Activity prediction

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1 Introduction

Now a days human life is mostly irregular due to the routine-less work hours. For tracking the pattern of human daily routine, stream-less human activity monitoring is useful. It is a process by which a system can identify different human daily activities based on the observations on the individuals action and his/her surroundings. Different types of audio, video, and ambient sensors can be used to track the activity information from the users' body. Now a days, besides these sensors, use of the cheap and user friendly wearable devices and smart-phones are more popular for activity recognition. In spite of a large number work has been done on Activity Recognition, a few works address the Activity Prediction problem. However, for human activity monitoring or health monitoring, activity prediction is equi-important with activity recognition because early knowledge of the activities use to compare with the recognize activities for studying the abnormality in the human daily activity pattern. Although several works study on the daily activity patterns, there is no such work on regularity patterns on the daily activities. To address this problem, we develop a recommended system for regular daily pattern users and send an alert to inform about the deviation of the activity.

2 State-of-art

Although activity recognition [1] has been studied for past decade, it is still an well popular field. Among the existing recognition techniques, wearable devices [2] and smartphone [3] based data tracking schemes are most known due to their user friendliness. Even if human activity recognition problem is well addressed in existing literature, there exists only a few work on the activity prediction in ambient monitoring applications. Nazerfard and Cook [4] proposed a activity prediction model using Bayesian networks. The model initially predicts future activity features based on the current feature set and the activity. Then the predicted future features are used to predict the future activity. A time series based activity model has been studied in [5] by Moutacalli *et al.* The authors applied ARIMA model to predict the activity start times and finally the predicted times used to predict the most likely performed activity. Minor *et al.* [6]

addressed the activity prediction problem using the imitation learning framework. However, all the existing approaches highlighted the RFID tag based sensors.

Besides the activity prediction, several works highlight the influence of daily activity patterns in the human activity monitoring. In [7], activity discovery based mechanism is used to identify the behavioral pattern of human activity. In the activity recognition model, machine learning techniques are used to map the stream of sensor data with the activity level. However, for online mode, several data present without any target activity class. To address this issue, the authors proposed an unsupervised method by combing the effect of activity discovery and activity recognition. In the activity discovery phase, the model identifies the sensor data patterns to partitions the unknown class intervals. The problem of long-range dependencies between distance time instants is considered in [8]. For addressing the issues, the authors proposed segmental pattern mining based algorithm for improving the sequential representations within the activity segments. The algorithm identifies the patterns for the activities performed on a time segment. A probabilistic learning model is used to match the patterns with the activity sequences. The only limitation of these works is the use of several RFID based sensors in the smart home. These works are mainly focused on the in-door activity pattern.

Huynh *et al.* incorporated the in-door as well as out-door activities of the users in [9] to design the daily recognition model. The model automatically discovered the pattern of the user's daily activities routine. The authors used probabilistic topic model to learn and discover activity pattern and finally recognize the daily routines. In the initial phase, supervised learning based method is used to assign the activity labels to the raw sensor data. These labels are further used for identifying the activity pattern in an unsupervised way. Finally, an unsupervised clustering algorithm is used for generating a vocabulary of labels and pattern extraction. The only dependency of this work is the use of wearable devices.

In [10], Chiang *et al.* studied the daily recorded life journal to identify the problem of the sedentary lifestyles. For continuous tracking the users' daily activity habits, they developed a portable activity pattern recognition system. The system takes the continuous activity records as an input and identifies daily activity patterns for a given user. The overall system offers self-review to users and informs clinical managers about the lifestyle of their patients. Although the work overcomes the overheads of the external infrastructure by using the smartphone, the activity pattern is focused only on the sedentary lifestyle.

A recent work [11] considers the power of accelerometer and gyroscope build-in a smartphone to recognize the human physical activities. They used supervised learning models naïvebayes and knn for activity recognition. In the initial phase of learning, the continuous sensor data stream are divided into several segments using sliding window with overlapping and without overlapping techniques. Thereafter, they proposed a feature selection mechanism to select a subset of discriminant features in an energy efficient way. Finally, classifiers are used to learn the offline training data and recognize the activity in online mode.

The authors analyzed the smartphone based continuous sensor data stream only for activity recognition. To the best of our knowledge, smartphone based activity prediction is not yet studied so far. For addressing the current gap in the existing literature, we are considering the problem of predicting the highly or piece wise routined activities of the users using only smartphone device.

3 Proposed Model

In this section, we present the activity prediction model for the highly or piece wise routined users to track the diversity in their lifestyle. Our proposed model initially identify the activity pattern types. Later it predicts the future activity and informs about this activity as a remainder. After that the system checks the activity and sends an alert to the user if the present activity differs from the previously predicted activity.

3.1 Activity Pattern Type Identification Model

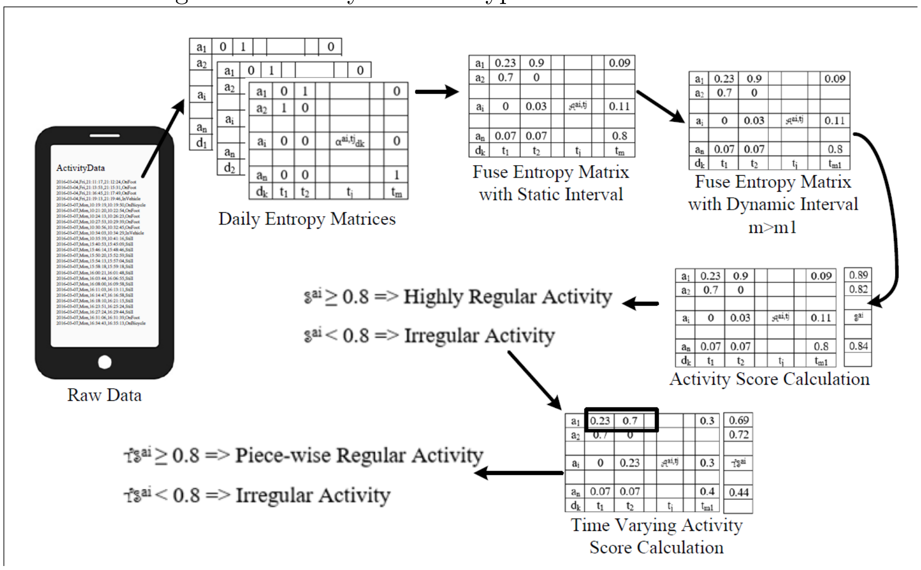
In our day-to-day life we perform several physical activities. Depending upon the activity patterns, users can be classified as highly routined, piece-wise routined, and routined-less users. We consider the activity pattern as highly routined if the users daily activities follow a similar pattern throughout the period. In case of partial similarity or existence of similar pattern found in some particular time stamp of a day, we classify as piece-wise routined. Other than these two categories, rest of the activity pattern are classified as routined-less. The schematic diagram of the activity pattern type identification model is shown in figure 1.

Dealing with the daily activity patterns, our primary requirement is streamless daily activity information of several users. For getting the continuous activity data, we use build-in sensors of smartphones. Initially, we log the sensor data with static time interval. Gradually, we increase the time interval keeping the accuracy of the data generation system same for minimizing the data storage. At the beginning of the model, the daily activity log is provided to generate the daily entropy matrix. The column and the row of the entropy matrix represents activity performed at any time stamp t_j and the time sequence of occurring any activity a_i. The daily entropy matrix is actually a boolean matrix which only contains the 0 or 1 element. At any time stamp t_j of day d_k, the entropy index of the activity a_i is denoted as:

$$\begin{aligned} \alpha_{d_k}^{a_i,t_j} &= 1 \text{ if } a_i \text{ performed at } t_j \text{ of day } d_k \\ &= 0 \text{ otherwise} \end{aligned} \tag{1}$$

We further combine the several daily entropy matrix information to find out fuse entropy matrix which helps to identify the regularity pattern of the user's lifestyle. Similar to the daily entropy matrix, fuse entropy matrix consists of activity occurrence information over the time. However, the sequence of several daily entropy index leads to form the fuse entropy matrix with values between 0

Figure 1: Activity Pattern Type Identification Model



and 1. The element of the fuse entropy matrix also called activity participation value is represented as:

$$\mathcal{A}^{a_i,t_j} = f(\alpha_{d_k}^{a_i,t_j}) \qquad \forall d_k \tag{2}$$

In addition to data collection using static time interval, we explore on the dynamic time interval. Primarily we increase the time interval uniformly throughout the time span. However, we found that the night activity is almost same for a large time interval whereas day activity incorporates much variety. Apart from this, if an activity performs daily at a specific time range with $\mathcal{A}^{a_i,t_j} = 1$, the used time intervals entirely infers a single time interval. Therefore, we dynamically distribute the time interval depending upon the activity and time. The importance of selecting the dynamic time interval is to track a fewer number of data points without compromising the accuracy of the data.

Based on the fuse entropy matrix, we plot the entropy graph for each activity. This shows the occurrence of the activity over the time. Towards the activity pattern type identification, we next goal is to calculate the activity score. It is simply a function of activity participation value which is defined as:

$$\mathcal{S}^{a_i} = g(\mathcal{A}^{a_i,t_j}) \qquad \forall t_j \tag{3}$$

The score value is significant for the recognition of the regular and irregular activities. Symbolically, we define that,

$$\begin{aligned} \mathcal{S}^{a_i} &\geq \mathcal{T}^{a_i} \Rightarrow \text{Highly Regular Activity} \\ &< \mathcal{T}^{a_i} \Rightarrow \text{Irregular Activity} \end{aligned} \tag{4}$$

where, $\mathcal{T}^{a_i}$ represents the threshold value of the activity score for the activity a_i. If the users have several highly regular activities, then those users follow routined lifestyle.

In our present day-to-day lifestyle, we found few people who followed routined activity schedule on a specific time of a day. To track those users activity, we again study the irregular activity data values and calculate the time varying activity score. This is computed as,

$$\mathcal{TS}^{a_i} = h(\mathcal{A}^{a_i,t_{k1}}, \mathcal{A}^{a_i,t_{k2}}, \cdots, \mathcal{A}^{a_i,t_{km}}) \quad \forall t_{ki} \in t_j \tag{5}$$

If the score value $\mathcal{TS}^{a_i}$ for a specific period of time $t_{k1} - t_{km}$ is greater than the threshold activity score value, we recommend that activity as piece-wise regular activity. We represent this with notation as,

$$\begin{aligned} \mathcal{TS}^{a_i} &\geq \mathcal{T}^{a_i} \Rightarrow \text{Piece-wise Regular Activity} \\ &< \mathcal{T}^{a_i} \Rightarrow \text{Irregular Activity} \end{aligned} \tag{6}$$

If the users have piece-wise regular activities, then those users follow piece-wise routined lifestyle. In the following sections, we discuss elaborately about characteristics of the highly and piece-wise routined lifestyle following users. The study of the routine-less users is beyond the scope of this work. Additionally, we observe that the activity pattern during the weekdays are significantly different from the activity pattern during the weekends. Therefore, we study separately activity patterns of weekdays and weekends.

3.2 Recommendation and Alert Generation Model

Due to heavy stressed life, people use to forget about their daily routine. Sometime people are not in such health condition to maintain their regular lifestyle. To track those people's activity, we initially propose a recommended system model and further extend this to an alert system.

Towards the goal of building recommendation system, we study the correlation between the adjacent time regular activities. As we observe that highly routined and piece-wise routined lifestyle follow an unique pattern, we consider only regular and piece-wise regular activities for our recommendation model. If two adjacent time activities $\mathcal{A}^{a_i,t_j}, \mathcal{A}^{a_i,t_{j+1}}$ are highly correlated, then prior to the occurrence of the prior time activity, the system generates an message to the user about his/her future activity. The correlation among the activities are defined as,

$$\mathcal{C}^{t_j,t_{j+1}} = \text{CoCoff}(\mathcal{A}^{a_i,t_j}, \mathcal{A}^{a_i,t_{j+1}}) \tag{7}$$

After sending the predicted activity message, the system slowly monitors the users current activity until the user reaches the time stamp zone with activity participation score 1. If the user performs different activity from the recommended one, the system generates an alert to the user informing about the deviation of his/her present activity.

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