A novel approach to classify human-motion in smart phone using 2d-projection method

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ABSTRACT
Classification of human motion is important for measuring the intensity of physical activities. Although the accelerometer in the smart phone has been used widely for classification, phone's various orientations lead to erroneous wrong classification of human motions during physical activity. Hence, in this paper, we present a 2D-projection method to infer users' horizontal (forward) and vertical (upward) acceleration from the phones' roll angle and horizontal and vertical acceleration. To validate our method, we collected acceleration and orientation data for six common physical activities, such as sitting, standing, walking, running, climbing-up stairs and climbing-down stairs. We then used the 2D-projection to transform phones' horizontal and vertical acceleration into users' horizontal (forward) and vertical (upward) acceleration. In the results of decision tree classification, we find that using acceleration based on users improves performance over using acceleration based on phone, while the classification of climbing-up stairs and climbing-down stairs is improved somewhat but is still insufficient. Furthermore, the number of misclassification between two activities with similar horizontal (forward) acceleration, such as walking and climbing-up or climbing-down stairs was reduced by using 2D-projection.

KEY WORDS
Smart phone, Acceleration, orientation, projection, Human-motion classification, Physical activity

1. Introduction

Accurate classification of human motion is important for analysis of physical activity (PA). PA is critically important for preventing and treating many chronic diseases in all ages [1]. Since the smart phone (SP) is small and carried for most of the day, it is used for estimating the intensity of PA and classifying human motions. For example, Kwapisz et al. used an SP's accelerometer to classify human motions [2]. However, it assumes that the SP's orientation and location is fixed while it is placed at various orientations and locations.

Different locations of an SP have different characteristics in classifying human motions. As we mainly focus on SP orientation in this study, we fixed the SP's location as the trouser pocket. Some previous works classified human motion with SP in the trouser pocket, where most males place their SPs [3]. Bieber et al. developed a method to detect PA and calculated the calories used over a period by assuming SP is carried in a trouser pocket [4].

Several previous studies presented orientation-independent approaches for considering SP's orientation problem. Mizell showed that the orientation-independent feature can be produced from the accelerometer signal averages [5]. However, this kind of operation will compute only horizontal acceleration. It is impossible to detect vertical acceleration because the horizontal axis is unknown [6]. Furthermore, the data from different SPs have different gravity measurements. [5]

Therefore, in this paper, we presented a new approach using 2D-projection method which may be able to compute vertical and horizontal acceleration and detect various activities more accurately by using acceleration and orientation signals.

2. Methodology

2.1 Subjects

Ten male subjects (age 27 ± 4 years, height 175 ± 7 cm, weight 76 ± 9 kg) volunteered for this study. All subjects had no self-reported abnormalities of PA. As trouser pocket is the most likely placement location for an SP, subjects located the phone in the subject's right trouser pocket. Subjects wore comfortable tracksuit bottom. We collected data for a set of six activities (sit, stand, walk, run, climbing-up stairs and climbing-down stairs). Six activities is the most common activity in daily life. The total period of all activities is 15~20min. In Table 1, there are the number of samples and percentages for the six activities. The duration of each sample is approximately 10 seconds. Some activities (i.e., climbing-up and climbing-down stairs) contain fewer examples than others, mainly because these activities took place under space constraints due to the short distance.

Table 1. Statistics of example per activity.

Activity	Number	%
Sit	1104	20.11
Stand	1107	20.16
Walk	1337	24.35
Run	1086	19.78
Upstairs	434	7.9
Downstairs	421	7.6
Overall	5489	100

2.2 Data acquisition

Activities were measured using an Android-based smart phone (Nexus One, HTC). This phone has an intrinsic 3-axis Accelerometer (BMA150, BOSCH) and magnetic field sensor (AK8973, AKM). The sensors in the smart phone collect acceleration and orientation data of the user's thigh movement. The sensor data was sampled and stored in SD cards using an android application. The android application sampled the sensor data at approximately 50Hz. Collected data was transmitted to a PC and analyzed using MatLab 2011a (Mathworks(R), USA).

2.3 Data transformation

During the classification of human motion, data collected from SP consists of accelerations and orientations in the local coordinate system (LCS) that relates specifically to the SP. As SP's orientation is changed by user motion, LCS has various and continuously changing configurations. In contrast, world (global) coordinate system (WCS) relates specifically to the user. WCS could only be changed by the basic direction of the user, such as left turn, right turn. Therefore, the classification of human motion should be based on the WCS. Our goal is to transform each data from LCS into the same standard as WCS. To transform the coordinate system, we project the phone's acceleration onto the user's forward and upward axes.

First, the acceleration and orientation data are preprocessed by low pass filter. A sixth order Butterworth low-pass filter with a cut-off frequency of 3Hz was used to remove noise from raw data. Then, the acceleration data ($\alpha_{raw(x)}$, $\alpha_{raw(y)}$) and one orientation data (Roll)(θ_{Roll}) are extracted from the preprocessed data.

The four accelerometer axes and one orientation angle are denoted as $\alpha_{raw(x)}$, $\alpha_{raw(y)}$, $\alpha_{\mathrm{Horizontal}}$, $\alpha_{\mathrm{vertical}}$ and θ_{raw} respectively, in Figure 1. $\alpha_{raw(x)}$ and $\alpha_{raw(y)}$ refer to the acceleration of SP screen's horizontal and vertical axes, respectively. The SP screen's horizontal axis points to the right, and the vertical axis points up from the SP screen. $\alpha_{\mathrm{Horizontal}}$ and $\alpha_{\mathrm{vertical}}$ refer to the acceleration of the user's horizontal and vertical axes, respectively. θ_{Roll} is the angle between gravity and the SP screen's vertical axis.

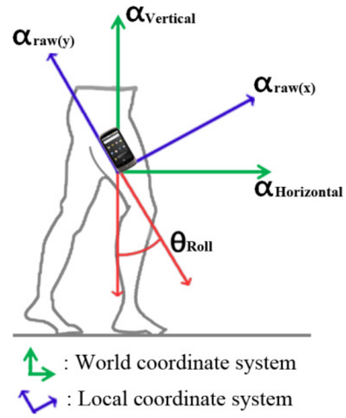

Figure 1. Accelerometer coordinate system in WCS and LCS

Let $\alpha_{\mathrm{proj(y)}}$ be the scalar projection of $\alpha_{raw(x)}$ and $\alpha_{raw(y)}$ onto the user's vertical axis, where $\alpha_{\mathrm{proj(y)}}$ is the subject's vertical (upward) acceleration. As the basic direction of the user does not change, we assume that most of user's vertical and horizontal acceleration reflect the SP's horizontal and vertical acceleration. $\alpha_{\mathrm{proj(x)}}$ can be derived in the same way as the $\alpha_{\mathrm{proj(y)}}$. $\alpha_{\mathrm{proj(x)}}$ is the scalar projection of $\alpha_{raw(x)}$ and $\alpha_{raw(y)}$ onto the user's horizontal axis, i.e.,

$$\begin{bmatrix} \cos(\theta_{raw}) & -\sin(\theta_{raw}) \\ \sin(\theta_{raw}) & \cos(\theta_{raw}) \end{bmatrix} \begin{bmatrix} \alpha_{raw(x)} \\ \alpha_{raw(y)} \end{bmatrix} = \begin{bmatrix} \alpha_{proj(x)} \\ \alpha_{proj(y)} \end{bmatrix}$$

In Figure 2, the acceleration of the user's vertical and horizontal axes can be computed using 2D-projection.

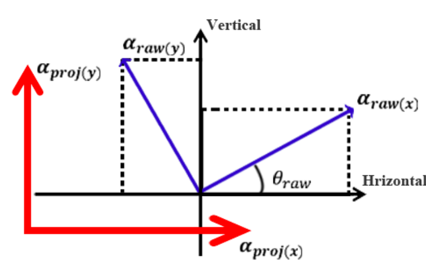

Figure 2. 2D-projection from LCS into WCS

2.4 Classification

Once the transformed data were prepared, we generated four time-domain features that can be obtained with minimal computation. The four features are mean and standard deviation for vertical and horizontal acceleration.

These four features are computed from the transformed acceleration in WCS; those were named as the transformed feature set (TFS). For the purpose of comparison, another four features are also computed from the raw acceleration in LCS, named as the raw feature set (RFS). We used the J48 decision tree (DT) classification techniques from the WEKA (http://www.cs.waikato.ac.nz/ml/weka/) data mining workbench. Ten-fold cross validation is used for all experiments.

3. Results

In the study, we collected acceleration and orientation data of six activities that involve daily routines of most peoples, such as sit, stand, walk, run, climbing-up stairs and climbing-down stairs. We transformed acceleration in LCS to WCS by using 2D-projection, as shown in Table 2.

Table 2. Means and standard deviations of the user's horizontal and vertical acceleration for six activities

Activity	Vertical Acceleration		Horizontal Acceleration	
	Mean	SD	Mena	SD
Sit	2.5637	0.1287	-2.8870	0.3141
Stand	10.302	0.0604	2.8284	1.9510
Walk	10.4171	1.8835	-5.9600	1.2289
Run	11.1058	4.5905	-8.6007	3.0852
Upstairs	9.1027	2.3267	-3.145	2.0289
Downstairs	8.9551	2.3555	-1.4259	1.6426

Table 3. Means and mean differences of the flexion/extension angles of the right thigh for six activities

Activity	Angle(°) (mean ± standard deviation)		
	Maximum	Minimum	Range
Sit	-12 ± 0.5	-10 ± 0.6	1 ± 0.8
Stand	21 ± 1.3	15 ± 0.7	6.2 ± 0.9
Walk	42 ± 15.8	-32 ± 11	74 ± 8.9
Run	78 ± 6.4	-38 ± 14.2	112 ± 8.5
Upstairs	32 ± 8.2	-28 ± 7.3	62 ± 5.6
Downstairs	26 ± 11.3	-32 ± 6.6	57 ± 9.5

Means and standard deviations of the six activities for angle of the right thigh are shown in Table 3. The wide range of the thigh's angle can be simply explained by the change of the SP's orientation. As some activities, such as walking, running, climbing-up stairs and climbing-down stairs, involve a wide range of thigh's angles, these activities have a greater effect on phone orientation. In contrast, sitting and standing have less effect on phone orientation.

Table 4. Accuracies of activity classification.

	% of records correctly predicted	
	RFS	TFS
Sit	99.90	99.54
Stand	99.72	99.72
Walk	91.17	95.88
Run	98.43	98.15
Upstairs	49.53	67.05
Downstairs	45.60	74.80
Overall	89.30	93.95

To see performance of 2D-projection, we classified six activities using the decision tree classification method and compared classification results of RFS and TFS. The prediction accuracies for the six activities from the classification result between RFS and TFS are shown in Table 4. The accuracies were confirmed by dividing the total number of samples into the correctly classified samples and using 10-fold cross-validation from WEKA. TFS in WCS have shown a higher accuracy than the RFS. With this, our results generally indicate that TFS (93.95%) can distinguish better than RFS (89.30%). Some activities, such as sit, stand, walk and run, can be classified to a high level of accuracy. In contrast, climbing-up and climbing-down stairs can be classified at low levels of accuracy. When RFS is used, the accuracy for climbing-up activity is 49.53% and the accuracy for climbing-down activity is 45.60%. When TFS is used, the accuracy for climbing-up activity is 67.05% and the accuracy for climbing-down activity is 74.80%.

Table 5. Confusion matrix for DT classification using RFS (A: Sit, B: Stand, C: Walk, D: Run, E: Upstairs, F: Downstairs)

		Predicted Activity					
		A	B	C	D	E	F
Actual Activity	A	1103	0	0	0	0	1
	B	0	1104	2	0	1	0
	C	0	0	1219	5	62	51
	D	0	0	15	1069	2	0
	E	0	0	**140**	2	**215**	**59**
	F	0	0	**149**	5	**88**	**192**

Table 6. Confusion matrix for DT classification using TFS (A: Sit, B: Stand, C: Walk, D: Run, E: Upstairs, F: Downstairs)

		Predicted Activity					
		A	B	C	D	E	F
Actual Activity	A	1099	0	0	0	0	5
	B	0	1104	2	0	0	1
	C	0	0	1282	0	7	42
	D	0	0	3	1066	17	0
	E	3	0	**42**	32	**291**	**66**
	F	0	0	**66**	2	**51**	**315**

For more accurate analysis, we used the confusion matrix. As shown in the confusion matrix (Table 5 and 6), when RFS is used for classification of climbing-up stairs and climbing-down stairs, the most common misclassification comes from walking which occurs 140 times in the classification of climbing-up stairs and 149 times in the classification of climbing-down stairs. Since these three activities have similar horizontal acceleration, the confusion matrices indicate that total prediction errors are due to confusion among three activities. When TFS is used for classification of climbing-up stairs or climbing-down stairs, the number of misclassification between walking and climbing-up stairs or climbing-down stairs decreases by half.

4. Discussion

In This paper, we have investigated PA classification using SP, simply by keeping it in right trouser pocket. Since SP's orientation is varying from motion to motion, user's orientation cannot be partially fixed or relatively fixed. Therefore we explore orientation-independent featu re extracted from acceleration in LCS by using 2D-projection.

In the classification results, some activities, such as sit, stand, walk, and run, can be classified to a high level of accuracy. In contrast, climbing-up and climbing-down stairs can be classified at low levels (under 50%) of accuracy. Therefore, we focused on these two activities. The confusion matrices indicate that prediction errors are due to confusion between two activities with similar horizontal acceleration. Since the mean of horizontal (forward) acceleration for walking, climbing-up stairs and climbing-down stairs activities are somewhat similar, these activities are often confused with each other.

Changing from LCS to WCS with 2D-projection could solve this problem. WCS provides more accurate information during the classification process because it reflects the user's horizontal (forward) and vertical (upward) axes more accurately, whereas LCS presents the SP's horizontal and vertical axes. As our results, we find that using 2D-projection achieves the best performance between two feature sets. Furthermore, when either RFS or TFS is used, the number of misclassification between climbing-up and climbing-down stairs has no significant improvement. We conclude that vertical acceleration is similar between climbing-up and climbing-down stairs activities and need new feature, such as zero cross rate, 75 percentile, to increase prediction accuracies.

As From our result, transformed acceleration in the WCS improved the classification accuracy of six activities especially between walking and climbing-up stairs or climbing-down stairs.

5. Conclusion

In this paper, we have proposed PA classification using 2D-projection with SP acceleration and orientation data. Our results indicate that 2D-projection can improve in Human-motion classification for six activities. In particular, in activities with similar horizontal acceleration, using 2D-projection can achieve better performance than using nothing. However, climbing-up and climbing-down stairs activities are still the hardest activity to recognize. For future work, we aim to investigate more reliable features, for instance, 75% percentile and 25% percentile could prove useful for classification of climbing-up stairs and climbing-down stairs. We expect that our research effect on the fields such as classification of physical activities, estimation of exercise intensity, and energy expenditure.

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