HASC Challenge: Gathering Large Scale Human Activity Corpus for the Real-World Activity Understandings

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ABSTRACT
Understandings of human activity through wearable sensors will enable the next-generation human-oriented computing. However, most of researches on the activity recognition so far are based on small number of test subjects, and not well adapted for real world applications. To overcome the situation, we have started a project named "HASC Challenge" to collect a large scale human activity corpus. By the end of 2010, by the collaboration of 20 teams, more than 6700 accelerometer data with 540 subjects have been collected through our project. We also developed a tool named "HASC Tool" for management, evaluation and collection of the large number of activity sensor data.

Categories and Subject Descriptors
H.5.2 [**User Interfaces**]: Interaction styles (e.g., commands, menus, forms, direct manipulation)

General Terms
Measurement, Experimentation, Human Factors

Keywords
Activity Recognition, Activity Understandings, Wearable Computing, Accelerometer, Wearable Sensor, Large Scale Corpus.

1. INTRODUCTION
Recent advancement of MEMS technology enables the installation of small sized accelerometers or gyroscopes on various information devices. By using such activity sensors, these devices can estimate its posture or status. However, most of the current devices only utilize these sensors for simple orientation and gesture recognition. Deeper understandings and recognition of human activity through these sensors will enable the next-generation human-oriented computing. To enable the real-world application by these kinds of wearable sensors, a large scale human activity corpus might play an important role. Human activities vary from person to person. Therefore it is not easy to find suitable features of activity signals for the robust recognition. Most researches on the activity recognition so far [8]~[26] are based on small number of test subjects, and not well adapted for real world applications.

To overcome the situation, we have organized a consortium named "HASC: Human Activity Sensing Consortium", and started a collaborative project for gathering a large scale human activity corpus. This project is named "HASC Challenge." In this paper, we first explain the importance of the large scale corpus, and then report the first result of HASC Challenge 2010. Main contributions of this paper are the proposal of the standard data format of the activity corpus, an open source data management tool (HASC Tool), results of HASC Challenge2010 with more than 6700 activity data and the way of gathering large scale corpus. Anyone can obtain the whole HASC2010 corpus if they give us the small portion(5 subjects) of their own gathered data based on the HASC data format.[1]

[1] If you want to contribute to the HASC corpus, please check http://hasc.jp/en.

2. Importance of Large Scale Corpus for the Activity Recognition

There are several research fields which are boosted by the large scale corpus.

2.1 Large Scale Corpus in the Other Field

In the field of speech recognition, a large scale corpus plays a really important role. Most recent speech recognizers are based on a HMM acoustic-model and a statistical language model[1]. These models are developed through machine learning based on the large scale speech corpora. So, the qualities or recognition-rates of the speech recognizers are proportional with the scale of the underlined speech corpus. To improve the recognition quality or to extend the system to support the different situation, development of a high quality and large scale corpus is crucial. Most popular example of the speech corpus is “DARPA TIMIT” corpus [2,3]. Thanks to the development of this corpus, a lot of continuous speech recognizers work better.

In the in-car activity field, we already gathered a huge scale corpus(more than 800 subjects) for various purposes [4,5]. This corpus enables in-car related researches.

In the field of image recognition, the most popular example is the area of face recognition [6,7]. There are several databases for facial images. Some of them are freely available. This situation makes the fast improvement of the facial recognition technologies.

2.2 Corpus for Activity Recognition

As far as we know, there is no public large scale corpus for the activity recognition area. Of course, there are several researches with the some scale of experiments [8, 9]. However, any of them have not published the data or the algorithms. Related projects such as IMADE room[27] is created for recording interaction data using iCorpusStudio. ALKAN[28] gathers activity data using mobile phones from about 200 participants. In ALKAN, participants perform arbitrary number of activities, so the number of collected activities differs among activity types and sensor positions. A part of ALKAN data is included in the HASC2010 corpus. As we have mentioned in the above, sharing the databases/corpus is a key of the improvement in the pattern recognition research and development field.

3. HASC Challenge

To overcome the situation, we have decided to create a large scale corpus for activity recognition with founding the consortium HASC (Human Activity Sensing Consortium). However, there are several issues which cannot simply be decided such as sensor types, number of sensors, sampling frequency, position of sensors and the kinds of activities. If we decide the application of the corpus, these parameters can be easily decided. However, our purpose of the corpus gathering is to boost the research of the activity recognition, it is not simple. As a result of long discussion, we have decided to start gathering a single accelerometer sensor data of simple activities with various kinds of sensors, positions and sampling rates. By publishing the data with various kinds of sensors, we believe researchers can find the better configuration of activity recordings.

So, we have planned “HASC Challenge” for gathering the corpus and technological evaluation.

3.1 Rules

In the planning phase of the challenge, we consider the following issues.

- HASC Challenge is not a contest. It is a “Technology challenge.”
- Each participant should gather at least five subjects with the following activities.
    - 5 set of 6 activities(20 seconds): stay, walk, jogging, skip, stair-up and stair-down.
    - 120 seconds of labeled activity sequence which includes all of above 6 activities. (Each activity should be longer than 5 sec).
- Each participant can use any kind of sensor but it should be available in the market.
- Activity data must be described in the HASC data format.
- Each participant will get all the activity data without label data of the sequence data. They can submit the result of the recognition in the label data format or submit the recognition algorithm.
- HASC steering member will evaluate the recognition rate.

3.2 Result of HASC Challenge2010

HASC Challenge 2010 symposium was held on Dec 8, 2010. Before the symposium, 20 teams have submitted their activity data. Finally, we got activity data of 540 subjects and 96 subjects with full dataset. Total number of activity data files is 6791 and total size is 966Mbytes (Table 1). The major types of sensors are iPhone / iPod Touch, and WAA-series (ATR). Distribution of weight and height of subjects are plotted on Fig. 1.

We also got the recognition result from 6 teams. However, this challenge is the first time and most of the participants were not experts of the activity recognition technology. So the recognition results are ranged from 38% to 72%.

From the experience of HASC Challenge 2010, we confirm the strong requirements of the activity corpus and the toolkit for the activity recognition. We also confirm the difficulty of the multi-party large scale data acquisition. We have defined the basic HASC data format, but we have not listed up all possibility of the meta-data such as sensor positions, subject’s shoes types and floor types. Every activity file has its own meta-data information. This means that we have to check 6791 meta-data files to standardize the vocabulary. Without the support of HASC Tool, we cannot check and handle this kind of large data files. Good tool and automation are crucial in this kind of work.

Table 1. Number of Acquired Files in HASC Challenge2010

Gender	Number of Subjects	Number of Files
Male	89	4032
Female	12	341
Unknown	439	2418
Total	540	6791

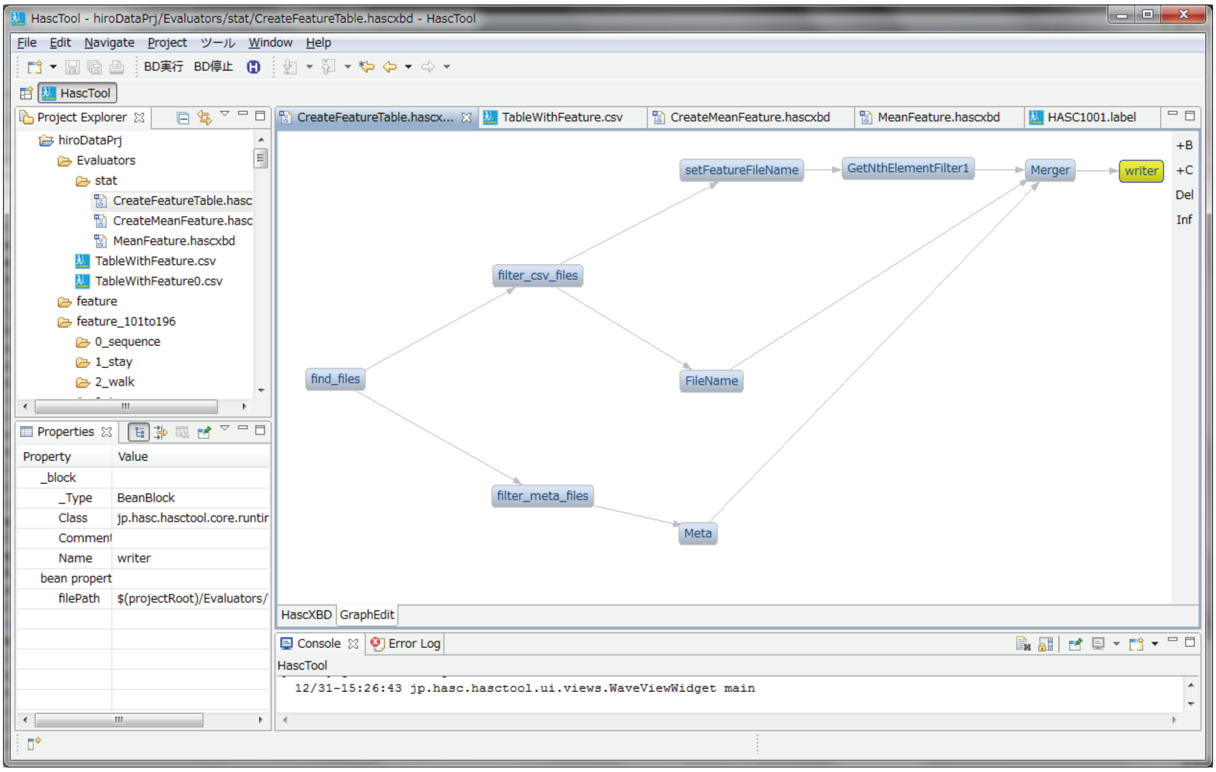

Figure 2. HASC Tool (graph editing mode).

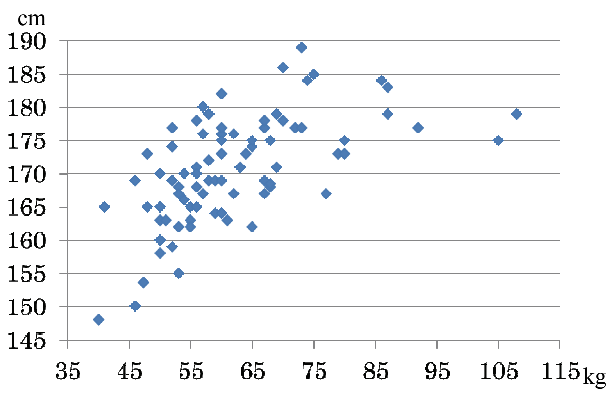

Figure 1. Subjects' Weight and Height on HASC corpus

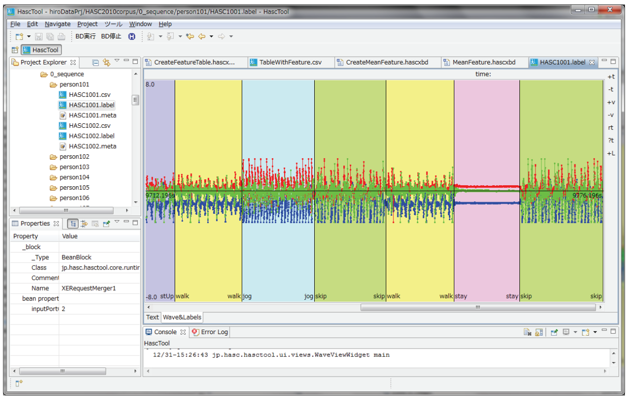

Figure 3. HASC Tool (labeling mode)

4. Toolkit for Activity Recognition

To boost the data handling and trial-and-error process of the signal processing, we have developed a new tool named "HASC Tool." Fig. 2 and 3 show screen images of HASC Tool[2]. HASC Tool is developed with Java and based on the famous IDE called Eclipse RCP.

HASC Tool has following features.

- Showing accelerometer signals and label data (Fig.3)
- Create a process block diagram graph called "XBD." By using "XBD," one can easily automate the various signal processing and file processing(Fig.2). Without this kind of automation, handling thousands of files is not easy.
- Real time / offline data acquisition with wireless sensors
- Connection with Weka Toolkit[3]

By using HASC Tool, we can exchange the process of activity recognition using XBD files.

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[2] HASC Tool is Apache 2.0 Licensed open source software. You can download it from http://en.sourceforge.jp/projects/hasc/

[3] Weka Toolkit is a data mining/ machine learning tool developed by Waikato Univ. (http://www.cs.waikato.ac.nz/ml/weka/)

4.1 HASC Data Format for Activity Data

To share the activity data or processing functions among the researchers and developers, activity data format must be standardized. We have defined the following data format as HASC data format for activity understandings.

- Activity Accelerometer data (.csv)
  We defined accelerometer data as a simple comma-separated values(CSV) format with time stamp and x, y, z axis-acceleration data. Time stamp is in the second time scale with floating point. So any sampling rate data can be stored with this format. Time stamp is not required to start from zero. Accelerations are in the gravitational acceleration unit (1G = 9.80665m/s^2).

  Sample of Accelerometer data : HASC1001.csv

```
9656.196248,-0.905609,-0.199234,0.144897
9656.206375,-0.905609,-0.163010,0.181122
9656.217099,-0.923721,-0.126785,0.217346
9656.226533,-0.905609,-0.090561,0.144897
  ..
```

- Label data format (.label)
  For each continuous activity data, “tag” or “label” is required to put on the activity time period. We defined a label data format as a CSV format with start-time, end-time and label-name.

  Sample of Label data : HASC1001.label

```
#targetfile: 0_sequence/person101/HASC1001.csv
9656.196248,9666.196248,walk
9666.196248,9676.251,jog
9676.251,9684.387,stay
9684.387,9696.387,stDown
  ..
```

  Line starts from ‘#targetfile:’ denotes the reference to the accelerometer data. This helps HASC Tool to show the label with the wave data.

- Meta-data information format (.meta)
  For each acceleration data, related information of the subject and the data acquisition condition are important. We defined a meta-data file format to record subject’s gender, weight, height, sensor’s terminal type, sampling rate and position. The style of the format is simple “attribute:value.”

  Sample of Meata-data file : HASC1001.meta

```
TerminalType: Apple;iPod touch
Frequency(Hz): 100
Activity: sequence
Gender: male
Height(cm):179
Weight(kg):69
Shoes: mule
Floor: asphalt
Place: outdoor
SensorPosition: waist pocket
SensorMount: free
```

5. CONCLUSION

In HASC Challenge 2010, we have gathered more than 6400 activity accelerometer data from 20 teams. From the experience, we confirm the strong demands for activity corpus from researchers and companies. We will continue to gather and make HASC Tool for the activity recognition standard toolkit.

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