_{chest}, S_{waist}, S_{side}, S_{thigh})} \\ & \times \frac{P(thigh|Sitting)}{P(S_{chest}, S_{waist}, S_{side}, S_{thigh})} \end{aligned} \tag{7}$$

III. Experiment

A. Data Collection

In this research, eight subjects ranged in age from 70 to 83 (76.50 ± 4.41 years) were recruited for trial. They were asked to perform eight scripted activities as shown in Table I with four sensors simultaneously recording, and each activity was repeated three times. Data was recorded from the sensors all to a laptop via Bluetooth.

Each continuous activity was separated into several components which belong to the following categories: Sitting, Standing, Lying and Walking. In the research, there are several activities which include the same component, but they are recorded in different scenarios. For example, Case 1 and Case 2 both consist of Sitting and Standing, but the signal may be different due to the different scenario. Using these datasets, the performance of the system can be investigated using real-life activities. In this paper, we define sitting, standing and lying as the static activities, and define walking and up stairs as the dynamic activities.

B. Data Analysis

As an preliminary evaluation, the calibration drift and sensor orientation affecting the recognition accuracies are discussed. Meanwhile, the accuracy comparison of using different number of sensors is also addressed. In this study, two types of evaluation procedure were adopted:

1) Setting 1: The datasets used to train the classifier and test the system are from the same subject. This method was used to test the in-use calibration algorithm.

TABLE I: The continues activities

	Description	Categories
Case 1	Sitting down and standing up from an arm chair	Sitting
Case 2	Sitting down and standing up from a kitchen chair	Sitting
Case 3	Sitting down and standing up from a toilet seat	Sitting
Case 4	Walking up and down stairs	Walking
Case 5	Sitting down and standing up from a bed	Sitting
Case 6	Lying down and getting up from a bed	Lying
Case 7	Getting in and out of a car seat	Sitting
Case 8	Walking 10m	Walking

2) Setting 2: The datasets collected from the seven subjects are used to train the classifier, and the one from the last subject is used to verify the recognition accuracies. This method was used to test the elimination of sensor orientation changing and the multi-sensor fusion.

Table II shows the comparison of the predefined calibration and the in-use calibration. It denotes that the drift of the calibration parameters can slightly affect the performance of the system, and the static activities are more sensitive to this drift compared to the dynamic activities. This is due to the recognition for the static activities mainly depends on the value of the Mean feature.

In Table III, the impact of sensor orientation changing on the recognition accuracies is addressed. The overall recognition accuracies adopting the body reference coordinate system are almost 50% higher than the ones using the device coordinate system. Especially, the static activities such as standing and sitting cannot be recognized using the device coordinate system. This is due to that the value of the Mean feature changes when the sensor orientation is changing. Thus, it is necessary to transform the signals from the device coordinate system to the body reference coordinate system.

Table IV denotes the maximum and minimum recognition accuracies fusing different sensors. The overall recognition accuracies rise with the number of sensors in the system. The overall recognition accuracies using one sensor or up to four sensors was 78.22%, 86.29%, 92.55% and 97.66% respectively. Therefore, even if one sensor was not working in the system, the recognition accuracy can also reach 92.55%. Therefore, the system can tolerate some network faults. The sensor attached to the waist performs best using a single sensor, and the combination using the sensor attached to the waist and other sensors can achieve a high accuracy.

TABLE II: recognition accuracies comparison of using the predefined parameters and the in-use calibration

Activities	Normal calibration	In-use calibration
Standing	89.76%	92.35%
Sitting	98.32%	99.48%
Lying	100.00%	100.00%
Walking	98.38%	98.45%
Up and down stairs	93.48%	93.52%

TABLE III: The recognition accuracies comparison of using the device coordinate system and the body reference coordinate system

Activities	Device frame	Body reference frame
Standing	0.00%	99.58%
Sitting	0.00%	100.00%
Lying	93.90%	100.00%
Walking	35.22%	93.55%
Up and down stairs	54.18%	84.34%

TABLE IV: The maximum and minimum recognition accuracies fusing different sensors

Location(W: waist, T: thigh, S: side of the body and C: chest)		
Sensors Num.	Max	Min
Single	W (80.43%)	T (70.88%)
Two	W + T (95.39%)	C + S (78.02%)
Three	W + S + T (97.26%)	W + S + C (80.00%)
Four	W + S + T + C (97.66%)	N/A

IV. CONCLUSION

In conclusion we have developed two algorithms for eliminating the impacts due to the calibration drift and the sensor orientation changing on the recognition accuracies of the system. Using the in-use calibration, the drift can be almost removed from the signals. The signal transformation between two different coordinate systems can significantly improve the classification performance. The increase of the overall accuracy can reach 50% or more in the worst situation.

Multi-sensor fusion can not only improve the performance of the system, but also tolerate some networks faults. Using four-sensor fusion, the recognition accuracy of 97.66% can be achieved using Setting 2. Meanwhile, the system can also work well when one sensor was not working. In addition, using a single sensor, the classification technique still achieves an average recognition accuracy of 78.22%.

V. ACKNOWLEDGEMENT

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