Real time Activity Recognition using Smartphone Accelerometer

Shuang Na[a,1], Kandethody M. Ramachandran [a,1,*], Ming Ji[b,1]

[a] *Department of Mathematics & Statistics, University of South Florida, 4202 E Fowler Ave, CMC 342, Tampa, Florida, USA*

[b] *College Of Nursing, University of South Florida, MDN Building, Room 2011, Tampa, Florida, USA*

Abstract

Human activity recognition (HAR) by smartphone with embedded sensors is applied in many areas, such as medicinal applications and sensor cars etc. In order to identify real-time activities, an online algorithm need be considered. The necessary constraints of online algorithms are that it should take less amount of running time and it can recursively update the model. The traditional preprocess method is to partition the time series into short and fixed length segments. However, these segments might not be longer enough to capture whole activity time interval. In this paper, we will first segment entire one activity as one time interval using Bayesian online detecting method. Then, we introduce two layer random forest classification for real time activity recognition on smartphone by embedded accelerometers. The first layer classify activities as static and dynamic activities, the second layer classify sub-classes depending on the first layer result. We evaluate the performance of our method based on six activities: walking, upstairs, downstairs, sitting, standing and laying on 30 volunteers. For the data considered, We get 92.4% overall accuracy based on six activities and 100% overall accuracy only based on dynamic activity and static activity.

Keywords: Bayesian online detection, Human activity recognition, Random

*Corresponding author
Email address: `ram@usf.edu` (Kandethody M. Ramachandran)

[1] Interdisciplinary Data Sciences Consortium

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1. Introduction

It has been estimated that there would be 6.1 billion smartphone users by 2020, which is about 70% of the population worldwide [1]. Smart phone is not only a communication equipment, but also a powerful tool with a variety of functions, such as photograph, radio, calculator, game and GPS, which contains camera, accelerometer, microphone, magnetic compasses and GPS sensors etc. The human activity recognition (HAR) problem using smartphone with built-in sensors include accelerometer and GPS that allow continuously monitoring human activity patterns (i.e. walking, running, sitting, etc.) of user who carry a smart phone everyday as well as personal medical care tracking. For instance, some people are concerned about how many calories they burn every day through exercise, or detecting an elder fell down and whether he/she require emergency aid. Comparing with other wearable sensors, due to the small size and multi-functionality of smartphone, it is more convenient and reasonable to carry cellphone every day.

The first project of HAR is discussed in [2] in late '90s. During 25 years, there were several approaches to improve the identifying process by wearing multiple sensors that set on several locations of the body ([3],[4],[5]). In [3], which indicates that multiple accelerometers distributed on different location of body has more effective recognition ability. In addition, application of complex methods such as statistics learning and machine learning also effect on improving identifying process ([6], [7], [8], [9]). An overview of HAR problem by wearable sensors is discussed in [10], which also compares HAR system, sensors, recognition method and evaluation systems. It claims it is hard to define the best detecting procedure because of different tasks, sampling rates, algorithms, computing speed and evaluation methods. Nevertheless, more sensors give better results in general. However, it's unreasonable to wear multiple equipments every day because of expense, complexity and inconvenience. Smart phone as a much used electronic product that has been widely applied for activity recognition (e.g. [7],[11],[12],[13], [14]). Therefore, smart phone based HAR becomes very important research field.

We present a real-time human activity recognition algorithm using sensor data generated from the tri-axial accelerometer built-in smartphone [13]. The six daily life activities discussed here are: walking, upstairs (walking upstairs), downstairs (walking downstairs), sitting, standing and laying. To deal with HAR problem, first we must partition the entire time interval into segments because raw data can not be used in classification algorithm directly. Then, extract meaningful features (mean, standard deviation, peak etc.) from every segments, which are applied for the classification algorithm, such as decision tree. Finally, we will train and test the identifying process. Because of limitation of cell phone's battery and CPU, we can not train the model on cell phone. Usually, the training process is either already learned on computer or happening on cloud computing through Internet. However, technology is developing with time, more and more types of cellphones are allowed to run training algorithm on it [14]. Therefore, the user can collect data and identify activities on their phone, it's more convenient when user wants to adapt the activity training model or when Internet is not available. On the other hand, it is also desirable to develop more efficient and less complex learning models so that training procedure can be processed on the cellphone. For the classification method, there are two types algorithm: online and offline learning ([15],[16]). Comparing with offline learning method, online learning can be applied to real time training data because it is able to adapt the model as new data being collected.

In this paper, we introduce combination of Bayesian online detection algorithm and two layer random forest classification, which can automatically identify human activities at certain time without user intervening, such that user dose not need to mark start time and end time for every activity. Using Bayesian online segmentation method to detect the time interval, we extract meaningful features based on entire activity time interval that considered as a segment. The features of entire activity contain more information than short time interval generated by fixed length time segmentation. For the training procedure, different classification layers use different features (section 2). The aim of first layer is to distinguish dynamic activities (walking, upstairs and downstairs) versus static activities (sitting, standing and laying). The main feature used in the first layer classifier is amplitude defined as $\sqrt{x_{i,1}^2 + x_{i,2}^2 + ... + x_{i,p}^2}$, x_i is i^{th} point with p-dimension. During the second layer classification processing, there are two separated classification training models A and B to classify different sub-classes. If we get static activity on the first layer for a certain interval, then we go through model A at second layer to further classify as sitting, standing or laying; otherwise, we go through model B at second layer to further partition into walking, upstairs or downstairs.

This paper is organized as follows. Section 2 presents the Bayesian online segmentation. Section 3 discusses two layers classification method. In section 4, we present the result of applying the methods introduced to a real time activity data. The conclusion is given in section 5.

2. Methodology

In the proposed human activity recognition(HAR), the first step of HAR is to separate the whole time series interval into small segments, which step is to pre-process the time series by reason of the raw individual observation can not be applied directly in classification methods. Usually, we partition the whole time series into equal length segments, the length of the segment could be 1.5s, 2s and 3s etc. However, these type of intervals are so short that can not capture enough information of activities. In this paper, we complete this step based on Bayesian online segmentation method introduced in section 2.1. This method detects change points between two patterns and it defines the time series between two change points as a segment, which procedure results in varying length time intervals rather than equal length and small segments. Next step, we need to extract features from each segment. The feature widely used so far are categorized as time-domain features, frequency domain features, wavelet features and Heuristic Features [17]. Here, we mainly use time-domain features and frequency-domain features. The review paper [10] discusses current classification methods that include decision tree, k-nearest neighbors, Bayesian, neural network, Fuzzy Logic , Support Vector Machines, Classifier ensembles, Regression methods and Markov models that are applied widely in many publications and applications. Then, we need to test our method on testing data and we use the accuracy and confusion matrix as the evaluation index. Fig 1 displays the process of real-time activity recognition.

2.1. Bayesian Online Segmentation

In this paper, we consider the three dimensional data points $x = (x_1, x_2, x_3)$ with frequency 50Hz that is generated by smartphone accelerometer. The task of classifying the human patterns from these sensor data is to group homogeneous data sets together and separate heterogeneous data sets. These observations are listed on time line, all observations between two change points construct a time series segment defined as a pattern. Those homogeneous observations are assumed to follow a multi-normal distribution and different patterns follows different multi-normal distributions. Therefore, to find the change point between two patterns becomes very important problem.

In [18] and [10], an overview of the human activity recognition process and discussion of segmenting methods. Bayesian online detecting method [19] can be used to prepare these segments automatically for classification. First we consider the concept of "run length" r_t, which is the length of the current run at time t and it is linear about time t. For example, if $r_t = 0$ at t=8, x_8 is a change point; if $r_t \neq 0$, we keep run one more and repeat the process. $x_t^{(r)}$ is defined as the set correspond to run length r_t. If r_t is zero, $x^{(r)}$ is empty set. For example, t=9, $r_t = 1$, then $x_9^{(r)} = \{x_8, x_9\}$. In order to find the posterior distribution $P(r_t|x_{1:t})$, we need generate a recursive joint distribution

$P(r_t, x_{1:t})$,

$$
\begin{aligned}
P(r_t|x_{1:t}) &= \frac{P(r_t, x_{1:t})}{P(x_{1:t})} \propto P(r_t, x_{1:t}) \\
&\propto \sum_{r_{t-1}} P(r_t, r_{t-1}, x_t, x_{1:t-1}) \\
&\propto \sum_{r_{t-1}} P(r_t, x_t|r_{t-1}, x_{1:t-1}) P(r_{t-1}, x_{1:t-1}) \\
&\propto \sum_{r_{t-1}} P(r_t|r_{t-1}) P(x_t|r_{t-1}, x_{t-1}^{(r)}) P(r_{t-1}, x_{1:t-1}) \qquad (1)
\end{aligned}
$$

Here, $P(r_t|r_{t-1})$ is prior probability , the joint distribution $P(r_t, x_{1:t})$ is called growth probability and $P(x_t|r_{t-1}, x_{t-1}^{(r)})$ is predictive probability. At every time recursion, we pick the r_t with the largest posterior probability, which r_t is also associated with the largest joint distribution in recent data. Next, we need get prior distribution $P(r_t|r_{t-1})$ and the predictive distribution $P(x_t|r_{t-1}, x_t^{(r)})$.

The run length has two directions: one direction is that no change point happens at time t and $r_t = r_{t-1}+1$, which means the new data still stays in same group and follows same distribution; another one is that a change point occurs, r_t drop to 0 with probability $H(r_t) = 1/\lambda$. Here, $H(r_t)$ is hazard function based on geometric distribution with parameter λ [20]. The prior distribution is:

$$
P(r_t|r_{t-1}) = \begin{cases} H(r_{t-1}) & \text{if } r_t = 0 \\ 1 - H(r_{t-1}) & \text{if } r_t = r_{t-1} + 1 \\ 0 & \text{otherwise} \end{cases} \qquad (2)
$$

The predictive probability $P(x_{t+1}|r_t, x_t^{(r)})$ is the marginal distribution integral the parameter vector θ correspond to current run length r_t, which only depends on the recent data set $x_t^{(r)}$, due to the distribution stays the same in recent data. Define it as following:

$$
P(x_{t+1}|r_t, x_t^{(r)}) = \int P(x_{t+1}|\theta) P(\theta_t^{(r)} = \theta|r_t, x_t^{(r)}) d\theta \qquad (3)
$$

Here, $\theta_t^{(r)}$ is the parameter of current run length. Assume the tri-dimensions sensor data $x = (x_1, x_2, x_3)^T$ follow three dimension multiple normal distribution with mean μ and inverse-covariance matrix $\Omega = \Sigma^{-1}$ and dimension $d = 3$.

The likelihood function of n data points is described as follows:

$$
\begin{aligned}
P(X_{1:t}|\mu,\Omega) &= (2\pi)^{-nd/2}|\Omega|^{t/2}exp\Big(-\frac{1}{2}\sum_{i=1}^{t}(x_i-\mu)^T\Omega(x_i-\mu)\Big) \\
&\propto |\Omega|^{t/2}exp\Big(-\frac{1}{2}\sum_{i=1}^{n}(x_i-\mu)^T\Omega(x_i-\mu)\Big) \qquad (4)
\end{aligned}
$$

For the prior distribution $P(\mu,\Omega)$, assume $\mu \sim \mathcal{N}(\mu_0,(\kappa_0\Omega)^{-1})$ normal distribution and $\Omega \sim Wi_d(T_0,\nu_0)$ Wishart distribution, so the prior distribution of combining both unknown parameters is:

$$
\begin{aligned}
&P(\mu,\Omega|\mu_0,\kappa_0,\nu_0,T_0) \\
&\propto |\Omega|^{1/2}exp\Big(-\frac{1}{2}(\mu-\mu_0)^T(\kappa\Omega)(\mu-\mu_0)\Big)|\Omega|^{(\nu_0-d-1)/2}exp\Big(-tr(T\Omega)/2\Big) \quad (5)
\end{aligned}
$$

Hence, the posterior distribution is:

$$
P(\mu,\Omega|X_{1:t}) \propto P(X_{1:t}|\mu,\Omega)P(\mu,\Omega) \propto \mathcal{N}(\mu|\mu_t,\kappa_t)Wi_d(\Omega|\nu_t,T_t) \qquad (6)
$$

where,

$$
\begin{aligned}
\kappa_t &= \kappa_0 + t \\
\mu_t &= \frac{\kappa_0\mu_0 + t\bar{X}_t}{\kappa_0 + t} \\
\nu_t &= \nu_0 + t \\
T_t &= T_0 + \sum(X_i-\bar{X}_t)(X_i-\bar{X}_t)^T + \frac{\kappa_0 t}{\kappa_0 + t}(\mu_0-\bar{X}_t)(\mu_0-\bar{X}_t)^T \qquad (7)
\end{aligned}
$$

Therefore, the update step for every one new data.

$$
\begin{aligned}
\kappa_{t+1} &= \kappa_t + 1 \\
\mu_{t+1} &= \frac{\kappa_t\mu_t + X_{t+1}}{\kappa_t + 1} \\
\nu_{t+1} &= \nu_t + 1 \\
T_{t+1} &= \frac{\kappa_t(X_{t+1}-\mu_t)(X_{t+1}-\mu_t)^T}{\kappa_t + 1} \qquad (8)
\end{aligned}
$$

Finally, the posterior predictive probability is

$$
P(X_{t+1}|X_t^r, r_t) = t_{\nu_t - d + 1}(\mu_t, \frac{T_t(\kappa_t + 1)}{\kappa_t(\nu_t - d + 1)}) \qquad (9)
$$

When a new data comes, the algorithm updates parameter and the joint distribution $P(r_t, x_{1:t})$, which approximates to posterior distribution $P(r_t|x_{1:t})$. This Bayesian method create t posterior distribution $\{P(r_t|x_{i:t})\})\}_{i=1}^{t}$ at every iteration time t, to pick up the r_t with highest posterior probability. If r_t change to 0 that means a new segment, x_t is defined as a change point. More detail is shown in Appendix.

Adjust online Bayesian method

Time consumption is one of the biggest issues of Bayesian online algorithm because the computing time is linear with number of observations, which makes computing time being linearly increasing with time. Here, we introduce sliding window method that is used to construct a fixed window size N, which is so large that includes at least a few activities segmentation. In this experiment we take $N = 10000$ that's equivalent to 200s. The adjusted online Bayesian method is to re-initial all parameters when starting a new sliding window and eliminates all old parameter information of last sliding window. The algorithm of adjust Bayesian online segmenting shows in Fig 2.

2.2. Two layer Classification

In this experiment, instead of extracting features from every small segment, such as 2s, we consider extracting features from the entire activity time segment constructed automatically by Bayesian Online Detection method. One reason of considering the feature of whole segment is that less feature calculation than feature computation of every 2s. Another reason is to classify the whole sequence rather than classifying subsequence that subsequence contains less information of activity process. In addition to the three dimensional data (x_i, y_i, z_i), there is another important measurement: the distance of a observation to the original point $(0, 0, 0)$ called magnitude, which is defined as $d_i = \sqrt{x_i^2 + y_i^2 + z_i^2}$. The feature we used here are following six type criterion:

1. Average of (x_i, y_i, z_i, d_i);
2. Standard deviation of (x_i, y_i, z_i, d_i);
3. Average of local maximum of (x_i, y_i, z_i, d_i);

4. Average of time difference between two consecutive local maximums of (x_i, y_i, z_i, d_i);

5. Skewness of (x_i, y_i, z_i);

6. Kurtosis of (x_i, y_i, z_i).

The observation can approximate as periodic wave and the repetitive peak can look as one of the characteristics that is used to distinguish different axises of different activities [12]. Because the wave of dynamic activities repeat quicker than static activities, the time gap between two consecutive peak of dynamic activities are shorter than static activities, which is also used as the indexes to distinguish the activities.

After time segmentation, this algorithm trains two layers classification. The first layer classifies the activities into two categories: dynamic activities (walking, up-stairs, down-stairs) and static activity (standing, sitting, lying). The training features of first layer classification only includes the first four criterion of d_i: average, standard deviation, average of local maximum and Average of time difference between two consecutive local maximums. These criterion of d_i are the biggest factors to distinguish dynamic and static patterns. For the second layer classification, there are two separated classification processes. One classifier trains and tests only on dynamic activity results into three classes: walking, upstairs and downstairs. Another classifier trains and tests on static activity that also result in three classes: sitting, standing and lying. Here, we apply random forest as classification method, which is the most widely used classifier and suitable for many types of data [14]. The two layer classification algorithm is displayed in Fig 2.2.

3. Experiment

The data source is provided by [21], where the experiments have been carried out with a group of 30 volunteers. They performed a protocol of activities composed of six basic activities: three static postures (standing, sitting, lying) and three dynamic activities (walking, walking downstairs and walking upstairs).

All the participants were wearing a smartphone (Samsung Galaxy S II) on the waist during the experiment execution. The captured 3-axial linear acceleration at a constant rate of 50Hz using the embedded accelerometer. Randomly choose 200s observations of a few volunteers show tri-axis observation of six activities in Fig 4. It is relatively easy to distinguish dynamic activities and static activities, because dynamic activities have stronger fluctuation than static activities. However, it is a challenge to identify the walking, upstairs and downstairs in dynamic group, as well as identifying sitting, standing and laying in static group. In addition , volunteers generate their characteristic wave stream that observations are quite different with each other when they even perform same action. For instance, in Fig4_testing, the z-axis data of around first 80s is less fluctuating than the z-axis data from 80s to 120s. On the other hand, the observations of different activities exhibited from different persons that could be same. Therefore, the combination of the sensor data from all volunteers is difficult to be detected due to the differences of pattern. The reason of training on combining data is that prototype created by such training set can be generally applied so that user don't require to record the start and stop time for specific activities.

The obtained dataset was randomly partitioned into two sets, where 70% of the data was selected as training data and 30% as the test data. The training set is applied to train two layers random forest in order to get the prototypes model. Subsequently, the model is used to classify the online segments using online Bayesian segmentation discussed before, and come with class label as output. First of all, let's check the automatically segmenting confusion matrix result in Table1 using Bayesian online segmentation algorithm, those error are caused by segmenting bias and delay with real boundaries. Here, we use majority vote to label the class of each segment.

Table1 the average error rate of bias and delay is 3.55%, which shows this algorithm can automatically and efficiently detect changing and find activities time interval. To compare with Bayesian online segmentation method, we use Sliding Window and Bottom-up(SWAB) [22] online segmentation algorithm as optional choice. SWAB is to process bottom-up algorithm during a large enough sliding window that can include a few segments. Unlike Bayesian method, SWAB require to define initial minimal segmentation length and final merged number of segments. In Table2, we display overall accuracy based on different scale of minimal length and number of segments. The accuracy is increasing as long as we increase number of segments and increase minimal length. However, increasing both criterion will result in segmentation meaningless. Therefore, we are uncertain to choose the best option. Compared with that, Bayesian method has less pre-defined requirement and hence more desirable.

Table 3 shows the testing accuracy of two times classifier based on Bayesian online segmentation. The overall accuracy is 91.4% for six states, the accuracy of static postures and dynamic activities is 100 %. By the overall accuracy of two groups, we can 100% detect whether the person move or not. From the estimated change points, we can estimate the length of time for a person to be active or sedentary.

For showing the reasoning of choosing random forest, we comparing the results of training by KNN, SVM, Boosting with Random forest in Fig5. The overall accuracy of Boosting and Random forest are very close and both higher than other two algorithm. Checking the accuracy of every activities, Boosting and Random forest generated result are better than others except for upstairs that SVM performs the best. Taken as a whole, Boosting and Random forest are the optimum choices. Nonetheless, the time complexity of boosting is $O(ndKlog(n))$ higher than the time complexity of random forest $O(ndlog(n))$,here n is number of observation, d is number of features and K is depth. Consider the task of real time pattern detecting, not only accuracy is important, less time consuming is also another criterion. Therefore, random forest is the better way to handle our data.

Based on Table1 segmenting outcomes, we can simultaneously input the result into two times classifier and output activity label immediately.

4. Conclusion

We present a real-time activity recognition algorithm, which is used to apply on smartphone platform for human activity identification. We introduce Bayesian online detection algorithm and two layers random forest classifier. Rather than extracting features from small segments that one activity time interval might contain a few such segments, this method computes features based on entire activity time interval. Different classify layers use different features in order to avoid meaningless features and save running time. The aim of first layer is to distinguish dynamic activities (walking, upstairs and downstairs) and static activities (sitting, standing and laying) using the amplitude as the key feature. The process of second layer is to distinguish the three behaviors in different categories. However, it is still a big challenge to differentiate walking and walking upstairs very well only based on accelerometer sensor data. We could get better result with regarding GPS data in the later work. In this work, performance has reached with overall accuracy for six states is 92.4%, and the overall accuracy for two categories: dynamic activities and static activities is 99.25%. In the future, a real-time detecting activity system can be designed on smartphone. Since it has been trained and it can automatically detect behavior change, therefore it's easy to handle without user knowledge of machine learning and instruct smartphone when user change behaviors. Even though the multivariate normality assumption is bit restrictive, we get good results. we plan to relax this assumption in the future work. Further, we also can extend the set of activity with low frequency and high frequency, such as quick walking, slow walking, quick running and jogging etc.

Appendix

The prior distribution of combination of normal distribution and Wishart distribution is:

$$
\begin{aligned}
&P(\mu,\Omega|\mu_0,\kappa_0,\nu_0,T_0)\\
&=\mathcal{N}(\mu|\mu_0,\kappa_0)Wi_d(\Omega|\nu_0,T_0)\\
&=(2\pi)^{-d/2}|\kappa_0\Omega|^{1/2}exp\Big(-\frac{1}{2}(\mu-\mu_0)^T(\kappa\Omega)(\mu-\mu_0)\Big)|\\
&\times\Omega|^{(\nu_0-d-1)/2}exp\Big(-tr(T\Omega)/2\Big)2^{-\nu_0 d/2}|T|^{-\nu_0/2}\Gamma_d(\nu_0/2)\\
&\propto|\Omega|^{1/2}exp\Big(-\frac{1}{2}(\mu-\mu_0)^T(\kappa\Omega)(\mu-\mu_0)\Big)|\Omega|^{(\nu_0-d-1)/2}exp\Big(-tr(T\Omega)/2\Big)
\end{aligned}
\tag{10}
$$

Therefore, we can get the posterior distribution:

$$
\begin{aligned}
&P(\mu,\Omega|X_{1:t})=\frac{P(\mu,\Omega,X_{1:t})}{P(X_{1:t})}=\frac{P(X_{1:t}|\mu,\Omega)P(\mu,\Omega)}{P(X_{1:t})}\propto P(X_{1:t}|\mu,\Omega)P(\mu,\Omega)\\
&\propto|\Omega|^{t/2}exp\Big(-\frac{1}{2}\sum_{i=1}^{t}(x_i-\mu)^T\Omega(x_i-\mu)\Big)\\
&\times|\Omega|^{1/2}exp\Big(-\frac{1}{2}(\mu-\mu_0)^T(\kappa\Omega)(\mu-\mu_0)\Big)|\Omega|^{(\nu_0-d-1)/2}exp\Big(-tr(T\Omega)/2\Big)\\
&\propto|\Omega|^{1/2}|\Omega|^{(\nu_0+t-d-1)/2}exp\Big(-\frac{1}{2}(\mu-\frac{\kappa_0\nu_0+t\bar{X}}{\kappa_0+t})^T(\kappa\Omega)(\mu-\frac{\kappa_0\nu_0+t\bar{X}}{\kappa_0+t})\Big)\\
&\times|\Omega|^{(\nu_0-d-1)/2}exp\Big(-tr(T\Omega)/2\Big)\\
&\times exp\Big((T_0+\sum(X_i-\bar{X})(X_i-\bar{X})^T+\frac{\kappa_0 t}{\kappa_0+t}(\mu_0-\bar{X})(\mu_0-\bar{X})^T)\Big)\\
&\propto|\Omega|^{1/2}|exp(-\frac{1}{2}(\mu-\mu_t)(\kappa_t\Omega)(\mu-\mu_t)^T)|\Omega|^{(\nu_t-d-1)/2}exp\Big(T_t\Omega\Big)\\
&\propto\mathcal{N}(\mu|\mu_t,\kappa_t)Wi_d(\Omega|\nu_t,T_t)
\end{aligned}
\tag{11}
$$

For the update step,

$$
\begin{aligned}
&\mu_{t+1} - \mu_t \\
&= \frac{\kappa\mu_0 + (t+1)\bar{X}_{t+1}}{\kappa + t + 1} - \frac{\kappa\mu_0 + t\bar{X}_t}{\kappa + t} \\
&= \frac{\kappa X_{t+1} + tX_{t+1} - \kappa\mu_0 - t\bar{X}_t}{(\kappa + t + 1)(\kappa + t)} = \frac{X_{t+1} - \mu_t}{\kappa_t + 1} \\
&\mu_{t+1} = \mu_t + \frac{X_{t+1} - \mu_t}{\kappa_t + 1} = \frac{\kappa_t\mu_t + X_{t+1}}{\kappa_t + 1}
\end{aligned} \tag{12}
$$

$$
\begin{aligned}
&T_{t+1} - T_t \\
&= X_{t+1}X_{t+1}^T - (t+1)\bar{X}_{t+1}\bar{X}_{t+1}^T + t\bar{X}_t\bar{X}_t^T + \frac{\kappa(t+1)}{\kappa+t+1}(\mu_0\mu_0^T - 2\mu_0\bar{X}_{t+1}^T + \bar{X}_{t+1}\bar{X}_{t+1}^T) \\
&- \frac{\kappa t}{\kappa + t}(\mu_0\mu_0^T - 2\mu_0\bar{X}_t^T + \bar{X}_t\bar{X}_t^T) \\
&\Big(\frac{(t+1)\bar{X}_{t+1} - X_{t+1}}{t} = \bar{X}_t\Big) \\
&= \frac{1}{Z}\Big[(\kappa_t + 1)\kappa_t X_{t+1}X_{t+1}^T - (t+1)^2\kappa_t\bar{X}_{t+1}\bar{X}_{t+1}^T \\
&+ t^2(\kappa_t + 1)\Big(\frac{(t+1)\bar{X}_{t+1} - X_{t+1}}{t}\Big)\Big(\frac{(t+1)\bar{X}_{t+1} - X_{t+1}}{t}\Big)^T \\
&- 2\kappa(t+1)\kappa_t\mu_0\bar{X}_{t+1}^T + 2\kappa t(\kappa_t + 1)\Big(\frac{(t+1)\bar{X}_{t+1} - X_{t+1}}{t}\Big) + \kappa^2\mu_0\mu_0^T\Big]
\end{aligned} \tag{13}
$$

where,

$$
\begin{aligned}
&Z = (\kappa + t + 1)(\kappa + t) \\
&= \frac{1}{Z}\Big[(\kappa_t + 1)^2 X_{t+1}X_{t+1}^T + (t+1)^2\bar{X}_{t+1}\bar{X}_{t+1}^T + \kappa^2\mu_0\mu_0^T - 2(\kappa_t + 1)(t+1)\bar{X}_{t+1}X_{t+1}^T \\
&+ 2\kappa(t+1)\mu_0\bar{X}_{t+1} - 2\kappa(\kappa_t + 1)\mu_0 X_{t+1}^T\Big] \\
&= \frac{1}{Z}\Big[(\kappa_t + 1)X_{t+1} - (t+1)\bar{X}_{t+1} - \kappa\mu_0\Big]\Big[(\kappa_t + 1)X_{t+1} - (t+1)\bar{X}_{t+1} - \kappa\mu_0\Big]^T \\
&= \frac{\kappa_t(X_{t+1} - \mu_t)(X_{t+1} - \mu_t)^T}{\kappa_t + 1}
\end{aligned} \tag{14}
$$

References

[1] Ericsson mobility report: 70 percent of world's population using smartphones by 2020, `https://www.ericsson.com/news/1925907` (June 2015).

[2] F. Foerster, M. Smeja, J. Fahrenberg, Detection of posture and motion by accelerometry: a validation study in ambulatory monitoring, Computers in Human Behavior 15 (5) (1999) 571–583.

[3] L. Bao, S. S. Intille, Activity recognition from user-annotated acceleration data, in: International Conference on Pervasive Computing, Springer, 2004, pp. 1–17.

[4] J. Cheng, O. Amft, P. Lukowicz, Active capacitive sensing: Exploring a new wearable sensing modality for activity recognition, in: International Conference on Pervasive Computing, Springer, 2010, pp. 319–336.

[5] M. Ermes, J. Parkka, L. Cluitmans, Advancing from offline to online activity recognition with wearable sensors, in: 2008 30th Annual International Conference of the IEEE Engineering in Medicine and Biology Society, IEEE, 2008, pp. 4451–4454.

[6] D. Anguita, A. Ghio, L. Oneto, X. Parra, J. L. Reyes-Ortiz, Energy efficient smartphone-based activity recognition using fixed-point arithmetic, J. UCS 19 (9) (2013) 1295–1314.

[7] D. Anguita, A. Ghio, L. Oneto, X. Parra, J. L. Reyes-Ortiz, Human activity recognition on smartphones using a multiclass hardware-friendly support vector machine, in: International Workshop on Ambient Assisted Living, Springer, 2012, pp. 216–223.

[8] P. Casale, O. Pujol, P. Radeva, Human activity recognition from accelerometer data using a wearable device, in: Iberian Conference on Pattern Recognition and Image Analysis, Springer, 2011, pp. 289–296.

[9] D. Vishwakarma, P. Rawat, R. Kapoor, Human activity recognition using gabor wavelet transform and ridgelet transform, Procedia Computer Science 57 (2015) 630–636.

[10] O. D. Lara, M. A. Labrador, A survey on human activity recognition using wearable sensors, IEEE Communications Surveys & Tutorials 15 (3) (2013) 1192–1209.

[11] A. D. Ignatov, V. V. Strijov, Human activity recognition using quasiperiodic time series collected from a single tri-axial accelerometer, Multimedia Tools and Applications (2015) 1–14.

[12] J. R. Kwapisz, G. M. Weiss, S. A. Moore, Activity recognition using cell phone accelerometers, ACM SigKDD Explorations Newsletter 12 (2) (2011) 74–82.

[13] J.-L. Reyes-Ortiz, L. Oneto, A. Ghio, A. Sama, D. Anguita, X. Parra, Human activity recognition on smartphones with awareness of basic activities and postural transitions, in: International Conference on Artificial Neural Networks, Springer, 2014, pp. 177–184.

[14] M. Shoaib, S. Bosch, O. D. Incel, H. Scholten, P. J. Havinga, A survey of online activity recognition using mobile phones, Sensors 15 (1) (2015) 2059–2085.

[15] G. James, D. Witten, T. Hastie, R. Tibshirani, An introduction to statistical learning 6.

[16] M. Mohri, A. Rostamizadeh, A. Talwalkar, Foundations of machine learning, MIT press, 2012.

[17] A. Avci, S. Bosch, M. Marin-Perianu, R. Marin-Perianu, P. Havinga, Activity recognition using inertial sensing for healthcare, wellbeing and sports applications: A survey, in: Architecture of computing systems (ARCS), 2010 23rd international conference on, VDE, 2010, pp. 1–10.

[18] A. Mannini, A. M. Sabatini, Machine learning methods for classifying human physical activity from on-body accelerometers, Sensors 10 (2) (2010) 1154–1175.

[19] R. P. Adams, D. J. MacKay, Bayesian online changepoint detection, arXiv preprint arXiv:0710.3742.

[20] P. A. Tobias, D. Trindade, Applied reliability, CRC Press, 2011.

[21] J.-L. Reyes-Ortiz, L. Oneto, S. Albert, X. Parra, D. Anguita, Transition-aware human activity recognition using smartphones, Neurocomputing 171 (2016) 754–767.

[22] E. Keogh, S. Chu, D. Hart, M. Pazzani, An online algorithm for segmenting time series, in: Data Mining, 2001. ICDM 2001, Proceedings IEEE International Conference on, IEEE, 2001, pp. 289–296.

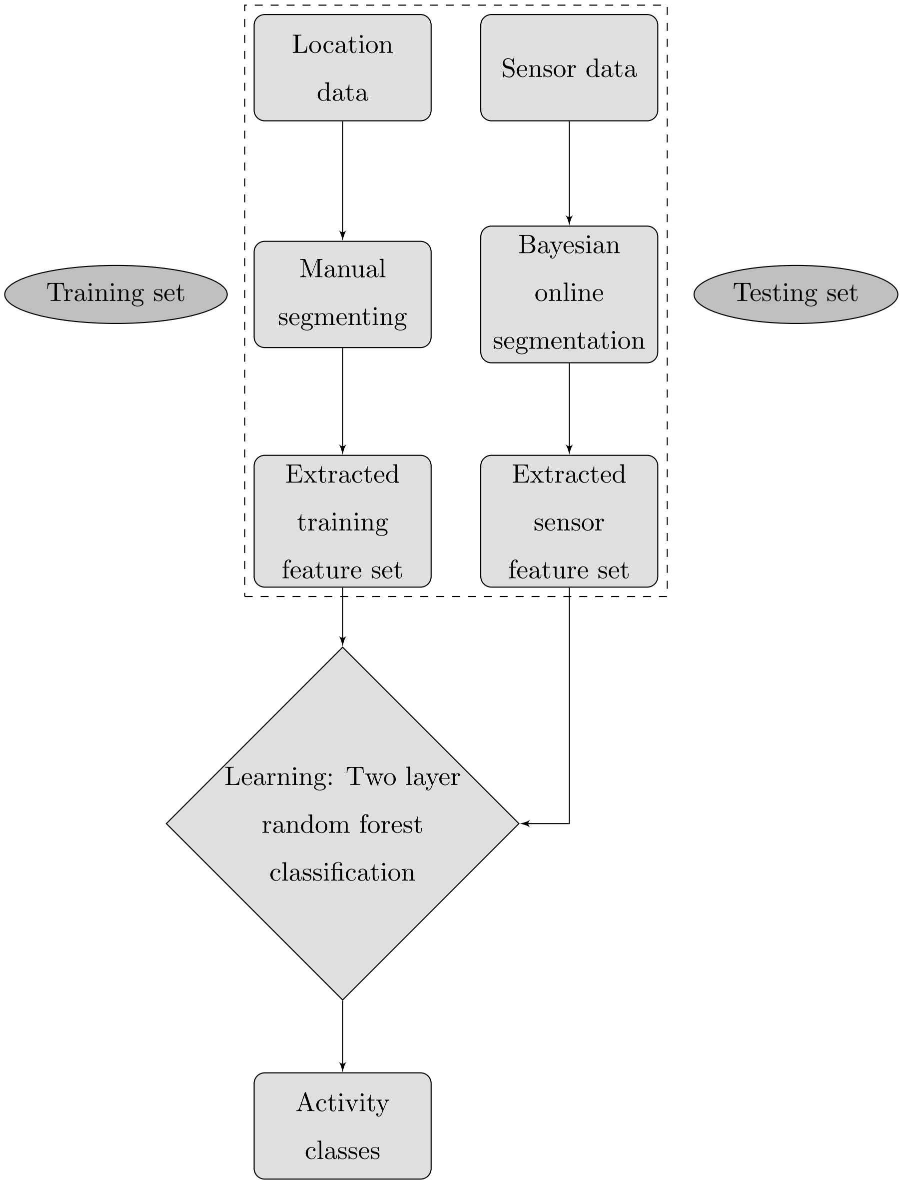

Figure 1: Online Activity Recognition Process

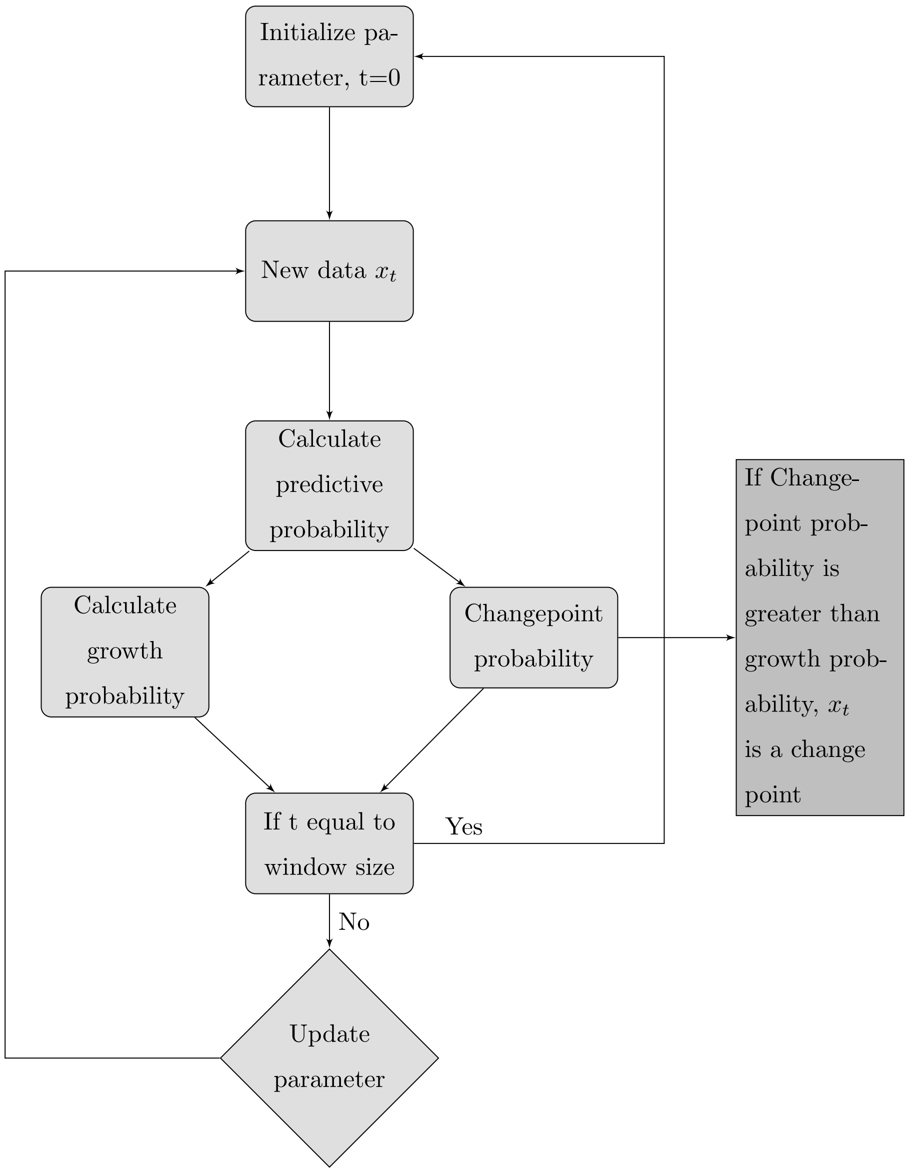

Figure 2: Bayesian Online Segmentation

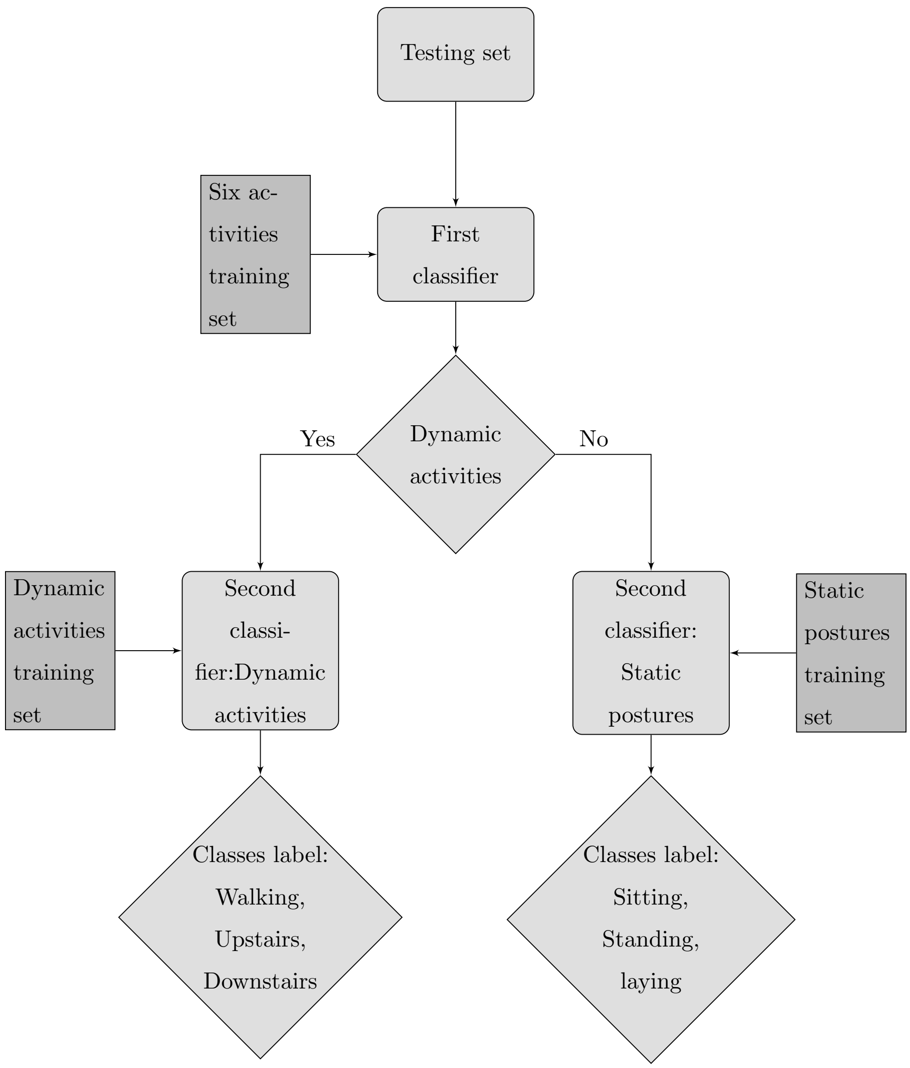

Figure 3: Fig3: Two layer Classification

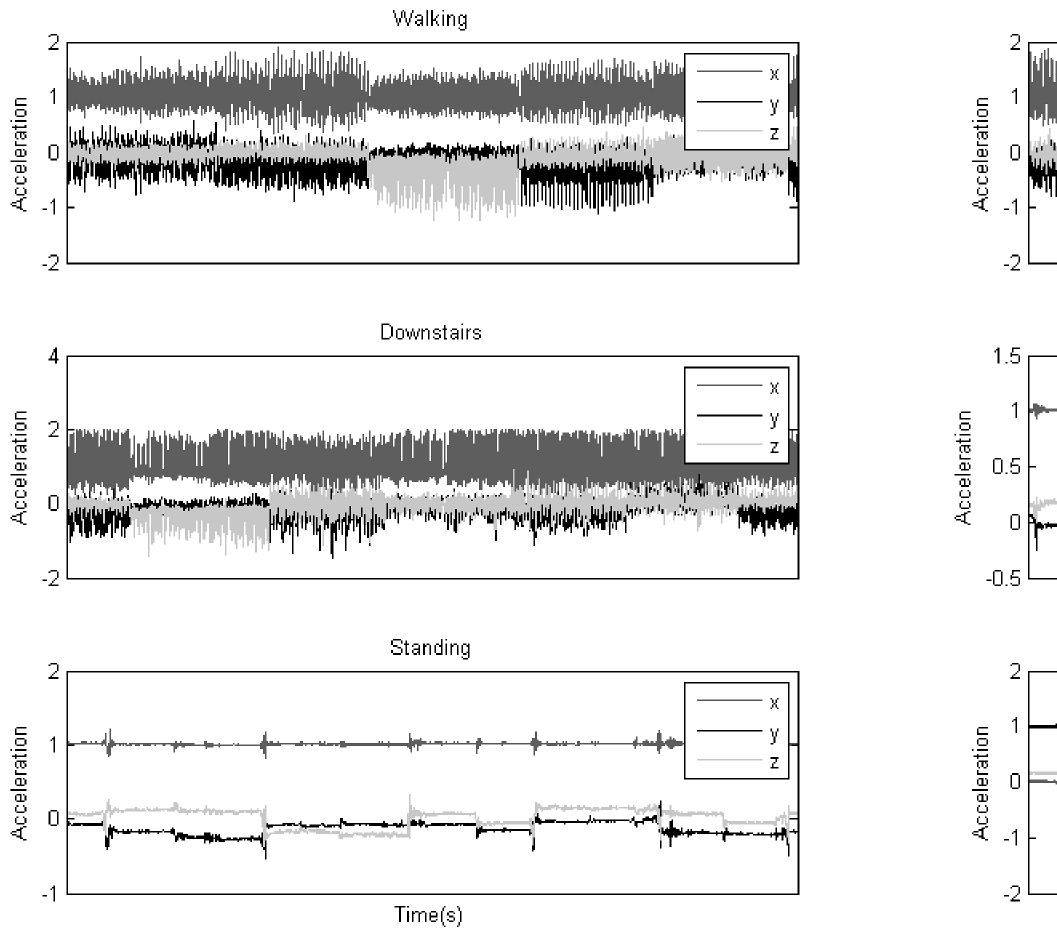

Figure 4: Acceleration plot of six activities

Table 1: Online Bayesian Segmentation Confusion Matrix

	Walking	Upstairs	Downstairs	Sitting	Standing	Laying
Walking	1	0	0	0	0	0
Upstairs	0	0.9601	0.0399	0	0	0
Downstairs	0	0.0451	0.9549	0	0	0
Sitting	0	0	0	0.9533	0.0265	0.0087
Standing	0	0	0	0.0477	0.9415	0
Laying	0	0	0	0.0078	0.0058	0.9749

Table 2: SWAB overall accuracy

	min len=2	5	10	20	30
num seg=25	0.8417	0.8444	0.8494	0.8793	0.8991
50	0.8854	0.8914	0.9022	0.9329	0.9534
100	0.9227	0.9386	0.9514	0.9688	0.9931
200	0.9658	0.9663	0.9739	0.9992	0.9981

Table 3: Online Two Layer Classification Confusion Matrix

	Walking	Upstairs	Downstairs	Sitting	Standing	Laying
Walking	26	3	0	0	0	0
Upstairs	3	50	1	0	0	0
Downstairs	0	3	51	0	0	0
Sitting	0	0	0	34	2	0
Standing	0	0	0	5	30	1
Laying	0	0	0	0	0	36

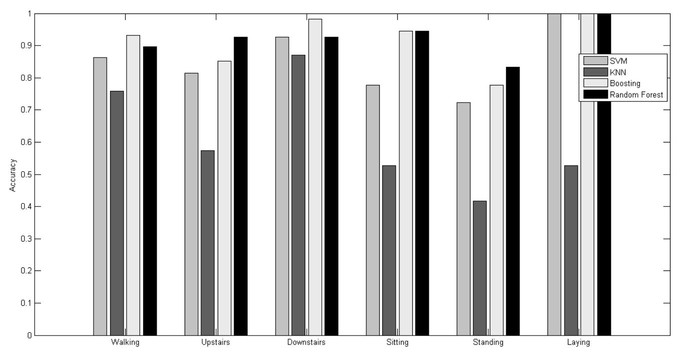

Figure 5: Accuracy of six activities using four classification methods (Bayesian segmentation)