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# A Light Weight Smartphone Based Human Activity Recognition System with High Accuracy

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# A Light Weight Smartphone Based Human Activity Recognition System with High Accuracy

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## Abstract

With the pervasive use of smartphones, which contain numerous sensors, data for modeling human activity is readily available. Human activity recognition is an important area of research because it can be used in context-aware applications. It has significant influence in many other research areas and applications including healthcare, assisted living, personal fitness, and entertainment. There has been a widespread use of machine learning techniques in wearable and smartphone based human activity recognition. Despite being an active area of research for more than a decade, most of the existing approaches require extensive computation to extract feature, train model, and recognize activities. This study presents a computationally efficient smartphone based human activity recognizer, based on dynamical systems and chaos theory. A reconstructed phase space is formed from the accelerometer sensor data using time-delay embedding. A single accelerometer axis is used to reduce memory and computational complexity. A Gaussian mixture model is learned on the reconstructed phase space. A maximum likelihood classifier uses the Gaussian mixture model to classify ten different human activities and a baseline. One public and one collected dataset were used to validate the proposed approach. Data was collected from ten subjects. The public dataset contains data from 30 subjects. Out-of-sample experimental results show that the proposed approach is able to recognize human activities from smartphones' one-axis raw accelerometer sensor data. The proposed approach achieved 100% accuracy for individual models across all activities and datasets. The proposed research requires 3 to 7 times less amount of data than the existing approaches to classify activities. It also requires 3 to 4 times less amount of time to build reconstructed phase space compare to time and frequency domain features. A comparative evaluation is also presented to compare proposed approach with the state-of-the-art works.



## Keywords

Human activity recognition, Reconstructed phase space, Time-delay embedding, Gaussian mixture models, Smartphone, Sensor, Accelerometer


## 1. Introduction

With the proliferation of context-aware systems and applications, the human activity plays an important role along with the location (Gheid et al., 2017). Recognition of human activities has importance in many research areas such as pervasive computing (Satyanarayanan, 2001), machine learning (Su et al., 2014), artificial intelligence, human computer interaction, healthcare (Torres-Huitzil and Alvarez-Landero, 2015), rehabilitation engineering (A et al., Fayezeen), assistive technology (Albert et al., 2017), social networking, and the social sciences (Lara and Labrador, 2013), (Osmani et al., 2008). Substantial research has been conducted to recognize human activities. One of the most significant and challenging tasks for pervasive computing systems is to offer correct and appropriate intelligence about peoples activities and behaviors (Lara and Labrador, 2013). Activity recognition systems are being used in large number in monitoring elderly people with dementia and people in rehabilitation (lvarez Concepcin et al., 2014). The functional status of a person is an important parameter in the area of assisted living and elderly care (Gani et al., 2017). This status is described mainly activities of daily living (ADL) (Hong et al., 2010). Also, it can be used to offer context-aware services to smartphone users like suitable application selections and content recommendation (Lee and Cho, 2011).

We used smartphones to capture these activities. They offer a range of useful sensors such as accelerometers, gyroscopes, orientation sensors, magnetometers, barometers, GPS, Wi-Fi, fingerprint, and near field communication (NFC) (Yi et al., 2012). Smartphones also have substantial computational power. Hence, use of the smartphone in the human activity recognition system eliminates the cost of additional devices and sensors (Lane et al., 2010). Most smartphones have built in tri-axial accelerometer sensors, which measure acceleration along the x, y and z-axes. The key challenge is to use the accelerometer sensors to model full body human motor activities. This paper presents a smartphone based human activity recognition system using Gaussian mixture models (GMM) of reconstructed phase spaces (RPS). Our approach uses raw accelerometer sensor data from one single axis to recognize 11 different activities including walking, walking upstairs and downstairs, running, standing, and sitting. We investigated the use of dynamical system and chaos theory to capture and then recognize the underlying dynamics of different human activities.

We evaluated our proposed system using two datasets (a collected dataset and a publicly available dataset) of acceleration measurements of 11 activities (Table 1). We collected accelerometer data for 10 different activities. The activities were performed by ten different participants carrying a smartphone in their pocket. We also used a dataset from the UCI Machine Learning repository (Anguita et al., 2013). It has accelerometer and gyroscope data for 6 activities performed by 30 participants. Both datasets were divided into training and testing sets. The training dataset was only used to train the system, while test datasets were used to test the accuracy. The proposed approach achieved 100% accuracy for individual models across all activities and datasets. It required 3 to 7 times less amount of data for the recognition than the existing approaches, such as Antos 2013 (Antos et al., 2014), Anguita et al., 2013 (Anguita et al., 2013), and Haq 2018 (ul Haq et al., 2018). Also, the time required to build the reconstructed phase space from the raw accelerometer sensor data was 3–4 times faster compared to extracting time and frequency domain features (Panwar et al., 2017).

Table 1. Activities and smartphone placement.

| Activity | Phone Placement |
|---|---|
| Walking | Pocket and Waist |
| Walking Downstairs | Pocket and Waist |
| Walking Upstairs | Pocket and Waist |
| Running | Pocket and Waist |
| Standing | Pocket and Waist |
| Sitting | Pocket and Waist |
| Laying | Waist |
| Elevator Down | Pocket |
| Elevator Up | Pocket |
| Driving | Pocket and Cup-holder |
| Baseline | Table |

We implemented our system in two different case studies. One case study took place in a rehabilitation clinic for remote monitoring, where the patients daily activities were reported to a cloud server from their smartphone. Physicians could access and assess patients activities based on the assigned task and daily routine. The second case study took place in the Hajj, the fifth pillar of Islam an annual pilgrimage of Muslims to Makkah, Saudi Arabia (Clingingsmith et al., 2009). The purpose was to track pilgrims' location based on their activities when they get lost (Gani et al., 2016). We present the comparative analysis of the proposed approach with the state-of-the-art works.

The summary of the contributions of this paper is:

- Use of time-delay embedding or reconstructed phase space to capture underlying dynamics of human body motion for different activities from smartphone accelerometer.
- Statistical learner that learns the underlying dynamics of human activities and maximum likelihood classifier to recognize those activities.
- An alternative approach to widely used machine learning techniques to recognize human activities from kinematics sensors (specifically accelerometer).
- Activity recognition system with a very good accuracy across 11 activities.
- Computationally inexpensive approach to activity recognition by using only one accelerometer axis.
- Evaluation of the approach using collected dataset and publicly available human activity dataset.
- Deployment of the system in two different case studies: 1) Location tracking of pilgrims using their activity information, and 2) Daily activity monitoring of patients in a rehabilitation clinic.
- Published collected human activity dataset in the public domain to enhance research in this area (http://ubicomp.mscs.mu.edu).

This research article is organized as follows. The related research is discussed in section 2. The background is discussed in section 3. The data collection process is presented in section 4. The methodology is discussed in section 5. The details of the experiments including training, testing, and results are discussed in section 6. The contributions are discussed in section 7. Finally the conclusions are presented in section 8.

## 2. Related research

There is extensive research focused on automated machine recognition of human activity (Liao et al., 2005), (Aggarwal and Cai, 1999), (Yan et al., 2012), (Yang, 2009), (Tapia et al., 2004), (Khan et al., 2015), (Wang et al., 2015). Use of computer vision has been one approach (Aggarwal and Cai, 1999). Computer vision approaches implement automatic human activity recognition from a sequence of images or videos where activities are performed by one or more persons (Saad Ali, 2007). Other research has used environmental sensors like a sound sensor on a floor, a light sensor in a room, radio frequency identification (RFID) as a door tag or wearable kinematic sensors like the accelerometer, and the gyroscope by placing them on different parts of the body (Maurer et al., 2006), (Tapia et al., 2004), (Bao and Intille, 2004), (Ravi et al., 2005) (Siirtola et al., 2009). The wearable device based systems are very expensive. These systems lack applicability on mobile devices due to high computational cost and excessive energy consumption. One of the disadvantages of the wearable activity recognition system is that the users face discomfort using the wearable devices. Also there is a risk of losing and forgetting the devices (lvarez Concepcin et al., 2014). Therefore, there is a need for special attention to energy consumption and computational cost when designing systems to recognize human activities using mobile devices (lvarez Concepcin et al., 2014).

An alternative approach leverages the increasingly ubiquitous smartphone. Compared to computer vision or wearable sensor approaches, smartphones offer many advantages. Smartphones do not require additional infrastructure, are unobtrusive, and have good and rapidly increasing computational power (Dernbach et al., 2012), (Brezmes et al., 2009), (Hache et al., 2010), (Zhang et al., 2010), (ul Haq et al., 2018). Most smartphone based approaches have focused on recognizing simple human activities such as walking, running, standing, walking up stairs, walking down stairs, sitting, and climbing. Some research has also considered recognition of more complex functional activities like brushing teeth, cleaning dishes, and vacuuming a floor (Lara and Labrador, 2013). The overview of smartphone based human activity recognition systems is shown in Fig. 1 (Su et al., 2014). Different activity signals are collected from the smartphone sensors. The signals are then processed to train a human activity recognition system and tested to recognize different activities. The approaches vary based on data preprocessing, number and type of sensors, mathematical models, and implementations. These systems output the classified human activities.

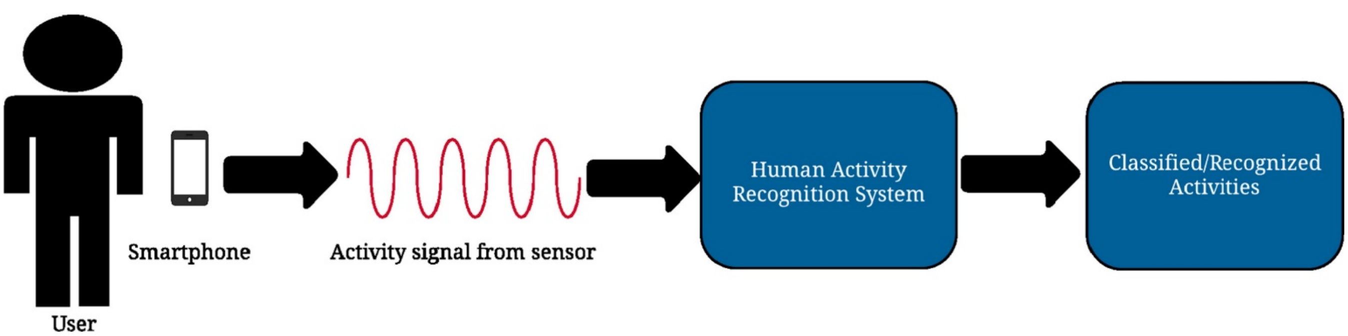


Fig. 1. Overview of the smartphone based human activity recognition system.

There has been a widespread use of machine learning techniques in wearable and smartphone based human activity recognition. One of the most common approaches is to extract statistical and structural features (time-domain features: mean, standard deviation, maximum, minimum, correlation (Su et al., 2014), (lvarez de la Concepcin et al., 2014), (Kwapisz et al., 2010), frequency-domain features: Fourier transform (Bao and Intille, 2004), Discrete Cosine transform (Altun and Barshan, 2010), and principal component analysis (PCA) (He and Jin, 2009)) from raw sensor data and then to use classification algorithms like logistic regression (Kwapisz et al., 2010), multilayer perceptron (Bayat et al., 2014), support vector machine (SVM) (He and Jin, 2009), (Jordan Frank et al., 2010), (ul Haq et al., 2018), decision tree (Jatobá et al., 2008), k-nearest neighbors (Maurer et al., 2006), naive Bayes (Tapia et al., 2007), hidden markov model (HMM) (Zhu and Sheng, 2009) (Su et al., 2014), (Lara and Labrador, 2013) (Antos et al., 2014) (Ravi et al., 2005), and convolutional neural network (Panwar et al., 2017). Gaussian mixture models have also been used to model human activities (Srivastava, 2012), (Piyathilaka and Kodagoda, 2013). Most of these approaches require extensive computation to extract feature, train model, and recognize activity class. They increase the power consumption on mobile and wearable devices, which limits the long-term activity recognition (Yan et al., 2012). The memory and computational complexity of the activity recognition system depends on the number of sensors, sampling frequency, number of extracted features, size of the activity cycle, and mathematical model (Lara and Labrador, 2013). Sun and Haq discussed different aspects of the activity recognition system varying mobile phone positions and orientations (Sun et al., 2010), (ul Haq et al., 2018). Yan discussed the effect of the sampling frequency and classification features on energy consumption (Yan et al., 2012). We have discussed the number of sensors, sampling frequency, and size of the activity cycle used in different studies in the following subsection.

The activity cycle is a set of time series observations (sensor data) that contains a complete execution of an activity pattern. The system won't be able to determine the performed activity if the time series observation does not contain a complete activity cycle (lvarez Concepcin et al., 2014). There are different strategies to select this window or segment so that it contains necessary time series observation (Bao and Intille, 2004) (Dernbach et al., 2012). Kwapisz used a 10 s window (comprised of 200 samples) from cell phone accelerometer at a sampling frequency of 20 Hz (Kwapisz et al., 2010). Authors argued that it was an adequate amount of time to capture several repetitions of the performed activities. They performed experiments with 10 and 20 s windows where 10 s segments produced better outcome. Reiss used a 5 s window at a sampling frequency of 100 Hz from three body mounted (mounted to the dominant arm, chest, and foot) sensors (Reiss et al., 2011). Lee used a smartphone accelerometer signal window of 5 s (60 samples) (Lee and Cho, 2011). There are some works where the activity window includes some percentage overlap of the immediate neighboring activity window (Bao and Intille, 2004) (Hong et al., 2010) (Inoue et al., 2015). Bao used a window of 512 samples (6.7 s of data) with 50% overlap to extract time and frequency domain features from 5 body mounted bi-axial accelerometer sensors (Bao and Intille, 2004). Ravi used a single tri-axial accelerometer (worn near the pelvic region) to form an activity window of 256 samples (5.12 s of data) with 50% overlap at a sampling frequency of 50 Hz (Ravi et al., 2005). Hong also extracted features from a 256 sample window overlapped with 128 samples (50% overlap) (Hong et al., 2010). Inoue recognized real nursing activities for a whole day by extracting features from a window of 5 s, overlapping every 2.5 s (Inoue et al., 2015).

Most of the existing research has focused on generalized activity recognition model to recognize unseen activities (Kwapisz et al., 2010) (Brezmes et al., 2009). Lockharty and Weiss discussed the impact of personalized model and generalized model in smartphone-based activity recognition (Weiss and Lockhart, 2012). They also discussed the benefits of the personalized or individualized activity recognition models (Lockharty and Weiss, 2014). They showed that the personalized models performed better than generalized models. The generalized models were unable to classify activities with good accuracy. They experimented with six activities (walk, jog, stair, sit, stand, and lie) using the widely used classification algorithms (decision tree, random forest, instance-based learning, neural networks, naive Bayes and logistic regression). The participant carried the android smartphone in their pocket. The 3 axes accelerometer sensor data were used to extract 43 statistical features. The personal model showed an average accuracy of 97% compared to the average accuracy of the hybrid model of 88%, whereas their combination provided even lower average accuracy of 70%. They showed that in order to improve the accuracy of the generalized models, it was better to get data from more users than to obtain more data from the same set of users.

There has been some work using dynamical system theory and chaos theory along with machine learning techniques (Saad Ali, 2007). Frank et al. used a wearable device (Intel mobile sensing platform (MSP) (Choudhury et al., 2008)) which contained a tri-axial accelerometer and a biometric pressure sensor (Jordan Frank et al., 2010). The device was clipped onto a belt at the side of the hip. They used three axes acceleration to form a single measure of magnitude. The series of acceleration magnitude were used to reconstruct phase space. They used principle component analysis (PCA) to extract features (9 largest eigenvalues) from the phase space. These 9 features along with gradient of biometric pressure were used to train and test a Support vector Machine (SVM) for 5 activities performed by 6 participants. They achieved an accuracy of 85%. Kawsar developed an activity recognition system using accelerometer and gyroscope sensor data from the smartphone, and pressure sensor data from the shoe (Kawsar et al., 2015). They used decision tree, Shapelet based classification (Ye and Keogh, 2009) and time-delay embedding based classification. The experiments were performed using only 4 activities (running, walking, sitting, and standing). They achieved 88.64% classification accuracy using the Shapelet based classification with pressure sensor data from the left shoe, which took 3.3 s. This is a very expensive system with respect to time. They achieved 100% classification accuracy using the time-delay embedding with one pressure sensor data from the left shoe. They did not mention the number of subjects who participated in the study, which would have significant impact on the classification accuracy. Also, they did not perform experiments with other widely tested activities, like walking upstairs and walking downstairs. Most of the existing approaches have lower accuracy in differentiating between these two activities and the walking activity (Huynh) (Bao and Intille, 2004) (Lara and Labrador, 2013).

In our approach, we used only one-axis acceleration from smartphone to capture underlying dynamics of the activities by reconstructing the phase space. We learned Gaussian mixture models from underlying dynamics to classify 11 activities performed by 40 participants placing the smartphone in two different body positions.

## 3. Background

A dynamical system is a model that describes the evolution of a system over time. It describes the temporal evolution of a system to capture the system's dynamics. A phase space represents all possible states of the system that evolve over time. The dynamics is the map that describes how the system evolves. Theory of dynamical systems attempts to understand and describe the temporal evolution of a system, which is defined in a phase space.

### 3.1. Reconstructed phase space

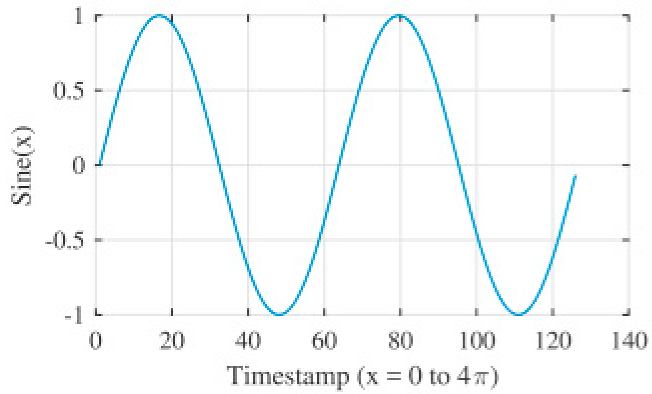
We use the representational capability of RPS to capture the underlying dynamics of the system from time series observations (accelerometer sensor data). The RPS is topologically equivalent to the original system (Takens, 1981). Given a time series *x*,

$$x = x_n, n = 1 \dots N$$

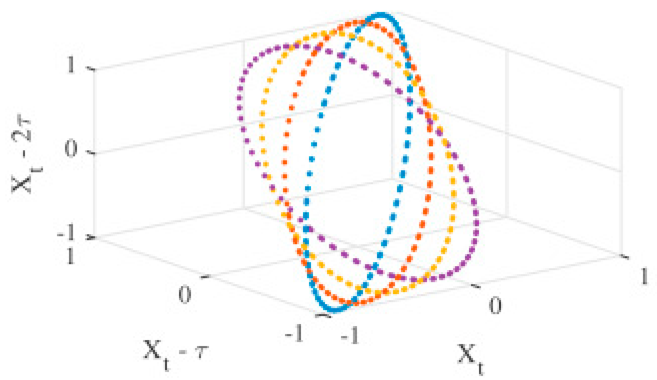
where *n* is the index and *N* is the total number of observations. We observe a sequence of scalar measurements in a time series that depends on the state of the system. We convert these observations into state vectors. These vectors are formed according to Takens delay embedding theorem,

$$X_n = [x_n, x_{n-\tau}, \dots, x_{n-(d-1)\tau}],$$

where $\tau$ is the time delay and *d* is the embedding dimension (Takens, 1981), (Whitney, 1936), (Sauer et al., 1991). This time-delay embedding reconstructs the state and dynamics of the unknown system from the observed measurements. This time delayed embedding of the time series is called the reconstructed phase space (Fang and Chan, 2013). The sine curve and the corresponding phase plot for different time lags are shown in Fig. 2. Here the sine curve represents the time series observation for the value of *x* from 0 to $4\pi$. This observation is then used to describe the evolution of the system (sine series) over time using phase space. The phase spaces are reconstructed using dimension $d = 3$ and time lag $\tau = \{3, 5, 7, 9\}$. The respective phase spaces are shown in different colors.




(a) Sine curve for value of $x$ from 0 to $\pi$




(b) Phase space of the sine curve for the dimension, $d = 3$ and time lag, $\tau = 3$ (blue), 5 (orange), 7 (yellow), and 9 (purple)

Fig. 2. Sine curve and its phase plot.

The reconstructed space is topologically equivalent to the original system. It preserves the dynamics of the underlying dynamical system if certain assumptions are made. The embedding dimension *d* needs to be greater than twice the box counting dimension of the original system (Povinelli et al., 2004). For most of the system where *d* is unknown, *d* is estimated using the false nearest-neighbor technique. The dimension of the RPS can be reduced using appropriate selection of the time lag. Though embedding theorems say nothing about the time lag, one of the data driven approaches to find a reasonable estimate of the time lag is to use the first minimum of the automutual information (Kantz and Schreiber, 2004).

### 3.2. Gaussian Mixture Models

We use Gaussian Mixture Models (GMM) to learn the underlying distribution of the dynamics represented by the RPS. We represent each activity class model using a GMM. The GMM is a parametric probability density function, which is a weighted sum of *M* Gaussian probability density function defined as (Reynolds, 2009),

$$p(\chi, \lambda) = \sum_{i=1}^{M} w_i p_i(x) = \sum_{i=1}^{M} w_i \boldsymbol{\mathcal{N}}(\chi, \mu_i, \Sigma_i)$$

where $M$ is the number of mixtures, $\boldsymbol{\mathcal{N}}(x; \mu_i, \Sigma_i)$ is a normal distribution with mean $\mu_i$ and covariance matrix $\Sigma_i$, and $w_i$ is the mixture weight satisfy the constraint that $\sum_{i=1}^{M} w_i = 1$. The parameters of a complete parameterized Gaussian mixture is denoted by $\lambda$,

$$\lambda = \{w_i, \mu_i, \Sigma_i\} i = 1, \dots, M$$

the parameters of the GMM are estimated using the Expectation-Maximization (EM) algorithm to maximize the likelihood of the data (Moon, 1996). The EM algorithm begins with an initial model $\lambda$ and then estimate a new model $\bar{\lambda}$ at each iteration, where $p(X \mid \bar{\lambda}) \geq p(X \mid \lambda)$ for a sequence of training vectors, $X = x_1, x_2, \dots, x_T$. Parameters are estimated using the following formulas:

$$\mu'_m = \frac{\sum_{t=1}^{T} p_m(x_t) x_t}{\sum_{t=1}^{T} p_m(x_t)},$$

$$\Sigma'_m = \frac{\sum_{t=1}^{T} p_m(x_t)(x_t - \mu_m)^T (x_t - \mu_m)}{\sum_{t=1}^{T} p_m(x_t)},$$

$$w'_m = \frac{\sum_{t=1}^{T} p_m(x_t) x_t}{\sum_{t=1}^{T} \sum_{m=1}^{M} p_m(x_i)}$$

### 3.3. Maximum likelihood classifier

A Bayesian maximum likelihood classifier computes likelihoods on each point $x_k$, from each of the learned model, $a_i$ using the following likelihood function (Moon, 1996):

$$p(X \mid a_i) = \prod_{k=1}^{T} p(x_k \mid a_i)$$

Once all the likelihoods are computed then the maximum likelihood class, $\hat{a}$ (i.e. classification) is found using the following equation (7).

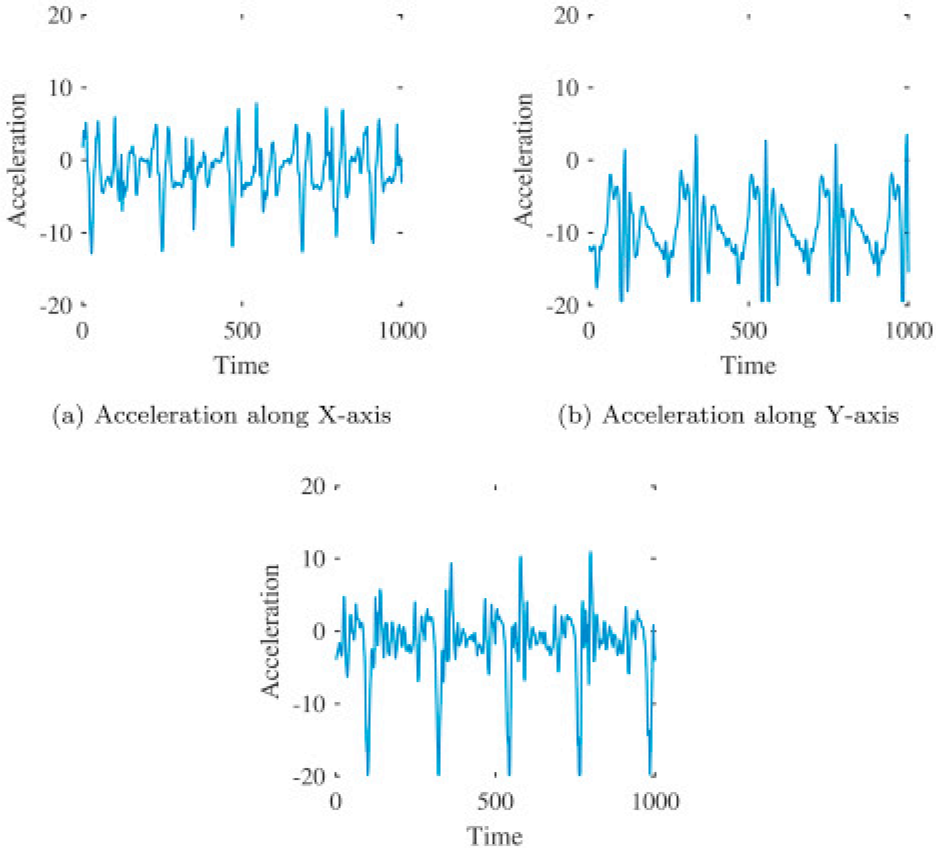
$$\hat{a} = \underset{i}{\operatorname{argmax}}\, p(X \mid a_i)$$

## 4. Experimental data acquisition

Wearable kinematic sensors, such as accelerometer and gyroscope, have been widely used in activity recognition systems. Smartphone platforms offer application frameworks and libraries to access the sensor data, such that it is easy to access and collect motion data from smartphones. Thus, smartphones provide a powerful mobile system with integrated sensors, inexpensive software development, and without the need for additional hardware. Practically, users are more comfortable carrying a smartphone than wearing multiple sensors on their body. We have used two different datasets (one through data collection and another publicly available human activity dataset) to perform the experiment. Both datasets contain raw data from built-in accelerometer sensor of the smartphone. The data were collected by placing the smartphone in four different positions (pant pocket, waist, table, and beside cup-holder (inside car)). The activities performed and phone placement are shown in Table 1.

### 4.1. Data collection

We collected accelerometer sensor data for different activities using UbiSen (Ubicomp Lab Sensor Application for Android). We used a Google Nexus 5 smartphone running Android OS 5.0. The participants placed the phone in their front pant pocket. They performed eight simple activities: walking, walking upstairs, walking downstairs, running, sitting, standing, elevator up and elevator down. We also collected sensor data during driving and when the phone was placed at a fixed place, like a table. For the driving activity, the phone was placed inside the pocket and also in the vehicle cup-holder. The accelerometer sensor data along the three axes for the walking activity is shown in Fig. 3. Here three different axes have three different but repetitive patterns. The accelerometer sensor data along the y-axis for all the activities are shown in Fig. 4.




(a) Acceleration along X-axis

(b) Acceleration along Y-axis

(c) Acceleration along Z-axis

Fig. 3. Acceleration along three axes for walking activity.

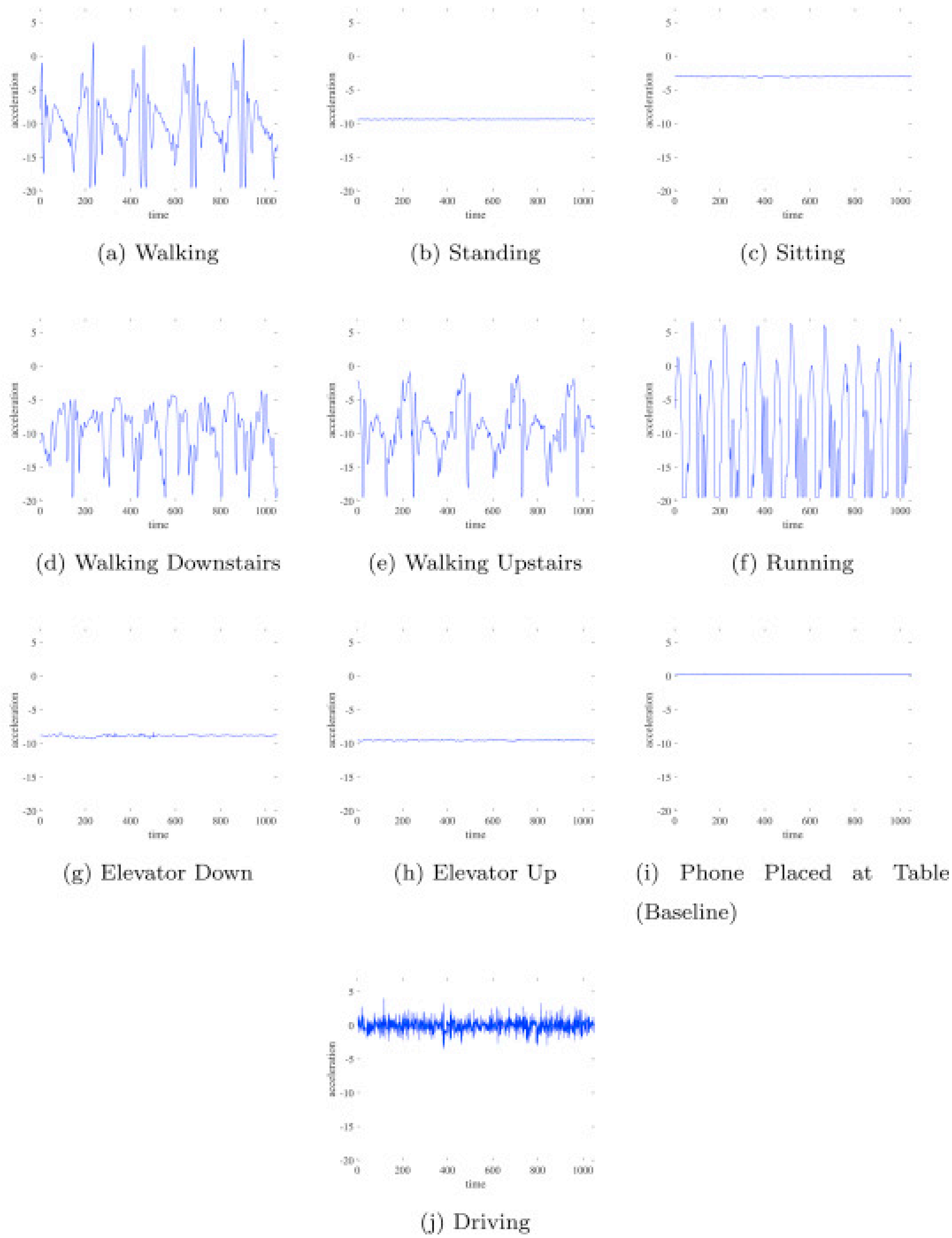


Fig. 4. Accelerometer sensor data along the Y-axis for 10 different activities.

There were 10 participants (age ranges between 20–35, both male and female) in the data collection event. Each participant performed 10 activities in an uncontrolled environment. Each activity was performed for a different time durations. Walking, running, standing, sitting, and phone placed at table (baseline) were performed for 2–3 min. Walking upstairs, walking downstairs, elevator up, and elevator down were performed for 1–2 min. Driving data were collected for approximately 10–15 min. In total we have 3 h 20 min of sensor data for 10 different activities performed by the participants.

## 4.2. Public dataset

We also used a dataset *Human Activity Recognition Using Smartphone Data Set*, from the UCI Machine Learning Repository. The data were collected from a group of 30 participants aged 19–48 years. Each participant wore a smartphone (Samsung Galaxy S II) on the waist and performed six activities: 1) walking, 2) walking upstairs, 3) walking downstairs, 4) sitting, 5) standing, and 6) laying down. The accelerometer and gyroscope sensor data were captured at a rate of 50 Hz. The noise filters were applied to preprocess the raw sensor data. The Butterworth low-pass filter was used to separate gravity from the acceleration signal. The dataset was partitioned randomly into training (70%) and testing (30%) set.

# 5. Experimental setup

We briefly discuss the process of training and testing the human activities in the following subsections. The overview of both phases is shown in Fig. 5.

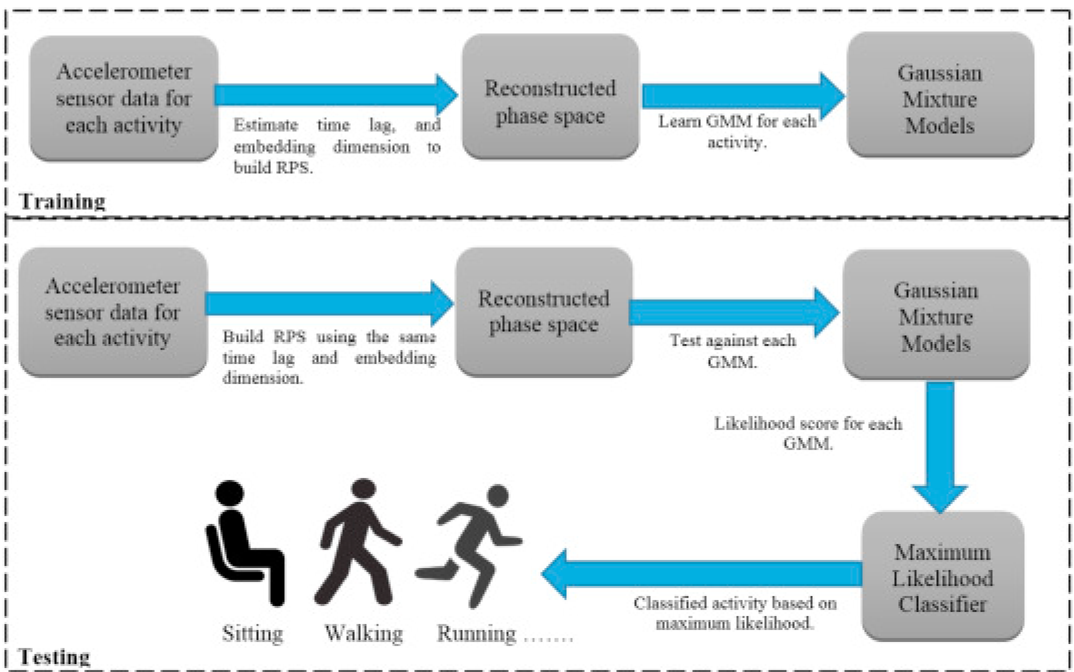



Fig. 5. Overview of training and testing phases of the proposed approach.

## 5.1. Training

The first step is to build RPS from accelerometer data for each activity using time lag and embedding dimension. We estimate the time lag and embedding dimension using the techniques discussed in section III. The time lag is estimated for each activity signal using the first minimum of the automutual information. Once all the time lags are estimated for each activity, then a time lag is selected for the RPS using the mode of the histogram of all estimated time lags. The global false nearest-technique is applied on each activity signal to calculate embedding dimension for RPS. Again, once embedding dimensions for all the signals are calculated, then an embedding dimension is selected for the RPS as the mean of all calculated dimensions. The mode and mean are taken so that most of the activity signals are able to unfold completely in the RPS. Once time lag and embedding dimension are selected, then we build RPS for each signal.

Once the RPS is built, we learn a GMM probability distribution for each activity signal class. Each GMM represents the corresponding model for the activity class. Thus, we have an array of models after the completion of the training phase. The size of this array is equal to the number of activity class.

### 5.2. Testing

To test activity signal, we create RPSs from the raw accelerometer sensor data using the same time lag and embedding dimensions (estimated in the training phase). Then we test RPS against all the GMMs (created in the training phase). It gives us likelihood probability for each activity model. Bayesian maximum likelihood classifier is used to classify test signal as a classified or recognized activity. This is done using the activity model class with the highest likelihood. The system outputs test signal as one of the classified activities.

We evaluate our system with quantitative assessment. The k-fold cross validation helps us to evaluate accuracy where k is the number of data partitions (Arlot and Celisse, 2010). It helps us to generalize the statistical analysis and overcome problems like over fitting of the algorithm on the training set. We also varied the system's parameters to analyze its robustness.

## 6. Experimental evaluation

We evaluated our approach using both the collected and publicly available datasets. We used individualized model to experiment with the collected dataset and generalized model for the public dataset. We used Matlab and Weka machine learning toolbox to perform the experiment. We tested our approach using both dataset and time-domain features with classification algorithms using the first dataset. We discuss the experimental details and results in the following subsections.

### 6.1. Experiment with our approach

We analyzed accelerometer sensor data (3 axes) for all the activities. We observed acceleration along different axes. We saw different patterns along these axes for different activities. Even when we looked only at the acceleration along the y-axis (as shown in Fig. 4), we also saw a uniquely distinguishable pattern for each of the different activities. The challenge was to build the model to capture the dynamics of the activities from this acceleration along the y-axis and differentiate one from another. We discuss training and testing phases in the following subsections in detail.
We used the raw sensor data along the y-axis to build reconstructed phase space with appropriate time lag and embedding dimension. We partitioned data into different activity cycles (number of partitions, $k = 40$) each containing 300–600 samples. During the data collection process we recorded videos of the footsteps. We selected the sample size by comparing activity (walking, walking upstairs, walking downstairs, and running) cycles with synchronized video observations for each of the activities and the corresponding sensor values at the same time. We selected the sample size to ensure that it contained more samples than the largest activity cycle. We also analyzed the effect of sample size on system's performance. To build the RPS, we took one subject from each of the different activity classes. Then we computed automutual information for different time lags. The first minimum of the automutual information is used to estimate the time lag for each activity class. The graph in Fig. 6a shows the automutual information of “walking upstairs” activity for different time lags. Here the first minimum of the automutual information is found for time lag value 5.

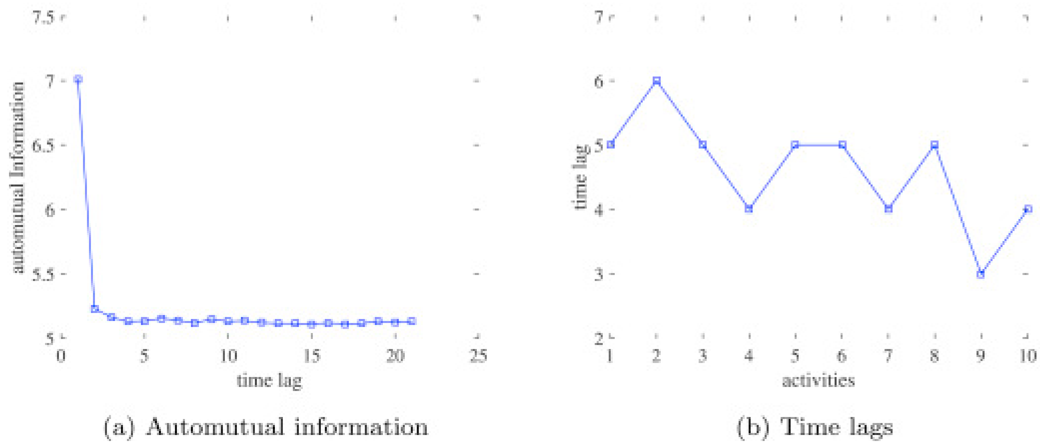


Fig. 6. Time lag estimation for walking activity.

We computed the time lag for all the activity classes. The mode of these time lags was used to estimate time lag for RPS, as shown in Fig. 6b for all the activities. We found time lag $\tau = 5$ in this process. Then we used this estimated time lag value to estimate embedding dimension. We computed percentage of false nearest-neighbors to determine the embedding dimension for each activity class. We took the mean of all calculated embedding dimensions to select embedding dimension for the RPS. We estimated the embedding dimension to be $d = 6$. We used these estimated values of time lag and embedding dimension to build RPS for each activity class. The RPSs for walking, walking downstairs, walking upstairs, running, sitting, and phone placed at table build with time lag, $\tau = 5$ and embedding dimension, $d = 6$ are shown in Fig. 7. The difference in underlying dynamics between the activities is represented by these RPSs. We used RPSs for each activity class to learn GMMs.

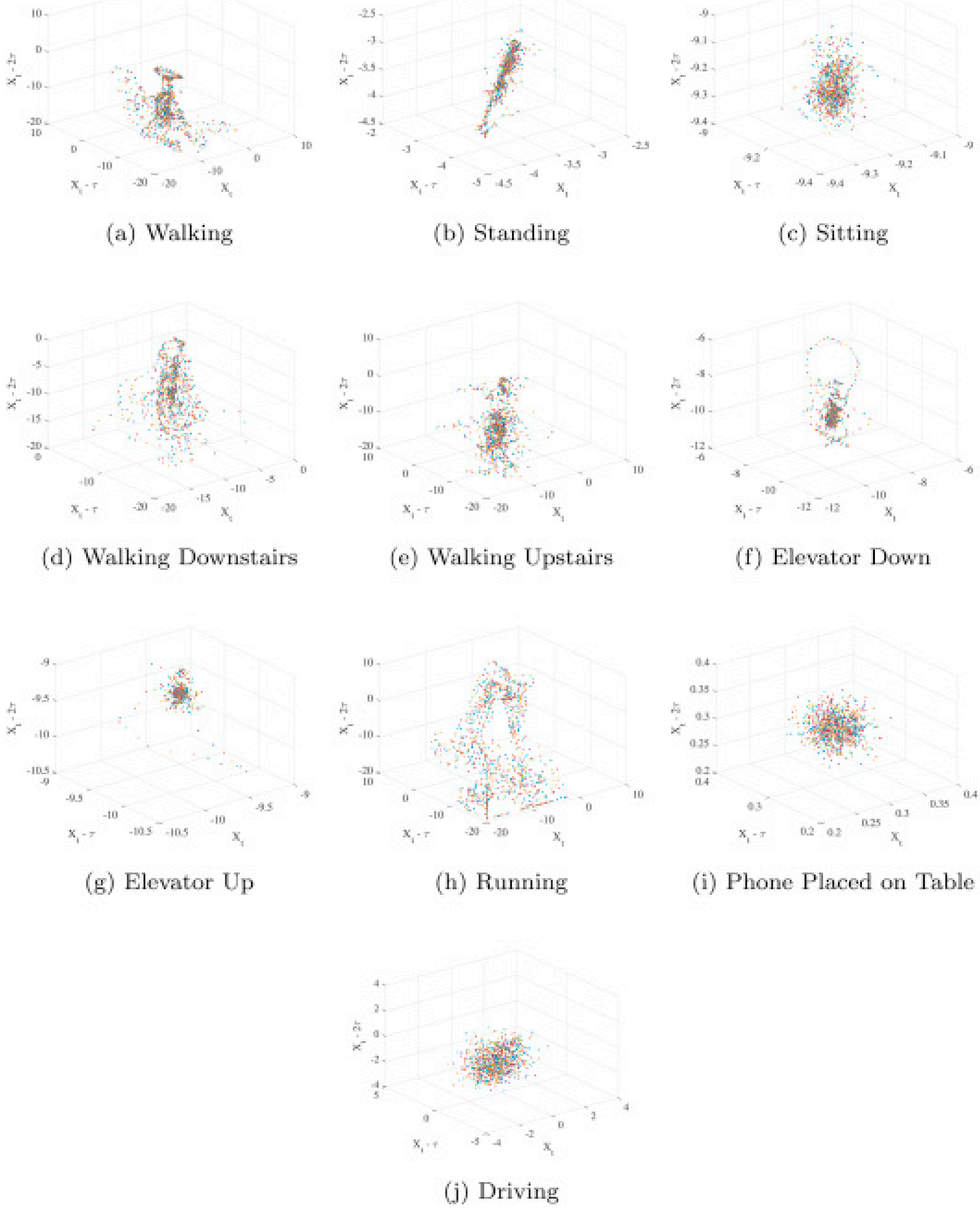



Fig. 7. Reconstructed phase spaces for time lag, $\tau$ = 5, and embedding dimension, $d$ = 6.

### 6.1.1. Testing

We evaluated all the subjects for each activity using each of the activity models (GMMs). At first the RPSs were generated using the same time lag and embedding dimension we used in the training phase. These RPSs were then tested against each of the activity class models. We estimated the likelihood of the RPSs against GMMs. We used m = 5 mixtures for GMM. We also changed the number of mixtures to see its effect on the systems performance. For each single subject of data, we computed all the likelihood probability (log probability) for each activity class model. Then we used a maximum likelihood classifier to identify the corresponding subject as one of the human activities. The classifier takes all the likelihood probabilities and outputs the activity class associated with the maximum probability. We used 10-fold cross validations to validate accuracy of the system. We took nine partitions at a time to train the system. The other one along with the training partitions were used to test the performance.

## 6.2. Experiment with time-domain features and classification algorithms

We performed experiments with time-domain features and classification algorithms used by state-of-the-art human activity recognition systems (Lee and Cho, 2014) (Derawi and Bours, 2013) (Dernbach et al., 2012) (Siirtola et al., 2009). We used following time-domain features: *1) mean, 2) max, 3) min, 4) standard deviation, 5) variance*, representing mean, maximum, minimum standard deviation, and variance of activity cycle respectively.

The features were extracted from each subject (as discussed in the previous section) for all the activities. The feature vector was formed using the features. We used the feature vector to train and test different classification algorithms. We analyzed the performance of the classification algorithms tabulated in Table 3.

Table 3. : Classification algorithms.

| **Family** | **Classifiers** |
|---|---|
| Decision Tree | Classificaiton and Regression Trees |
| Bayesian | Bayesian Network, Naïve Bayes |
| Artificial Neural Networks | Multilayer Perceptron |
| Maximum Margin Classifier | Support Vector Machine |
| Instance Based | k-Nearest Neighbors |
| Rule based classifier | Decision Table |
| Regression | Logistic Regression |
| Classifier Ensembles | Bagged Trees, Random Forest |

## 6.3. Experiment with time and frequency domain features

We performed experiments with time and frequency domain features used in *Human Activity Recognition Using Smartphone Data Set* (Anguita et al., 2013) for each axis acceleration. We extracted 60 features for each axis and used Decision Tree, SVM, Weighted KNN, Bagged Trees along with SVM with Gaussian Karnel (technique Anguita (Anguita et al., 2013) used) to perform the experiment.

## 6.4. Results

We present quantitative evaluation of the system in this subsection. The confusion matrix for all the activity classes are also presented. For each row, the corresponding true activity class is the positive class and the rest of the activity classes were considered as negative class. To describe the performance, we obtained the following terms from the confusion matrix: 1) True Positives (TP) is the number of positive activity classes that were classified as positive, 2) False Positives (FP) is the number of negative activity classes that were classified as positive, 3) True Negatives (TN) is the number of negative activity classes that were classified as negative, and 4)False Negatives (FN) is the number of positive activity classes that were classified as negatives.

Then, we computed the performance for all the activity classes from using these terms as follows:

$$Accuracy = \frac{TP + TN}{TP + FP + TN + FN}$$

**6.4.1. Collected dataset**

There were 10 participants, and for each of the activities we took 40 partitions into consideration; therefore, a total of 400 instances for each class of activity. We used individual activity models for each of the participants. We changed different parameters of the model to check for robustness. The confusion matrix is shown in Table 2. All 400 instances in each row were classified correctly. We also performed experiments with the rest of the data (not included in the 40 partitions) and found similar results.

Table 2. Confusion Matrix for the individualized model of collected dataset using proposed approach.

| Activity | Predicted Class | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| | | Walking | Downstairs | Upstairs | Running | Sitting | Standing | Elev. Down | Elev. Up | Baseline | Driving |
| True Class | Walking | 400 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| | Downstairs | 0 | 400 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| | Upstairs | 0 | 0 | 400 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| | Running | 0 | 0 | 0 | 400 | 0 | 0 | 0 | 0 | 0 | 0 |
| | Sitting | 0 | 0 | 0 | 0 | 400 | 0 | 0 | 0 | 0 | 0 |
| | Standing | 0 | 0 | 0 | 0 | 0 | 400 | 0 | 0 | 0 | 0 |
| | Elev. Down | 0 | 0 | 0 | 0 | 0 | 0 | 400 | 0 | 0 | 0 |
| | Elev. Up | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 400 | 0 | 0 |
| | Baseline | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 400 | 0 |
| | Driving | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 400 |

We changed the size of training set from 1000 samples to 3000 samples and size of each activity cycle from 200 samples to 600 samples. For each of the combinations we tested system's accuracy. The performance of the system for all the configurations is shown in Fig. 8. The performance increased as we increased the size of the training set and activity cycle. We observed that most of the activities had cycle length around 260–270. The incorrect partitioning of the activity cycle did not contain enough evidence for respective activity class. Hence the system was unable to capture the underlying dynamics of the activity. Thus increasing the size of activity cycle helped each cycle to contain enough information about the activity class. The accuracy of the system was consistent when the activity cycle contained enough information and the model was trained with the underlying dynamics.

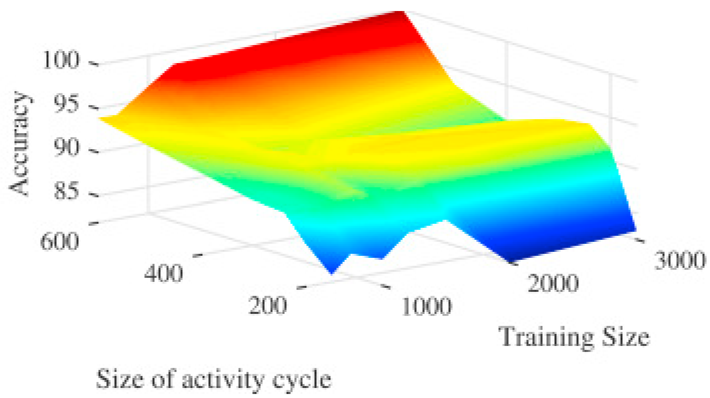



Fig. 8. Performance of the system with respect to number of sample in training set and activity cycle.

We also changed the number of mixtures for GMMs from $m = 1$ to $m = 7$. We combined this change in number of mixtures with change in size of each activity cycle discussed above. The performance of the system for all the configurations is shown in Fig. 9. The performance was stable with 100% accuracy for all the configuration having at least activity cycle size of 300 and 5 mixtures. We observed that the system was unable to classify activity cycle with number of mixtures less than or equal to 3, even though activity cycle contained enough evidence (*size* = 300 to *size* = 600). Therefore the number of mixtures was not enough to maximize the likelihood of the RPS.

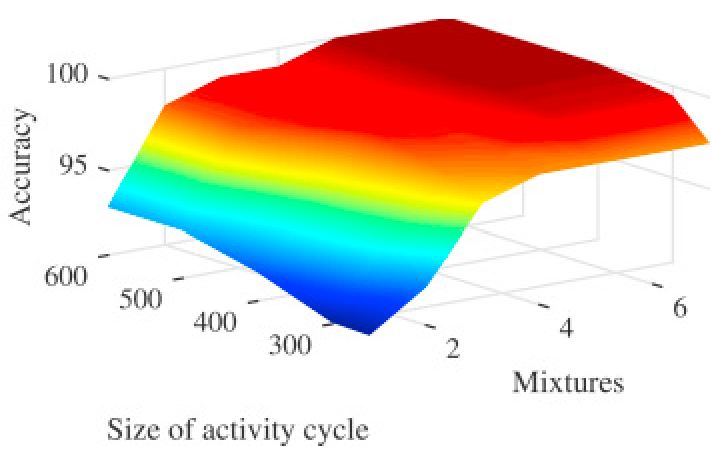



Fig. 9. Performance of the system with respect to number of Gaussian mixtures and size of activity cycle

The performance of the classification algorithms using time-domain features is shown in Fig. 11. The acronyms used in the figure are as follows: a) Our: Our Approach, b) BT: Bagged Trees, c) LR: Logistic Regression, d) RF: Random Forest, e) DTb: Decision Table, f) W-KNN: Weighted K-Nearest Neighbor, g) SVM, h) Artificial Neural Network, i) NB: Naive Bayes, j) BN: Bayesian Network, and k) DT: Decision Tree. We tested 10 classification algorithms using 5 time-domain features for each individual model. We achieved 90%–91% accuracy for Bayes Network, Naive Bayes, Multilayer Perceptron, SVM, KNN, and Bagged Trees. We achieved accuracy of above 83% for other classification algorithms. In contrast to these approaches, our system achieved an accuracy of 100%. Our system is able to classify all the activities from y-axis acceleration with 100% accuracy. We have shown the models are able to capture the underlying dynamics when activity cycle contains enough information about activity. The classification algorithms are not very successful with above mentioned extracted time-domain features from the same activity cycle. We present the precision and recall for each activity class in Fig. 10 for the public dataset. We observed that the highest precision and recall are for the sitting and laying activities and lowest are for the walking and taking stairs.

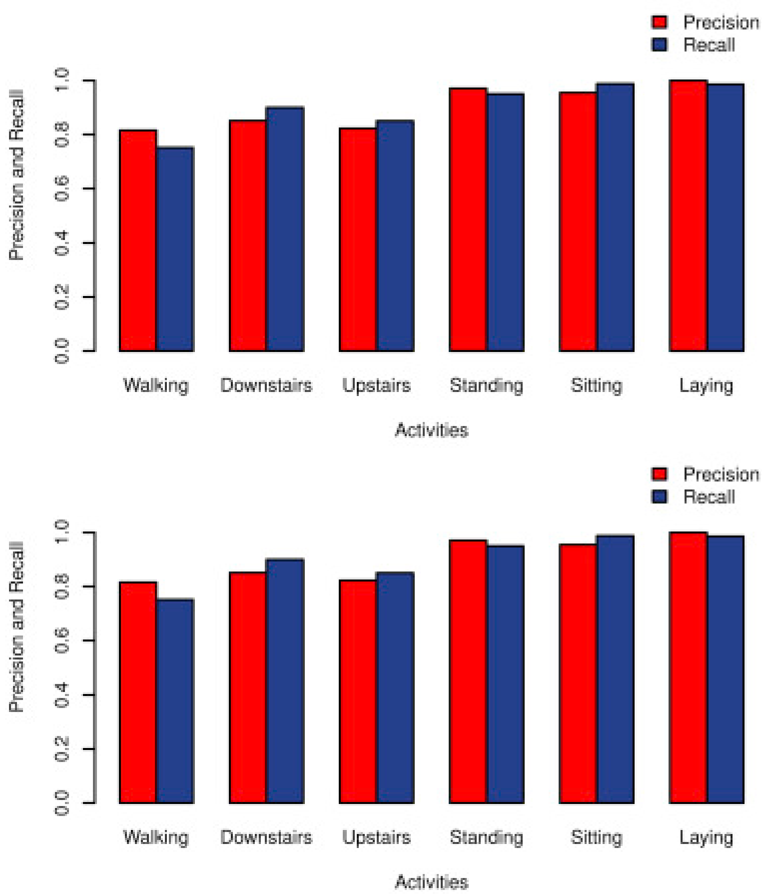



Fig. 10. Precision and recall for each activity class (Public Dataset).

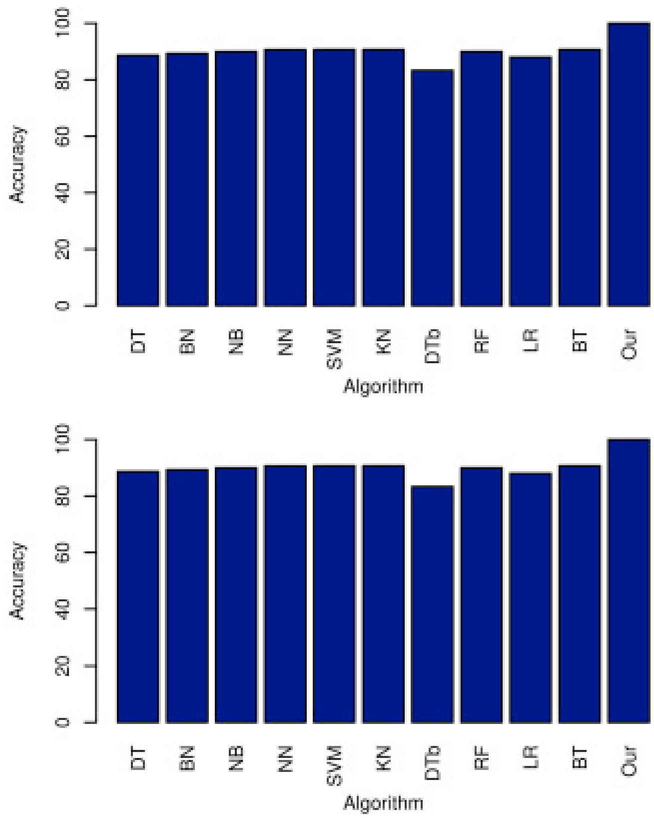



Fig. 11. Algorithm Performances using 1-Axis Acceleration (Our Dataset).

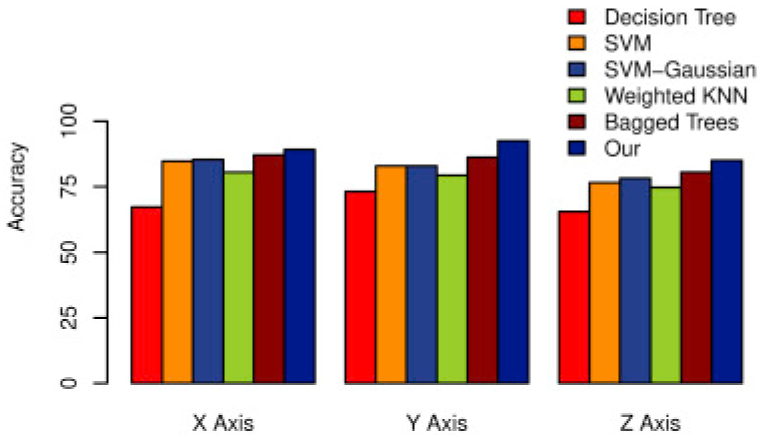
#### 6.4.2. Public dataset

We applied our approach on the public dataset. We used generalized model of each activity for all the participants. The confusion matrix for this experiment is shown in Table 4. The accuracy of the system for the generalized model is 90%. For each row, the corresponding true activity class is the positive class and the rest of the activity classes were considered as negative class. We also compared our work with Anguita (Anguita et al., 2013) using 60 time and frequency domain features, and present the results in Fig. 12. Our approach achieves highest accuracy (90%) compared to other approaches (Decision Tree (Bao and Intille, 2004) (Ravi et al., 2005), Support Vector Machine (Derawi and Bours, 2013) (Attal et al., 2015), K-Nearest Neighbors (Paul and George, 2015) (Sani et al., 2017), and Bagged Trees (AK et al., 2017)) and the approach used in Anguita (Anguita et al., 2013).

Table 4. Confusion Matrix for the generalized model of public dataset using proposed approach.

| Activity | | Predicted Class | | | | | |
|---|---|---|---|---|---|---|---|
| | | Walking | Downstairs | Upstairs | Standing | Sitting | Laying |
| True Class | Walking | 278 | 37 | 55 | 0 | 0 | 0 |
| | Downstairs | 33 | 297 | 0 | 0 | 0 | 0 |
| | Upstairs | 30 | 15 | 255 | 0 | 0 | 0 |
| | Standing | 0 | 0 | 0 | 361 | 19 | 0 |

| | | | | | | | |
|---|---|---|---|---|---|---|---|
| | Sitting | 0 | 0 | 0 | 5 | 402 | 0 |
| | Laying | 0 | 0 | 0 | 6 | 0 | 409 |



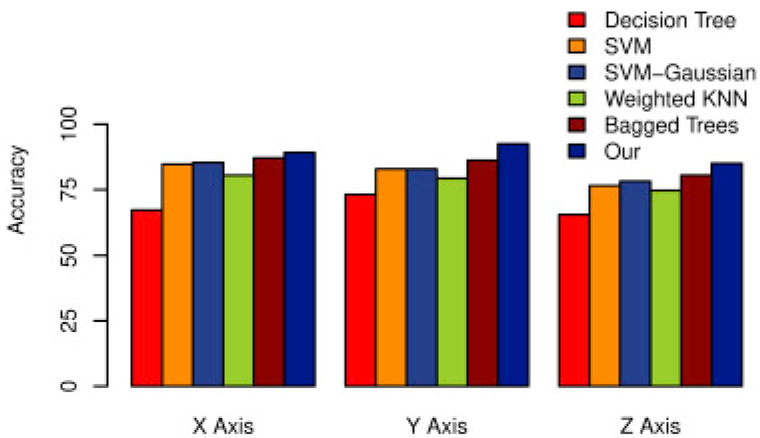




Fig. 12. Performance of algorithms using 1-axis acceleration (UCI Dataset) (Anguita et al., 2013).

## 7. Discussion

We presented a human activity recognition system for smartphones. We leveraged the built-in accelerometer sensor to identify users' current activity. For the first dataset of 10 participants, out of 10 activities, we achieved 100% accuracy for all the activities using our approach. We used individualized models for each of the participants for. For the same dataset, we extracted 5 time-domain features and applied 10 classification algorithms. We achieved the largest accuracy of 91% using these techniques.

We also compared (Fig. 11) our work with Anguita (Anguita et al., 2013) using 60 time and frequency domain features. We present a comparative analysis of our work with state-of-the-art techniques in Table 5. We compare activities, methodology, sensors, extracted features, number of subjects, and performance for each of the works. Compared to the existing approaches we achieved a very good accuracy for personalized model even with a less amount of data. This gives us the opportunity to easily create a high accuracy personalized activity recognition model. We also presented time required to build RPS

(Povinelli et al., 2004) and extract time and frequency domain features from the acceleration signal (Anguita et al., 2013) of sample size 128 and 600 in Fig. 13. The time required to extract features (7 features and 66 features respectively) is 3–4 times higher than building RPS. Also, the time to recognize activity class is fast, taking an approximate time of 0.0715 ms.

Table 5. Comparison of representative past works on AR.

| Work | Activities | Methodology | Sensors | System | Features | Subjects | Accuracy |
|---|---|---|---|---|---|---|---|
| Derawi and Bours (2013) | Gait, 3 speed walking | Cross DTW, SVM, BN, RT, MLP | 3 axis Acc | Smartphone | 24 | 25 | 99 81.9, 89.3% [a] |
| Li et al. (1802) | 5 | CNN and LSTM | 3 axis Acc | Wearables | 12 | Unknown | 91% [b] |
| Antos et al. (2014) | 5 | HMM, SVM | 3 axis Acc | Smartphone | 106 | 12 | 90.8, 88.1, 95.2% [c] |
| Casale et al. (2011) | 6 | Random Forest | 3 axis Acc | 1 Wearable | 20 | 14 | 94% |
| Bao and Intille (2004) | 20 | DT | 2 axis Acc. | 5 Wearables | 40 | 20 | 84% |
| Ravi et al. (2005) | 8 | NB, SVM, kNN, DT, Plurality Voting | 3 acis Acc | 1 Wearable | 12 | 2 | 73–99% [d] |
| Anguita et al. (2013) | 6 | SVM | 3 axis Acc and Gyr | Smartphone | 561 | 30 | 96% |
| Kwapisz et al. (2010) | 6 | ST, LR, ML NN | 3 axis Acc | Smartphone | 43 | 29 | 83% [e] |
| Attal et al. (2015) | 6 activities, 6 transitions | kNN, SVM, GMM, RF, HMM, k-Means | 3 axis Acc, Gyr, Mag | 3 Wearables | 168 | 6 | 99,83% [f] |
| Takeuchi et al. (2009) | 2 activities, 4 transitions | HMM | 1 Axis Acc | Wearable | 6 to 20 | 3 | 70–80% |
| Rokni et al. (2018) | 10 activities | CNN | 3 Axis Acc | 5 Wearables | 43 and 1170 | 29 | 95% |
| Our | 11 | RPS, GMM, MLE | 1 axis Acc. | Smartphone | RPS | 40 | 100, 90% [g] |

Acronyms: DTW: Dynamic Time Warping, MLP: Multilayer Perceptron, Acc: Accelerometer, MOE: Mixture-of-Experts, GLCT: Global-local co-training, Orn: Orientation, Mag: Magnetometer, Prox: Proximity, Gyr: Gyroscope, CNN: convolutional neural network, LSTM: Long Short-Term Memory network.

aWalking (Individualized: 99%, Generalized: 81.9%) Gait: 89.3%.

bDateset 1: 91.7%, Dataset 2: 92.56%.

cMean 90.8% (Known location), 88.1% (Unknown location), highest 95.2% (pocket).

dVaries in different settings.

eMean.

fSupervised: 99%, Unsupervised: 83%.

gIndividual: 100%, Generalized: 90%.

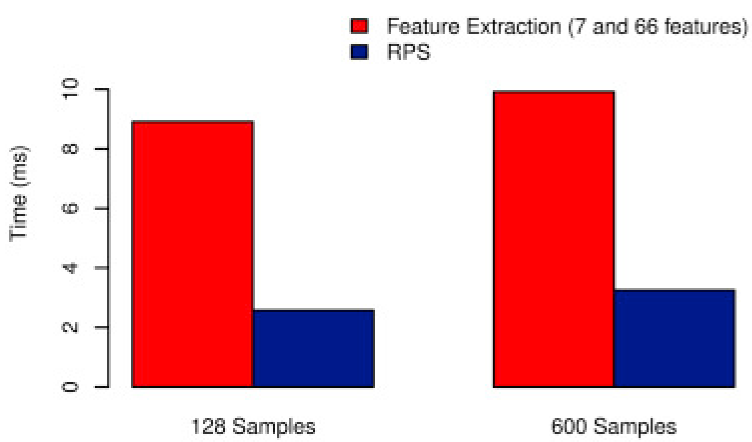


Fig. 13. Time required to extract features and build RPS.

For the second dataset we applied our approach and used a generalized model. However, the system was able to classify 6 different activities of 30 participants with an accuracy of

90%. We achieved 99% accuracy for sitting and laying activity, and 95% for standing. The overall accuracy increases to 95% when we increased the number of samples in the activity cycle. When we used individualized models, the system was able to classify the activities with an accuracy of 100%. Hence, our approach is able to recognize 11 different activities for 40 different users varying the smartphone placement between the pocket and waist. This is only using the observation from one single axis accelerometer data for personalized models.

The walking, walking upstairs, and walking downstairs are classified with an accuracy of 75%, 90%, and 85% respectively. It looks like the system is unable to fully capture dynamics for these three activities. If we look at the misclassified instances, we see that all the misclassified instances were classified between these three activities interchangeably. Also by observing RPSs for these activities we saw that they had a similar dynamics. When we placed the smartphone on the waist, these three activities showed similar dynamics based on the acceleration along y-axis. We considered grouping these three activities as one activity, named, “walk”, and then classifying it. We then found that the system was able to classify the walk activity with 100% accuracy.

We think that the representational capabilities of time-delay embedding (RPS) captures the underlying dynamics well from the time series acceleration. The higher dimensional representations also helps GMM to learn well from RPS. Compared to existing approaches where the goal is to extract time and frequency domain features to learn signal patterns, this approach (RPS + GMM) focuses on understanding underlying dynamics that describes the temporal evolution of the activities that evolve over time. The better RPS understands underlying dynamics, the better GMM learns, leading to higher accuracy compared to existing approaches.

In this paper, we investigated the performance and applicability of the dynamical systems and chaos theory in smartphone based human activity recognition system. We also used time-delay embedding or reconstructed phase space to capture underlying dynamics of human body motion for 11 different activities from smartphones’ accelerometer sensor. Most of the proposed and existing approaches used three axes acceleration along with other sensors (3-axes gyroscope, pressure, magnetometer) to recognize activities. In contrast to these approaches, we only used one axis acceleration to recognize activities. This reduces the computational and memory complexity of the system by reducing the size of data (from 3 to 7 time series to 1 time series) that needs to be processed. Moreover, most of the machine learning techniques require extensive computation and occupy large memory because of the large number of attributes that are present in the feature vectors (Lara and Labrador, 2013). Building RPSs are less complex and less expensive than these techniques. This is very helpful for implementation of the system on the smartphone. We also reduced computational and memory complexity by considering a small sample size.

We used a statistical learner to train captured underlying dynamics in the RPSs and used maximum likelihood classifier to classify activities.

We implemented our system (as android application) in two different case studies: 1) a rehabilitation clinic, to track patients daily activities and assess assigned task and daily routine, 2) the Hajj, to track pilgrims' location based on their activities. We used Android platform for the implementation. We published our dataset on a public domain website to enrich human activity dataset and accelerate research in this area.

## 8. Conclusion

We experimented with an alternative approach to extensively used machine learning techniques in human activity recognition from kinematics sensors (accelerometer) and achieved a very good accuracy. We also investigated the performance of the proposed approach using collected and publicly available human activity recognition datasets. We present a comparative study and an analysis. Application of the proposed system in wearable sensor based activity recognition can be researched further. The analysis of the experiment and results from the case studies can be a future work. Investigation of the proposed approach using 3-axes acceleration and other sensors can be researched further. The functional or complex activities comprise of a simple activity and a particular function. For example, when a person is reading a book, it is most likely that the person is sitting somewhere. Thus, simple activities provide influential information about complex activities. We developed this simple activity recognition system to progress our work on the complex activity recognition system, where this simple activity will be considered as one of the inputs beside location and time to predict functional activities (Gani et al., 2017). Also, a long-term monitoring of simple activities will facilitate estimation of composite activities and provide important parameters to evaluate quality of life.

Human activity recognition plays a very important role in many research areas and applications. Therefore, a support system that will provide information about current activity of a user by hiding all the complex details behind activity recognition is an in-demand service for these areas. We have started to implement the proposed activity recognition system on the smartphones' application framework as a service. The applications from the application layer and other services from the application framework will be able to access it to get the activity information. This service will make building HAR applications easier.

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