Pattern Recognition of Human Activity Based on Smartphone Data Sensors Using SVM Multiclass

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Abstract. Mobile devices are increasingly sophisticated while smartphones continue to make the latest generation that immerses the supporting tools needed in everyday life such as cameras, GPS, Microphones, and various sensors such as light sensors, a direction sensor, acceleration sensor (i.e., accelerometer) and the gyroscope sensor. This study aims to classify human activities from the accelerometer and gyroscope sensors on a Sony z3+ smartphone. To implement our system, we collect labeled accelerometer and gyroscope data from eight users when they carry out daily activity. Every activity was recorded for 22 seconds, total data that we use every activity is 2000 data with the total amount of data is 16000 data. This data we classify using the Multiclass Support Vector Machine (SVM) method reaches 97.40% accuracy using a 70% ratio as training data and 30% as test data, the classification process takes 5 seconds to classify the data.

Keywords: Activity, Recognition, Accelerometer, Sensor, Support Vector Machine.

1 Introduction

Mobile phones only can be used for call and sending a message. But as time goes by a mobile phone can be used to perform various tasks, for example for typing, internet, chatting, editing photos, sending emails, playing games, navigators, compasses, and we even use smartphones to monitor our health through recording activities, finding our location on maps, watching videos, and buying products on the Internet[1]. People-centric sensing says[2] using a smartphone as a sensing. Smartphones are now popular and its a need for people in recent years[3]. At first, the mobile phone components were very simple, but now a mobile phone has various sensors embedded in it.

With this sophistication, today's mobile phones are called smartphones, the smartphone can be called because it has a variety of sensors that make a cell phone has many features. Embedded sensors on Smartphones can be utilized now. One of the advantages of introducing this activity is able to predict the potential for a user's fall[4] and it immediately sends notifications to the right people (i.e., family or medical staff)[5] and also it can provide information even though the user is sitting, walking, running, standing, sleeping, getting up, going upstairs and going downstairs. From the results of reading the sensor information can be used in this study to design the system in classifying the results of sensor data

This sensor output is in the form of data where the data generated has hundreds or even thousands of records. Of course, the data cannot be read or understood only by looking at it or reading it directly. To find information that is not known before, potential[6] knowledge that

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serves to assist in decision making. One computational method that discusses the above problem is Data Mining. One method in data mining is the classification method, which is a technique of grouping data obtained based on the pattern produced previously. There are several models of classification of which is by using Support Vector Machine (SVM). Support Vector Machine produces good accuracy, but specifically, there are still overlapping classifications

Researchers[7] clustered using Multiclass Support Vector Machine (SVM) to understand human behavior and integrate daily user activities and their social context with computer systems with six activities using 2947 patterns with 96% accurate results. The researcher[8] used a head movement controller system (HEMOCS) by installing Head-mounted Display (HMD) devices such as Google cardboard reading the results of accelerometer and gyroscope sensor data with analyzing of attitude data including yaw, roll, and pitch to play music players. The results show that there are some errors, especially the head movement with an average accuracy of 80%. This error occurs because the head moves at various speeds. The researcher[9] uses the backpropagation neural network classification method in identifying five daily activities online using the real-time system. For the noise reduction process, researchers used the Linear Acceleration API from Android, even though they had used the API, the resulting accuracy was 95%, using a total of 2035 data. Researcher[10] in another study used the Nearest-Neighbor algorithm classification method to recognize head movements down, up, left, right, left angle, right tilt, left-left, right-right and under-down based on the accelerometer and gyroscope sensors with 95% accuracy.

In the purpose of this study Pattern recognition of Human Data Activity Based on Sensors Smartphones using an accelerometer and gyroscope sensor. We use the Multiclass SVM classification method that can classify and regression in identifying eight activities sitting, walking, running, standing, sleeping, waking up, going upstairs and going downstairs to find the best hyperplane in solving constraints in the form of inequalities to find solutions to problems

2 Proposed Method

The application of human activity patterns in this study using accelerometer sensors and sensor gyroscope on smartphones. Several procedures were carried out so that the sensor output pattern can be classified.

2.1 Accelerometer Sensor

The accelerometer is a sensor used to measure acceleration, detect and measure the vibration (vibration) of an object. The Accelerometer sensor measures acceleration due to the movement of objects attached to it. The accelerometer is also capable of detecting device orientation which can provide useful information for activity recognition. The accelerometer was initially inserted into the device to support advanced gameplay and to allow automatic screen rotation[11]. Accelerometer sensors were inserted on an Android smartphone which usually functions to determine the degree of slope of the smartphone. This sensor function will read three axes from different directions to change the screen display from landscape to portrait or vice versa so that the display menu and applications on the smartphone will adjust the position of the smartphone. The accelerometer sensor used has 3 degrees of freedom, measuring acceleration along the x, y, and z-axes. The x-axis is horizontal to the right, the y-axis is vertically pointing up however the z-axis is pointing out the front surface of the screen.

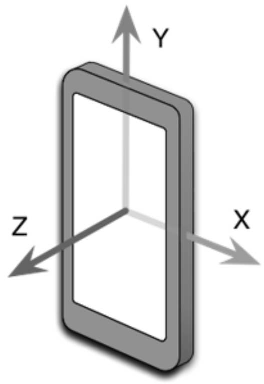

Fig. 1. The Accelerometer axis on a smartphone

2.2 Gyroscope Sensor

A gyroscope is a tool for measuring and maintaining orientation, based on the principle of angular momentum. Mechanically, the gyroscope is a rotating wheel or disk where it is free to take an orientation[3]. So that by utilizing the angular velocity data can be seen the slope angle of an object.

Fig. 2. Illustration of the gyroscope sensor on a smartphone

2.3 Human Activity Recognition (HAR)

Human Activity Recognition (HAR) aims to identify actions taken by someone who was given a set of observations on himself and the surrounding environment[7]. In this study, the device used is an Android smartphone. The action of a person can use various sensors on a smartphone such as a sensor Gyroscope, Accelerometer, GPS, and Camera, but in identifying the behavior of a person, can use the Gyroscope and accelerometer sensors

2.4 Support Vector Machines (SVM)

SVM is a classification of learning machine methods that work on the principle of Structural Risk Minimization (SRM) to find the best hyperplane that separates two classes in input space, which determines classification decision functions by minimizing empirical risk[12], as

$$R = \frac{1}{l}\sum_{i=1}^{l}|f(x_i) - y_i|, \tag{1}$$

where l and f represent sample sizes and classification decision functions, each SVM aims to determine the dividing hyperplane in the optimal classifying class to provide low error generation errors In some cases the function of classification decisions in a problem separated linearly is represented by

$$f_{w,b} = sin\ (w\ .x\ + b). \tag{2}$$

A hyperplane is needed to meet limited minimization, such as

$$\begin{aligned} &Min: \frac{1}{2}w^T \\ &y_1\ (w.x_i + b) \geq 1. \end{aligned} \tag{3}$$

For cases that cannot be separated linearly, minimization problems can be modified to allow data points will be misclassified. SVM able to be applied to a multi-class classification by combining SVM[12].

2.5 Performance Evaluation

The level of errors in classification appears in the performance evaluation of the classification method. Calculating the error value in the classification can use the confusion matrix[13].

In measuring performance using confusion matrix, there are 4 (four) terms as a representation of the results of the classification process. The four terms are True Positive (TP), True Negative (TN), False Positive (FP) and False Negative (FN). True Negative Value (TN) is the number of negative data detected correctly, while False Positive (FP) is negative data but detected as positive data. Meanwhile, True Positive (TP) is positive data that is detected correctly. False Negative (FN) is the opposite of True Positive, so data is positive, but it is recognize as a negative data

Table 1. Confusion Matrix/Contingency

Actual /Prediction	Path	Run
True	TP	FN
False	FP	TN

To determine the performance of each classification method evaluated it appear from the accuracy, specificity, sensitivity. measurement using the following equation

$$Accuracy = \frac{TP + TN}{TN + FP + FN + TP} \quad (4)$$

$$Sensivity = \frac{TP}{TP + FN} \quad (4)$$

$$Specificity = \frac{TN}{TN + FP} \quad (5)$$

3 Experimental Research

In this section, we explain our experiments and experimental results, then organize and discuss us in the introduction of human activities using accelerometer and gyroscope sensors on smartphones

3.1 Dataset

In the data retrieval tool used is a Sony z3+ smartphone using an accelerometer and gyroscope sensor found on the smartphone. Consists of eight subjects to do some human activities such as sitting, walking, running, standing, sleeping, waking up, going upstairs and going downstairs where each recording activity takes 22 seconds, the accelerometer and gyroscope sensored.

record results are safe in the .csv format. The accelerometer and gyroscope sensors produce six attributes consisting of Accelerometer x, y, z, and Gyroscope axes x, y, z-axis

Table 2. Dataset Activities

Actual /Prediction	Amount Of Data
Sitting	2000
Walking	2000
Running	2000
Standing	2000
Lie down	2000
Wake up	2000
Upstairs	2000
Downstairs	2000
Total	16000

3.2 Implementation

The dataset was obtained from the gyroscope and accelerometer sensors uses a Sony z3+ smartphone then labels each activity after that sorting 2000 data for each activity — obtained as many as 16000 records for eight activities. We used eight different subjects in data collection where each subject performed eight different activities for 22 seconds. Each subject in each activity has a ratio of 70% with 1600 number of records as training data and 30% with a total of 400 records as test data.

In the proposed approach, the classification is used to identify user activity based on sensor data extracted. We use two classifiers, namely multiclass support vector machine (SVM)[14].

Fig. 3. Mounting the Smartphone on the thigh

4 Result and Discussion

In this session, Providing experimental results we classify eight activities using the Support Vector Machine (SVM) method. In Table III, Table IV, Table V shows the confusion matrix[15] accuracy in each activities.

Table 3. Confusion Matrix Of The Classification RBF Kernel

activities	Sitting	Walking	Running	Standing	Lie down	Wake up	Upstairs	Downstairs	accuracy
Sitting	581	0	6	0	0	5	8	0	99,52
Walking	0	497	28	0	0	0	32	43	96,08
Running	0	22	498	0	5	1	34	40	95,17
Standing	1	0	2	588	1	5	2	1	99,69
Lie down	0	0	9	0	583	0	8	0	99,38
Wake up	0	0	1	2	0	593	3	1	99,52
Upstairs	2	29	46	1	2	2	479	39	99,92
Downstairs	1	34	38	0	5	3	36	483	94,98
AVG									**97,40**

Table 4. Confusion Matrix Of The Classification Polynomial Kernel

activities	Sitting	Walking	Running	Standing	Lie down	Wake up	Upstairs	Downstairs	accuracy

Sitting	584	3	0	3	1	4	3	1	99,46
Walking	0	457	40	0	0	0	38	65	93,32
Running	1	42	458	0	10	6	37	46	94,25
Standing	2	0	2	585	0	9	2	0	99,50
Lie down	2	0	5	2	587	1	2	1	99,40
Wake up	1	0	4	3	0	588	4	0	99,23
Upstairs	3	67	33	1	1	3	448	44	94,21
Downstairs	1	37	49	0	4	2	40	467	93,96
AVG									**96,73**

Table 5. Confusion Matrix Of The Classification Linear Kernel

activities	Sitting	Walking	Running	Standing	Lie down	Wake up	Upstairs	Downstairs	Accuracy
Sitting	549	4	6	2	0	7	26	6	98,21
Walking	8	354	108	3	0	12	68	47	90,77
Running	11	67	352	7	29	30	50	63	89,69
Standing	4	0	7	556	9	17	6	1	98,33
Lie down	0	0	18	1	521	10	14	36	97,40
Wake up	7	0	24	9	7	546	6	1	96,56
Upstairs	3	75	36	9	2	18	400	57	91,56
Downstairs	2	51	48	5	8	17	35	434	91,52
AVG									**94,33**

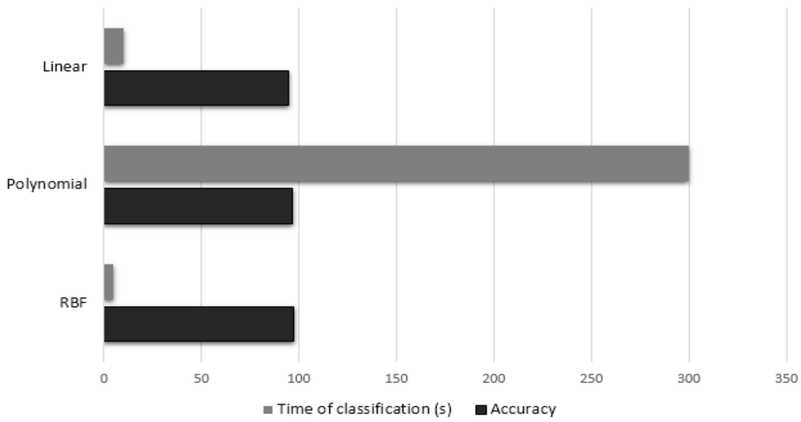

Fig. 4. SVM accuracy and time of classification

Table 4 shows a decrease in accuracy of 96.73% when using Kernal Polynomial and in Table 5 displays the lowest accuracy of 94.33 %% using a Linear kernel. From the three kernels used, it appears in Table II, the highest accuracy using the Support Vector Machine method with the RBF kernel

Fig. 4 looks at the SVM kernel classification time chart each kernel has its advantages for classifying data. The longest classification time is in Polynomial with a classification time of 300 seconds, the second order is in Linear with a classification time of 10 seconds and the fastest time is in RBF with a classification time of five seconds. Although polynomials require a classification time of 300 seconds but have better accuracy than linear with a difference in accuracy of 2.4%.

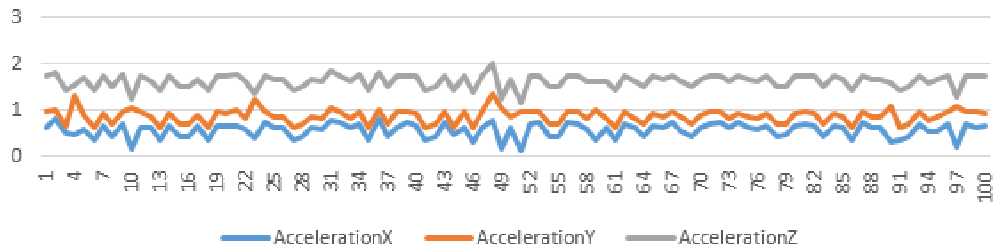

Fig. 5. Sitting Graph

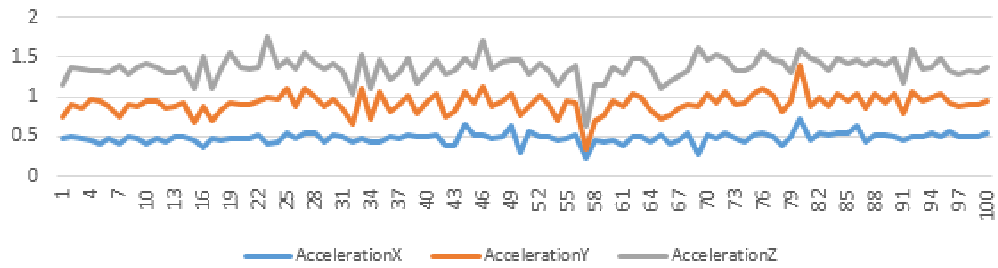

Fig. 6. Walking Graph

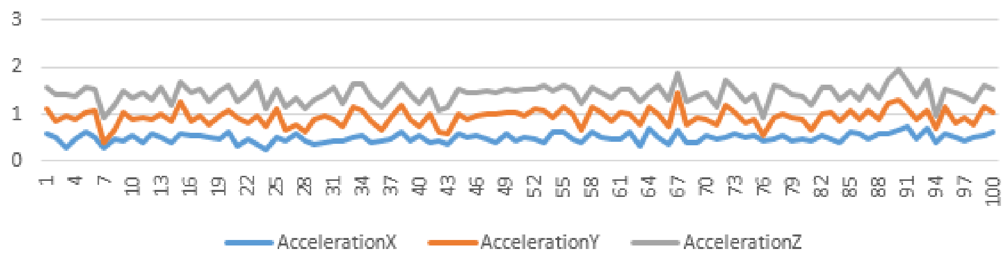

Fig. 7. Running Graph

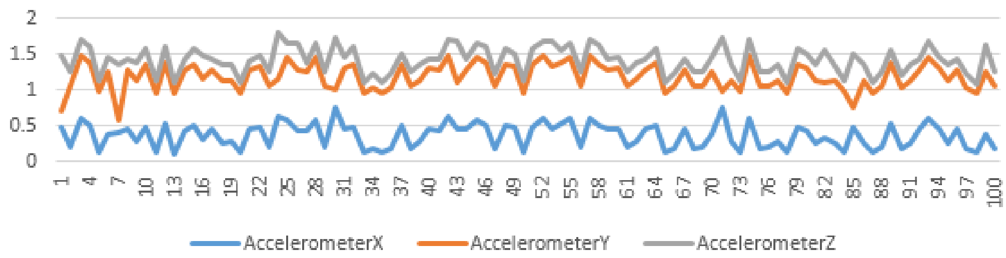

Fig. 8. Standing Graph

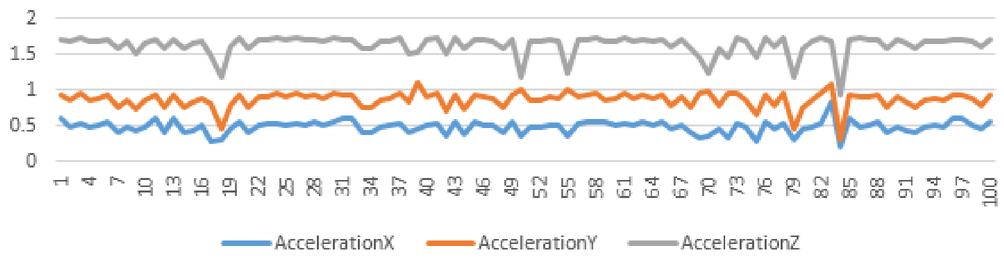

Fig. 9. Lie Down Graph

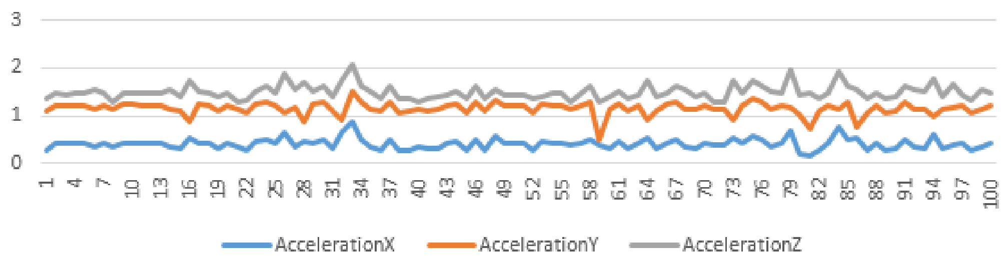

Fig. 10. Wake up Graph

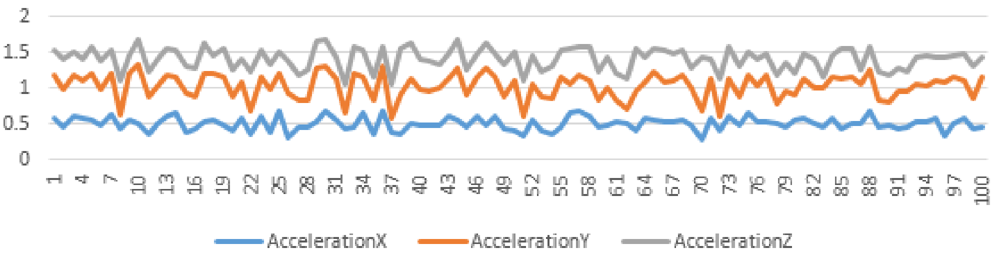

Fig. 11. Walking up stairs Graph

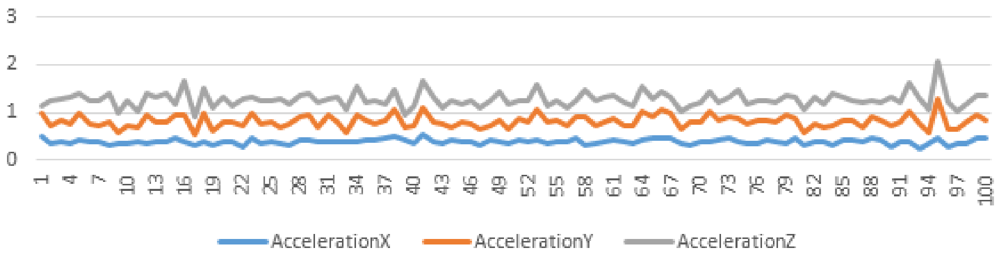

Fig. 12. Walking downstairs

4 Conclusion

In this paper, we present a classification method of Support Vector Machine (SVM), using a smartphone that has an accelerometer and gyroscope sensor. In the experiment, smartphone data collection was placed on the front right thigh with a vertical position with the help of an adhesive device to maintain the position of the smartphone. Every activity takes 22 seconds with Android software that was installed on the smartphone, the output of the data activity is in the form of values from the accelerometer and gyroscope, each of which has x, y, and z-axes. The raw data of the sensor value is processed to find the Min value and the Max value which then transforms each value. The collected data is classified using SVM with a ratio of 70% as training data and 30% as test data. The test data using the RBF SVM obtained the expected results with an accuracy of 97.40% with a time classification of data for five seconds.

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