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Accurate Activity Recognition using a Mobile Phone regardless of Device Orientation and Location

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***Abstract*—This paper investigates two major issues in using a tri-axial accelerometer-embedded mobile phone for continuous activity monitoring, i.e. the difference in orientations and locations of the device. Two experiments with a total of ten test subjects performed six daily activities were conducted in this study: one with a device fixed on the waist in sixteen different orientations and another with three different device locations (i.e., shirt-pocket, trouser-pocket and waist) in two different device orientations. For handling with varying device orientations, a projection-based method for device coordinate system estimation has been proposed. Based on the dataset with sixteen different device orientations, the experimental results have illustrated that the proposed method is efficient for rectifying the acceleration signals into the same coordinate system, yielding significantly improved activity recognition accuracy. After signal transformation, the recognition results of signals acquired from different device locations are compared. The experimental results show that when the sensor is placed on different rigid body, different models are required for certain activities.**

Keywords-activity recognition; mobile phone; accelerometer; device-orientation independent; device-location independent

I. INTRODUCTION

To provide a suitable support for users under different conditions, various types of sensors, such as accelerometers, gyroscopes, light sensors, or GPS, have been used for capturing user contexts. Body Sensor Networks (BSNs) [1, 2] have been designed and developed as platforms for which these sensors can be integrated. The technology is renowned for its promising uses in many application areas ranging from healthcare [3, 4], sport [5, 6, 7], to gaming and intelligent interfaces [8, 9]. Nowadays, mobile phones are being increasingly used on daily basis and become vital to everyday life of the users. Mobile phones are popularly deployed in a BSN as a data aggregator or an intermediate server for lightweight processing [10, 11]. Embedded with many diverse and powerful sensors, these devices can also be considered as a sensing node.

Activity recognition is an important research topic in the field of context awareness. It has been illustrated in many studies that an accelerometer is capable of capturing most basic activities [12, 13, 14, 15]. A tri-axial accelerometer is now embedded in several mobile phones. Since a mobile phone is being carried by users on daily basis, it is a suitable tool for continuous monitoring of user activities.

Phone-based activity recognition has been investigated in many studies [16, 17, 18, 19, 20]. For example, Bieber et al. [17] presented a mobile application for identifying physical activities and calculating the amount of daily calories expenditure using a tri-axial accelerometer. Most of the previous studies, however, assume the acceleration signals are collected from a known fixed device location and orientation [17, 20, 21]. The main issue in phone-based activity monitoring arises when the devices are carried in different locations and styles [22, 23].

Mizell [24] illustrated that signal average can be used to approximate the gravity component, which is considered as the vertical axis of the device in many studies. In [25], orientation-independent features extracted from vertical and horizontal components of the acceleration signals have been investigated. The estimation of vertical component may not be accurate when non-bipedal activities (e.g. lying) are involved. Thiemjarus [22] suggested that to estimate the vertical component or device orientation acceleration signals acquired during dynamic activities should be observed. In [26], weightlessness features are proposed. Based on the assumption that while user performing activities such as run or jump, our body will leave the ground and stay in a weightlessness state revealing the vertical axis of the accelerometer.

Major approaches for dealing with variations in device placement include 1) use robust features that are independent to device placement, 2) use a set of models specific to each detected device placement, 3) use a transformation matrix for rectifying the acceleration signal prior to classification. With the first approach, a single unified model can be used regardless of differences in device location/orientation. For the second approach, a rule-based framework for activity recognition was proposed in [27]. In the study, mean of dynamic activities was used for inferring device orientation, from which the appropriate set of activity classification rules and threshold parameters can be selected. In [22] and [28], the dynamic mean is used to estimate the rotational angles of the device while the sensor is placed in different orientations at the waist. The rotation matrix is used to transform the input signals into the same reference coordinate system. With signal transformation, significant improvement in subject-independent recognition accuracy can be achieved with datasets from one or a few specific orientations, saving a lot of effort in data collection. It was observed in the studies, however, that relying on the vertical axis reference, only the rotation angle around the forward-axis can be directly estimated.

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This paper proposes a combination of techniques for handling with both device orientation and location issues in activity monitoring with a mobile phone. Section II describes the setup of two activity recognition experiments involved in this study. In Section III, a projection-based method for estimating transformation matrix for handling with different device orientations is proposed. Section IV and V describe the activity recognition experiments, along with the results, for different device orientations and locations, respectively. Section VI concludes this paper.

II. DATA COLLECTION AND EXPERIMENT SETUP

In this study, two activity recognition experiments were performed using a tri-axial accelerometer embedded in an iPhone [29]. An Xcode application that executes both on the phone and PC side has been developed to facilitate data acquisition and annotation process. The first experiment is used to investigate the device orientation issues and the second experiment is used to investigate scenarios when different device locations are also taken into account.

In the first experiment, the device was placed on user's waist (L3). Five subjects, aged between 22 to 36 years old, were asked to perform an activity routine twice in each of the sixteen device orientations as shown in Figure 1.The activity routine consists of lying (A1), sitting (A2), standing (A3), walking (A4), running (A5) and jumping (A6). Each activity last for ~5seconds. A sampling rate of 50 Hz was used.

Figure 1. The sixteen device orientations.

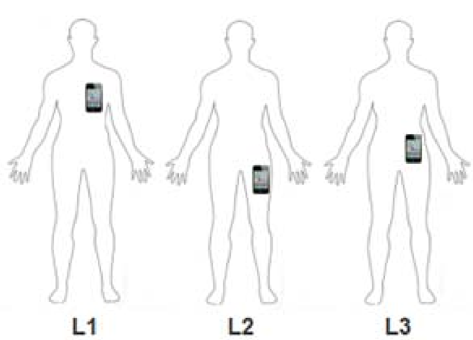

Figure 2. Device locations: shirt-pocket (L1), trouser-pocket (L2) and waist (L3).

In the second experiment, five different subjects were asked to perform the same activity routine twice while carrying the device. As shown in Figure 2, the device is placed in three different locations, namely in the shirt-pocket (L1), in the trouser-pocket (L2), at the waist (L3) in two orientations (O7 and O3). At the waist, the acceleration signals were also acquired from two additional orientations, i.e. O5 and O1, which will be denoted as L4. All of the device locations and orientations in this experiment are the realistic on-body placement of mobile phone carried by most users [30].

III. PROJECTION-BASED TECHNIQUE FOR DEVICE ORIENTATION TRANSFORMATION

The acceleration signals are varied since the mobile phone can be carried in many different places and orientations. The signal transformation is used to generate uniform signals from different placements and orientations. The basic idea is to transform all input signal into the same global reference coordinate system.

First, the input signals are preprocessed by normalization with mean and standard deviation. Then the three axes of the global reference coordinate namely the vertical axis, the forward axis, and the sideward axis, are computed from this normalized signals. The vertical axis can be identified based on the mean of the dynamic portion of the signals. To separate static and dynamic activities, variance magnitude is used and then mean of normalized dynamic signals is calculated as in [9].

Let w be the mean of the dynamic portion, which is the vertical axis of the global coordinate system. To find the forward axis, we assume that most of the activity is in forward-backward direction. Hence, the forward direction can be computed from the principal axis of data on the plane perpendicular to w. From the above discussion, the forward axis can be found in two steps; the first step is to project the signal onto the plane perpendicular to w, then compute the principal axis on this data. The first step is done by subtracting the signal along the vertical axis:

$$x_t^{'} = x_t - (x_t^T w)w \tag{1}$$

where $x^{'}$ is the removed acceleration signals along vertical axis, x is a raw acceleration signals. The second step is done by performing eigen-decomposition on the covariance matrix of this projected data:

$$C = \frac{1}{T}\sum_{t=1}^{T}(x_t^{'} - \mu^{'})(x_t^{'} - \mu^{'})^T \tag{2}$$

where $\mu^{'}$ is the mean of the projected data, calculated as follows:

$$\mu^{'} = \frac{1}{T}\sum_{t=1}^{T} x_t^{'} \tag{3}$$

It should be noted that the forward axis is parallel to the main eigenvector of the covariance matrix. However, by analyzing only the data distribution, one cannot distinguish between the movement backward with normal positioned device and the movement forward with device turned backward. In this work where the data collection is performed in predefined order of activities, one may simply turn the main eigenvector such that the first observation is always positive:

$$\text{if } \; x_1'^{T} u \; < 0 \; \text{ then } \; u = -u \tag{4}$$

where u is the eigenvector corresponding to the largest eigenvalue. u will be used as forward axis of the global coordinate system. In real application, this corresponds to the device calibration prior to the use of the system. It is also worthy noted that with detailed analysis of the projection of signals along the u axis, one may automatically identify the forward direction. This will be further investigated in our future works.

Lastly, the sideward axis can be found by considering the cross product between the vertical and the forward axes:

$$v = u \times \mu \tag{5}$$

using these three axes, u , v , and w , one may construct the transformation matrix as follows:

$$T = \begin{bmatrix} u_x & u_y & u_z \\ v_x & v_y & v_z \\ w_x & w_y & w_z \end{bmatrix} \tag{6}$$

IV. Experiement with Different Device Orientations

To validate the method described in Section III, the datasets acquired from the first experiment were used. In the experiment, the mobile phone was placed on the user's waist in sixteen different device orientations.

We preprocessed the acceleration signals by mean subtraction, then transformed the signals by transformation matrix calculated using the method described in Section III. Figure 3 shows the acceleration signals before and after the signal transformation. Signals from all of the sixteen device orientations are transformed into the same reference coordinate system.

TABLE I. Training datasets used in the first activity recognition experiment.

	Orientation
T1	O1
T2	O2
T3	O1, O3, O5, O7
T4	O2, O4, O6, O8
T5	O1, O3, O5, O7, O9, O11, O13, O15
T6	O2, O4, O6, O8, O10, O12, O14
T7	O1, O2, O3, O4, O5 ,O6 ,O7, O8, O9, O10, O11, O12, O13, O14, O15, O16

Due to the uniformity of the acceleration signals, we can use signals acquired from any orientation(s) as the training dataset. To investigate how different training datasets may affect the activity recognition accuracy, different training datasets were constructed from signals acquired during the first iteration of activity routine as shown in Table 1. For classification, instance-based learning with k=3 [31] was used. To construct a feature vector, mean and standard deviation were calculated over the 3D acceleration signals using a fixed window size of 1 second and a shifted window of size 0.25 second. Two classification methods are compared as follows:

- **Method I:** Classification without signal transformation
- **Method II:** Classification with signal transformation

Table 2 and Table 3 show the classification results of Method I and Method II when applied across all the sixteen orientations, respectively. The test datasets were constructed from signals acquired during the second iteration of the activity routine. The results show that, using only data acquired from a single device orientation (training set T1 or T2), classification with signal transformation performs better than classification without signal transformation by ~42-51%. The results also show that the amount of training dataset can affect the recognition accuracy. When data from all orientations was used for training, Method II achieved the best accuracy of 86.36%, which is still 5.8% higher than that achieved by Method I. Most misclassifications were resulting from the limited power of the features in discriminating running and jumping activities. Without signal transformation, static activities are highly confused when some orientation was missing from the training dataset.

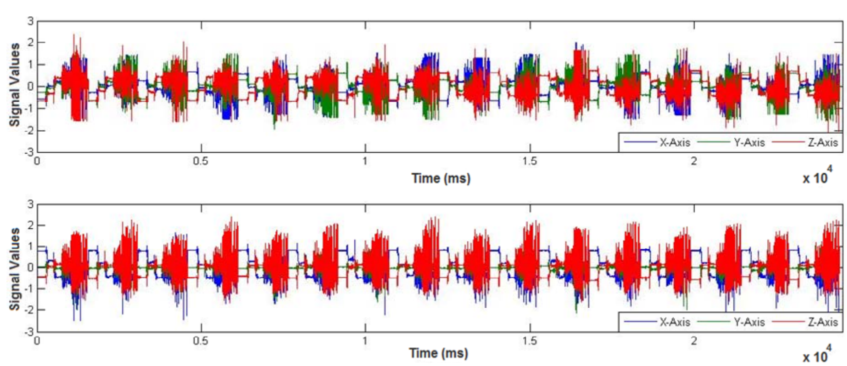

Figure 3. A comparison of a concatenated normalized acceleration signals acquired from 16 different device orientations while test subject performing 6 activities: signals without transformation (top) and signals transformed by the transformation matrix estimated using the method described in Section III (bottom).

TABLE II. ACCURACY COMPARISON FOR THE SIX TRAINING DATASETS USING METHOD I.

Training Set	Activity						
	A1	A2	A3	A4	A5	A6	Overall
T1	33.54%	37.50%	44.59%	18.63%	30.25%	17.93%	30.55%
T2	25.47%	31.88%	25.48%	21.12%	5.56%	37.24%	24.21%
T3	50.93%	37.50%	45.22%	42.24%	54.32%	28.97%	43.45%
T4	42.86%	38.13%	48.41%	36.02%	21.60%	46.90%	38.79%
T5	100.00%	66.88%	76.43%	88.82%	81.48%	33.79%	75.26%
T6	91.93%	77.50%	74.52%	81.37%	39.51%	68.28%	72.20%
T7	92.55%	85.63%	82.17%	85.71%	74.07%	61.38%	80.55%

TABLE III. ACCURACY COMPARISON FOR THE SIX TRAINING DATASETS USING METHOD II.

Training Set	Activity						
	A1	A2	A3	A4	A5	A6	Overall
T1	98.14%	91.88%	58.60%	88.20%	42.59%	58.62%	73.26%
T2	100.00%	55.63%	79.62%	97.52%	43.83%	80.69%	76.11%
T3	100.00%	90.00%	87.26%	93.79%	62.96%	60.00%	82.66%
T4	100.00%	71.88%	91.72%	95.03%	67.28%	75.17%	83.62%
T5	100.00%	90.00%	89.81%	91.93%	70.37%	62.07%	84.36%
T6	100.00%	78.75%	92.99%	92.55%	67.90%	73.79%	84.46%
T7	100.00%	85.00%	91.08%	91.93%	74.07%	75.17%	86.36%

V. EXPERIMENT WITH DIFFERENT DEVICE LOCATIONS

To investigate the effect of device locations, the datasets acquired from the second experiment were used. The three different device locations are shirt-pocket (L1), trouser-pocket (L2) and waist (belt-enhancement) (L3). L4 denotes the waist location with different device orientations. For data analysis, the acceleration signals were first preprocessed by mean subtraction. Figure 4 shows a comparison of the acceleration signals concatenated over different device orientations across different device locations. The left column indicates the normalized signals without any transformation and right column indicates the acceleration signals after the transformation. After the signal transformation, all of the acceleration signals acquired from different locations share more similar patterns. The acceleration values along the three axes are still quite distinct due to the different placement of the device.

For classification with 3-NN, four training datasets were constructed based on the dataset acquired using a specific device orientation for each location (L1 to L4). That is, the orientation O7 is used for locations L1 to L3 and the orientation O1 is used for the location L4. Again, signals acquired during the first iteration of activity performance were used for constructing training datasets and second iteration as the test datasets. Table 4 shows the subject-independent classification results of Method I and Method II when signals acquired from both device orientations in the same location were used as the test datasets. The results show that waist is the best device location compared with others, followed by shirt-pocket and trouser-pocket, respectively. The low recognition accuracy for trouser-pocket is because lying and sitting become more difficult to classify based on the orientation of the leg, and that the device is moving along with the leg while the user performing dynamic activities. The proposed signal transformation technique (Method II) can improve the recognition accuracy in all cases.

To access if the same recognition model can be shared across different device locations, the four training datasets were tested on datasets acquired from different locations. The classification results are shown in Table 5. The results show that using a waist model (L3 or L4) an accuracy of ~70% and ~50% can be achieved on signals from trouser pocket and shirt pocket, respectively. The misclassifications of trouser pocket signals are mainly due to confusion between jumping and running as well as sitting misclassified as lying. For shirt pocket signals, sitting and walking are mainly misclassified as standing, running are misclassified as jumping.

When the trouser pocket model (L2), >70% accuracy can be achieved on classifying waist signals. This is due to lying being misclassified as sitting, sitting as standing and running as jumping. On the shirt pocket signals, the accuracy drops to 38.55%.

Although the shirt pocket model (L1) performs better than the trouser pocket model (L2) in Table 4 it performs the worst when used for classifying signals acquired from other locations. Still, the model performs better on waist signals (42.5-44.06%) than shirt pocket signals (36.85%).

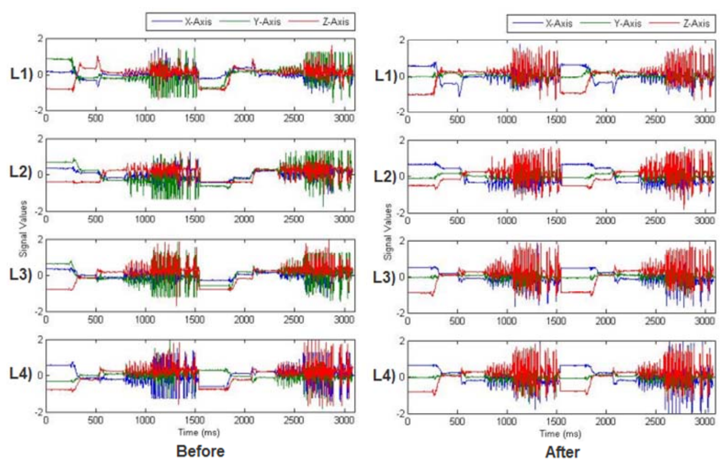

Figure 4. A comparison of concatenated normalized acceleration signals acquired from different locations (2 orientations each) while the test subject was performing six activities before and after signal transformation.

TABLE IV. A COMPARISON OF CLASSIFICATION ACCURACY WITH AND WITHOUT SIGNAL TRANSFORMATION (EXPERIMENT II). THE MODEL IS TRAINED WITH THE DATASETS ACQUIRED IN A FIXED DEVICE ORIENTATION, AND TESTED WITH DIFFERENT DATASETS ACQUIRED FROM DIFFERENT DEVICE ORIENTATIONS (SAME LOCATION).

Location		Activity						
		A1	A2	A3	A4	A5	A6	Overall
Method I	L1	45.28%	69.53%	84.68%	58.65%	65.08%	85.71%	68.31%
	L2	47.66%	20.47%	69.29%	47.76%	71.43%	41.28%	49.86%
	L3	50.00%	97.66%	91.27%	92.31%	64.84%	81.13%	80.39%
	L4	49.07%	96.83%	93.70%	90.70%	76.92%	84.11%	82.67%
Method II	L1	94.34%	92.97%	88.71%	91.73%	79.37%	81.25%	88.07%
	L2	85.98%	69.29%	92.91%	96.27%	84.13%	69.72%	83.42%
	L3	100.00%	96.09%	88.10%	96.15%	87.50%	82.08%	91.71%
	L4	96.30%	96.83%	92.13%	96.12%	80.00%	82.24%	90.65%

TABLE V. A COMPARISON OF CLASSIFICATION ACCURACY WITH SIGNAL TRANSFORMATION. THE MODEL IS TRAINED WITH THE DATASETS ACQUIRED IN A FIXED DEVICE ORIENTATION, AND TESTED WITH DIFFERENT DATASETS ACQUIRED FROM DIFFERENT DEVICE ORIENTATIONS (DIFFERENT LOCATIONS).

Location		Activity						
Train	Test	A1	A2	A3	A4	A5	A6	Overall
L 1	L1	94.34%	92.97%	88.71%	91.73%	79.37%	81.25%	88.07%
	L2	100.00%	10.24%	3.94%	0.00%	69.84%	51.38%	36.85%
	L3	100.00%	31.25%	15.08%	21.54%	73.44%	30.19%	44.06%
	L4	100.00%	32.54%	0.79%	13.95%	79.23%	35.51%	42.50%
L 2	L1	0.00%	3.13%	85.48%	21.80%	40.48%	81.25%	38.55%
	L2	85.98%	69.29%	92.91%	96.27%	84.13%	69.72%	83.42%
	L3	74.53%	53.91%	99.21%	89.23%	50.00%	75.47%	73.62%
	L4	76.85%	69.05%	96.06%	88.37%	54.62%	71.03%	76.07%
L 3	L1	91.51%	12.50%	78.23%	36.09%	26.19%	75.89%	51.58%
	L2	95.33%	44.88%	78.74%	81.34%	91.27%	39.45%	72.05%
	L3	100.00%	96.09%	88.10%	96.15%	87.50%	82.08%	91.71%
	L4	95.37%	96.83%	90.55%	93.02%	87.69%	77.57%	90.37%
L 4	L1	90.57%	13.28%	59.68%	33.08%	20.63%	83.04%	48.01%
	L2	96.26%	43.31%	82.68%	92.54%	76.19%	56.88%	74.66%
	L3	99.06%	92.97%	90.48%	96.92%	80.47%	80.19%	90.06%
	L4	96.30%	96.83%	92.13%	96.12%	80.00%	82.24%	90.65%

With mean and standard deviation of the transformed dynamic acceleration signals, perfect classification of device locations can be obtained. This information can be used for automatic selection of a location-specific classification model. By combining the proposed orientation transformation method with a set of location-specific classification models trained with datasets acquired from a specific orientation, the system can achieve ~90% classification accuracy.

VI. CONCLUSION

In this paper, we investigated both device location and orientation issues in using a mobile phone for continuous monitoring of physical activities. A projection-based method for estimating device orientation and signal rectification has been proposed. Two experiments have been conducted using a mobile-phone embedded with a tri-axial accelerometer. Activity recognition experiments with sixteen device orientations and three device locations show that the resulting transformation matrix can successfully rectifying the acceleration signals acquired from different device orientations as reflected by significant accuracy improvement.

Three device locations have been observed, namely shirt pocket, trouser pocket and waist (belt enhancement). Based on the experimental results, out of the three locations, user waist is the best position for device placement. It is suggested that a different set of features or improved transformation method can be used to eliminate the signal variation due to different placement of the device on the same rigid body. However, when the device is placed on a different rigid body (e.g. leg and waist), detecting device location is required for selecting a location-specific model.

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