Impersonal Smartphone-based Activity Recognition Using the Accelerometer Sensory Data

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***Abstract*—Smartphone-based activity recognition focuses on identifying the current activities of a mobile user by employing the sensory data which are available on smartphones. A light-weight model and less inquiry users for true activities, are necessary for deploying the activity recognition on a mobile platform for identifying activities based on new sensory data in real time. In this paper, we propose a new smartphone-based activity recognition framework for evolving sensory data stream called *ISAR*. It stands for Impersonal Smartphone-based Activity Recognition. *ISAR* model is built using annotated sensory data from a panel of user as training data and are applied to the new users. Our new model is an offline and online phase. In offline phase, we propose a new method for finding the threshold value which used to distinguish between dormant activities and energetic activities. Only a set of the energetic activities are used to build a light-weight classifier model. In online phase, we introduce the recognition technique of unannotated streaming sensory data with different activities. The experimental results using real human activity recognition data have conducted and compared with STAR model in terms of the accuracy and time complexity. Our results indicates that *ISAR* model can perform dramatically better than STAR model. Moreover, *ISAR* can utilize better than STAR model in real situation, especially across different users and without inquiry users.**

***Keywords*—Activity recognition, Streaming data, Unsupervised learning**

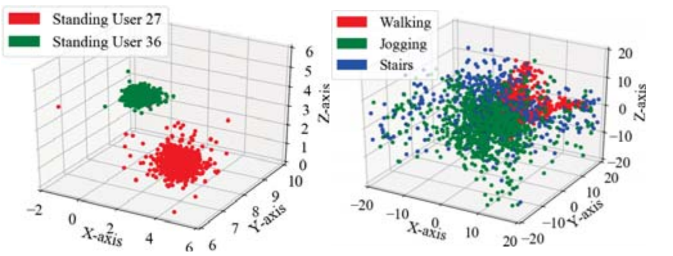
I. INTRODUCTION

In recent years, smartphone-based activity recognition has been extensively explored in the research of mobile computing due to its importance for context-aware application [1]. These applications can be used for healthcare and fitness monitoring. In addition, smartphones not only serve us a communication medium, but also are equipped by powerful CPU and GPU [2]. Modern smartphones have incorporated diverse and powerful sensors including accelerometers. They can be useful for many purposes. One of these purposes can be monitoring the physical activity from sensory data [2].

The objective of the smartphone-based activity recognition is to analyze the continuous sensory data and identify the occurrence of the current activities with high accuracy [3]. Therefore, how to be able recognize the human activities such as sitting, standing, walking, running, upstairs and downstairs by analyzing those sensors data, is interesting issue for many researchers and developers. There exists many researches that widely studied with different approaches. Most of researches focus on traditional classification techniques such as support vector machine (SVM), decision trees, k-nearest neighbor algorithm (k-NN), artificial neural network, etc. The classifier model is trained and tested using the collected and annotated data by domain expert. When the model is ready to use, the classifier model is used to predict activities from the continuous sensory data. Since all the traditional classification learning techniques use prior knowledge of collected data to build the classifier models in external environment, and the obtained models are static and general model. So they are not suitable for classifying when the users' activities profiles or personalization of users' activities change. The recognition model will be retrained to update the model.

Many researches try to improve the classification learning techniques without retraining the whole data set. MARS [3] algorithm is dynamic classifier model and is built to facilitate the adaptation of the classifier while the user's activities patterns change without retraining the model. During the training phase, user performs the activities and annotates interactively the data gathered from the sensors using a user interface. These annotated data are saved to built the recognition model in offline learning algorithm. The MARS model is anytime updated on-board the mobile devices in incremental manner when new labeled data are incorporated by user. Therefore, MARS is a personal model which users must provide labeled training data.

The recent and interesting model is STAR model introduced by Abdallah and the team [4]. The STAR model is an impersonal and adaptive activity recognition that incrementally learns from evolving sensory data stream. The recognition and adaptive process can perform on a mobile phone device with limited resources. The STAR model build a learning model from a set of labeled data obtained from one user, and then adjust the model to fit the new particular users in incremental learning manner without requiring labeled training data from those users. It seems like the STAR model can be generalization model, however, it has some limitations. If the model fail to detect the occurrence of activities to new users. It dues to the pattern of doing activities of new users are different to the pattern of the user used to create the model or the orientation difference of mobile device. Then the active learning is performed to inquire the users about true activities. For example, Fig. 1(a) depicts the snapshot of the "Standing" activity of different users in WISDM dataset which used to build STAR model. This figure illustrates that "Standing" are totally misclassified for new users if such users activities are different to the user used to create the model. In addition, Fig. 1(b) shows the overlapping among three activities including "Walking", "Jogging", and "Stair", that will lead to getting in poor recognition accuracy and then the active learning will be performed. Moreover, there are some researches [5], [6] attempt to solve the limitations of STAR model by adding other sensors such as gyroscope, GPS, and other body-worn sensors. Although it makes increase accuracy of activity prediction, it takes more time to calculate and cannot proceed on mobile device.



(a) (b)

Fig. 1. (a) 3D scatter plot of the WISDM dataset. (b) 3D scatter plot of three activities of one user. Each activity is represented by different color.

In this paper, we propose new activity recognition for evolving sensory data stream called ***ISAR***, which stands for Impersonal Smartphone-based Activity Recognition. The proposed framework is a accelerometer based and light-weight framework for identifying the occurrence activities from the continuous sensory data. *ISAR* is an offline and online phase. In offline phase, we build classifier model from a set of annotated sensory data based on characteristics of activities and clustering approach. The online phase is recognition component which can proceed on-board the mobile phone for real-time data. Our main contributions in this work are: (1) we propose the new method for distinguishing the activities based on their characteristics. Our new method can be used for identifying the sensory data into two types of activities that are dormant and energetic activities from incoming unlabeled data. (2) The new classifier modeling and recognition component are introduced to deal with the overlapping data and to cut off any inquiry the users about true activities

II. Related Works

The immense research in smartphone-based activity recognition has widely used the learning methods. Most of learning methods are the supervised learning algorithms. In existing supervised learning, the annotated data is gathered to train a classifier model offline in the external environment. Then the constructed model is deployed for recognition the occurrence activities. Nevertheless, the obtained model is static model which cannot deploy in a realistic situation. Because phone-based sensors typically produce streaming data which are various kinds of change. This is the one of the main causes should be concerned if we create the personal model with the annotated of data from a panel of users [7]. For example, Lockhart and the team [8] developed a smartphone-based activity recognition named Actitracker. It uses Random Forest to generate the activity recognition model with the annotated of data from a panel of users, but it will generate much more accurate personal model when retaining the model for a specific user is perform [8].

A few researches have considered the streaming data for human activity recognition. MARS [3] stands for Mobile Activity Recognition System which can identify the occurrence of activity in streaming data from mobile device. Since, the model type of MARS is personal model which use training data only from the user who utilizes the model. So in the training phase, the user makes a gesture activity and labels interactively the data gathered from the sensors via a graphical user interface. the annotated data will be processed on-board by the incremental Naïve Bayes compared with C4.5 decision tree. In the recognition phase, the new incoming unlabeled data is classified using the built model. From the experiments, MARS shows the feasibility to execute and update the model from a stream of sensory data based on individual users labeled data.

Another approach is proposed by Abdallah and the team called STAR model [4]. STAR stands for STream learning for mobile Activity Recognition which is smartphone-based dynamic recognition for evolving sensory data streams. In offline phase, this phase aims to build learning model for activity recognition. A learning model represents a set of annotated data for each activity in term of sub-clusters. Each sub-cluster is extracted the summary information used to describe and distinguish it from other sub-clusters. The online phase is executed on board the smartphone for real time recognition. It composes of recognition and adaptation components. The recognition component uses to predict activities in each sliding window using cluster-based approach and then an ensemble technique is applied on clusters of each window [4]. STAR model uses four measurements including Distance, Gravity, Density and Deviation. These four measures are used to assess the similarity of each new cluster with sub-clusters in learning model. If all measures or three measures vote for the same sub-cluster, the learning model is unnecessary to update the summary information of such sub-clusters. Otherwise, if it gives equal votes or each measure chooses different sub-cluster, the active learning occurs that means the true label is provided by user. In this case, incremental learning is performed to refine the characteristics of such sub-clusters. Although, STAR is an efficient model which can deal with the continuous data stream and avoid retaining the model when a new user utilizes the system. However, STAR model can be misclassified for the new users if their activities are different to the users used to create the model. Since, STAR model uses data from WISDM, there exists the overlapping among

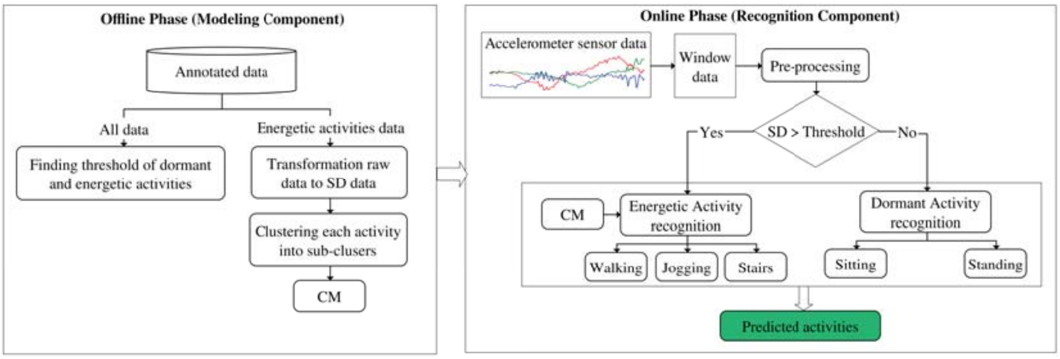


Fig. 2. The Impersonal Smartphone-based Activity Recognition framework (*ISAR*).

three activities including "Walking", "Jogging", and "Stair". This leads to getting in poor recognition accuracy, and then the active learning will be performed.

III. ISAR Framework

In this section, we introduce our new mobile activity recognition framework for streaming sensory data, named *ISAR*. The *ISAR* framework is divided into offline phase for modeling component and online phase for recognition component as shown in Fig. 2.

A. Data understanding

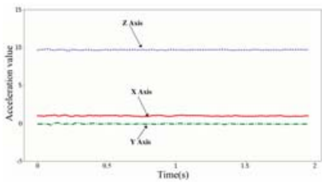
In this work, we exploit the real activity recognition dataset for creating our proposed impersonal model. Thus, all experiments are conducted on WISDM dataset [9]. This annotated dataset contains data collected from user's mobile phone accelerometer sensor in laboratory conditions. A large number of users carry a smart phone in their front pants leg pocket and perform to walk, jog, sit, stand, upstairs and downstairs for a specific periods of time. In all activities, the accelerometer data were collected every 50 ms, so we got 20 samples per second [9]. This dataset contains more than one million labeled accelerometer sensory data called *annotated data*. The example of WISDM dataset is shown in Fig. 3.

Sample	Lable	Timestamp	ax	ay	az
s_1	Sitting	14824292218000	-4.99	-2.26	7.88
s_2	Sitting	14824342298000	-4.99	-2.30	7.96
s_3	Sitting	14824392255000	-5.01	-2.30	8.01
$\vdots$	$\vdots$	$\vdots$	$\vdots$	$\vdots$	$\vdots$
s_i	Sitting	$\vdots$	ax_i	ay_i	az_i
$\vdots$	$\vdots$	$\vdots$	$\vdots$	$\vdots$	$\vdots$
s_N	Sitting	$\vdots$	ax_N	ay_N	az_N

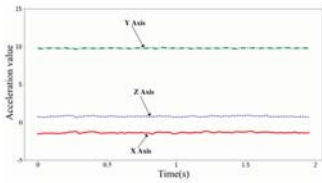
Fig. 3. The example of annotated data of sitting activity data provided by WISDM.

B. Offline phase

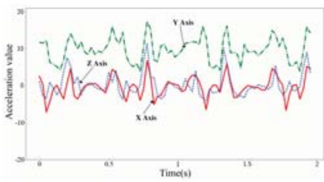
In *ISAR* framework, we begin with building the modeling component in offline processing. The modeling component aims to build a classifier model (*CM*) used for activity recognition component in online phase. To deal with the overlapping problems, the pattern of acceleration is considered. For further using, the acceleration values of x, y, and z axes are called x, y, and z values respectively. Figs. 4(a) and 4(b) plot the acceleration values of three axes of sitting and standing. As seen in these figures, the x, y, and z values are almost steady state [10], so sitting and standing are *dormant activities*. The acceleration lines of both activity have different remarkable features as well. For sitting, the x values are close to y values, but the z values are deviate from the other acceleration values. For standing, on the other hand, the y values have the greatest values and deviate from x and z values, but the x values are close to z values [10]. Figs. 4(c), 4(d), and 4(e) show the acceleration of three axes of walking, stairs, and jogging respectively. All these acceleration graphs illustrate that the x, y, and z acceleration values are very significantly, so these three activities are called *energetic activities* [10].



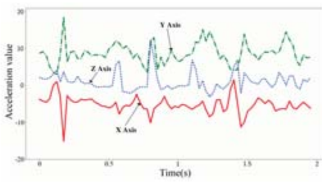
(a) Sitting



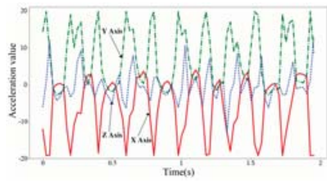
(b) Standing



(c) Walking



(d) Stairs



(e) Jogging

Fig. 4. The deviation of the acceleration values of x, y, and z axes of the five activities.

Let act be the set of activities in *annotated data*, act is composed of the set of samples S, which $S =$

$\{s_1, s_2, \ldots, s_i, \ldots, s_N\}$ where N is the number of samples in each activity. Each s_i is defined as a $4-tuple$, (ax_i, ay_i, az_i, t_i) where t_i is the activity label of the sample s_i. The modeling component is consisted of three steps as the following.

Step 1: Converting the acceleration values to the standard deviation values. First, for each acceleration value s_i,the magnitude datum M_i is computed using equation (1) [11]. Then, for each activity we employ a fixed window of size n samples used for calculating the standard deviation SD_j using equation (2). In this work, n is determined as 20 samples.

$$M_i = \sqrt{ax_i^2 + ay_i^2 + az_i^2} \tag{1}$$

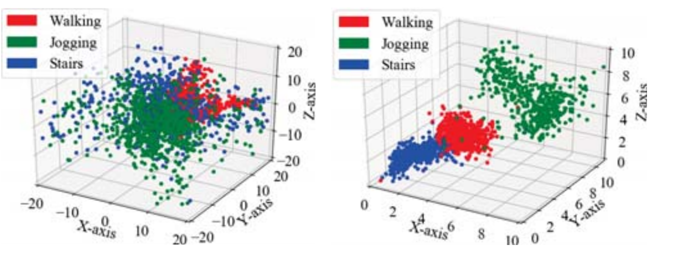
where M_i, is the magnitude of acceleration value i, $i = 1, 2, 3, ..., N$.

$$SD_j = \sqrt{\frac{1}{n-1}\sum_{i=1}^{n}(M_i - \bar{M_j})^2} \tag{2}$$

where SD_j is the standard deviation of samples within window j of each act, and $\bar{M_j}$ is the average of samples within window j.

Step 2: Finding the threshold value used for classifying between dormant and energetic activities in online phase. First, the minimum of the standard deviation of energetic activities and the maximum of the standard deviation of dormant activities are computed. Then the $Threshold$ (see **Algorithm** Offline Phase) is obtained by averaging these two values.

Step 3: Building the classifier model (*CM*). Only energetic activities including walking, running, and stairs, are used to build *CM*. Since the overlapping problem emerges from these three activities as illustrated in Fig. 5(a), so the original data of these three activities are transformed to SD space as illustrated in Fig. 5(b). This figure shows transformation to SD space which can overcome the overlapping problem. Thus, for each activity, a fixed window of size 20 (n) samples are used for calculating the standard deviation of each acceleration axis.



(a) (b)

Fig. 5. (a) Scatter plot of energetic activities data. (b) Scatter plot of energetic activities data in SD space.

After that, we apply the clustering-based approach to split each energetic activity into K sub-clusters (sc). For preliminary study, K is set to 3 for each energetic activity. In this work, we use the Gaussian mixture model (GMM) for clustering data. Finally, we extract only the statistics summary of each sub-cluster and discard the data from the system to save the memory. Because the *CM* must be processed on board of mobile device. The statistics summaries of sub-clusters include the following.

- $Weight_{sc_k}$ is the total number of data samples that belong to the sub-cluster k.
- $Centroid_{sc_k}$ is the center of sub-cluster k. For d dimensional data sample, K is the number of sub-clusters. $Centroid_{sc_k}$ is also a d dimensional vector of the average value of the samples inside the k^{th} sub-cluster as equation (3). So, we defined $Centroid_{sc_k}$ = $(c_1, c_2, \ldots, c_l, \ldots, c_d)$, as follow,

$$c_l = \frac{\sum_{i=1}^{m} P_{il}}{Weight_{sc_k}}, \tag{3}$$

where c_l is the centroid of the l^{th} feature, and P_{il} is the l^{th} feature of the i^{th} sample inside the sub-cluster sc_k.

All details are described in **Algorithm** Offline Phase

Algorithm 1: Offline Phase (Modeling Component)

Input : N_ζ = set of annotated data of all activities.
Output: (1) $CM = \{Centroid_{sc_1}, Centroid_{sc_2}, \ldots, Centroid_{sc_k}\}$,
(2) $Threshold$.

for *each act in annotated data* **do**
  for *each window j* **do**
    Compute M_i for each sample using eq. (1)
    Compute average magnitude $\bar{M_j}$ of window j.
    Compute standard deviation SD_j using eq. (2).
  end
end
Find the maximum of standard deviation of dormant activities SD_{max}.
Find the minimum of standard deviation of energetic activities SD_{min}.
Compute $Threshold = \frac{SD_{max}+SD_{min}}{2}$.
for *each energetic activity act* **do**
  Let D be the empty set.
  for *each window j* **do**
    Compute the average values $(\bar{ax}_j, \bar{ay}_j, \bar{az}_j)$ of each acceleration values x, y, and z.
    Compute the standard deviation of each acceleration values $Std = (SD_{ax_j}, SD_{ay_j}, SD_{az_j})$.
    $D = D \cup Std$.
  end
  Cluster D into k sub-clusters using GMM algorithm.
  Compute $Centroid_{sc_k}$ of all sub-clusters and add to CM.
end

C. Online phase

This section describes how to utilize *ISAR* for identifying the occurrence activities when dealing with the continuous sensory data stream. Thus, the recognition component is used to predict the activities in the data stream with a single pass and throw away of data, and can perform on the smartphone with limited resources. Fig. 2 also shows the process of recognition component in the streaming environment. Firstly, a continuous fixed size of sliding window is applied to segment the stream of data, and each small data chunk is performed the following steps.

Step 1: In *pre-processing* step, we compute the magnitude of acceleration value for each datum in the chunk by using equation (1), and compute the standard deviation of all samples in that data chunk by using the same formula of equation (2), denoted as SD.

Step 2: If SD is less than the $Threshold$ value obtained from offline phase, then all data in such data chunk will be the dormant activities. Otherwise, all data in such data chunk will be the energetic activities.

Step 3: For dormant activity, we found that the distances among acceleration value x, y, and z are significantly different and can be used for separating the sort of activity. The average of acceleration values x, y, and z is calculated denoted as $\bar{a}x$, $\bar{a}y$, and $\bar{a}z$ respectively. Then, the distance between the average value is computed by using equations (4) and (5). Therefore, sitting and standing activities can be distinguished using the proposed rule-based as follows:

If $Dist(\bar{a}x, \bar{a}z) > Dist(\bar{a}x, \bar{a}y)$ then activity is sitting.
If $Dist(\bar{a}x, \bar{a}y) > Dist(\bar{a}x, \bar{a}z)$ then activity is standing.

$$Dist(\bar{a}x, \bar{a}y) = \sqrt{\bar{a}x^2 - \bar{a}y^2} \tag{4}$$

$$Dist(\bar{a}x, \bar{a}z) = \sqrt{\bar{a}x^2 - \bar{a}z^2} \tag{5}$$

For energetic activity, the incoming data chunk is considered as the new sub-cluster. Thus, we compute the standard deviation of all acceleration values in such data chunk. After that, the classifier model (*CM*) deploys the Euclidean distance to assess the similarity of the new sub-cluster with *CM* sub-clusters. Then, the classifier model decides on the predicted label as the sub-cluster with the nearest distance.

All of the details are described in **Algorithm** Online Phase.

Algorithm 2: Online Phase (Recognition Component)

Input : (1) Set of non-stationary streaming data,
(2) $CM = \{Centroid_{sc_1}, Centroid_{sc_2}, \ldots, Centroid_{sc_k}\}$,
(3) $Threshold$.
Output: The predicted activities (P_{act}).

while *stream is not empty* **do**
  for *each fixed size window* j **do**
    Compute M_i using eq. (1) of each sample in window j.
    Compute average $\bar{M}_j$ of window j.
    Compute standard deviation SD_j using eq. (2).
    if $SD_j < Threshold$ **then**
      Compute the average values $(\bar{a}x_j, \bar{a}y_j, \bar{a}z_j)$ of each acceleration values x, y, and z.
      Compute $Dist(\bar{a}x,\bar{a}y)$ and $Dist(\bar{a}x,\bar{a}z)$ using eq. 4 and 5.
      if $Dist(\bar{a}x,\bar{a}y) > Dist(\bar{a}x,\bar{a}z)$ **then**
        P_{act} = standing
      else
        P_{act} = sitting
      end
    else
      Compute the average values $(\bar{a}x_j, \bar{a}y_j, \bar{a}z_j)$ of each acceleration values x, y, and z.
      Compute the standard deviation of each acceleration values $Std = (SD_{ax_j}, SD_{ay_j}, SD_{az_j})$.
      Find the nearest sub-cluster w such that
      $w = argmin_{k=1,\ldots,K}(||Std - Centroid_{sc_k}||)$.
      Set the activity of sub-cluster sc_w to P_{act}.
    end
  end
end

IV. The Experiments

In this section, we describe the evaluation of our proposed framework and report the experimental studies on the public database WISDM [9].

A. Experiments setup

To evaluate the recognition quality of *ISAR* framework, this work uses WISDM dataset for testing the model. This dataset consists of 18 users that each user performed the five activities. There are 1,078,140 samples for sitting data, 1,001,980 samples for standing data, 5,594,020 samples for walking data, 3,062,720 samplse for stairs data and 4,445,160 samples for jogging data. Since, *ISAR* is the impersonal model, so we use the notion of k-cross-validation to evaluate the model. In this work, k is set to 18 which is the same as the number of users. Thus, one user is used for the training data, and the remaining $k-1$ users are a validation data for testing model. The cross validation process is repeated k folds. The results of k folds can be averaged to produce the overall results. Since *ISAR* framework is a smartphone-based and uses only accelerometer sensor like STAR framework, so we will compare the performance between *ISAR* and STAR in terms of accuracy and time complexity.

B. Experimental results and discussions

In this section, we report the experimental results of *ISAR* and STAR models for activity recognition on WISDM dataset. Since STAR model incorporates active learning for evolving data stream when the model cannot identify the occurrence activities by inquiry user for true label. Therefore, we implemented STAR model into two types which are STAR with active learning and STAR without active learning. For STAR with active learning, when the model cannot recognize the incoming activities of the testing data and active learning will be required, we use the actual labeled data of testing data as the answers obtained from the users. The summary results obtained from the experiments that presented in Table I. This table indicates the predictive accuracy accordance with each activities. The percentage numbers in parentheses show the number of inquires users for true label of STAR model with active learning.

In Table I, it demonstrates that STAR model achieves high level of accuracy every activity. When comparing between *ISAR* and STAR with active learning, Table I shows that *ISAR* model can achieve the good performance. For dormant activities, standing and sitting, *ISAR* can accomplish accuracies above 90%. For energetic activities, jogging is easier to recognize than stairs and walking because jogging extremely changes in acceleration value and rather separated cluster as illustrated in Fig. 5(b). For walking and stairs, they are much more difficult to identify because their characteristics are quite close and their clusters are still overlapping. Although there exist some overlapping problem. *ISAR* can still recognize walking and stairs activities quite well than STAR with and without active learning, because *ISAR* model does not need users to assign the true activities for the unidentified activities.

In addition, both of *ISAR* and STAR are light-weight model and can utilize the models for real time activity recognition. So we performed the analysis of processing time by comparison with these two models as shown in Table II. First, we begin with analysis *ISAR* processing time. The main computational complexity in offline phase arises from two main processes that are finding the threshold value and clustering algorithm. In finding the threshold value, we consider all the stored annotated data, so the computational complexity is $O(Nm)$ where N is the number of annotated data and m is the number of windows. For clustering approach, we apply GMM clustering for energetic activities to build classifier model (*CM*) with a complexity of $O(kmi)$ where k is the number of sub-clusters and i is the number of iterations to perform the clustering. In online phase, *ISAR* performs only recognition processing by considering each window, so the processing time is $O(mn)$ where n is the number of instances within a single window. For STAR model, it also applied the GMM clustering approach to create the learning model, thus the computational complexity of creating the learning model is $O(kNi)$. The online phase of STAR model consists of recognition and adaptation components. The recognition component identifies incoming activities in each window with a clustering-based technique by partitioning into two sub-clusters. Thus, the complexity for clustering data in each window is $O(2ni)$ and the recognition technique in STAR complexity is $O(k)$ where k is the number of sub-clusters in the learning model. While the processing time of the incremental adaptation technique is $O(nk)$. If we consider the utilization in real environment. *ISAR* is more applicable than STAR model, because clustering technique does not require in *ISAR* model.

TABLE I. THE PREDICTION ACCURACY OF THREE MODELS.

Techniques	Standing	Sitting	Walking	Jogging	Stairs
ISAR (%)	90.26	96.43	60.77	79.41	49.22
STAR without active learning (%)	24.08	18.93	27.00	25.96	21.03
STAR with active learning (%)	77.24 (52.6%)	95.64 (79.0%)	73.05 (45.5%)	81.43 (55.0%)	59.10 (39.3%)

TABLE II. THE COMPUTATIONAL COMPLEXITY OF *ISAR* AND STAR MODELS.

Techniques	Offline Phase	Recognition	Adaptation
ISAR	$O(Nm) + O(kmi)$	$O(mn)$	-
STAR	$O(kNi)$	$O(2ni) + O(k)$	$O(nk)$

V. CONCLUSIONS

Smartphone-based activity recognition is an important viewpoint in developing pervasive applications such as healthcare, elderly care and fitness monitoring when dealing with evolving streaming data. In this paper, we research on the physical activity recognition based on accelerometer embedded in mobile devices. We have developed *ISAR*, an impersonal and light-weight model for identifying activities in a non-stationary sensory streaming data. The *ISAR* model is developed by using annotated sensory data from a panel of user as training data and are applied to the new users. The offline-online framework is used in *ISAR* model. In offline phase, we build classifier model from a set of annotated data based on characteristics of activities and clustering-based approach. In online phase, the recognition component is utilized on-board the mobile phone for non-stationary data.

ISAR's ability to distinguish the activities based on their characteristics – dormant and energetic activities is one of our contributions which *ISAR* can recognize the activities quite well. In addition, *ISAR* model does not inquire users to assign the true activities when the unidentified activities occur. The developed framework is evaluated with the real datasets. The experiments showed that *ISAR* model could successfully identify activities from the evolving data stream and could apply across different users. As a future work, we plan to improve the recognition component in online phase that may further enhance the accuracy of *ISAR* model.

VI. ACKNOWLEDGEMENT

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