Effects of Number of Subjects on Activity Recognition - Findings from HASC2010corpus -

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ABSTRACT
In recent years, there are many researches about the human activity recognition. In the most of these researches, the activity recognition experiments are performed with only a small number of subjects. Additionally, there is no public database of activity data or reference information about the suitable number of subjects. To overcome the situation, we have collected "HASC2010corpus" with more than 6000 activity data from more than 500 test subjects. In this paper, we report the result of the experiments on the effects of the number of subjects as a basic reference for the field of activity recognition research. By using the part of HASC2010corpus, we performed a large number of evaluations with the user-dependent / user-independent data, different number of the features, and the different number of subjects. In the case of using user-dependent data, decision tree classifiers showed the activity recognition results with an overall accuracy rate of 70% on 67 subjects. The result of experiments shows the importance of the large number of subjects especially on the user-independent data. The result also suggests that by using more advanced features and more large number of subjects, the activity recognition rate might be improved.

Categories and Subject Descriptors
I.5.4 [Applications]: Signal processing

General Terms
Experimentation

Keywords
Activity Recognition, Activity Understandings, Wearable Computing, Accelerometer, Wearable Sensor, Large Scale Corpus, Number of Subjects

1. INTRODUCTION
Recent advancement of MEMS technology enables the installation of small sized accelerometers or gyroscopes on the various kinds of information devices. By using such activity sensors, these devices can estimate posture or status. However, most of current devices only utilize these sensors for simple orientation and gesture recognition. Deeper understanding 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, an advanced level human activity recognition technology is required. Human activities vary from person to person. So it is not easy to find suitable features of activity signals for the robust recognition. Most of researches on the activity recognition so far [1]-[12] are based on small number of subjects, and not well adapted for real world application. Additionally, there is no public database of activity data or reference information about the suitable number of subjects.

To overcome the situation, we have made a consortium named "HASC: Human Activity Sensing Consortium", and started a collaboration project for gathering a large scale human activity corpus. This project is named "HASC Challenge". To date, we have gathered more than 6000 activity data from more than 500 test subjects. We called the corpus as "HASC2010corpus. [1]"

In this paper, we report the result of the experiments on the effects of the number of subjects as a basic reference for the field of activity recognition research. By using the part of HASC2010corpus, we performed a large number of evaluations with the user-dependent / user-independent data, different number of the features, and the different number of subjects.

In the following section, we first explain the related activity recognition researches, and then report the first result of HASC Challenge2010. In section 4, we report the result of the experiment. The main contribution of this paper is the analysis on the number of subjects with user-dependent and user-independent data from HASC2010corpus. By using the publicly available corpus and HASC Tool, anyone can easily follow our result. So this can be the reference information in the field of activity recognition.

2. Related Work
There are many researches on the field of activity recognition. In the following, we show some of them (Table 1).

Bao [5] applied biaxial accelerometer sensor for recognition of 20 types of activities such as walk, run, and bicycle. The sensors were attached to subject's hip, wrist, arm, ankle, and thigh. Recognition accuracy of the activities were over 80% by using 20 subjects' data.

Chang [4] attempted to recognize 9 types of weight exercises such as bench press and dead lift using dumbbell for well-balanced weight exercise. Two accelerometers are attached subject's grove and waistband. Recognition accuracy of the activities was around 90% by using 10 subject's data.

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

Lee [13] proposed a determination method of user's location and transition by using two kinds of sensor modules. One module includes a biaxial accelerometer attached to the subject's waist pocket. The other module includes a digital compass attached to the subject's waistband. Recognition accuracy of the activities was over 90% by using 8 subject's data.

Lester[6] applied the sensor board which includes eight kinds of sensors for recognition of 8 types of activities such as walk, stand, sit, stairs up and stairs down. Lester also targeted recognition of 3 types of sensor positions such as waist, shoulder and arm. Recognition accuracy of the activities was around 96 % by using 2 subject's data.

Berchtold [1] proposed mobile device "ActiServ" which includes activity recognition system. In this research, 10 types of activities such as sit, stand and bicycle is recognized. As a result, ActiServ produces recognition rates of over 97% for the individual user.

As you can see, these researches on the activity recognition used different approaches in terms of the sensor type, the number of sensors, the sensor placement, and the number of subjects. Therefore these researches cannot easily be compared with each other. Additionally, it is not well known how many subjects are needed suitable for the activity recognition.

Table 1. Related Works of Activity Recognition using Sensors

	Target activity	Num. of Sensors	Num. of Subjects	Recognition accuracy
Bao [5]	walk, run, bicycle, etc. (20 types)	5	20	over 80%
Chang [4]	weight exercises (e.g. bench press) (9 types)	2	10	around 90%
Lee[13]	ambulation	2	8	over 92%
Lester[6]	walk, stand, sit, stairs up, stairs down, etc. (8 types)	8	2	around 96%
Berchtold [1]	walk, stand, bicycles, etc.(10 types)	2	20	over 97%

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 be simply decided, such as sensor types, number of sensors, sampling frequency, sensor placement and the kinds of activities. Upon determining 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 a 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" to gathering the corpus and technological evaluation.

3.1 HASC Corpus

On HASC Challenge2010, we constructed "HASC2010corpus" which included large variety of activity data with different sensor

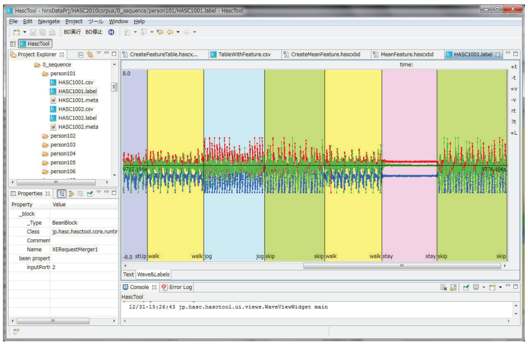

Figure 1. HASC Tool (labeling mode)

types, sensor placements and sampling rates. For each subject, we required to collect both the "learning data" and the "sequence data." The learning data consisted of 6 activities such as stay, walk, jog, skip, stair up and stair down. As learning data, we collected 5 sets of 6 activities from each subject which was measured for 20 seconds. As sequence data, we used 120 seconds of labeled activity data which included all of the above 6 activities. In the sequence data, each activity must be longer than 5 seconds.

We got 540 subjects activity data and 96 subjects with full dataset. The total number of activity data file was 6791 which included 25.8 million measurement points comprising a total size of 966Mbytes. The total measurement time was 30.1 hours while the major types of sensors used were iPhone / iPod Touch, and WAA-series (ATR).

From the experience of HASC Challenge2010, we confirmed the strong requirements of the activity corpus and also the toolkit for the activity recognition.

3.2 HASC Tool

To boost the data handling and trial and error process of the signal processing, we have developed a new tool named "HASC Tool"[2] (Fig1). HASC Tool is based on the famous IDE called Eclipse and connected with WEKA Toolkit[3]. By using HASC Tool, we can easily perform the various routine works such as this evaluation simply by using XBD files.

4. ANALYSIS ON NUMBER OF SUBJECT

In this section, we report the result of the experiments on the effects of the number of subjects as a basic reference for the field of activity recognition research. By using the part of HASC2010corpus, we performed a large number of evaluations with the user-dependent / user-independent data. Different number of the features, and the different number of subjects.

4.1 Activity Data Set

We experimented about human activity recognition from HASC 2010corpus. In this experiment, we used the "learning data" (5 set of 20 seconds data for 6 activities from each subject) for the

[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/)

learning data of machine learning. We also used the "sequence data" (120 seconds of continuous multi-activity data with label) as test data. We selected the activity data which is recorded with the "waist" sensor placement. Finally, we selected 67 subjects which match with these requirements from HASC2010corpus.

4.2 Selection of Feature

Bao, Chang and Lee conducted the activity recognition by using some features of activity data and applied them to machine learning. They used various features such as mean, variance, standard deviations, energy and correlation features. From the purpose of this experiment to be a basic reference data, we used only simple features which are used by many researchers.

In HASC2010corpus, activity data is a sequence of 3-axis accelerometer signal. We first calculate the norm of 3-axis acceleration data. Then we evaluated the activity data by using only two features of mean and variance of norm. We then evaluated the activity data using seven features such as mean, variance, energy of each frequency band (four types) and zero crossing rates. In each experiment, features were computed on 256 samples windows of acceleration data with 64 samples overlapping between consecutive windows. We used C4.5 decision tree [9] on WEKA toolkit.

4.3 User-dependent Data Analysis

In the user-dependent data analysis, we conducted the activity recognition by gradually increasing the number of subjects from 1 to 67. When the number of subjects is 1 or 67, activity recognition was performed for all cases. When the number of subjects is 5, 10, 20, 30, 40, 50 and 60, we created some groups by selecting subject randomly. When the number of subjects is between 5 and 60, the total number of all cases is too large. So we just randomly selected 20 sets of subjects for each number of subjects.

Figure 2 shows the results of the overall activity recognition rate by user-dependent data analysis. In this figure, the number of subjects is shown on the x-axis while recognition rate is shown on the y-axis. The graph shows the mean values of the recognition rate and the vertical lines on the graph show the standard deviation of each number of subjects.

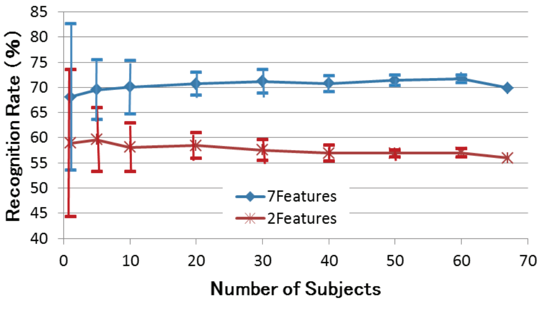

Figure 2. Activity Recognition Using User-dependent Data.

The activity recognition rate by using 2 features was 55-60%. The activity recognition rate by using 7 features was 68-73%, and it always outperformed the rate by using 2 features. Table 2 is confusion matrix by 67 subjects' data on 7 features. This is result of activity recognition by using user-dependent data.

Table 2. Confusion Matrix of 67 Subjects with 7 Features On User-dependent Data.

%	stay	walk	jog	skip	stUp	stDown
stay	90.06	2.02	1.20	0.97	2.73	3.03
walk	1.53	52.81	3.45	2.81	25.34	14.07
jog	0.93	3.32	70.55	16.20	1.42	7.58
skip	1.32	1.07	16.13	75.92	2.34	3.22
stUp	1.61	18.47	0.67	0.40	58.69	20.16
stDown	3.37	7.00	1.03	1.24	15.90	71.46
Overall	69.91					

4.4 User-independent Data Analysis

The user-dependent data analysis is not enough to apply activity recognition to the real world. It is impossible to collect all users learning data. We conducted the user-independent data analysis.

In the user-independent data analysis, we conducted the activity recognition by gradually increasing the number of subjects from 1 to 60. When the number of subjects is 5, 10, 20, 30, 40, 50 and 60, we created some groups by selecting subject randomly. When number of subjects is 1, activity recognition was performed for all cases. When number of subjects is between 5 and 60, the total number of all cases is too large. So we just randomly selected 20 sets for each number of subjects. This means that when we use n subjects as a learning data, we use the rest of 67-n subjects for test data.

The Figure 3 shows the results of the overall activity recognition rate by the user-independent data analysis. The format of Figure 3 is same as Figure 2.

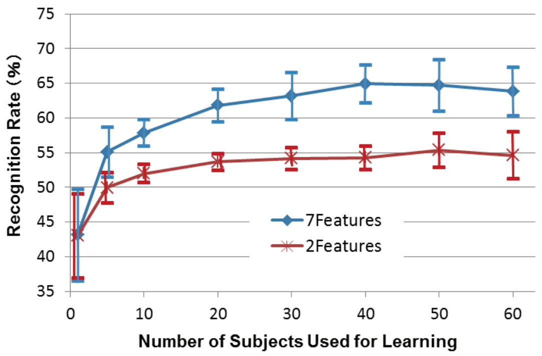

Figure 3. Activity Recognition Using User-independent Data.

The activity recognition rate by using 2 features was less than 57%, and the activity recognition rate by using 7 features was less than 66%. The recognition rate of 7 features was always higher than 2 features. The activity recognition rate by using user-independent data was less than using user-dependent data. The recognition rate by using 7 features and 2 features tended to rise as the number of subjects increases. However when number of subjects is larger than 50, this rate tend to decline. Table 3 is confusion matrix by 60 subjects data on 7 features. This is the best result of activity recognition in 20 set by using user-independent data.

Table 3. Confusion Matrix of 60 Subjects with 7 Features on User-independent Data.

%	stay	walk	jog	skip	stUp	stDown
stay	91.51	2.00	0.21	0.41	4.72	1.15
walk	0.37	71.16	3.81	1.62	17.27	5.76
jog	0.06	1.53	70.40	16.26	2.10	9.66
skip	1.03	4.93	38.97	50.70	2.68	1.68
stUp	1.71	26.09	0.58	0.00	51.54	20.09
stDown	2.78	14.74	0.00	0.70	1.83	79.95
Overall	69.21					

4.5 Discussion

We pointed out the necessity of large-scale human activity data at AH2011[10] and constructed large-scale human activity data named HASC2010corpus at HASC Challenge2010. Our user-dependent data analysis shows that the activity recognition rate is unrelated to the number of subjects. We think that the reason for this lack of correlation is caused by the closeness of the data. For each closed experiment, the activity data of the test subject is contained in the learning data. This may make the learnt decision tree to be partially adapted to the subject. For the real world application, it is not suitable that the system requires pre-acquisition of the user's activity data. In the user-independent data analysis, if the number of subject is smaller than 50, the activity recognition rate by using 7 features and 2features tends to rise as increasing the number of subjects. The result is not high compared to the user-dependent data analysis. In these experiments, we just used basic features which are popularly used in the field of activity recognition. It is probable that the activity recognition rate can be improved by using more advanced features and larger–scale activity corpus.

5. CONCLUSION

In this paper, we report the human activity recognition experiments on the user-dependent / user-independent activity data to confirm the effect of the number of subjects for the learning data. From results of these experiments, we confirmed importance of the large number of subjects especially for the user-independent data. Openness of the data is very important in the real world. The results also suggest that by using more advanced features and more large number of subjects, the activity recognition rate might be improved.

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