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Filter Based Sensor Fusion for Activity Recognition using Smartphone

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***Abstract*— Activity Recognition based on the sensors available on a smartphone is becoming a widely researched area. Smartphones are capable of collecting vital data from the sensors. These sensors include acceleration sensors, position sensors, vision sensors, audio sensors, temperature sensors and direction sensors. In this paper we propose a filter based sensor fusion system that uses smartphones accelerometer and gyroscope data to identify activities performed. The data collected from the accelerometer and gyroscope is labeled according to the activity that is performed. Stastical features such as Mean, Standard Deviation and Skewness are extracted from the data. Accelerometer and gyroscope data are combined using Complementary Filter and Kalman Filter, and the stastical features are extracted. The classification and prediction is performed by Support Vector Machine (SVM). The experiment results show that the data fused using the Kalman Filter has higher accuracy than raw data and Complementary Filter.**

***Index Terms*—Activity Recognition, Accelerometer, Gyroscope, SVM, Complementary Filter, Kalman Filter, Mean, Standard Deviation and Skewness**

I. INTRODUCTION

SMARTPHONES are becoming an integral part of everyone life nowadays. The capabilities of a smartphone are much more than just making phone calls. Each and every smartphone is loaded with a variety of sensors that can record various types of data such as the smartphones status and the environment data. These data provide the researcher with new opportunities for exploring various implementation of the smartphone. Activity Recognition is one such area where the smartphones data can be used to identify the activity that is currently performed by the user.

Activity Recognition has innumerable applications such as medical, security, entertainment, and tactical scenario. The accelerometer and gyroscope data available from the smartphone are used in Activity Recognition. The accelerometer is a dynamic sensor capable of measuring acceleration force. The force may be static, measure of velocity and position, or they could be dynamic, vibration or impact. Accelerometer uses tri-axial system to identify the velocity in each axis as shown in Fig. 1 (a). The gyroscope is a device used for navigation and measure the angular velocity. The Gyroscope senses angular velocity along the tri-axis as shown in Fig. 1 (b). These two sensor data has the necessary information to recognize an activity.

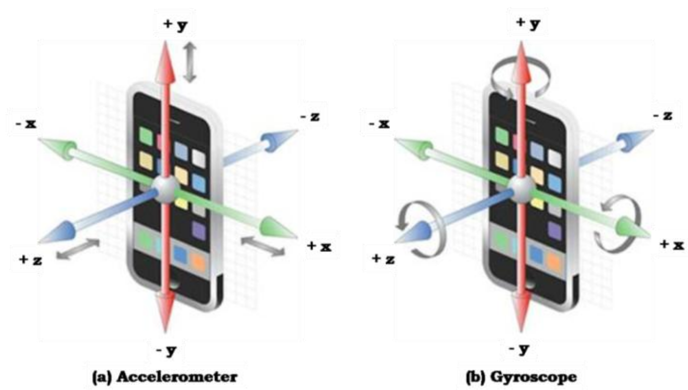

Fig. 1. Accelerometer and Gyroscope

The data from the accelerometer is a measurement of all the forces that are working on the smartphone, it will also have a lot more than just the gravity vector. The accelerometer measurement is easily disturbed by even a small force that acts on the smartphone. To get a reliable data from the accelerometer it has to be filtered using a low pass filter. The data from the gyroscope is accurate and it is not susceptible to external force. But due to the integration over time, the gyroscope measurement has the tendency to drift, not returning to zero when the smartphone is in its original position. To get a reliable data from the gyroscope it has to be filtered using a high pass filter. To overcome the drawback of the two sensors we propose a novel approach of sensor fusion based on Complementary Filter and Kalman Filter. The data from the two sensors are fused using the Complementary filter and Kalman Filter which gets the best of two data and generates the new data.

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Statistical features are extracted from the raw accelerometer and gyroscope data, Complementary Filter fusioned data and Kalman Filter fusioned data. The classification is done using SVM. The main objective of this work is to create an activity recognition system that is less susceptible to sensor errors.

The remainder of the paper is organized as follows. Section II describes the related works. Section III presents the outline of the work. Section IV discusses the techniques used. Section V elaborates the experimental setup. Section VI concludes the paper.

II. Related Work

In [1] the authors have compared different sensor data, feature spaces and feature selection methods to identify the method that increase the efficiency and reduce the computational cost of smartphone based activity recognition. The authors have developed a smarthpone app to collect the data and send the data to the server for activity recognition. The results show that the Bayesian Network classifier gives high recognition accuracy of 96.21%.

A digital low-pass filter is designed in [2] to isolate the component of gravity acceleration from that of body acceleration generated in the acceleration data from the user's mobile phone. Various classifiers were tested using different statistical features for multiple human subjects in real world conditions. Using average of probabilities as the fusion method the authors achieved an overall accuracy rate of 91.15%.

In [4] a Hierarchical Activity Recognition Framework is proposed that extends the Naïve Bayes approach for the processing of activity modeling and real-time activity recognition. The algorithm proposed by the authors has a higher accuracy rate than the Naïve Bayes approach. This also enables user's activity recognition within a mobile environment. The average classification accuracy for the fifteen activities classified by the proposed algorithm is 92.96%.

In [5] the authors have analysed the issues and possible solutions regarding activity recognition of a user using mobile devices. The author's have considered the activity detection and recognition based on acceleration sensors. The authors state that the limited processing and storing capabilities of the mobile devices make the signal processing and recognition more difficult. The collected date is communicated to a supervisory center for data processing.

A physical activity recognition which uses discrete variables obtained from accelerometer is presented in [6]. The proposed system performs discretization process for each variable, thus allowing efficient recognition of activities with less energy usage. The whole recognition process in done on the smartphone, which identifies the activity performed and the frequency at which the activity is done. The authors state that the proposed energy efficient system maintain accuracy along with a battery backup of 27 hours without recharging.

A detailed survey on Human Activity Recognition (HAR) based on wearable sensor is done in [7]. The survey gives a clear picture of the application areas of HAR. The learning approaches used either supervised or semi-supervised is explained. The used of offline or online system for the recognition purpose is discussed. The issues and challenges in the HAR were elaborated.

In [8] the author's have presented a novel system that uses a mobile phone to recognize and record the motional activities of a person. Sensory data is collected on a mobile phone from the wireless sensors that measuring the intensity of motions which are attached to the user body parts. The mobile phone application recognizes the activities based on the prelearnt activity in real-time. The authors have used feed-forward backpropagation neural network for efficient pattern recognition.

A novel hardware friendly multiclass classification approach is proposed in [11] for human physical activity recognition suing inertial sensors of the smartphone. In the proposed method the authors have used fixed-point arithmetic for computation in the standard Support Vector Machine (SVM). The authors state that the proposed method improves in terms of computational cost while maintaining similar accuracy when compared to traditional SVM.

In [12] the authors have explored the behavior of various motion sensors available on a smartphone in the activity recognition process. The smartphone sensors that aide in the process of activity recognition are accelerometer, gyroscope and magnetometer. The author's state that based on the analysis of data set collected from ten participants performing seven activities with smartphone at different positions the sensors except magnetometer are capable of identifying activity.

In [18] the authors have proposed a complementary filter for attitude estimation of fixed-wing Unmanned Aerial Vehicle (UAV). The authors use complementary filer to combine the accelerometer output with that of gyroscope output to maneuver the UAV. The complementary filter proves to be a simple and effective attitude filter for UAV.

The authors have presented the data fusion system for mobile robot navigation in [22]. For the guidance of autonomous robots and vehicles two or more different sensor are used to obtain reliable data for controlling the system. In this work the authors have fused odometry and sonar signals using Extended Kalman Filter and Adaptive Fuzzy Logic System. The authors state that the fused signal is more accurate than any of the original signals considered separately.

III. Outline Of The Work

The outline of the work is depicted in Fig. 2. The work starts with collection of Accelerometer and Gyroscope data from the smartphone. The collected data is preprocessed; in this stage the data is stored without any change as raw data, along with this the data is combined using Complementary Filter and Kalman Filter labeled as Complementary Filtered Data and Kalman Filtered Data respectively. Statistical features are extracted from the preprocessed data. The preprocessed data is separated as 5 second, 10 second, 15 second and 20 second data for statistical features extraction. Statistical features such as Mean, Standard Deviation and Skewness are extracted from the data. In the final step classification of the various Activities is performed by SVM

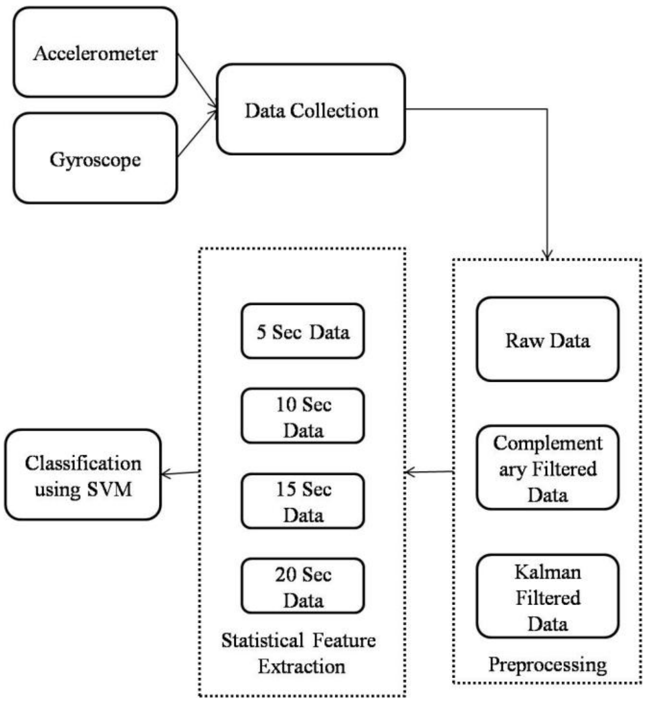

Fig. 2. Outline of the Work

IV. Techniques

A. *Statistical Feature*

Feature extraction using statistical method is employed in this work. The list of statistical features that are used is given in Table 1.

TABLE 1
STATISTICAL FEATURES

Features	Equation
Mean	$\frac{\sum X}{N}$
Standard Deviation	$\sigma = \sqrt{\frac{\sum(x-\mu)^2}{N}}$
Skewness	$\frac{Mean - Mode}{Standard\ Deviation}$

Mean is the central tendency measure. It is defined as the value obtained by adding together all the items in series and dividing the total by the number of items in that series. $\sum X$ is the summation of all the items in a series and N is the total number of items in the series.

Standard Deviation is an absolute measure of dispersion. It is the square root of the arithmetic average of the squares of the deviations of the given observation measured from the arithmetic mean. x represents each value in the series. μ is the mean of the series. N is the total number of items in the series.

Skewness is the measure of symmetry, or the lack of symmetry. A data series is symmetric if it looks the same to the left and right of the center point. Skewness can be either positive skewness or negative skewness. Mode is the most repeated value in the series.

B. *Complementary Filter*

Complementary Filter [23] is a simple method to fuse data from different sensors by taking the best form each sensor. In this work the complementary filter is implemented to fuse the data obtained from accelerometer and gyroscope. A simple complementary filter is shown in Fig. 3. The complementary filter performs low-pass filtering on the data obtained from accelerometer, and high-pass filtering on the data obtained from gyroscope, and fuses these estimates are combined to obtain an all-pass estimate.

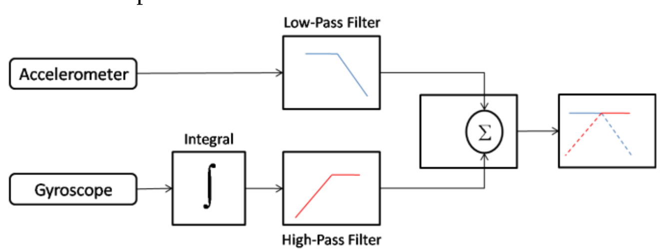

Fig. 3. Complementary Filter

C. *Kalman Filter*

The Kalman Filter [17, 20, 23, 24] is a mathematical tool developed by Rudolph E. Kalman in 1960 to make an estimation of an observed variable using a predictor-update set of equations. Kalman filter is based on the complementary filtering principle. A typical Kalman filter is shown in Fig. 4.

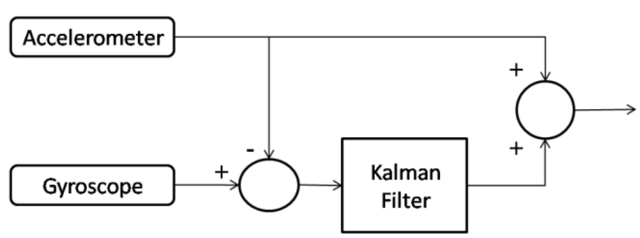

Fig. 4. Kalman Filter

The input for the Kalman filter is the data collected from Accelerometer and Gyroscope. From the given data the noise is calculated and given to the Kalman filter, which iteratively removes the error rate from the data. The final output of the Kalman Filter is a more stable data without noise.

D. *SVM*

SVM [11], [13] is a supervised machine learning algorithm which uses model for pattern recognition. SVM training algorithm is given a set of training examples, in which all the data belong to any one of two categories, from which models are built that assigns new examples into the appropriate category. An SVM model represents the data from the training set as points in space, mapped in a way that the data from different category are separated by a clear wide gap. New examples are then mapped into that same space and predicted to belong to a category based on which side of the gap they fall on.

SVM is a learning machine that classifies an input vector X using the decision function: f (X) = <X, W>+ b. SVMs are hyper plane classifiers and work by determining which side of the hyper plane X lies. In the above formula, the hyper plane is perpendicular to W and at a distance $b / \|W\|$ from the origin. SVM maximize the margin around the separating hyper plane. The decision function is fully specified by a subset of training samples. This subset of vectors is called the support vectors shown in Fig. 5.

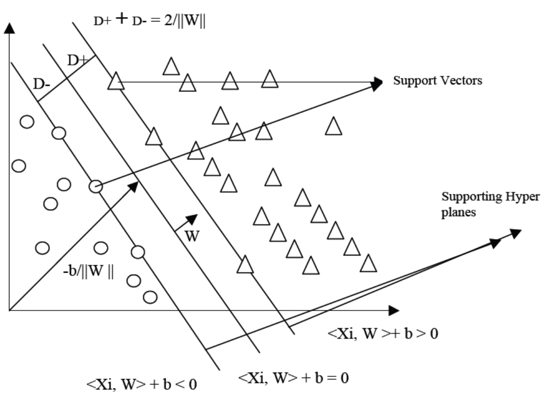

Fig. 5. Support Vectors lying on supporting hyper planes

V. EXPERIMENTAL SETUP

The activity recognition system is implemented by using the data collected from accelerometer and gyroscope sensor form smartphone. The collected data are combined using the complementary filter and Kalman Filter. Classification is performed by SVM.

A. Dataset

The dataset for the activity recognition system is used from [12]. The data is collected for seven physical activities performed by ten participants. The activities performed are walking, running, sitting, standing, jogging, biking, walking upstairs and walking downstairs. The activities are performed for 3 minutes. The data is collected by placing five smartphones on five body positions, right jeans pocket, left jeans pocket, belt position, right upper arm and right wrist. The sampling rate for data collection is fixed as 50Hz, i.e. 50 data per second.

B. Data Preprocessing

The data preprocessing done in this work is depicted in Fig. 6. The collected is divided into small segments for feature extraction. The data is divided into four different categories, 5 second data, 10 second data, 15 second data and 20 second data. From the segmented data statistical feature are extracted. Extracted features are used for classification with SVM.

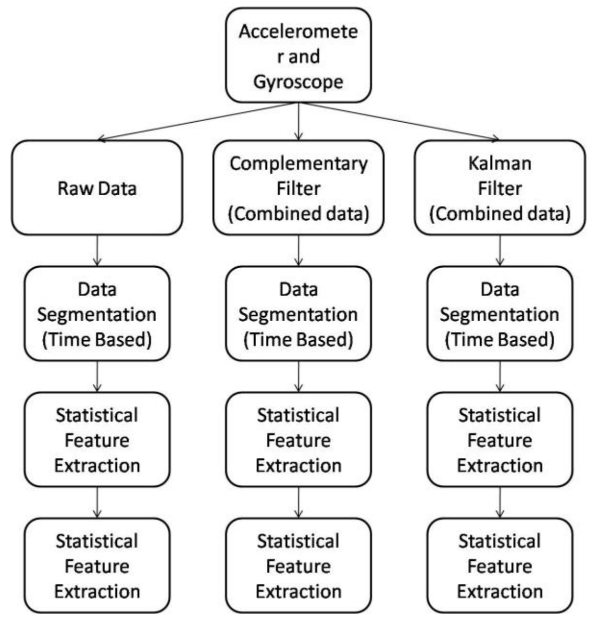

Fig. 6. Data Preprocessing

C. Classification Using SVM

SVM classification is implemented on the three preprocessed datasets, raw data, Complementary Filtered data and Kalman Filtered data. In the raw data classification the data obtained from the accelerometer and gyroscope are kept as is. Accelerometer and Gyroscope reading are shown in Fig. 7.

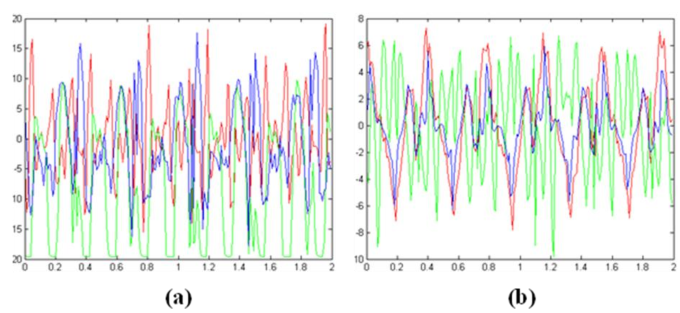

Fig. 7. (a) Accelerometer Data (b) Gyroscope Data

The data is separated into different time segments. From each time segment the statistical features are extracted. SVM classification is performed using the extracted features. The accuracy of the classification of Raw Data is shown in Fig. 8. It is observed that among the time segmentations 15 Second segmented data provides good accuracy.

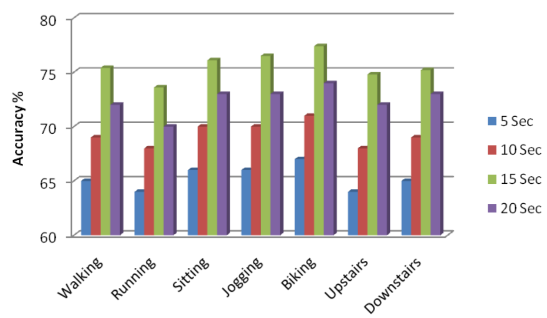

Fig. 8. Raw Data SVM Classification Accuracy

Accelerometer and Gyroscope data are fused using the complementary filter for the second dataset. MATLAB is used of the implementation of Complementary Filter. The fused data is shown in Fig. 9.

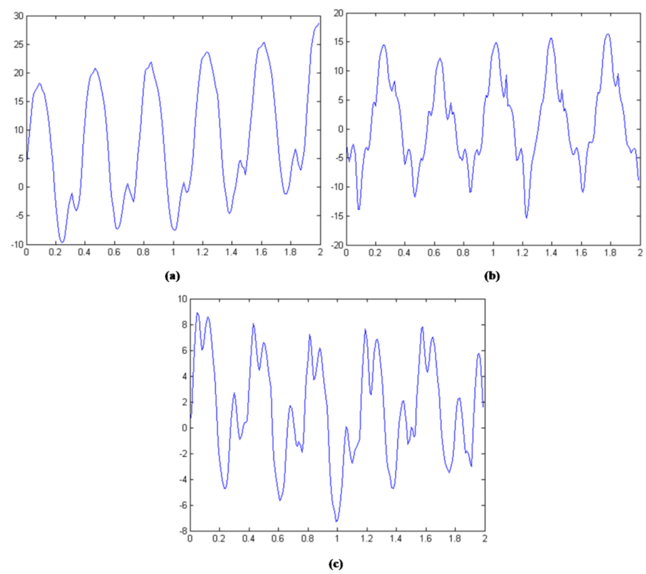

Fig. 9. Complementary Filtered Data (a) X-axis (b) Y-axis (c) Z-axis

Combine data is segmented based on time. Statistical features are extracted from the time segmented data. Accuracy of the SVM classifier is shown in Fig. 10. The results show that SVM classifier performs well for the 15 Second data.

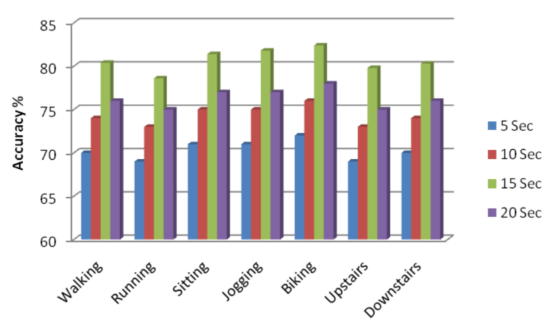

Fig. 10. Complementary Filter SVM Classification Accuracy

Kalman Filter is implemented through MATLAB code. Accelerometer and Gyroscope data are combined to form the fused data as shown in Fig. 11.

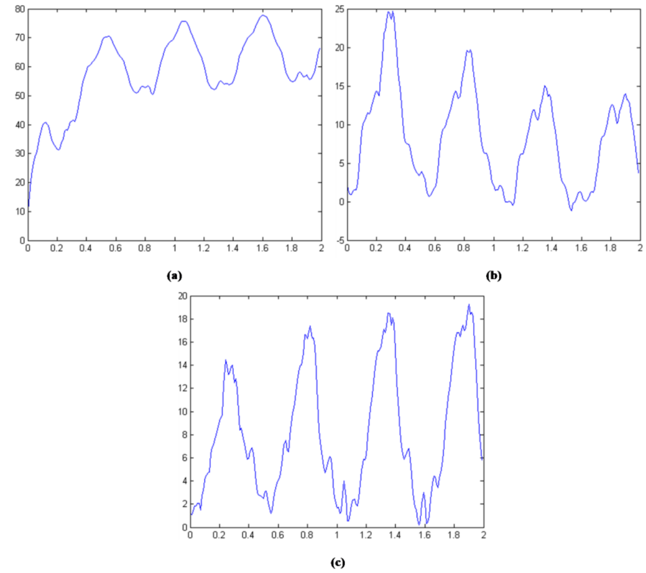

Fig. 11. Kalman Filtered data (a) X- axis (b) Y-axis (c) Z-axis

Kalman filtered data is segmented based on time and subjected to statistical feature extraction.SVM classification accuracy for the Kalman Filtered data is shown in Fig. 12. The results show that Kalman Filtered data has the highest accuracy compared to that of Raw data and Complementary filtered data.

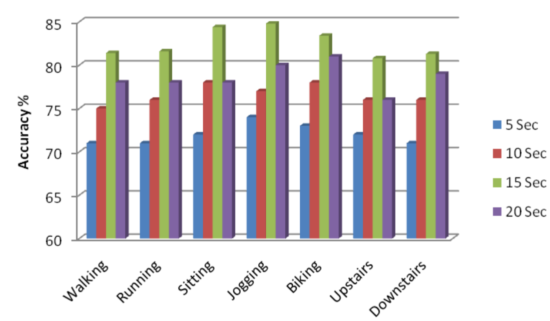

Fig. 12. Kalman Filter SVM Classification Accuracy

VI. Conclusion

In this work, we have proposed a filter based sensor fusion system that uses smartphones accelerometer and gyroscope data to identify activities performed. The data from accelerometer and gyroscope are collected with the placement of smartphone on five different body positions performing seven different activities by ten participants for 3 minutes duration. Three categories of dataset are formed for classification, first Raw data, second Complementary Filtered data and third Kalman Filtered data. All the three datasets are segmented into different time segments such as, 5 second, 10 second, 15 second and 20 second. Statistical features are extracted from the time segmented data. Extracted features are used in SVM classification.

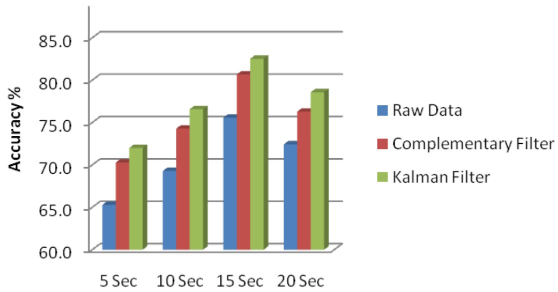

Fig. 13. Overall SVM Accuracy

The overall accuracy of the SVM classifier is shown in Fig. 13. Form the results it is observed that 15 second data give good accuracy over all the three categories of data. Among the three categories of data, Kalman Filtered data has high classification accuracy of 82%.

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