Full Model for Sensors Placement and Activities Recognition

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Abstract
We implemented a wired sensors system that supports activities identification. The system consists of Raspberry Pi, MPU6050 (accelerometers and gyrometers), and TCA9548 (1 to 8 multiplexer). Our experimental results show that when 6 MPU6050 attached to the right arm, right wrist, chest, waist, right thigh, and right ankle, the activities of standing, sitting, lying, walking, running, going upstairs, going downstairs, drinking water, and dumbbells activities could be identified with high accuracy. The system can connect up to 128 sensors, but under a practical sampling rate, the number of sensors should not be greater than 15. The system shall be used for finding the optimal locations for a multi-sensor wearable system (for examples, clothes or shoes).

Author Keywords
Human Activity Recognition; Wearable sensors; physical activities

ACM Classification Keywords
I.5.2 [Pattern Recongnition]: Design Methodology - Pattern analysis

Introduction
Many wearable devices were developed to automatically record the daily life of physical activities of a person [11,

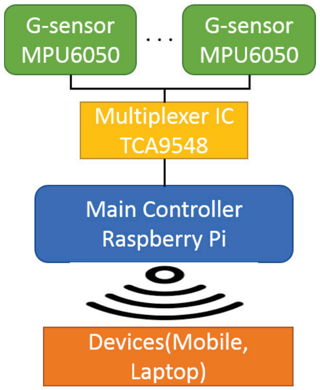

Figure 1: System architecture diagram. The multiplexer gathers the signal from the sensors for the main controller (the Raspberry Pi), then a wireless connect from the R-Pi to a post processing computer.

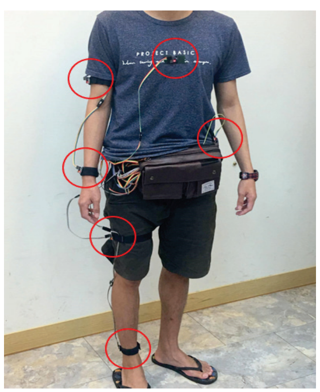

Figure 2: The red circles show the position of the sensors.

12]. For example, using a mobile phone to access signals from a wearable device equipped with sensors to recognize a certain human activities [2, 5]. Most of the previous researches were limited to only one sensor. In the foreseeable future, we could have clothes with many sensors so that acquiring more accurate and complete information is possible. Designing the optimal placement of sensors will be an issue.

In this study, we implemented a multi-sensor system using Raspberry Pi, MPU 6050, and TCA9548 (a 1-8 multiplexer). Experiments has been done using a six-sensor system. MPU6050 is a six-axis accelerometer/gyroscope. We placed six MPU6050 on the right arm, right wrist, chest, waist, right thigh and right ankle. The Raspberry Pi collected data from the six sensors one by one in a fixed sequence, and relayed the data to a post-processing computer. The kind of the activities were identified by the post processing. After applying the feature selection technique [7], we are able to determine the key features. By placing the sensors in different location, we can find out the best placements for sensors. That helps us to design a wearable device system.

System introduction

The Raspberry Pi access data from TCA9548 multiplexer through two serial IO ports, SDA0 and SCL0. The inputs of TCA9548 are at most 16 sensors, the Raspberry Pi then reads the sensors by the time sharing technique. This approach ensures the data synchronization and the correctness of the data read from the sensors. Because Raspberry Pi can connect 8 multiplexers, the system can connect to at most 128 sensors. In practice, more than 20 sensors may cause insufficient sampling rate. The sensor is not necessary to be a MPU6050. If the output signal of sensor is analog, an analog-to-digital converter is required.

In this study, the multiplexer accessed 6 MPU6050s connected by multi-core DuPont lines. For a six-sensor system, the sampling rate was 140 Hz, and a 13-sensor system, the sampling rate was 80 Hz. To identify the activities of a person, the sampling rate of 60 Hz is enough. The protocol for data transmission between Raspberry Pi and the post-processing computer was UDP (User Datagram Protocol). The system architecture is shown in Figure 1.

The data read from each sensor were divided into 140 samples to form a block. All blocks are not overlapped. Let $\mathbf{a} = [a_x, a_y, a_z]$ and $\mathbf{g} = [g_x, g_y, g_z]$ respectively represent the linear accelerations and gyroscope angular velocity in three directions. We computed features from $\mathbf{a}$ and $\mathbf{g}$. For each $x \in \{a_x, a_y, a_z, g_x, g_y, g_z\}$ in a block, we computed the mean, variance, and root mean square. Let $\|\mathbf{a}\| = \sqrt{a_x^2 + a_y^2 + a_z^2}$ and $\|\mathbf{g}\| = \sqrt{g_x^2 + g_y^2 + g_z^2}$. For each $\|\mathbf{a}\|$ and $\|\mathbf{g}\|$ in the block, we calculated the mean, the maximum, and the minimum as features. For each $\|\mathbf{a}\|$ and $\|\mathbf{g}\|$ in the block, another four features were obtained by applying the Kurtosis analysis and Skewness analysis [8] to quantify the data distribution for classifying. To infer the rotation of an object, we used quaternions [10] to represent $\|\mathbf{g}\|$, the computed value is a feature. Some other features were obtained from the frequency domain. The Fast Fourier Transform (FFT) was applied to $\|\mathbf{a}\|$ and $\|\mathbf{g}\|$ in the block. We calculated the power spectral density and the entropy of the magnitudes of frequencies. Therefore, there were totally 32 features used for activities recognition. All features then were normalized to the range of [0,1] for training and classification. Based on a SVM classification algorithm, the classification model is trained using the features obtained from the blocks of data.

Classified as →	a	b	c	d	e	f	g	h	i	Recall
a	230	0	0	0	0	0	0	0	0	1
b	0	243	0	0	0	0	0	0	0	1
c	0	0	245	0	0	0	0	0	0	1
d	0	0	0	314	0	0	1	0	0	.99
e	0	0	0	2	164	0	1	0	0	.98
f	0	0	0	0	0	167	0	0	0	1
g	0	0	0	0	0	0	236	0	0	1
h	0	0	0	0	0	0	0	204	0	1
i	0	0	0	0	0	0	0	0	115	1
Precision	1	1	1	.99	1	1	.99	1	1	

(a)

Classified as →	a	b	c	d	E	f	g	h	i	Recall
a	230	0	0	0	0	0	0	0	0	1
b	0	243	0	0	0	0	0	0	0	1
c	0	0	245	0	0	0	0	0	0	1
d	0	0	0	312	0	0	3	0	0	.99
e	0	0	0	1	163	0	2	1	0	.98
f	0	0	0	0	0	167	0	0	0	1
g	0	0	0	0	0	0	237	1	0	.99
h	0	0	0	0	0	0	0	204	0	1
i	0	0	0	0	0	0	0	0	115	1
Precision	1	1	1	.99	1	1	.98	.99	1	

(b)

Classified as →	a	b	c	d	e	f	g	h	i	Recall
a	230	0	0	0	0	0	0	0	0	1
b	0	243	0	0	0	0	0	0	0	1
c	0	0	245	0	0	0	0	0	0	1
d	0	0	0	311	1	0	2	1	0	.99
e	0	0	0	2	163	0	2	0	0	.98
f	0	0	0	0	0	167	0	0	0	1
g	0	0	0	0	0	0	236	2	0	.99
h	0	0	0	0	0	0	0	204	0	1
i	0	0	0	0	0	0	0	0	115	1
Precision	1	1	1	.99	.99	1	.98	.99	1	

(c)

Figure 3: The confusion matrix of (a) 6 sensors with 9 activities. (b) 3 sensors. (c) 2 sensors. a = standing, b = sitting, c = lying down, d = walking, e = running, f = dumbbells exercise, g = going upstairs, h = going downstairs, i = drinking water.

Experimental Validation

Four volunteers (one female and three males) were involved in our experiments. At first, we placed six sensors on right arm, right wrist, chest, waist, right thigh and right ankle shown as Figure 2. The activities were standing, sitting, lying down, walking, running, dumbbells exercise, going upstairs, going downstairs, and drinking water. The confusion matrix of six sensors is shown in Figure 3(a). As shown in the figure, our methods did well with the accuracy of 99.79%. And then we used only three sensors placed on right wrist, waist and right ankle. The result is shown in Figure 3(b) and the accuracy was 99.58%. Finally, we used only two sensors placed on right wrist and right ankle. The result is shown in Figure 3(c) and the accuracy was 99.48%. The activities including seven common daily activity and two special activities, which were drinking water and dumbbells exercise. If we removed the special activities and evaluated the performance again. The accuracy of six sensors was 99.76%, three sensors was 99.51%, and two sensors was 99.40%.

Table 1 shows the comparisons of our method with a previous methods proposed by Geo et al. [3], Moncada-Torres [9], Bayat et al. [1], and Gupta et al. [4] respectively.

We also modify the windows size of sampling from 140 to 100. We can identified activities in less time, but the accuracy dropped. Table 2 shows the performances of different windows size, difference number of sensors, and difference number of activities. Therefore, our method performed well with good accuracy with changing the sampling rate.

Feature Selection

This work uses feature selection to assess the relevance of features for recognizing the activities. Feature selection can reduce the amount of data and accelerate the recognition.

Reference	Placement	Detected Activities	Average Accuracy
Gao et al., 2014	Chest, waist, thigh, side	5	96.4%
Moncada-Torres, 2014	Chest, Thigh, Ankle	16	89.08%
Bayat et al., 2014	pocket, Hand	6	91.15%
Gupta et al., 2014	Waist	6	98%
Our method	Wrist, Ankle	9	99.40%
Our method	Wrist, Ankle	7	99.48%

Table 1: Comparison with other methods. The “Placement” column describes the location of the sensors.

We used Relife’s feature selection [6], which is an iterative algorithm to calculate the weight of each feature. Therefore, we can obtain the important features for recognizing certain activities. We tested the most important feature (top quartile weight) for recognizing the activities and obtained the accuracy was 97.2%. The rank of the sensor placements is shown in figure 4. We found that the ankle and thigh are the most important features because of they directly relate the movement of whole foot.

Conclusion

In this paper, we implemented an activities recognition system that can accurately classify seven daily activities and two special activities. Because each activity has different time period, we should select a large block size for gathering sufficient samples from sensors for accurate recognition. The propose system can help us to design wearable

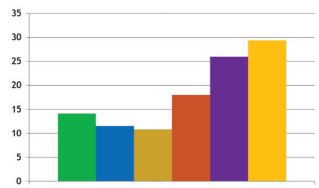

Figure 4: The importances of the sensors are presented as the height of the bar. From left to right, we have the bar chart for the arm, wrist, chest, waist, thigh, and ankle. The most important one is the ankle, and the second important is the thigh.

Window size	Using sensors	Detected Activities	accuracy
100	2	7	98.62%
100	3	7	99.28%
100	6	7	99.50%
140	2	7	99.40%
140	3	7	99.51%
140	6	7	99.76%
100	2	9	98.83%
100	3	9	99.40%
100	6	9	99.57%
140	2	9	99.48%
140	3	9	99.58%
140	6	9	99.79%

Table 2: Accuracy of the presented method for different block size.

devises to determine the critical position for sensors to recognize the activities. The results indicate that prototype of our system can achieve the goal.

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