A Large Scale Gathering System for Activity Data with Mobile Sensors

Yuichi HATTORI and Sozo INOUE
Kyushu Institute of Technology,
1-1 Sensui-cho, Tobata-ku, Kitakyushu,
804-8550, Japan.
sozo@mns.kyutech.ac.jp

Go HIRAKAWA
Network Application Engineering Laboratories Ltd,
1-4-4-6, Hakata-eki-mae, Hakata-ku, Fukuoka,
Fukuoka, Japan.
hirakawa@nalab.jp

Abstract

In this paper, we show a large-scale activity gathering system with mobile sensor devices such as smart phones and accelerometers. We gathered over 35,000 activity data points from more than 200 people over approximately 13 months. We describe the design rationale of the system, and analyze the gathered data through statistics, clustering, and application of an existing activity recognition method. Our results show that there is a challenging field for activity recognition in larger-scale activity data.

1 Introduction

If human activity can be objectively measured, we can expect various applications. For example, lifestyle aspects can be quantified and used for prevention of lifestyle-related diseases.

In this research, we aim to gather open data sets for evaluating activity recognition methods which already exist or will be proposed in the future. For this, we developed a large-scale activity data gathering system named *ALKAN*. ALKAN is a server-client system to gather a large number of missions with mobile sensor devices such as smart phones with accelerometers. It enables a simple way of recording, and semi-automatic way of uploading activities.

In this paper, we show the design of ALKAN, and show the data obtained by large-scale experiments by over 200 users and over 35,000 activities. It reveals new challenges for activity recognition, in the sense that there are more complex situations in real activities than laboratory settings.

This paper is organized as follows. Related work is described in Section 2. The ALKAN system is described in Section 3. Gathered activity data are overviewed in Section 4. Section 5 shows the nature of gathered data by applying an existing activity recognition method. Section 6 gives the summary and discussion for future work.

2 Related Work

In the literature, a lot of work has tried to recognize activities with sensor devices, but most of them acquire activity data in semi-artificial environments, and the users have been instructed to make certain movements. In contrast to these research methods, our work collects large-scale activity data through daily, real life movement.

Bao and Intille discusses how to learn activity recognition from annotation data of users[1]. They explained the procedures and examples of each activities in advance to users, and eliminated the variance of annotation. Upon which, they collected the data of 5 sensors on the body, and obtained 84% of accuracy. Our work also uses parts of the same feature vectors as Bao et. al., but our work use single sensor, and we focus on the system to enable gathering activity data.

Berchtold et. al. propose an activity recognition service with mobile phones and achieves 97% accuracy at best for 20 subjects[2]. While our system is similar to this work, our system focuses on gathering open data for activities with accurate labels with low stress.

HASC Challenge is a promotion to gather open activity data from multiple laboratories, and has 6,700 accelerometer data from 540 subjects in total[3]. While their work is not a system proposal, our approach is to provide a platform system to gather activity data anytime and anywhere.

3 ALKAN System

To collect activity data efficiently, we developed a large-scale activity gathering system named ALKAN. Next we describe the requirement analysis and the system design.

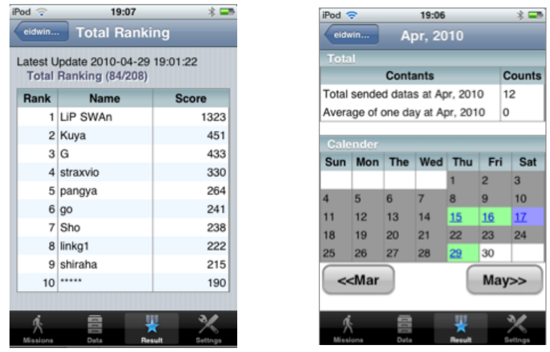
3.1 Requirements

For collecting large scale activity data, the following requirements are addressed.

1. Accuracy: labels, such as activity classes and the position of a device on the body, are accurately added.
2. Usability: users can record activity data anytime and anywhere, with minimum stress.
3. Motivation: users need motivation to promote recording activity data.

(a) (b)

Figure 1. Mission views in ALKAN: (a) select activity class, (b) select device position, and start sensing.



(a) (b)

Figure 2. Statistical information viewed in a web browser in ALKAN: (a) ranking of the number of activities, and (b) calendar of activity history.

4. Flexibility: labels must be extended if a new activity class or new position is discovered. Also, the utilization or application of the activity classes might be changed accordingly.

5. Scalability: the system can record data from numbers of users.

To address requirement 1, we introduce the idea of "mission". A *mission* is a sequence of choosing an activity class, choosing the position on the body, and performing the activity. Using this method, users can record activities anytime they want, and the label is accurately stamped within deviations of few seconds. For requirement 2, we adopted smart phones as mobile sensor devices. Most smart phones are equipped with 3-axis accelerometers, storage, and wireless communication, which enables recording activity data anytime. The data can be uploaded to the server when it is connected to the network. For requirement 3, we prepared several feedback services, which can be extended even for domain specific applications. For requirement 4, we provide feedback services that are dynamically updated to users through web browser interfaces on mobile devices. For requirement 5, smart phone client software is easy to scale up by installing client software through application deploying services. On the other hand, the server can be scaled up by existing distributed web technology.

3.2 System Architecture

The ALKAN system consists of mobile device clients and a server. A user records missions using the mobile device client. The information is uploaded to the server when it is online and accumulated in the server database. The user can view statistical information of the uploaded data, such as a calendar of activity history and rankings, by connecting to the web server through the mobile device or another web browser on a PC.

As for the client, we developed both for iOS and Android OS, which has the following functionalities:

- Mission execution: users first select an activity class as in Fig. 1(a) and a position as in Fig. 1(b). Then they start the activityand finish.The sensor can record GPS information and the three axis accelerometer data at 20Hz.
- View and send mission history: users can view the recorded mission history and add comments to each mission as an annotation. Users can also delete missions if s/he does not wish to upload to the server.
- View statistical information of the server: the software shows a web browser to access the server and show show statistical information, such as ranking as in Fig. 2(a) and calendar history as in Fig. 2(b).

The server gathers the activity data sent from clients, stores it to the database, and calculates and serves statistical information as a web server. An example of current statistical information displayed is the total/individual rankings of the number of executed missions among users. Other statistical information is the history of executed missions for each user. Users can view the start/end date/time, activity class, positions, and GPS information linked from a calendar format. This is similar to lifestyle-related services in which users records their own lifestyles.

The communication between a client and the server is done over HTTP. Upon connection, the client is authenticated by a user account, and XML or CSV-formatted data are passed between the client the server. In XML-formatted data, activity classes and position list are provided by the server to clients, and the metadata for each mission is uploaded. Sensor data is in CSV format and currently contains the data from the three axis accelerometer and GPS coordinates, but it can be easily extended by adding columns.

4 Collected Activity Data

Since December 3, 2009, we have delivered 216 iPod-Touchs as mobile sensors to university students and staff.

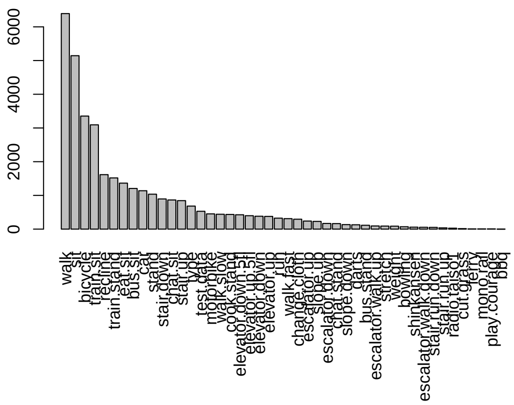


Figure 3. Histogram of collected activity classes

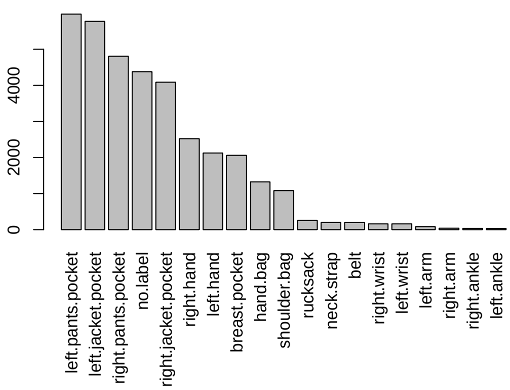


Figure 4. Histogram of collected device positions on the body

So far, 216 devices were delivered. We asked users a favor to collect activity data once a day on average. In this section, we investigate the property of gathered activity data.

The *activity classes*, which are the types of activities, are based on "Exercise Guide 2006" by the Ministry of Health Labour and Welfare, Japan, which gives a guideline to calculate *mets*: the strength of each activity. Additionally, some vehicle activities and classes for recreational events, such as "bbq" and "darts" were added. In total, we adopted 46 activity classes and 19 device positions.

We acquired activity data continuously, and reached 35,310 activity data at the beginning of February 2011. Fig. 3 shows the number of missions for each activity type. From the figure, we can see that simple daily life activities were the sources of most collected data.

Fig. 4 shows the number of missions for each position. Together with no labels, "pants pocket" and "jacket pockets" are the majority. Unsurprisingly, positions such as "ankle", "arm", and "belt" are hardly collected. "neck.strap" data are also rarely collected, but may be more frequently collected in office situations. The reason why "rucksack" data are not collected often likely because putting a device in and out of a rucksack is cumbersome, though it is more popular among students.

Next, to know the differences of recording durations among activity classes, we applied hierarchical cluster analysis with Ward's minimum variance method with euclidean distance for mean durations of each activity class. Fig. 5 is the dendrogram of the clustering result, after dropping the activities with under 100 missions. From the figure, we can first divide the activity classes with a non-negligible distance into 2 clusters.From this, we can infer that there are both classes of longer duration and shorter duration.

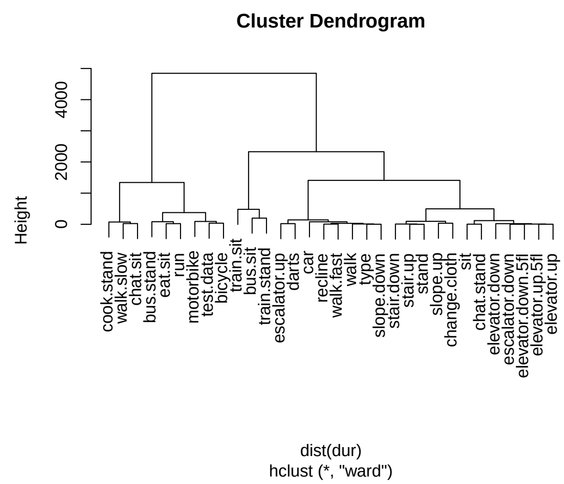


Figure 5. Dendrogram of hierarchical clusters of activity classes by durations

4.1 Lessons learned

From the long-running and large-scale data collection, we can conclude the following:

1. The ALKAN system is well designed and developed. Since the system is stable and the data has been collected constantly, we can infer that the requirements for usability, motivation, and scalability addressed in Sec.3.1 are satisfied as far as we have operated.
2. The number of data collected is unbalanced in activity classes. When we use the data for training the activity recognition model, there is no problem if the imbalance is caused by the probability distribution in natural life, but since this might also be caused by the ease of recording data for each activity using ALKAN, we have to balance them in some way.
3. The durations have distributions with specific variance, but it can be used for clustering activity classes. This means this knowledge can be used for improving recognition techniques for sequences of activities.

Table 1. F-measures(%) for each activity recognition algorithm

Activity Class	Rpart	NB	1-NN	SVM
eat.sit	10.74	5.19	17.58	22.40
bicycle	40.91	46.61	36.64	45.10
car	37.69	16.82	25.38	44.65
sit	33.77	55.09	30.42	35.76
stand	2.64	1.71	11.11	7.68
train.sit	36.77	8.79	23.83	22.48
train.stand	48.89	62.67	38.12	44.56
walk	54.16	50.95	42.03	53.09

5 Activity Recognition

In this section, we demonstrate activity recognition based on Bao et. al.[1]. The goal of this section is not to improve the accuracy of activity recognition, but to show the nature of gathered data by ALKAN using a standard method.

As addressed in Sec. 4.1, the number of data collected has large biases. Therefore, we sampled missions in a way that the sampled set has the same number of positions, activity classes among positions, users for each pair of position and activity, and samples for each combination of position, activity, and user. We adopted the position of "left.pants.pocket", picked 40 users, and sampled 1 activity data for each pair of activity and user. By this sampling, we obtained 8 activity classes.

We extracted feature vectors from the 3-axis accelerometer data. At first, we removed 10 seconds of the beginning and ending, since it will include the action of touching, attaching, or operating the mobile sensors. Thus, we omitted data under 20 seconds. After that, time windows of 5-second durations are extracted at first, shifting 2.5 seconds for each extraction. For the time window, we calculated mean, frequency-domain energy, and frequency-domain entropy for each axis, as in Bao and Intille. Moreover, correlations among axes, which are single sensor versions of Bao and Intille., are calculated.

Next, for training, we used 1) a recursive partitioning tree, 2) a naive Bayes classifier, 3) nearest neighbor classification, and 4) a support vector machine with radial basis function kernel for the feature vectors.

To evaluate the accuracy of recognition, we applied a special case of cross validation. We first picked up the subset for each activity, divided the users into n groups, and then divided the feature vectors according to the user groups. This is to maintain the balance of the numbers of each activity and user. The result is that users for training and testing are different. We took 3-fold cross validations.Tab. 1 is the F-measures for each activity class and algorithm.

From the table, we get worse accuracy shown by Bao and Intille[1], although we used the same feature vectors. Aside from using a single sensor, the following are considered:

- A mobile sensor is not firmly fixed to the body, but shaken in the pocket.
- The number of users is as large as 40 users. It may make the feature vectors non-general.
- Activity classes are similar to each other. As we can imagine, similar activity pairs such as "eat.sit"–"sit" and "sit"–"train.sit" are often mis-recognized.
- Actual activities may have varieties. Since users have performed activities in their own situations, environments could differ greatly on each trial.
- Labels are ambiguously understood by users.

Although these factors will decrease the recognition accuracy, they can produce a more challenging data set for activity recognition since these situations are more realistic than laboratory settings, which most of the existing work studied.

6 Conclusion

In this paper, we developed an activity data gathering system using mobile sensor devices. We also described the gathered data, and presented activity recognition results to show the nature of obtained data.

ALKAN data are open and free to use. The users of ALKAN have already agreed with opening the data to public. Open data is necessary since several techniques have been proposed for activity recognition. Methodologies must be evaluated using the same data set. ALKAN could be the platform for evaluating existing or future activity recognition methodologies.

References

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