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Design and Implementation of Data Collection & Analysis Tool for Healthcare Parameter Monitoring using Inverse Low Pass Filter

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Abstract

Background: Health of an individual can be determined by monitoring his daily activities. Human Activity Recognition (HAR) is a process, used to record these activities. The first step of HAR involves collection of Data from various Sensors, which is challenging due to the requirement of interfacing of hardware Sensors. Researchers either do hardware interfacing themselves or just analyse already available dataset. In the literature, many measures are proposed to calculate the human activities by using the Accelerometer data. But, different activities recorded by Accelerometer are not accurate due to presence of gravity component. Also there is requirement of identification of appropriate Machine learning algorithm for HAR.

Objective: To facilitate the researchers in hassle free data collection for monitoring HAR and finding optimal cutoff frequency to remove gravity component present in accelerometer data. Also detecting suitable machine learning model for HAR.

Methods: An application has been developed using Inverse low pass filter with an optimal threshold value to compute cut-off frequency for the removal of gravity component from accelerometer data. 8 different machine learning models are trained and tested for examining suitability of models on the collected data at server. Accuracy and execution time are considered as validation parameters.

Results: Gravity Component is removed and data gathered by using 0.6 alpha is providing 0.05 mean acceleration in static state. Among Various ML models k Nearest Neighbor is providing 93.17 per cent of accuracy with 0.187486 sec of execution time.

Conclusion: Removal of Gravity component is optimised by our method and out of various ML model kNN is identified as suitable model for HAR.

Keywords: Activity Detection, Context Detection, Gravity Removal, Inverse Low Pass Filters, Machine Learning

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1. Introduction

Health is at the top primacy by the research community. Everyday some new application and new technology is coming to facilitate the health conscious people. This involves measuring user context and providing relevant results or suggestions. HAR is the major area which is helping in finding user context and daily energy consumption of healthy people, regular health monitoring of old people, smart home monitoring etc. One can determine the activity and figure out the health status of a person. As per the activity performed by the user and the duration of that performed activity determination of health condition and recommendation according to that is possible. This Human Activity recognition is a four step process which includes Data collection, Feature Extraction, Learning and Prediction. All phases are crucial; however as data collection is first step; if it is flawless one can rely on the output of other phases. Collection of data is callenging task as it involves sensor interfacing and communication module to communicate the data from sensor to the server. This needs hardware integration knowledge and low sensor level programming. Thus to fill this gap an application is developed to reduce the burden of interfacing of sensors so that researchers can directly use the application to gather data for their choice of activity.

The gathering of data can be done by interfacing various sensors available in smart devices or wearables like accelerometer, gravity sensor, gyroscope etc. [1]. Mostly people have used accelerometer for the detection of motion [2-4]. The output of accelerometer is erroneous due to presence of gravity component. The data collected with errors cannot be utilized for further processing. In this paper we have tried to remove those errors of gravity component by using inverse low pass filter in the data collection application. We have validated the work on 8 different activities sitting, standing, walking, running, sitting down, standing up, ascending stairs, and descending stairs. After noise removal the data is sent on server for storage and further processing. There are various machine learning models available for the classification of activity. Researchers have used different classification models for their work, but suitability of ML models with respect to HAR is not explored much. This paper also determines the suitability of ML models by applying on the collected dataset for further analysis of activity recognition.

The organization of the paper is as follows: section 2 presents the literature review, followed by research gaps and objectives in section 3, section 4 covers the proposed work, section 5 describes experiments and results; and section 6 is conclusion with future scope.

2. Literature Review

Activity Recognition is important parameter being used for various applications like Fitness & health care, monitoring of elderly people, assistive technology, navigation, activity of daily life (ADL), military and security etc. [5-8]. It is healthcare parameter which needs to be monitored regularly if person wants to live fit. Human disorders are coming due to unhealthy daily lifestyle [9]. Researchers have used deep learning method for determining calamities like cancer [10]. Hop field neural network have been used for determining diabetes [11]. Secure healthcare framework for big data is being provided so that no loss of personal data should take place [12]. If someone determines the activity and it's duration in early stage and monitors it regularly the various health's related problem could be avoided. Activity involves walking, running, eating, walking upstairs & downstairs and many more [13-14]. The process of Activity Recognition is shown in figure 1.

This contains 4 main steps i.e. Collection of data, extraction of features, learning and prediction [15], also termed as sensing, feature mapping, modeling and prediction & communication. In first phase of data collection various mobile sensors sense the user activity and environmental data. These data are raw in nature thus with the process of windowing and signal processing various features are extracted like min, max which are minimum and maximum value of x, y, z axis of accelerometer in time domain feature, FFT-Fast Fourier Transform which calculates frequency component of signal and Spectral Energy which computes energy distribution of signal as frequency domain features, Mean and variance as statistical Features etc. [16].

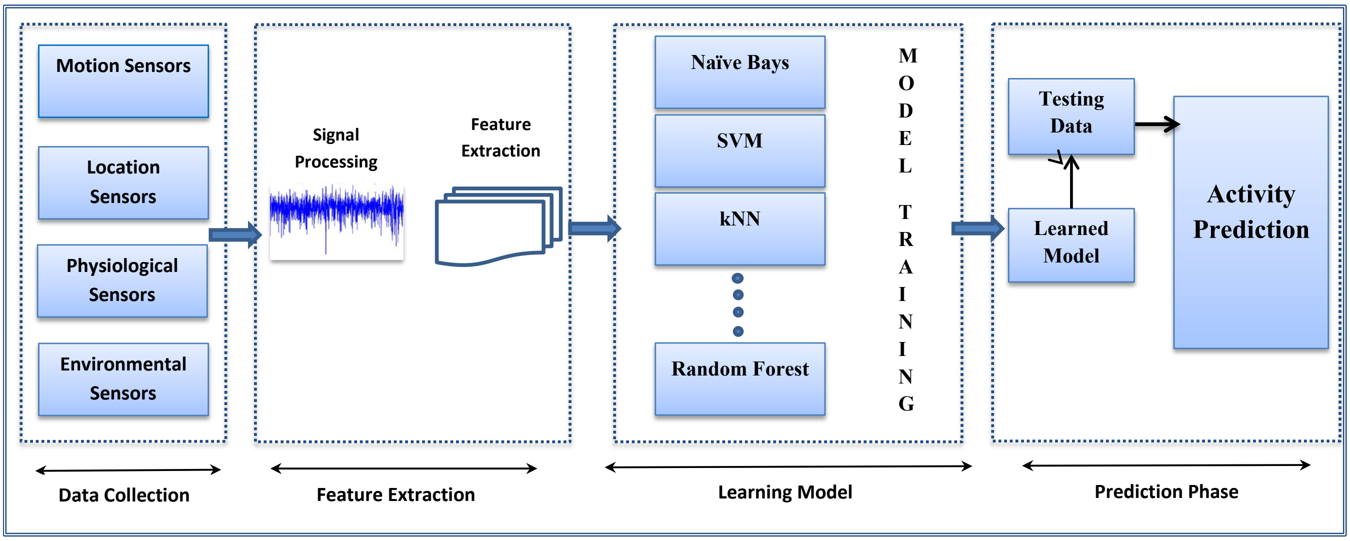

Figure 1. Activity Recognition Process

These features are then fed to various supervised machine learning (ML) models such as Naïve Bays, k Nearest Neighbours (kNN), Support Vector Machine (SVM), Random forest and many more, which trained themselves as per input values [17]. This trained model is then applied on testing data, if the model predicts it correctly that model is suitable for the purpose. Non supervised learning like clustering can be also used for data separation into classes [18-19]. Since mobile crowd sensing provides the facility to utilize mobile users as a volunteer for sensing and sharing their huge sensor data, supervised learning method can be used easily. The various sensors which can be used for data collection are accelerometer, magnetometer, GPS, gyroscope, camera etc [20]. Researchers also say fusion of sensors can be done for better accuracy of activity recognition, but it increases complexity [21-22]. Mostly accelerometer has been used for detecting motion. Accelerometer provides raw values of three different axes x, y and z, whose directions are predetermined. This raw data is the acceleration of each axis with respect to g-force. The value of acceleration due to gravity does not change as it is a constant force which is $9.8\ m/s^2$. However other forces which are responsible for the transition changes over time. If the slow changing forces can be filtered out by using any filter then the remaining forces are the fast changing ones like the forces being applied to the phone. Researchers suggest that this force of gravity is the reason of error in the data being collected for activity recognition [23].

The removal of error due to gravity can be done by using various methods. The Signal Magnitude Vector (SMV) is used along with low pass filter to remove the acceleration error received from ankle placed sensor [24]. This removes high frequency components and passes low frequency or slowly changing elements. But this is not suitable for fast transition activities like changes from one state to another state. Low pass filter is suggested to remove gravitational factor (DC part) from body acceleration (AC part) [25-27]. The comparison of various methods can be viewed in table 1.

Table 1. Comparison of Filters Used for Noise Removal

Sr. No	Paper	Parameters			
		Method used for Noise Removal	Type of filter	Cut of Frequency	Remarks
1	Xing Su, Hanghang Tong, and Ping Ji [1]	Band Pass	-	-	To remove both gravity component and high frequency noise.
2	Andrea Mannini and et. al [24]	Low Pass	4th order Butterworth filter	15 Hz	Used for removing high frequency noise.
3	Akram Bayat, Marc Pomplun, Duc A. Tran [25]	Low Pass	Digital low pass filter	0.25	To get ambulation data low pass filtered data was subtracted from original signal along all three axes.
4	Pierluigi Casale, Oriol Pujol, and Petia Radeva [26]	Both High Pass & Low Pass	-	1 Hz	-
5	Ming Jiang and et al. [27]	Low Pass	Infinite impulse response (IIR) low-pass filter	10 Hz	Used for sensor's misplacement error removal purpose.
6	Lukas Gorzelniak, and et al. [28]	High Pass, Low pass	4^{th} order Butterworth filter	0.2 Hz	Three Different Methods (Euclidian norm minus one [ENMO], Euclidian norm of the high-pass filtered signals [HFEN], and HFEN plus Euclidean norm of low-pass filtered signals minus 1 g [HFEN]) were compared
7	M. J. Mathie, A.C.F. Coster, N.H. Lovell, B.G. Celler [29]	High Pass	Finite impulse response Filter	0.25 Hz	High pass filters were suggested to use directly with 0.25 Hz as it is consistent with the frequencies used by other researchers.
8	Jeen-Shing Wang and Fang-Chen Chuang, [30]	High Pass	-	-	Not much information provided
9	H. Leutheuser, D. Schuldhaus, and B. M. Eskofier [31]	Low Pass	third-order elliptic low pass filter with an infinite impulse response	0.25 Hz	Gravitational component is removed
10	Ortiz, J. L. R [32]	High Pass	3^{rd} Order Butterworth	0.3 Hz	Body motion acceleration signal is separated from the joint effect of the gravitational force and the acceleration due to body motion.
11	Davide Anguita, et al. [33]	Both High Pass & Low pass	Butterworth filter	0.3 Hz and 20 Hz	Higher noise and Gravity component both are removed
12	Doherty A, Jackson D and et.al. [34]	Low Pass	4^{th} order Butterworth filter	20 Hz	One gravitational unit ($1g=9.81 m/s^2$) is subtracted from the vector magnitude, and the remaining negative values are reduced to zero

3. Research Gap and Objectives

The cut off frequency determines the percentage of accuracy during removal of low slow changing force of gravity. Researchers have used 0.25 Hz [29], [31] in their research work for removing gravity component. The optimal cut off frequency for excluding gravity component ranges from 0.1 to 0.5 Hz [35]. We find a gap of non-availability of optimal cutoff frequency for activity recognition. Thus in this paper Removal of Gravity component by using inverse low pass method has been proposed. By using this method, slow varying background frequency (gravitational component) can be filter very easily from transient components or body acceleration (higher frequency). A gap of non-availability of suitable classification model for activity recognition is also found. Thus to fill all these gaps objectives of this paper are:

1. Developing an application for android based smartphones using inverse low pass filter for hassle free data collection for activity recognition.
2. Finding optimal cutoff frequency using inverse low pass filter for gravity removal.
3. Finding an optimal classification model for activity recognition using self-collected dataset.

4. Proposed Work Architecture

The objective of this work is to provide user a hassle free data collection and analysis tool for android based smart phones using inverse low pass filter. The proposed architecture (figure 2) can be viewed in two parts: First Mobile Node and Second Static Server.

The Mobile Node which is in the hand of user consist of Sensing and application unit. In this unit the mobile sensor Accelerometer is used for sensing data. This data is captured by Application program. This application program is responsible for noise removal (present due to gravity) and transferring data to the server. For the removal of noise inverse low pass filter method has been used. This is a method which calculate the new value from the old value by applying Low Pass Filter on the data received from accelerometer, then this low pass filtered value is subtracted from original signal along all three axes (in the same function) to get high frequency data. This high frequency is determining the actual motion of device representing detection of movement.

It is also proposed that value of alpha should be judiciously chosen for the removal of gravity component as it is the parameter for the detection of cut off frequency. The optimal cutoff frequency suggested lies between 0.1 to 0.5 Hz and the alpha value corresponding to these frequencies varies from 0.6 to 0.9.

The Algorithm proposed for finding optimal value of alpha is:

1. Set the value of alpha at 0.6
    a. Start the mobile application to collect the raw data.
    b. Send the collected value to the server.
    c. Find the overall acceleration A.
    d. Select min(A)
    e. Increase alpha = alpha+0.05.
    f. If alpha = = 0.9
        i. Go to step 2
        ii. Else go to step a.
2. Select alpha corresponding to min(A) as the optimal value.

By varying the value of alpha from 0.6 (0.53 Hz) to 0.9 (0.08 Hz), it is proposed to find out optimal alpha for getting optimal cutoff frequency. The formula used for Low pass filter [36] is calculated as:

$$gravityV[i] = alpha * gravityV[i] + (1 - alpha) * event.value[i] \tag{1}$$

Where, alpha is smoothing factor, whose value can range from 0 to 1. If it is near to 1 the new value will be $event.value[i]$, the most recently collected value (where i = {0, 1, 2} representing x, y and z axis), and if alpha = 0 the new incoming value will not be modify.

This gravity component is subtracted from the incoming sensor event value as shown in equation 2 and we receive noiseless data.

$$x_i = event.value[i] - gravityV[i] \tag{2}$$

Where x_i is 0, 1, 2 i.e value in x, y and z axis of three axis accelerometer.

The value of alpha represents cutoff frequency, it is determined by using equation 3 [37]:

$$alpha = \frac{\tau}{\tau + \Delta t} \tag{3}$$

Where, τ is the low pass filter's time constant determined by cutoff frequency f_c as in eq. 4 and Δt is event delivery rate which is set at 0.2 sec by default in case of SENSOR_DELAY_NORMAL of android.hardware.SensorManager .

$$\tau = 1/(2\pi f_c) \tag{4}$$

The optimal alpha giving less error is determined at Server and intimated to the mobile node. The mobile node then starts removing noise by using this new optimal alpha. This noiseless accelerometer sensor data is now sent to the server for further processing.

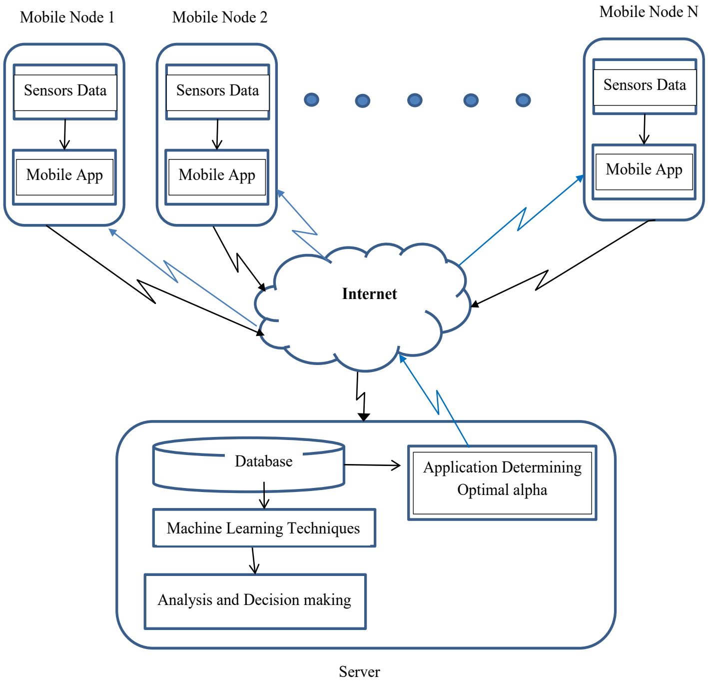

Figure 2. Proposed Architecture

The Server is storing all data received from different mobile nodes in its database. After that the data is divided in ratio of 70-30 for training and testing purpose respectively. On the training dataset 8 popular machine learning models Decision Tree (DT), k Nearest Neighbor (KNN), Support Vector Machine (SVC), Naïve Bays (NB), Random Forest (RFC), Adaboost, Bagging, and Extra Tree are applied so that they can learn the activity and generate their models. These learned models are then tested on remaining 30% of data for the detection of activity. The results from all models are then analyzed and model giving best accuracy is opted for further activity recognition.

5. Implementation & Results

The overall experiment can be divided into two parts; first Noise Removal using Inverse low pass filter and second Detection of activity by applying machine learning models on the collected data.

<u>Experiment part 1</u>: The removal of gravity constituent is done by using inverse low pass filter as mentioned in section 3. The android based smart device was kept idle on flat stationary wooden table (state is termed as Idle state) and the acceleration along each axis was determined by using three axis accelerometer (inbuilt in smart devices) marked as sensor 1, an android based application is implemented for collecting data as shown in Figure. 3.

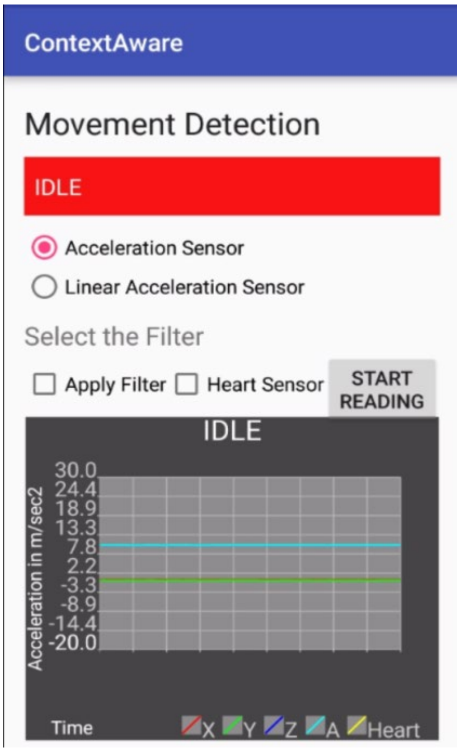

Figure 3. Application for data collection & Noise Removal

The overall acceleration (also known as signal magnitude vector) is calculated by using equation 5:

$$A = \sqrt{A_x^2 + A_y^2 + A_z^2} \qquad \textbf{(5)}$$

The overall acceleration (Table 2) shows that when the device is stationary then also value of z component is available, it is because of gravity component g ideally $g = 9.8\ m/s^2$, but it can vary +/- 4 g in practical [24].

Table 2. Overall Acceleration in Idle Case without filter (alpha = 0)

Activity Name	X	Y	Z	Acceleration	Alpha
IDLE	0.3286	0.2222	10.470	10.4775	0
IDLE	0.3286	0.2222	10.470	10.4775	0
IDLE	0.3286	0.2222	10.470	10.4775	0
IDLE	0.3286	0.2222	10.470	10.4775	0
IDLE	0.3286	0.2222	10.470	10.4775	0
IDLE	0.3286	0.2222	10.470	10.4775	0
IDLE	0.3286	0.2222	10.470	10.4775	0
IDLE	0.3286	0.2222	10.470	10.4775	0
IDLE	0.3286	0.2222	10.470	10.4775	0
IDLE	0.3286	0.2222	10.470	10.4775	0
IDLE	0.3286	0.2222	10.470	10.4775	0
IDLE	0.3286	0.2222	10.470	10.4775	0

After applying the inverse low pass filter (ref section 3) with taking alpha as 0.7, it is visible in Table 3 that the gravity component is removed and acceleration value is $0.36\ m/s^2$ (approx) for this period of time.

Table 3. Acceleration in Idle Case with filter (alpha = 0.7)

Activity Name	X	Y	Z	Acceleration	Alpha
IDLE	0.1662	0.0851	0.3151	0.3663	0.7
IDLE	0.1662	0.0851	0.3151	0.3663	0.7
IDLE	0.1662	0.0851	0.3151	0.3663	0.7
IDLE	0.1662	0.0851	0.3151	0.3663	0.7
IDLE	0.1662	0.0851	0.3151	0.3663	0.7
IDLE	0.1662	0.0851	0.3151	0.3663	0.7
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IDLE	0.1662	0.0851	0.3151	0.3663	0.7
IDLE	0.1662	0.0851	0.3151	0.3663	0.7
IDLE	0.0898	0.0576	0.1148	0.1567	0.7
IDLE	-0.0532	0.0107	-0.0491	0.0732	0.7
IDLE	0.0397	0.0310	0.0570	0.0760	0.7
IDLE	-0.0313	-0.0060	-0.1481	0.1515	0.7
IDLE	0.1950	0.0979	0.4121	0.4663	0.7

Likewise by varying the value of alpha from 0.6 to 0.9 (incrementing with 0.05) keeping the mobile node in Idle state, data from various mobile node for Acceleration is collected (three times for 1 minute each), and sent at server. The application program running at server calculated the mean for each alpha and find out the optimal value. The mean with lesser value is ideal for noise removal. Researchers have suggested 0.25Hz as Ideal frequency, and alpha corresponding to this frequency is 0.76. However in Table 4 it is visible that the lowest mean is at alpha = 0.6 (cut off frequency= 0.53 Hz), thus it can be said that optimal frequency for gravity removal is 0.53 Hz, and this value is used for the rest of our experiments.

For the experiment 8 different activities have been considered with inverse low pass filter. Starting with the activity 'sitting' in which user is not moving and holding the smart phone in his left hand, figure 4 (left) it is visible that the x (red color) and y (green color) components of accelerometer is nearby to zero, whereas z (blue) component is near to 9.8, which indicates that user is not in motion then also value of z due to gravity is received. Cyan color is representing the total acceleration (using equation 4).

Table 4. Mean of Acceleration at different Alpha Value.

Alpha	Acceleration Mean
0.60	0.05697
0.65	0.20414
0.70	0.13308
0.75	0.32894
0.80	0.12556
0.85	0.19053
0.90	0.21980

When high pass filter is applied to the same activity sitting it is visible in figure 4 (right) that the entire x, y and z component of accelerometer are now at zero, showing gravity component or erroneous data has been removed.

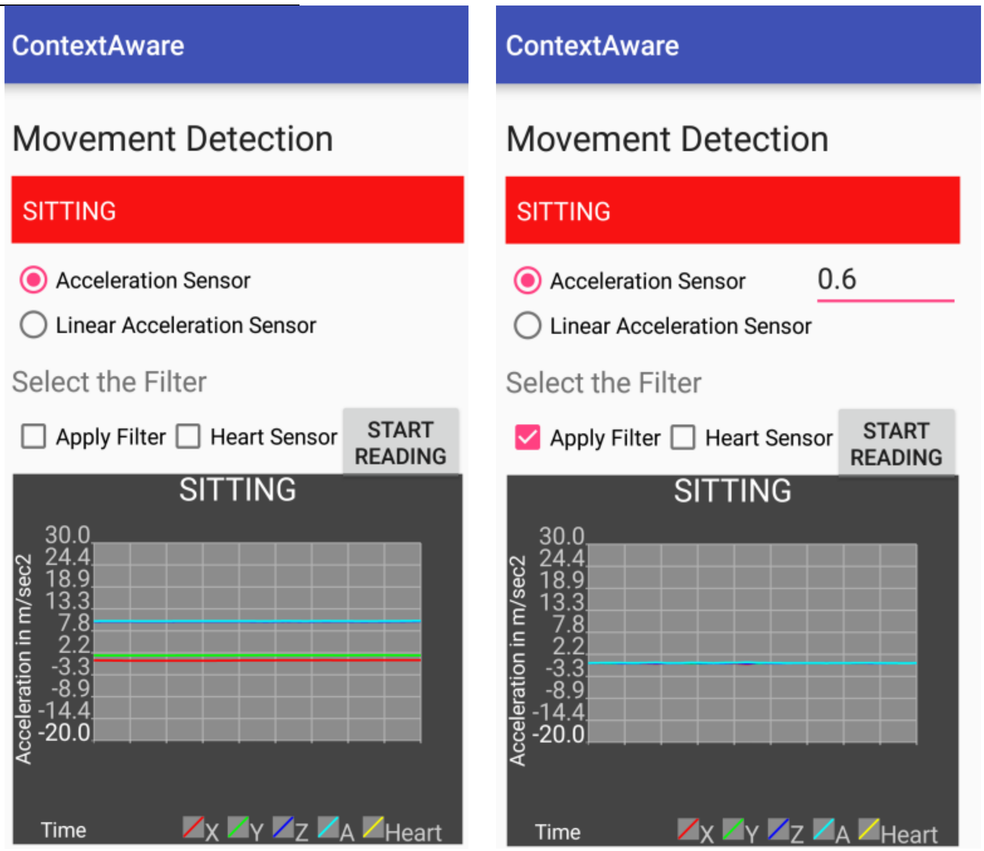

Figure 4. Accelerometer Data in Sitting Position (left without ILPF, right with ILPF)

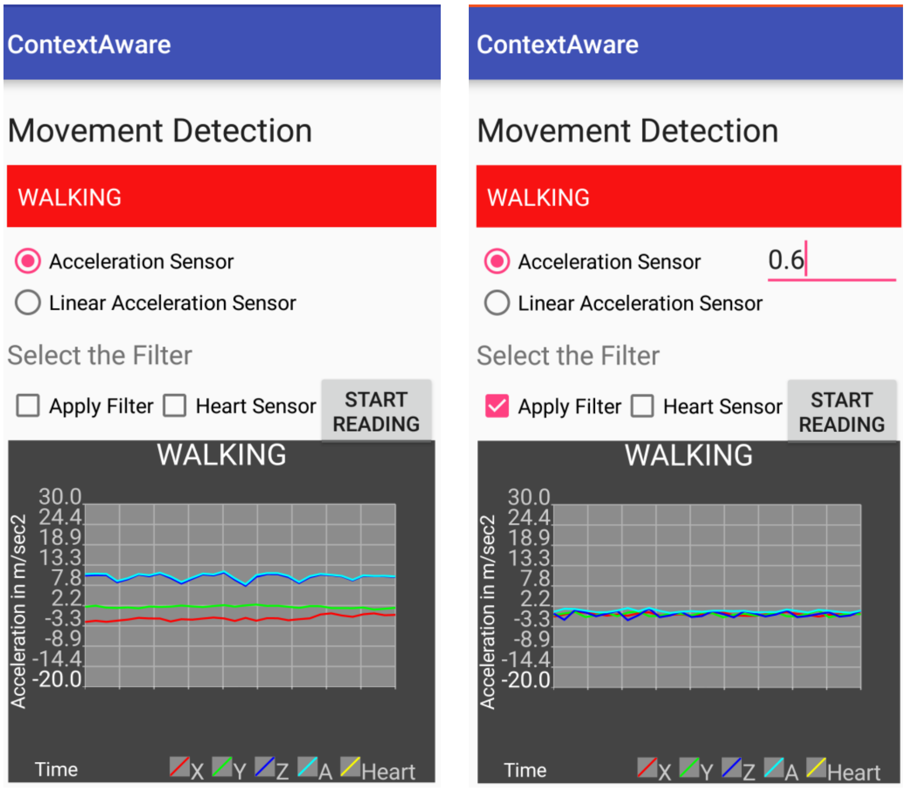

Figure 5. Accelerometer Data for Activity Walking (left without ILPF, right with ILPF)

Likewise the technique is applied to each activity. However, only three activities Sitting, Walking and Running are shown here. It is visible in figure. 5 and 6 that for Walking and Running also, the gravity component of accelerometer have been removed by applying inverse low pass filter.

Thus the data which will be gathered for further processing by using this process will be free of the gravity error and can signify the real transition or motion. The constant downward gravity element belonging to accelerometer is removed by using inverse low pass filter and high frequency transient changes can be figured out.

Experiment part 2: The methodology used for analysis in this part is shown in figure 7. The data is collected from accelerometer with frequency of 60 Hz for 10 different activities, shown in Table 5. The detail of activities is given in Table 6.

While collecting the data the smart device was kept in left hand palm for right handed persons and in right hand palm for left handed people, reason being to start or stop the application one needs his active hand. The activity was performed for maximum 2 min and minimum till the finishing of the activity (as in case of standing up and sitting down). The data was collected by starting the activity first, then starting the application for data collection and it was stopped before finishing the activity to avoid the misleading data collection.

After collection of data feature extraction is done and only 6 features were considered i.e x, y, z, signal magnitude vector (Acceleration), Mean, and Standard Deviation. This has been done to find out the best suited model with low dimensional features. Then the whole data set is divided into 70% for training purpose and 30% for testing purpose. 8 different machine learning models which were mostly used by researchers i.e Decision Tree, KNN, SVM, Naïve Bayes, Random Forest, Adaboost, Bagging, and Extra Tree were trained by using the training data.

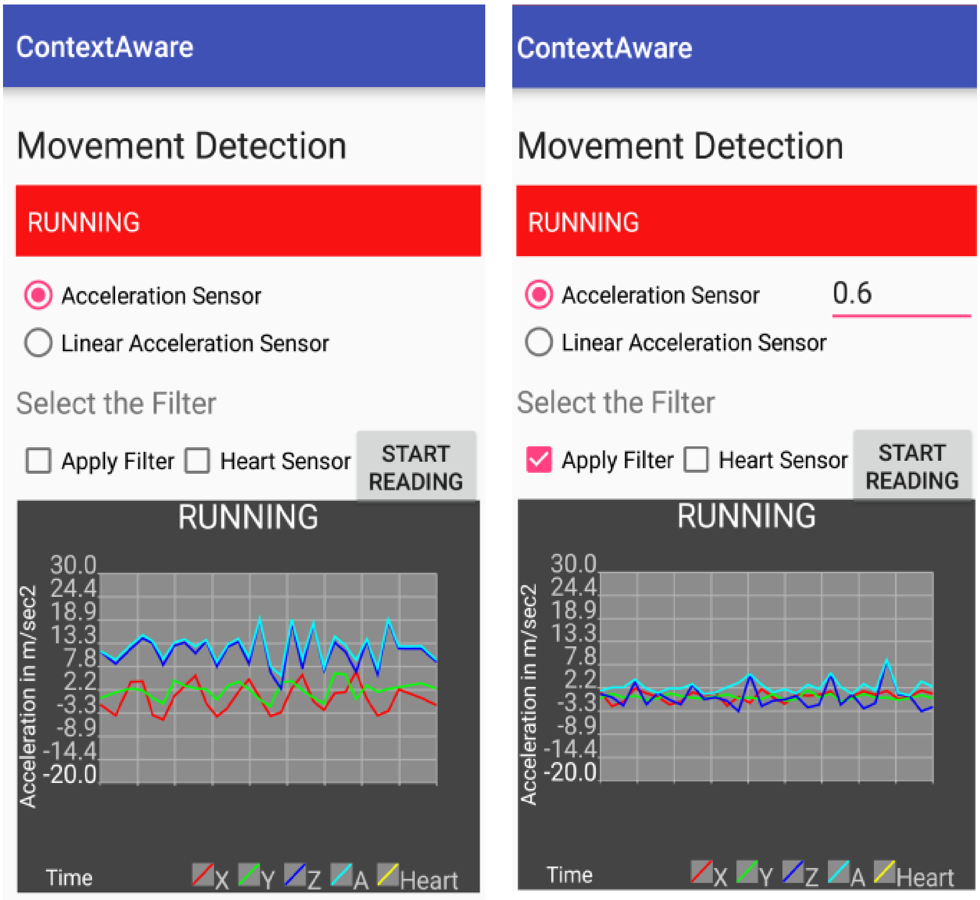

Figure 6. Accelerometer Data for Activity Running (left without ILPF, right with ILPF)

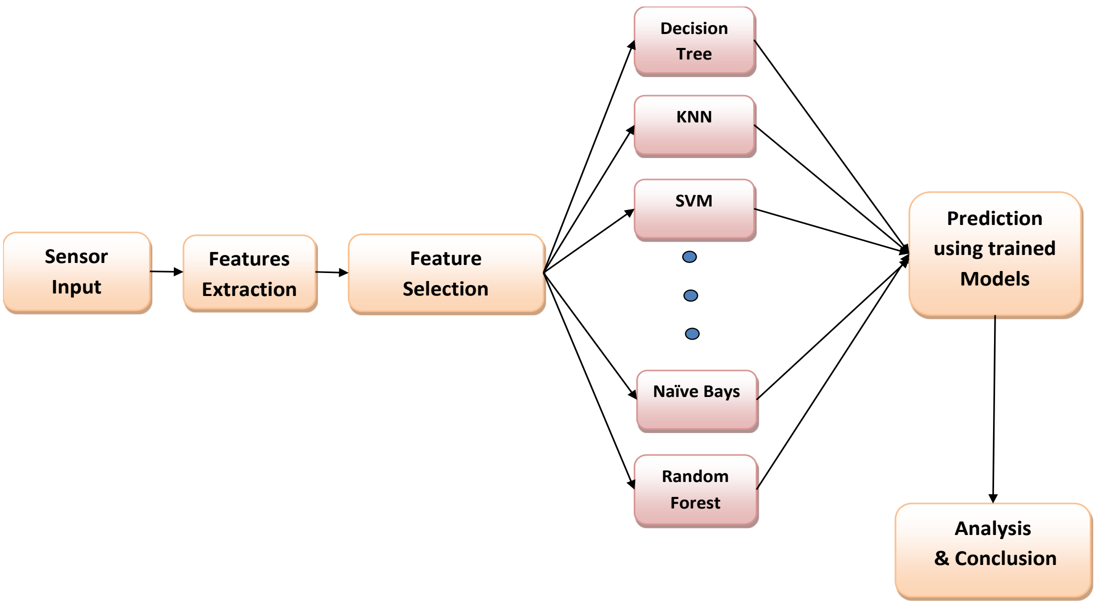

Figure 7. Methodology used for Analysis

All models in their default setting in Anaconda navigator (Jupyter Notebook, Python) is used for training and testing purpose.

Table 5.Details of Sample collected per activity

S.No.	Activity ID	Activity	No. of Samples
1.	1	STANDING	729
2.	2	WALKING	1415
3.	3	RUNNING	3421
4.	5	SITTING DOWN	602
5.	6	STANDING UP	741
6.	7	ASCENDING STAIRS	478
7.	8	DESCENDING STAIRS	1291
8.	12	SITTING	1938
9.	13	UNKNOWN	349
10.	14	IDLE	1636

These trained models were applied on the testing data set. The output of activity recognition is shown in figure 7. This shows that with less dimensional data of only 6 features kNN, Random Forest and Bagging Classifier provides good accuracy (93% approx.) for the purpose of activity recognition.

The Execution Time chart, shown in Figure 8 shows that SVC classifier is taking highest execution time, whereas Naïve bays and Extra tree are taking much lesser time.

Selecting all three classifiers with good accuracy and comparing them by considering their execution time as shown in figure 9, it is visible that kNN is providing good accuracy in lesser time for low dimensional dataset.

Table 6. Details of Activities

S.No.	Activity ID	Activity	Remarks
1.	1	STANDING	Person is standing at one position
2.	2	WALKING	Person is walking with normal speed
3.	3	RUNNING	Person is running
4.	5	SITTING DOWN	Person is sitting to chair or bed or floor from standing position
5.	6	STANDING UP	Person is standing up from sitting position
6.	7	ASCENDING STAIRS	Person is ascending stairs with normal speed
7.	8	DESCENDING STAIRS	Person is descending stairs with normal speed
8.	12	SITTING	Person is sitting on chair or bed or on floor
9.	13	UNKNOWN	Activity not mentioned
10.	14	IDLE	When smart device is kept idle for the removal of gravity component

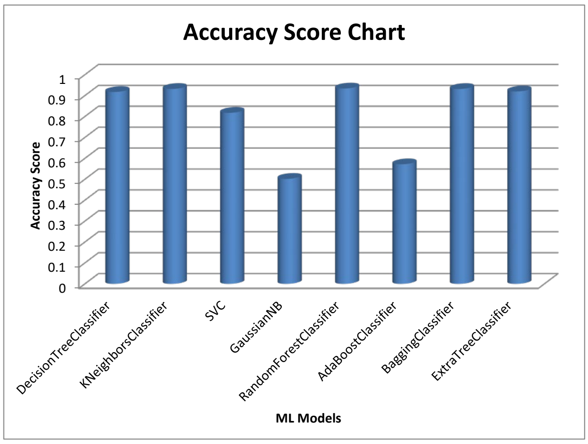

Figure 7. Accuracy Score Chart of ML Models

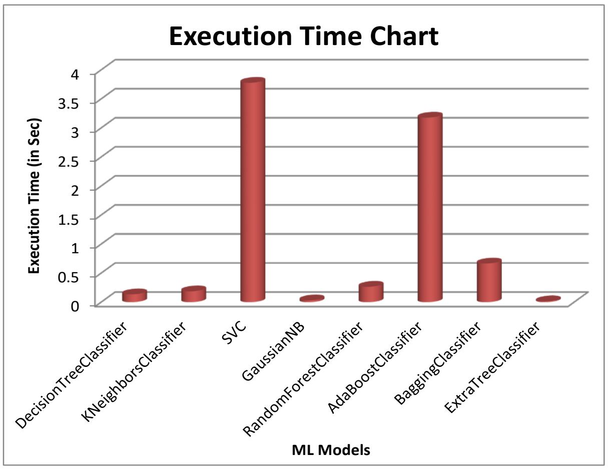

Figure. 8 Execution Time Chart of ML Models

6. Conclusion and Future Scope

It is concluded that by applying inverse low pass filter on healthcare parameters i.e daily activities like standing, walking, sitting, using stairs etc. the error present due to gravity component in raw data of three axis accelerometer can be removed. In addition keeping cutoff frequency as 0.53 Hz (alpha 0.6) provides good result in error removal. This paper also concludes that for the purpose of Human activity recognition kNN, Bagging and Random Forest machine learning models provide good accuracy.

In future heart rate, gyroscope and other sensors of healthcare can be included in this application for the collection of data and some more new coming ML models can be trained and tested. This application will be used to collect online data for more different activities, which can be utilised for further analysis on human health.

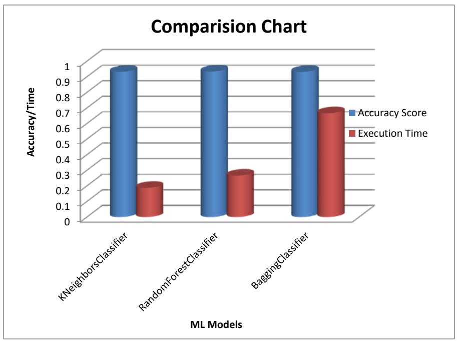

Figure 9. Comparison Chart of ML Models

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