Community based multi-group activity prediction and member identification

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1. INTRODUCTION

Background: Human activity recognition is a process by which a system can identify different human activities based on the observations on the individual's action and his/her surroundings [1]. However, human beings are social by nature and like to build community depending upon a common point of interest and common characteristics. Therefore, for getting complete knowledge of an individual's activities, community based activity recognition – an extension of single activity recognition [2] and group activity recognition [3] is necessary. Additionally, for community activity 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 certain change in the community activity pattern.

Scope: a scenario where we can contribute For demonstrating the scenario, a community of teachers and students can be considered. The common point of interest of the community or the community activity is learning. In this community, there are three types of study group, namely, general studies, social studies, and physical education studies. General studies incorporate lecture (one user standing and rest sitting) and experiment (all users standing). Social studies include tree plantation (majority sitting and a few standing) and lecture (one user standing and rest sitting). Physical education studies consist of exercise (all users except one standing, sitting, lay down) and lecture (one user standing and rest sitting). The problem we can address is, given a population, can we uniquely identify these three different classes, namely general study, social study and physical education studies?

Limitation of the literature and our contribution: Besides the recognition, the current state-of-art of group activity recognition focuses on the group affiliation detection and group formation [3]. However, for recognizing the multi-group activities within a community, a system is required to support the intra-group and inter-group activities as well as the activity of entire community. Intra-group activity recognition includes group formation and group detection within the community whereas inter-group activity recognition incorporates group member movement from one to another group. In addition to the identifying group activities, the proposed system should automatically detect the disaster. During disaster, one can expect a sharp change in the activity pattern inside the community. Therefore, a properly trained system may predict and identify the disaster and generate an alert of a possible emergency.

Current step towards contribution: For automatically identify the members of the community and their overall activity, individual member's identification is required. Every member in a community may not perform same activities at a specific time in a day. On the other side, the users' pattern may vary with the community activity. We can consider a scenario of walking activity. A person may walk in general at a speed of $4km/h$ but whenever that person walks with his/her friend, the speed reduces to $3km/h$. Therefore, long term analysis of users' activity is really essential to capture the routine of a particular user. In spite of a few works exist on accelerometer data based user identification system in the current state-of-art [4], to the best of our knowledge, activity based user identification is not yet studied. One of the major advantage of using smartphone is minimize the initial infrastructure setup cost. On the other side, the detection of similar types of activities such as cooking and brushing is really challenging using only smartphone.

Towards this direction, we develop a recommendation system to identify the users based on their past and current performed activities. The system continuously identifies the users and generate alert to the user only if the system monitors any different activity pattern. The combination of the recommendation and alert system will as a whole monitor the individual's daily activity and track the irregularity in his/her life by comparing different activities over the time scale.

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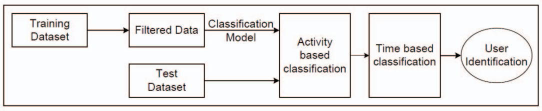
Figure 1: User Identification Model



2. PROPOSED SYSTEM

In this section, we discuss the user identification model as as presented in Figure 1. In this model, the activity leveled raw sensor data are used to train the system. As the real time tracked data usually contains noise data, we filter the raw data before feeding to the identification model. The classification model is used to train the system in two steps – Activity based classification and Time based classification. During the first step, the system selects two major activities performed in a day for each users. Then the system create bins for each activities and keep the users information in the respective activity bin based on highest activities value. In the second step, we use k-nn classifier to classify the users from the activity bin. Finally, the test dataset is inserted to the user identification model to identify the user rather members of the group.

3. PRELIMINARY EXPERIMENT AND RESULT

We initially use Microsoft Geolife dataset for user identification. The dataset contains GPS trajectory of 24 labeled users in a period of over three years. The activities are transportation mode that the user have chosen during the data tracking period. The major activities performed by the users in the dataset are 'Bike', 'Bus', 'Car', 'Subway', and 'Walk'. As the labeling of the activities performed by the users, it contains few noisy activity information. We remove those noisy labeling based on the speed of the users which are calculated from the respective users' GPS trace. Figure 2 shows before and after filtering of an user' activity data. Each line and symbol represent a particular day and activity, respectively.

We feed the filtered activity information to the activity based classification phase. In this phase, the system calculates activity with highest duration, maximum occurrence count based on the raw time and activity information of the users for each and every day. During the time based classification step, the system calculates first start time (180 minute bin), total duration (60 minute bin), max trip duration (60 minute bin), trip count from the previous step information. Finally, we use this features to classify the users within the activity bin by applying k-NN classifier. In addition to this two step classification process, we also perform one step user identification (Baseline experiment) using the raw GPS trace and date information. The user identification accuracy (in %) is shown in the Table 1. It shows that user identification using activity and time information outperforms for all the activities over the GPS and time information. Our model identifies the users with more than 70% accuracy except for walk activity. As the walking pattern of the users contains general movement of the user, we are receiving low accuracy. In future, we plan to remove general movement information from the current walking data for generating pure walk data.

Figure 2: Filtering Results

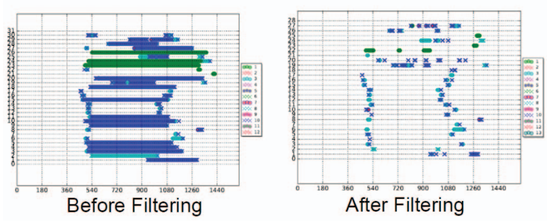


Table 1: Model Accuracy in % (using k-NN classifier)

Activity	Proposed Model	Baseline Model
Bike	**85**	69
Bus	**82**	65
Car	**83**	79
Subway	**70**	68
Walk	**44**	32

4. OBSERVATION

In this section, we summarize our current achievement. We have observed that our proposed system identifies the users with one an average accuracy 72.8%, whereas the baseline achieves 62.8%. Motivated by the results of these labeled dataset, we plan to extend this work using our own human daily activity dataset.

5. REFERENCES

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