

Master's Thesis

Modeling and Discovering Human Behavior from Smartphone Sensing Life-Log Data

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A dissertation submitted in partial fulfillment of the requirements for the Master of Engineering in Computer Engineering.

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(Abstract)

Today, personal data is becoming a new economic asset. Personal data which generated from our smartphone can be used for many purposes such as identification, recommendation system, and etc. In this research, we have collected user personal data from many users, around 37 students during 2 months. We develop new approach that can be used to identify human behavior motifs based on user personal data from their smartphone. The data which generated by users smartphone are heterogeneous because those data produced by variety of sensors. Sometimes, the data from one or more sensors does not available. To handle that problem, we use many of sensors and tried to combine them rather than only use one of sensor. We have implemented our approach to demonstrate the feasibility and effectiveness of our approach to identify human behavior. Furthermore, we evaluate our approach and present the details in this thesis.

1. INTRODUCTION

1.1 Overview

Nowadays, smartphone capability has increased significantly. Smartphone has equipped with high processor, bigger memory, bigger storage and etc. With this equipment, smartphone has capability to running complex application. Many sensors also has embedded to the smartphone. With those sensors and log capability of smartphone, we can develop many useful system or application in different domain such as healthcare (elderly monitoring system [1] [2]) human fall detection [3] [4], transportation (monitoring road and traffic condition [5]), personal [6] [7] and social behavior [8] [9], environmental monitoring (pollution [10], weather) and etc. To develop such system, we have to collect the user personal data and then analyze it. In this research, we have collected user personal data to identify human behavior. Every person has unique behavior (behavior model). Example cases, in the context of daily behavior: Alice is research student in one of university in Korea. Every working day, he wakes up, takes a shower, breakfast, and goes to his campus at 8:40 AM. He living in dormitory, he walks from dormitory to his lab (campus) takes 10 minutes. Usually, he arrived in his lab at 9 AM and then sits on his chair and starts working. This example is one of the human daily routine in working day. Based on this story, we can used Alice's smartphone sensor data to define and build Alice's behavior model.

There are two ways to collect personal data from the users based on user involvement. First, participatory sensing and then the second, opportunistic sensing. Participatory sensing means the application still need user's intervention to complete their task. The examples for such application need user to taking text input for each time period, taking picture and etc. On

the other hand, opportunistic sensing means application does not need user's intervention to complete their task, users not involved in making decisions instead smart phone itself make decisions according to the sensed and stored data. In this thesis, to collect user personal data, we follow opportunistic method because we do not want to bothering user much. Based on those data, we identified human behavior and create their behavior model.

1.2 Contribution

Our contribution in this work are: (1) We have developed an application data collector which can collect user personal data and its following opportunistic method. This application does not bothering users, there is nothing to do after user install this application. (2) We have developed system that can identify human behavior based on their smartphone personal data. (3) Instead of identifying human behavior we also have developed system which can create human behavior model.

2. DATASET

2.1 Data Acquisition

This section explain about the data acquisition, we divide this section to three main parts are: application data collector, dataset description, and dataset that used in this research. Application data collector's section explain about our application which is used in this research to collect user personal data. Dataset description's section explain about our dataset itself, dataset that we have collected from user's smartphone. Dataset that used in this research's section explain about the lists of data that we used in this research. Not all data that we collected are used in this research, we only use several data which related with our research goals.



Figure 2-1. Funf Open Sensing Framework



Figure 2-2. User personal database in user smartphone

2.1.1 Application Data Collector

To develop application data collector, we do not create from scratch, we use Funf library. The Funf Open Sensing Framework is an Android-based extensible framework, originally developed at the MIT Media Lab, for doing phone-based mobile sensing. Funf provides a reusable set of functionalities enabling the collection and configuration for a broad range of data types. Funf is open sourced under the LGPL license. Figure 2-1 shows Funf framework can collect many of sensing from smartphone such location, movement, communication and usage, social proximity, and many more. In this thesis, we do not describe details about Funf

architecture, more details about Funf architecture can be seen in the main site of Funf¹ and also Funf developer site².

Table 2-1. List of probes and time period of recording

No.	Probes	Interval,duration (s)
1.	Location	300
2.	Wi-Fi	300
3.	Bluetooth	300
4.	Battery	300
5.	Call Log	86400
6.	SMS Log	86400
7.	Applications Installed	86400
8.	Hardware Info	86400
9.	Contacts	86400
10.	Browser Search Log	86400
11.	Browser Bookmark	86400
12.	Light Sensor	120,0.07
13.	Proximity	120,0.07
14.	Temperature	120,0.07
15.	Magnetic Field	120,0.07
16.	Pressure	120,0.07
17.	Activity Log	120,0.07
18.	Screen Status	120,0.07
19.	Running Application	120,0.07

2.1.2 Dataset Description

Our application follows opportunistic sensing method. It because we do not want to bothering user much. To do that, we have to define the time (interval and duration) first in our application. Interval means how many times in second system will send data request to the smartphone. An example, we set interval 300 seconds means 5 minutes so application will

¹ <http://www.funf.org/>

²² <https://code.google.com/p/funf-open-sensing-framework/>

request and store the data for every 5 minutes. Duration is the measure of continuance of any object or event in time. Duration is used in sensor's data because without duration is useless to collect the sensors data. An example of duration setting, when we set interval 120 seconds or two minutes and duration 0.07 s means the application will send data request to the smartphone for every 2 minutes and the system will record the data during 0.07 seconds. Table 2-1 shows the interval and duration of each probes. Those interval and duration have been tested and we thought those setting was optimum one. We can change those setting by change the value on the string.xml in android project. Figure 2-3 shows the string.xml file in the android project directory and Figure 2-4 shows inside the string.xml file, we can change the values of interval and duration in that file.

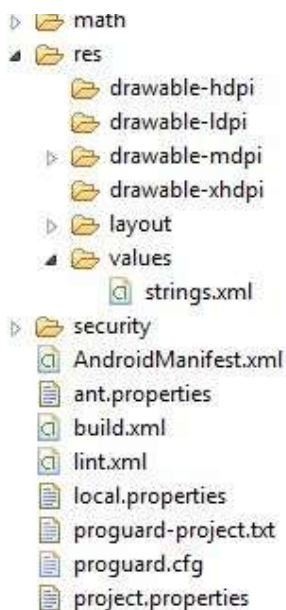


Figure 2-3. Strings.xml file in project directory

```
{
  "@type": "edu.mit.media.funf.probe.builtin.ContactProbe",
  "@schedule": {
    "interval": 86400,
    "opportunistic": true,
    "strict": true
  }
},

{
  "@type": "edu.mit.media.funf.probe.builtin.LightSensorProbe",
  "@schedule": {
    "interval": 120,
    "duration": 0.07,
    "opportunistic": true,
    "strict": true
  }
},

{
  "@type": "edu.mit.media.funf.probe.builtin.ProximitySensorProbe",
  "@schedule": {
    "interval": 120,
    "duration": 0.07,
    "opportunistic": true,
    "strict": true
  }
},
}
```

Figure 2-4. Inside the string.xml file

To make easy, we classify the data that we want to collect to three of categorization, are:

1. On Request Data (Current Data)
2. Historical Data (Saved in Android database system)
3. Continuous Data (Sensors data)

On request data means we ask the current values (information) from android system such as location, battery, nearby Bluetooth and etc. Historical data means the data that stored in android database system so we only need to access and copy those data from android database system to our application, the example of historical data are contact, call log, SMS log, and etc. Continuous data means we can get those data continuously such as sensor data (accelerometer, gyroscope, magnetic field, and etc).

We are living in time dimension space, every event has time variable. In our data, every value that returned from the user smartphone has timestamp value. Funf already has features to define timestamp, Funf using UNIX UTC (Coordinated Universal Time) which is (Unix time or POSIX time or Unix timestamp) is the number of seconds that have elapsed since January 1, 1970. To convert UNIX time to the human readable time, we can use POSIX function in R or another programming language. Data that we collected using our application will be stored in SQLite database format with (*.db) extension, the view of data can be seen in Figure 2-2. To open those database, we can use SQLite browser that can be download in SQLite browser main site³. The table in all of databases contain four columns, *_id* is automatically generated by database engine, *name* means the name of probes (sensors), *timestamp* column is time when system store the data to the phone's storage, and *value* is the value that returned from the sensors. Table 2-2 shows the list of probes (sensor

³ <http://sqlitebrowser.org/>

data) that provided by our application. The total of probes which provided by our application are 19 probes and we use 9 probes in this research.

Table 2-2. List of probes and types

No.	Name of Probes	Explanation	Used
On Request Data			
1.	SimpleLocationProbe	GPS data (user location)	X
2.	WifiProbe	Nearby Wi-Fi signals	X
3.	BluetoothProbe	Nearby Bluetooth signals	X
4.	BatteryProbe	Battery status	X
Historical Data			
1.	CallLogProbe	User call log	X
2.	SmsProbe	User SMS log	X
3.	ApplicationsProbe	List of application installed	
4.	HardwareInfoProbe	User's smartphone hardware info	
5.	BrowserBookmarksProbe	User Bookmarks	
6.	BrowserSearchesProbe	User Browser log	
7.	ContactProbe	User contact (phonebook)	
Continuous Data			
1.	LightSensorProbe	Measures the ambient light level (illumination) in lx	
2.	ProximitySensorProbe	Measures the proximity of an object in cm relative to the view screen of a device.	
3.	TemperatureSensorProbe	Measures the temperature of the device in degrees Celsius (°C).	
4.	MagneticFieldSensorProbe	Measures the ambient geomagnetic field (x, y, z) in μT	
5.	PressureSensorProbe	Measures the ambient air pressure in hPa or mbar.	
6.	ScreenProbe	Screen phone (on and off)	X
7.	RunningApplicationsProbe	List of running applications	X
8.	ActivityProbe	User activity log based on accelerometer sensor (none, low, and high activity)	X

To understand the value from each probes, we give the example value of location data, the name of probe is "*Simple Location Probe*". Location is one of the most important information

from the user. Location value that returned by our application is like in the box below:

```
{ "mAccuracy":1625.0, "mAltitude":0.0, "mBearing":0.0, "mElapsedRealtimeNanos":21989372000000, "mExtras":{ "networkLocationSource":"cached", "networkLocationType":"cell", "noGPSLocation":{ "mAccuracy":1625.0, "mAltitude":0.0, "mBearing":0.0, "mElapsedRealtimeNanos":21989372000000, "mHasAccuracy":true, "mHasAltitude":false, "mHasBearing":false, "mHasSpeed":false, "mIsFromMockProvider":false, "mLatitude":35.1837595, "mLongitude":126.9052379, "mProvider":"network", "mSpeed":0.0, "mTime":1403484137091}, "travelState":"stationary"}, "mHasAccuracy":true, "mHasAltitude":false, "mHasBearing":false, "mHasSpeed":false, "mIsFromMockProvider":false, "mLatitude":35.1837595, "mLongitude":126.9052379, "mProvider":"network", "mSpeed":0.0, "mTime":1403484137091, "timestamp":1403484137.255}
```

That data which from location probes is representing a geographic location. A location can consist of a latitude, longitude, timestamp, and other information such as bearing, altitude, velocity and etc. All locations generated by the *LocationManager* are guaranteed to have a valid latitude, longitude, and timestamp (both UTC time and elapsed real-time since boot) and all other parameters are optional. The details documentation about the data itself can be accessed in our projects site⁴, open “Data Documentation” directory. In this research, we use location data but we do not use all of those data, probably in this case, we only use longitude and latitude data to define user location. The reason why our application collect all of those data is probably another researchers want to use those data such as bearing, accuracy and etc for another purposes.

We store the data from all of students in archive file. The size of all of data after extracted is around 28.7 GB. Extracted data contain 47 directories in different name for each student’s

⁴ <https://github.com/rischanlab/Rfunf>

data. The result of data summarization which contain with name of directories, size, starting point, and ending point can be seen in Table 2.3. Starting point means when the student start the application, and ending point means when the student stop the application.

Table 2-3. Data Summarization from 47 students.

No.	Data ID	Size (MB)	Starting Point	Ending Point
1.	ENFP_0719	628	6/30/2014 8:26	8/20/2014 0:18
2.	ENFP_0773	664	6/26/2014 12:34	8/18/2014 4:58
3.	ENFP_2012	661	6/27/2014 6:11	9/2/2014 3:57
4.	ENTJ_5868	6890	6/27/2014 5:31	8/13/2014 0:00
5.	ENTJ_6454	121	6/26/2014 5:32	8/6/2014 18:53
6.	ENTJ_6966	272	7/2/2014 7:24	8/19/2014 11:22
7.	ENTP_5623	455	6/30/2014 4:49	8/19/2014 20:57
8.	ESFJ_2301	145	6/27/2014 5:31	8/20/2014 2:58
9.	ESFJ_9284	158	6/26/2014 12:34	8/18/2014 4:58
10.	ESFP_0912	278	6/26/2014 5:28	8/18/2014 8:53
11.	ESFP_3295	-		
12.	ESFP_4634	486	6/27/2014 5:25	8/20/2014 4:10
13.	ESFP_7467	607	6/26/2014 5:27	8/19/2014 7:18
14.	ESTJ_0371	2390	7/3/2014 16:21	8/16/2014 21:03
15.	ESTJ_3022	183	6/26/2014 5:28	8/18/2014 23:22
16.	ESTJ_5071	1920	7/2/2014 2:34	9/11/2014 1:49
17.	ESTJ_5190	258	7/30/2014 6:04	8/24/2014 1:43
18.	ESTJ_5824	173	6/26/2014 5:29	8/18/2014 3:51
19.	ESTJ_6510	756	6/27/2014 5:30	8/20/2014 8:09
20.	ESTP_4301	232	6/26/2014 5:29	8/20/2014 4:39
21.	ESTP_5154	990	6/27/2014 5:31	8/13/2014 0:00
22.	INFP_1993	432	6/26/2014 5:31	8/20/2014 0:31
23.	INTJ_5498	342	6/26/2014 5:28	8/20/2014 2:49
24.	INTJ_7906	312	6/14/2014 11:00	8/16/2014 23:01
25.	INTP_3739	1030	6/27/2014 5:28	8/18/2014 5:58
26.	INTP_6399	199	6/26/2014 5:29	8/12/2014 8:32
27.	INTP_9712	180	6/26/2014 5:37	8/16/2014 18:05
28.	ISFJ_2057	183	6/27/2014 5:32	8/14/2014 23:19
29.	ISFJ_2711	767	7/31/2014 0:51	8/20/2014 6:59
30.	ISFJ_7328	133	6/30/2014 7:09	8/19/2014 23:37
31.	ISFP_4030	2380	6/27/2014 6:11	9/2/2014 3:57

32.	ISFP_4282	613	6/27/2014 5:27	8/20/2014 2:46
33.	ISTJ_0178	158	6/26/2014 5:28	8/19/2014 5:05
34.	ISTJ_0386	284	6/26/2014 5:27	8/19/2014 7:18
35.	ISTJ_2068	339	6/26/2014 5:29	8/18/2014 5:30
36.	ISTJ_2837	186	6/27/2014 5:27	8/22/2014 5:41
37.	ISTJ_3052	131	6/27/2014 5:27	8/20/2014 3:41
38.	ISTJ_4659	325	7/2/2014 2:34	9/11/2014 1:49
39.	ISTJ_4667	156	6/26/2014 5:29	8/15/2014 10:44
40.	ISTJ_4700	170	7/3/2014 6:50	8/25/2014 13:08
41.	ISTJ_4753	363	6/26/2014 5:29	8/18/2014 23:48
42.	ISTJ_4968	95	7/3/2014 16:21	8/16/2014 21:03
43.	ISTJ_9139	473	7/3/2014 16:21	8/20/2014 5:57
44.	ISTJ_9576	198	7/4/2014 1:00	8/18/2014 7:12
45.	ISTP_3948	500	6/26/2014 5:29	8/20/2014 1:28
46.	ISTP_7676	365	6/27/2014 5:31	8/19/2014 22:11
47.	XXXX_XXXX	434	6/27/2014 5:31	8/21/2014 6:02

2.1.3 Dataset that used in this research

Table 2-2 List of probes and types shows that all of data that we collected from user's smartphone. Not all of those data are used in this research. We give symbol ("X") in the last column (*used column*) to the data which we used in this research. The data that we used are: On request data: GPS location, Nearby Wi-Fi, Nearby Bluetooth, Battery; Historical data: Call log and SMS log; Continuous data: Smartphone screen, Running applications, user activity log. The total dataset that we used are 9 probes.

The total of students who participated are 47 students. From those data not all data are full available. Some of students does not have SMS log, or another data, the reason they do not have SMS data probably he prefers to uses application messenger such as Kakao, Whatsapp, etc instead of SMS application. In this research, we use data from 37 students which all of data are available during 2 months.

2.2 Data Pre-processing

The data which collected from user's smartphone are not clean, means the data has a noise

and duplication. In this section, we explain about the data pre-processing which is contain with two subchapters are data cleansing and data transformation.

2.2.1 Data Cleansing

Funf library which we used as base of our application, has a problem in historical data collection. Historical data is the data which has been stored in android database system such as contact, SMS log, call log, and etc. We use 86400 second interval, means the application copy those data from android database system to our application database one time every day. It makes duplication in our database and we have to care about it. Another problem is system does not always work well, sometimes something wrong happened and the user's smartphone return value such as NA, error, or/and has no value. We use R programming language to create module which can remove this duplication and clean the noisy data.

2.2.2 Dataset Transformation

As we mentioned in data description's section that the size of all of the data is around 28 GB. To process those of data, when we load all of those data in the same time it will spend computer resource especially RAM. R environment system will load all of data that will be process in RAM. To handle that problem, we have to define what kind of data that we want to use and store those data to another file, in this case, we use csv files.

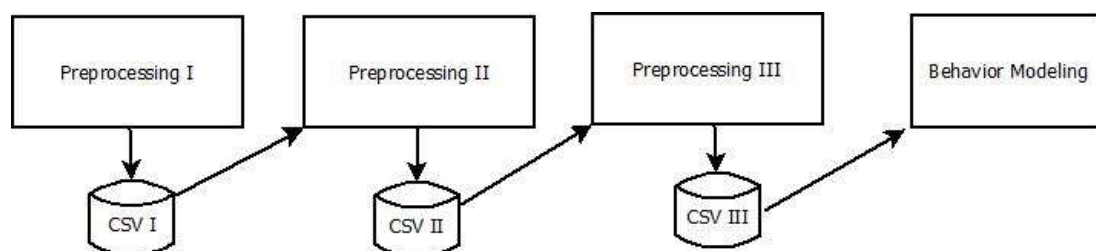


Figure 2-5. Data preprocessing flows

We have three kind of preprocessing modules and each module will store new data to csv

file. Figure 2-5 shows preprocessing process and dataset transformation from preprocessing I until behavior modeling module. Preprocessing I will load all of raw data, removing duplication data, cleansing data, and select the most important data that have been defined. Preprocessing I will store the result data to the CSV I database. Preprocessing II will load the CSV I data not the raw data, in this process features extraction applied. The result of Preprocessing II stored in CSV II. Preprocessing III load the CSV II data and transform the data to the fit format before creating behavior model applied. This ways will reduce time processing and computer resource's usage.

2.3 Feature Extraction

Features are functions of the original measurement variables that are useful for classification and/or pattern recognition. Feature extraction is the process of defining a set of features, which will most efficiently or meaningfully represent the information that is important for analysis and classification. In this stage, before we are extracting the features we have to define first what the features that we want to use.

2.3.1 Define Human Activity and Behavior

To extract the features, we have to know first what the human behavior is. In this thesis, we define that human behavior is human daily activities which carried out continuously. As we mentioned in introduction section, about the Alice' daily activities from he wakes up until arrives to his lab room in working day. We call that Alice's activities are Alice's behavior because that activities carried out continuously by Alice in his working day.

In terms of human daily activities, we have to consider about four important things are:

1. What kind of activity (e.g. meeting, studying, exercising, and etc)
2. When the activity happened (e.g. around 9 AM)

3. Where is the location when activity happened (e.g. Lab's room)
4. Interaction with (e.g. Meeting with whom: his lab members, and etc)

We tried to extract the features from the raw dataset based on those four points. We also have to consider about possibilities, probably same activities happened but in different time and location, or maybe different activity but in same time and location, and vice versa.

2.3.2 Features Description and Extraction

Based on our raw dataset and after we define the human behavior itself, the features that we proposed are:

- What kind of human activity
 - The important thing that we have to know is because of our application follows opportunistic method to collect user personal data, so we do not have activity label in our dataset.
 - We only have activity status (none, low, and high), these status based on accelerometer sensor activity.
 - We use sum of variance to detect the user activity, if the variance sum more than or equal to 10 float it will be return high activity, if the variance sum value between 3 float and less than 10 float it will be return low activity and else is none activity.
 - We use this data to define the user activity, even though we do not know the name of activity (activity label) but we still now the user activity pattern (none, low, and high) these values can be used to detect user behavior.
- When the activity happened
 - Every values in our dataset has timestamp value. The timestamp value following UNIX timestamp, we have to transform to human timestamp.
 - Date and time are used as features in this research.
- Where is the location

- Rather than living in time domain we also live in place domain (location).
- In this research, we use three of features to define the location are GPS, nearby Wi-Fi, and nearby Bluetooth. GPS is used for defining the user location in outside and nearby Wi-Fi and nearby Bluetooth can be used to define user location inside building.
- Interaction with (user interaction)
 - We divide user's interaction to two of kind interactions, first is interaction between users and their smartphone, and second is interaction between users and another users (between human).
 - User -> Smartphone interaction
 - Battery, based on this data, we can know when the user usually charge their battery and etc.
 - Smartphone screen, this data can be used as base information about user's smartphone usage.
 - Running applications, means the list of current applications that user used (time(when), name of applications, and duration)
 - Human -> Human interaction
 - SMS Log
 - Call Log
 - SMS and Call log can be used as the base information as the user interaction with others people.

Table 2.4 shows the list of our features and the values. We select three of the most important values from each probes data.

1. The *value1* of Activity Probes filled by ("*none*", "*low*", and "*high*").
2. The values of GPS are *value1* is latitude and *value2* is the longitude.
3. The values of Wi-Fi probe are *value1* is name of Wi-Fi SSID, *value2* is the mac address of Wi-Fi hardware, and the *value3* is the signal strength of the access point.

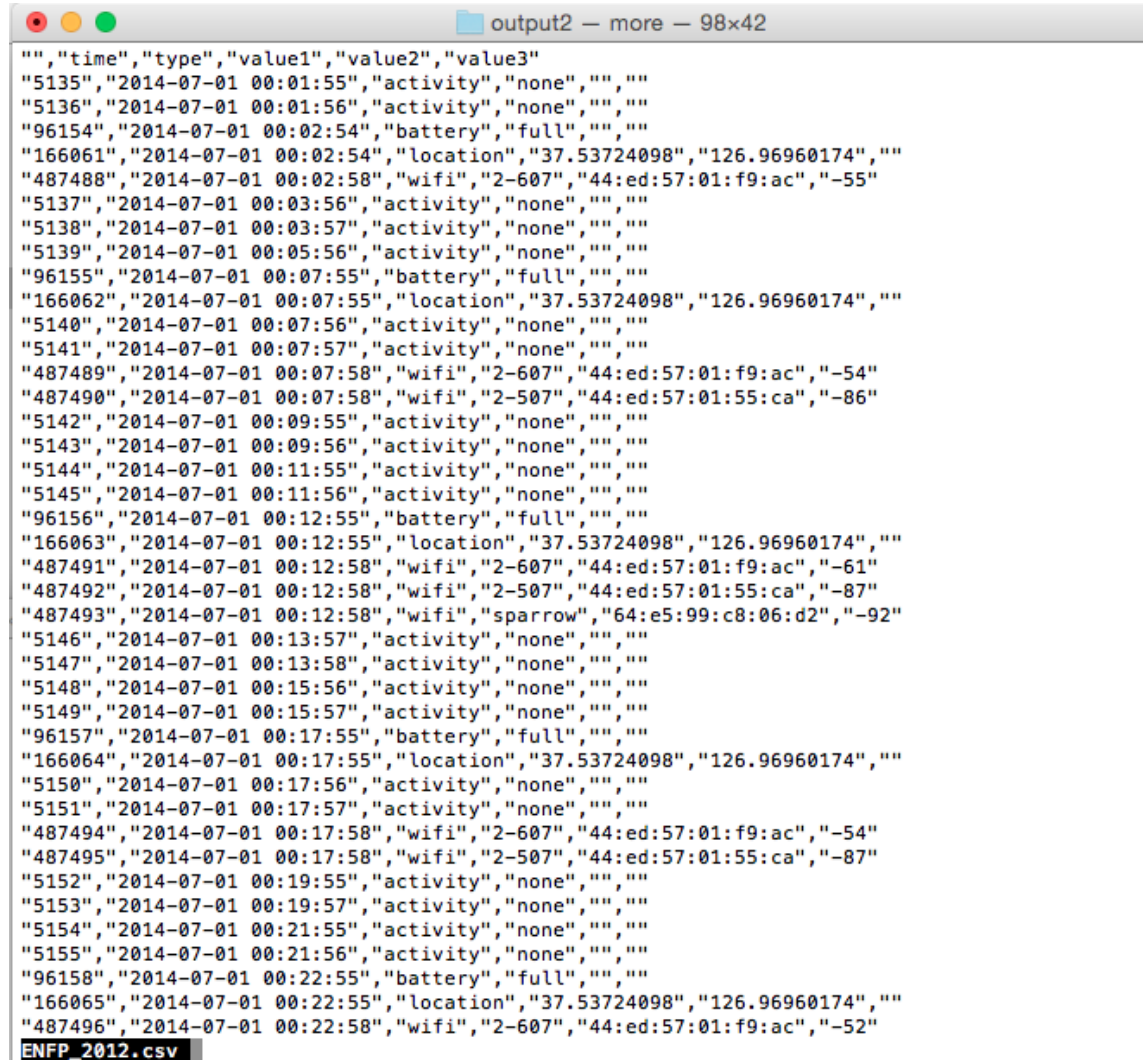
4. Bluetooth probe only has single value, *value1* is the name of nearby Bluetooth devices.
5. Battery probe has only one value, *value1* filled by (“*charging*”, “*discharging*”, and “*full*”).
6. The *value1* of Screen probe filled by “ON” or “OFF”
7. Running application probe has two important values are *value1* is the application name and *value2* is the duration of the application’s usage.
8. Call Log and SMS Log has three of values, *value1* is the number of person who (call/receive call, sent SMS, or receive SMS), *value2* is the types, means incoming and outgoing for the call, and inbox or sent message for the SMS, and the last *value3* filled by time duration for the call and text length for the SMS log.
9. All of rows data values has timestamp.
10. We define these all features in Pre-Processing II.

Table 2-4. List of features and the values

No	Name of Probes	Value1	Value2	Value3
1.	ActivityProbe	Status (“ <i>none</i> ”, “ <i>low</i> ”, and “ <i>high</i> ”)		
2.	SimpleLocationProbe	Latitude	Longitude	
3.	WifiProbe	List of nearby SSID	MAC	Signal strength (dB)
4.	BluetoothProbe	List of nearby Bluetooth devices		
5.	BatteryProbe	Status (“ <i>discharging</i> ”, “ <i>full</i> ”, and “ <i>charging</i> ”)		
6.	ScreenProbe	ON/OFF		
7.	RunningApplicationsProbe	Apps name	Duration	
8.	CallLogProbe	Number	Types	Duration
9.	SmsProbe	Number	Types	Text length

The example output of the features extraction can be seen in Figure 2-6. First columns is an ID, and then the second column is the time with the format (*yyyy-mm-dd hh:mm:ss*). Third

column is type, means the name of probes, to make easy to read we change *ActivityProbe* to *activity*, *SimpleLocationProbe* to *location*, *WifiProbe* to *wifi*, and etc.



```

", "time", "type", "value1", "value2", "value3"
"5135", "2014-07-01 00:01:55", "activity", "none", "", ""
"5136", "2014-07-01 00:01:56", "activity", "none", "", ""
"96154", "2014-07-01 00:02:54", "battery", "full", "", ""
"166061", "2014-07-01 00:02:54", "location", "37.53724098", "126.96960174", ""
"487488", "2014-07-01 00:02:58", "wifi", "2-607", "44:ed:57:01:f9:ac", "-55"
"5137", "2014-07-01 00:03:56", "activity", "none", "", ""
"5138", "2014-07-01 00:03:57", "activity", "none", "", ""
"5139", "2014-07-01 00:05:56", "activity", "none", "", ""
"96155", "2014-07-01 00:07:55", "battery", "full", "", ""
"166062", "2014-07-01 00:07:55", "location", "37.53724098", "126.96960174", ""
"5140", "2014-07-01 00:07:56", "activity", "none", "", ""
"5141", "2014-07-01 00:07:57", "activity", "none", "", ""
"487489", "2014-07-01 00:07:58", "wifi", "2-607", "44:ed:57:01:f9:ac", "-54"
"487490", "2014-07-01 00:07:58", "wifi", "2-507", "44:ed:57:01:55:ca", "-86"
"5142", "2014-07-01 00:09:55", "activity", "none", "", ""
"5143", "2014-07-01 00:09:56", "activity", "none", "", ""
"5144", "2014-07-01 00:11:55", "activity", "none", "", ""
"5145", "2014-07-01 00:11:56", "activity", "none", "", ""
"96156", "2014-07-01 00:12:55", "battery", "full", "", ""
"166063", "2014-07-01 00:12:55", "location", "37.53724098", "126.96960174", ""
"487491", "2014-07-01 00:12:58", "wifi", "2-607", "44:ed:57:01:f9:ac", "-61"
"487492", "2014-07-01 00:12:58", "wifi", "2-507", "44:ed:57:01:55:ca", "-87"
"487493", "2014-07-01 00:12:58", "wifi", "sparrow", "64:e5:99:c8:06:d2", "-92"
"5146", "2014-07-01 00:13:57", "activity", "none", "", ""
"5147", "2014-07-01 00:13:58", "activity", "none", "", ""
"5148", "2014-07-01 00:15:56", "activity", "none", "", ""
"5149", "2014-07-01 00:15:57", "activity", "none", "", ""
"96157", "2014-07-01 00:17:55", "battery", "full", "", ""
"166064", "2014-07-01 00:17:55", "location", "37.53724098", "126.96960174", ""
"5150", "2014-07-01 00:17:56", "activity", "none", "", ""
"5151", "2014-07-01 00:17:57", "activity", "none", "", ""
"487494", "2014-07-01 00:17:58", "wifi", "2-607", "44:ed:57:01:f9:ac", "-54"
"487495", "2014-07-01 00:17:58", "wifi", "2-507", "44:ed:57:01:55:ca", "-87"
"5152", "2014-07-01 00:19:55", "activity", "none", "", ""
"5153", "2014-07-01 00:19:57", "activity", "none", "", ""
"5154", "2014-07-01 00:21:55", "activity", "none", "", ""
"5155", "2014-07-01 00:21:56", "activity", "none", "", ""
"96158", "2014-07-01 00:22:55", "battery", "full", "", ""
"166065", "2014-07-01 00:22:55", "location", "37.53724098", "126.96960174", ""
"487496", "2014-07-01 00:22:58", "wifi", "2-607", "44:ed:57:01:f9:ac", "-52"
ENFP_2012.csv

```

Figure 2-6. Sample output of the features extraction in Pre-Processing II.

2.3.3 Human and Machine Time

Machine is different with human, machine can calculates and shows the time in exactly time such as 00:22:44:34 (millisecond) but human could not do that. As a human, usually when we want to do activity in term of time we said on hour and minutes. An example is when we have agreement with someone, usually we said “OK, we have meeting at 9.30 AM”, we

never said “OK, we have meeting at 09:30:00:00 (until millisecond)”. In this research, we transform the time machine to human machine. We create the module to transform time machine to human machine in module Pre-processing III.

2.3.4 List of the Final Features

Figure 2.5 shows the result of features extraction from Pre-processing II module. We still have some problem on that result. We create Pre-processing III module to make our dataset fit enough before applying behavior modeling module. Another reason is more features mean more time to processes, light features means light time, so we try to find the most valuable features from all of those features. The process in the Pre-processing III module are:

1. Time change, from machine time to the human time. In this research, to convert machine time to human time we tried to round time with the setting:
 - a. If minute less than 30 minutes will be round down
 - b. If minute more than or equal to 30 minutes will be round up
2. Change GPS location value. We change the value of the GPS to “**moving status**” that value filled by “*same*”, “*little*”, or “*long*”. Note: 0.0001 degree= 11.1132 m.
 - a. If the previous value of GPS location not change, it means no movement, so the value filled by “*same*”.
 - b. If the moving distance between 0.0001 ~ 0.0005, it means little movement, so the value filled by “*little*”.
 - c. If the moving distance more than 0.0005, it means long movement, so the value filled by “*long*”.
 - d. To determine the value 0.0005 is based on experience of plotting, we

have tried to plot those point and we decide to use that value to distinguish little and long movement.

3. Remove “*discharging*” from the Battery value. The value of battery status are: “*charging*”, “*discharging*”, and “*full*”. We thought that default value is “*discharging*” because usually users use their phone in discharging mode so we remove this value and only use “*charging*” means when the user charge their phone and “*full*” means the battery was full.
4. Remove “*none*” from the Activity value. “*none*” value means idle, we tried to use “*low*” and “*high*” activity as our features.
5. Aggregate the values of Wi-Fi and Bluetooth. When we see Figure 2-6, in same time the value of Wi-Fi is one SSID in one row, and also for the Bluetooth. That is because every 5 minutes our application store the lists of nearby access points and Bluetooth devices and each value stored in rows. In this module, if the time is same the sensor values will be aggregate in one row.
6. Aggregate the values of Call Log and SMS log. In this preprocessing, we use only two of values from call log and SMS log and we combine to one columns. The values of call log and SMS log that we used are “type and number”. An example of value of call log “*incoming 1bae527e84708183049d8e892a1c959a492ee6a9*”. Even the number was hashed but if the number is same, it has same hash value so we still have pattern information.
7. Removing values such as text length and duration from SMS log and call log, duration from running application probe, MAC and signal strength from nearby

Wi-Fi probe. The reason why we did not use these features because our purpose is to find the similarity of data pattern, the value of call duration, application usage duration will make the data quite different. Probably, we will use those data in different approach but not in this approach.

The example of final features based on the result from Pre-processing III can be seen in Figure 2-7. The final features are: Timestamp with format (“*yyyy-mm-dd hh:mm*”) the time until minute, Day means the name of the day (weekday), HT means human time, filled by result from rounding of time, Sensor Name means the name of probes such as *activity*, *wifi*, *location*, *bluetooth*, and etc, Sensor value means the values of the sensors.

```
output3 — more — 108x42
Timestamp,Weekday,HP,Sensor Name,Sensor Value
07/01/2014 0:01,Tuesday,00:00,location,long
07/01/2014 0:01,Tuesday,00:00,wifi,KT_WLAN_C1BF, iptime
07/01/2014 0:02,Tuesday,00:00,activity,low
07/01/2014 0:02,Tuesday,00:00,activity,low
07/01/2014 0:04,Tuesday,00:00,runapps,com.buzzpia.aqua.launcher
07/01/2014 0:04,Tuesday,00:00,runapps,com.facebook.katana
07/01/2014 0:04,Tuesday,00:00,runapps,com.buzzpia.aqua.launcher
07/01/2014 0:04,Tuesday,00:00,runapps,net.daum.android.cafe
07/01/2014 0:06,Tuesday,00:00,location,long
07/01/2014 0:06,Tuesday,00:00,wifi,KT_WLAN_C1BF, iptime
07/01/2014 0:11,Tuesday,00:00,location,long
07/01/2014 0:11,Tuesday,00:00,wifi,KT_WLAN_C1BF, iptime
07/01/2014 0:14,Tuesday,00:00,activity,low
07/01/2014 0:14,Tuesday,00:00,activity,low
07/01/2014 0:15,Tuesday,00:00,runapps,com.buzzpia.aqua.launcher
07/01/2014 0:15,Tuesday,00:00,runapps,com.nhn.android.search
07/01/2014 0:16,Tuesday,00:00,runapps,net.daum.android.cafe
07/01/2014 0:16,Tuesday,00:00,location,long
07/01/2014 0:16,Tuesday,00:00,wifi,KT_WLAN_C1BF, iptime
07/01/2014 0:19,Tuesday,00:00,runapps,com.nhn.android.search
07/01/2014 0:20,Tuesday,00:00,runapps,net.daum.android.cafe
07/01/2014 0:21,Tuesday,00:00,location,long
07/01/2014 0:21,Tuesday,00:00,wifi,KT_WLAN_C1BF
07/01/2014 0:26,Tuesday,00:00,location,long
07/01/2014 0:26,Tuesday,00:00,wifi,KT_WLAN_C1BF
07/01/2014 0:31,Tuesday,01:00,location,long
07/01/2014 0:31,Tuesday,01:00,wifi,KT_WLAN_C1BF, iptime
07/01/2014 0:36,Tuesday,01:00,activity,high
07/01/2014 0:36,Tuesday,01:00,location,long
07/01/2014 0:36,Tuesday,01:00,activity,high
07/01/2014 0:36,Tuesday,01:00,wifi,KT_WLAN_C1BF
07/01/2014 0:37,Tuesday,01:00,runapps,com.facebook.katana
07/01/2014 0:37,Tuesday,01:00,runapps,net.daum.android.cafe
07/01/2014 0:40,Tuesday,01:00,activity,high
07/01/2014 0:41,Tuesday,01:00,location,long
07/01/2014 0:41,Tuesday,01:00,wifi,KT_WLAN_C1BF, iptime
07/01/2014 0:46,Tuesday,01:00,location,long
07/01/2014 0:46,Tuesday,01:00,activity,low
07/01/2014 0:46,Tuesday,01:00,wifi,KT_WLAN_C1BF
07/01/2014 0:51,Tuesday,01:00,location,long
INTJ_5498_HP.csv
```

Figure 2-7. Sample output of the features extraction in Pre-Processing III (Final Features).

3. HUMAN BEHAVIORS MODELING

Figure 3-1 shows the data visualization example in the same day for four days from two of students. Look at the different pattern from both of the users and if we observe the result of plot for more than one weeks we will see the pattern obviously. Based on our observation, we

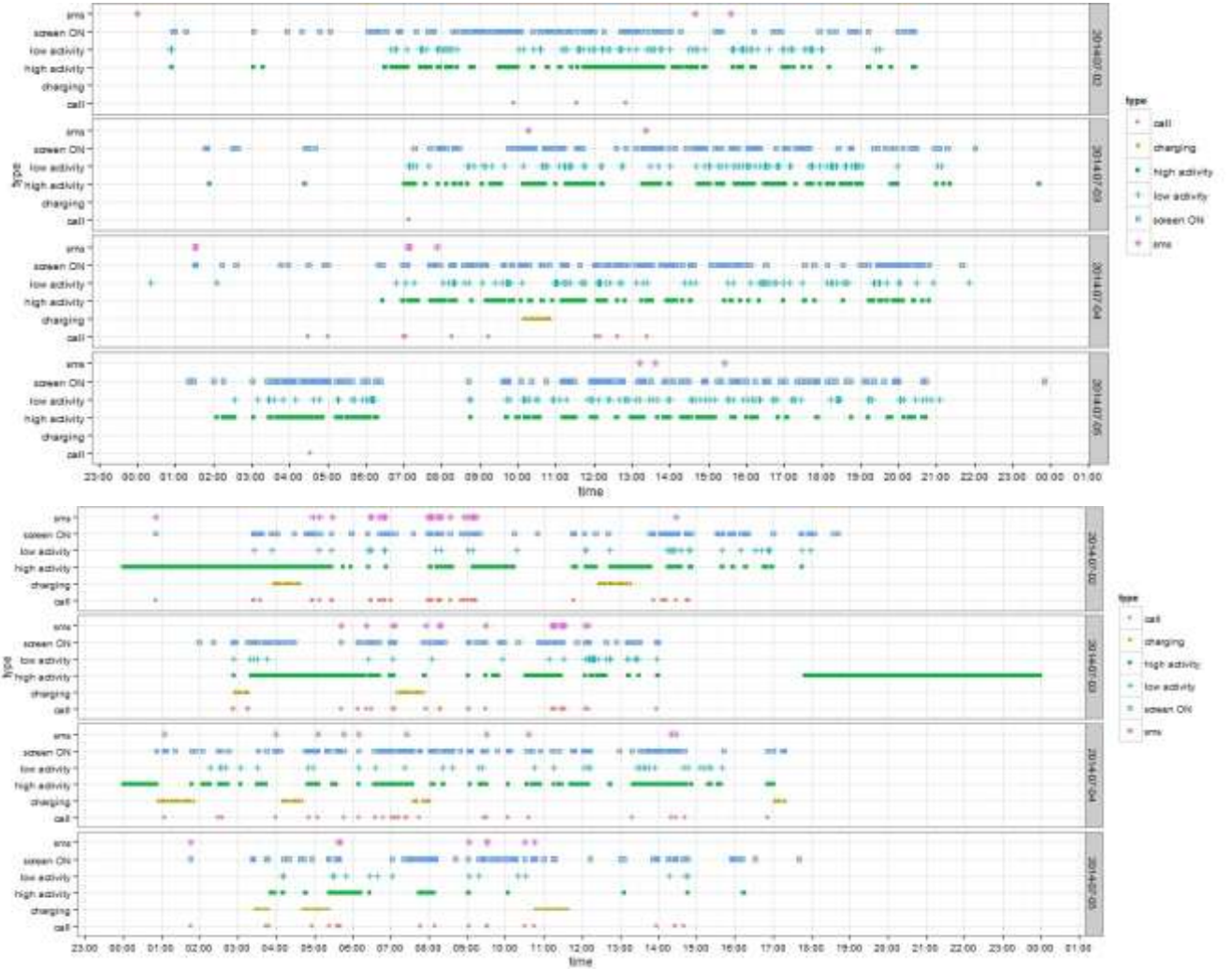


Figure 3-1. Example data visualization from two of students in the same day for four days.

sure that the data features in user personal data log can be used for many purposes such as user identification and classification, recommendation, and etc. In this section, we explain about our research background and the problem statement, and our proposed methods to achieved our goals.

3.1 Background and Problem Statement

As we mentioned before that many of researchers focus on one feature such as focus to use accelerometer sensor for human gait identification [11], accelerometer sensor for basic activity recognition [12], and magnetic field sensor for location identification [13] and etc. Those approaches which is using one feature is good to know that feature is reliable or not. When we use only one feature, the problems are the lack of sensor accuracy and data loss. We have to realize that the data from user's smartphone are uncertainly data. Not all data are in good condition, sometime probably the sensor has problems so sensor does not return the value and etc. Another problem is many of researchers mentioned that their approach can achieved good accuracy but they forget if they use experiment environment to collect their research data. When users use their phone in real environment, they will use like in their natural life. We have to consider about realistic data, means the data which the true of real data in real environment. In this research, we define what the realistic data is, the explanation can be seen below:

1. In realistic environment, user has different types and brand of smartphone and each smartphone has different types of sensors and hardware specification and capabilities.
2. We could not expect the human actions and their activities, they will do actions and activities as they want.
3. There is no ideal data collection that can record user personal data for every day 24 hour non-stop, it will drain the battery and spend smartphone resources.
4. There is no ideal data collection that can record all of data without any data loss.
5. When we decide to use many of sensors rather than focus only one sensor, we have to realize that the data from smartphone are heterogeneous data because the data came from multiple sensors and multiple source information.

Based on those reasons, we proposed our approach which is modeling human behavior based

on user smartphone data log by combining many sensors data. In this approach, we tried to develop our system which can deal with realistic data.

3.2 Proposed Methods

In this section, we explain about our proposed methods. First is about overall architecture of our system, the algorithm that we use to find similar patterns and also method that we use to create user behavior model.

3.2.1 Overall architecture



Figure 3-2. Finding similar pattern in different days same week (one window, size: 2 days)

We have dataset less than 2 months (8 weeks). We use one month dataset to build user behavior model and then use the remaining data to testing our approach performance. Figure 3.2 sketches our proposed method to find similar pattern in all of our dataset, the explanation of that figure can be seen below:

1. First, we define the window size. In this research, we use window size is two, means two days.
2. We remove the last day of weekday (Sunday) because when we use window size is two and the first day start from Monday, so the windows are “Monday-Tuesday”, ”Wednesday-Thursday”, “Friday-Saturday” the remaining is “Sunday”, so we remove it.
3. We applied Algorithm 3.2 to find similar pattern between days inside the window.

Algorithm 3.2.

```
Data : D, w
Result : All Detected Group in a Window
grpAll, grpTemp, grpPrevious<- NULL
dataValue, dataValueNext <- NULL
while (D in w) for all of D do
    dataValue <- D.current.day
    dataValueNext <- D.next.day
    grpTemp <- findingSimilarPatterns(dataValue, dataValueNext)
    if (grpTemp in grpPrevious) then
        grpNew <- merge(grpPrevious, grpTemp)
        grpAll <- add(grpNew)
    else
        grpAll <- add(grpTemp)
```

3.2.2 Similar Patterns Detection

Time	Sensor Name	Sensor Value
13:00	location	same
13:00	wifi	1-AP, iptime
14:00	runapps	kakao
14:00	location	long
15:00	runapps	kakao
15:00	location	little

Time	Sensor Name	Sensor Value
13:00	location	same
13:00	wifi	1-AP, iptime
14:00	battery	charging
14:00	wifi	D-link
15:00	runapps	kakao
15:00	location	little

Group-1 = 13:00,location,same | 13:00,wifi,1-AP,iptime
Group-1 = 13:00,location,same | 13:00,wifi,1-AP,iptime
Group-2 = 15:00,runapps,kakao | 15:00, location, little
Group-2 = 15:00,runapps,kakao | 15:00, location, little

Figure 3-3. Find similar pattern algorithm overview

We use BCH $BCH_2(n_c, k, t)$ to denote a binary BCH code, where n_c is the code length of bits, k is the key length of bits and t is the error correction capability. The binary cryptographic key m of length k is generated randomly corresponding to each user and then be encoded into the codeword c of length n_c using $BCH_2(n_c, k, t)$ encoding scheme. After that, we bind the extracted binary gait template with c yielding secured δ . The method used to bind these two binary strings is *exclusive-OR* operation. We summarize all of essential steps both in enrollment phase and verification phase in our system as following

4. EXPERIMENTAL RESULTS

4.1 Result and Discussion

4.1.1 Behavior Identification

```
G2,"19:00, location, same|19:00, bluetooth, DTVBluetooth|"
G2,"19:00, location, same|19:00, bluetooth, DTVBluetooth|"
G2,"19:00, location, same|19:00, bluetooth, DTVBluetooth|"
G2,"19:00, location, same|19:00, bluetooth, DTVBluetooth|"
G2,"19:00, location, same|19:00, bluetooth, DTVBluetooth|"
G3,"20:00, location, same|20:00, bluetooth, DTVBluetooth|"
G3,"20:00, location, same|20:00, bluetooth, DTVBluetooth|"
G3,"20:00, location, same|20:00, bluetooth, DTVBluetooth|"
G3,"20:00, location, same|20:00, bluetooth, DTVBluetooth|"
G7,"06:00, screen, OFF|06:00, location, same|"
G7,"06:00, screen, OFF|06:00, location, same|"
G7,"06:00, screen, OFF|06:00, location, same|"
G7,"06:00, screen, OFF|06:00, location, same|"
G7,"06:00, screen, OFF|06:00, location, same|"
G7,"06:00, screen, OFF|06:00, location, same|"
G7,"06:00, screen, OFF|06:00, location, same|"
G7,"06:00, screen, OFF|06:00, location, same|"
G7,"06:00, screen, OFF|06:00, location, same|"
G7,"06:00, screen, OFF|06:00, location, same|"
G7,"06:00, screen, OFF|06:00, location, same|"
G7,"06:00, screen, OFF|06:00, location, same|"
G7,"06:00, screen, OFF|06:00, location, same|"
G7,"06:00, screen, OFF|06:00, location, same|"
G7,"06:00, screen, OFF|06:00, location, same|"
G9,"12:00, battery, charging|12:00, bluetooth, ESVH-PC|12:00, location, same|12:00, runapps, com.lge.launcher2|"
G9,"12:00, battery, charging|12:00, bluetooth, ESVH-PC|12:00, location, same|12:00, runapps, com.lge.launcher2|"
G9,"12:00, battery, charging|12:00, bluetooth, ESVH-PC|12:00, location, same|12:00, runapps, com.lge.launcher2|"
G9,"12:00, battery, charging|12:00, bluetooth, ESVH-PC|12:00, location, same|12:00, runapps, com.lge.launcher2|"
G9,"12:00, battery, charging|12:00, bluetooth, ESVH-PC|12:00, location, same|12:00, runapps, com.lge.launcher2|"
G9,"12:00, battery, charging|12:00, bluetooth, ESVH-PC|12:00, location, same|12:00, runapps, com.lge.launcher2|"
G9,"12:00, battery, charging|12:00, bluetooth, ESVH-PC|12:00, location, same|12:00, runapps, com.lge.launcher2|"
INTJ_8928_groups.csv
```

Figure 4-1. An example of output from our system (grouping result)

Total 8500 patterns are extracted from the dataset by using our segmentation algorithm.

Around $\frac{8500}{38}$ patterns corresponding to each volunteer are split into two separated parts. The first part is used for training (*T-part*) and the remaining is used for prediction (*P-part*). Second, we analyze the impacts of installation errors to segmentation algorithm and the classification accuracy. Note that a perfect accuracy rate of segmentation is achieved when using our algorithm with the transformed *Z*-signal. All gait cycles are detected and segmented correctly. Table 4.2(b) illustrates the performance of the segmentation task with/without fixing disorientation error. As discussed above, the periodicity of walking is only represented well in transformed *Z*-signal. Without rectifying such issues, the segmentation algorithm could not determine precisely the regularity of gait cycles caused by *Z*-signal's instability. Therefore, each segmented pattern could not only represent a sequence of consecutive gait cycles well. That leads features extracted from these patterns could not represent the characteristics of walking style of individuals as well. As a result, the classification accuracy rate is contaminated. Even with using segmentation based on fixed length, the best achieved classification rate at length of 3000 ms is also worse (79.53%).

4.1.2 Time Execution and Performance

Looking at the case of the Euclidean distance distribution of real-valued templates, the discrimination is likely to be low. In a more details, the distribution areas of same and different users mostly distribute from 0 to 0.2. That means gait templates between users are likely to be similar. Therefore, applying a threshold-based classification on such templates will result in a high error rate. From our experiment, we observe that extracting binary templates using the quantization method not only makes such templates be applicable to binding with binary BCH codewords but also increase the discrimination property. This is because binary templates only contains bits having high reliable. As shown in the Figure 4.3, the Hamming distances of intra-

and inter- class templates are more discriminant and distribute mostly around 0.2 and 0.5 respectively. Templates between users are more dissimilar so that determining an appropriate threshold to classify such templates is more straightforward to achieve an acceptable error rate.

5. RELATED WORKS

User personal data log from smartphone can be used for many purposes such as user identification, user classification, recommendation system, mood detection and etc. In this section, we explain about previous works which related with exploring user personal data log that collected from user's smartphone. Smartphone log consist of many of data such as contact, call log, SMS log, GPS, Wi-Fi, Bluetooth, and many more as that we have explained in previous chapters. We can choose which data or information features that we want to explore. For example is contact data, from this data we can explore many thing. [11] they collected the contact lists and then analyzed using several features such as communication intensity, regularity, medium, and temporal tendency. By using machine learning techniques and their methods they can achieved up to 90 % accuracy to classify life facets/type of relation in contact (family, work, social). Another interesting research which based on smartphone contact conducted by [12], they proposed *SmartPhonebook*, it is like an artificial assistant which recommends the candidate *callees* whom the users probably would like to contact in a certain situation. The approach is they used social contacts based on the contact patterns, while it extracts the personal contexts based on the contact patterns, the personal contexts means such as the user emotional states and behaviors from the mobile log. They use Bayesian networks for handling the uncertainties in the mobile environment.

Another previous works which used call log and SMS log, such as [9], they tried to predict the spending behavior for couples in terms of their tendency to explore diverse businesses, become loyal customers, and overspend. They use the social features such as face to face interaction, call, and SMS logs. The main purpose of this research is for business area, they

said that the smartphone log could be used for predicting customer type such as loyal customers or overspend. They found that using their approach social features could be better predictors of spending behavior of a couple than personality variables. Previous work which based on location features, an example done by [13] they said how proximity, location, and user personality such as friendship could play important role in understanding user behavior. They found three things: friendship (SMS contacts and Facebook friendship) in proximity has a significant impact on traffic consumption, personality tends to impact application preference and consumption. Still based on location data, research which done by [14], they utilize location information which can obtained from phone sensors (GPS, Wi-Fi, GSM, and accelerometer sensors). They proposed a new framework to discover places of interest based on location where the user usually goes and stays for a while.

Not only those features that can be exploited, another example are, based on list of application installed in android devices which done by [15]. This paper, the authors tried to investigate how user traits can be inferred by single snapshot of installed apps. They use SVM with minimal external information such as the religion, relationship status, spoken languages, and countries of interest, and the user is parent of small children or not. They collected data from over 200 smartphone user, and the list of installed apps, by using their approach, they achieved over 90 % of precision.

From those that we mentioned above no one which care about user privacy. In this related works, we also found previous research which consider about user privacy, research by [16] . They proposed a different approach that use multimodal mobile sensor and log data to build framework called *mFingerprint*. *mFingerprint* is user modeling framework which can uniquely depict user. The thing that make this framework different with others is this framework does not expose raw sensitive information from the mobile device such as the exact location, Wi-Fi access points, or apps installed so it will save user privacy. By testing on 22 users during 2 months, with their approach they can achieve 81% accuracy across 22 users

over 10 day intervals. Our application also does not expose the sensitive information such as name and phone number in smartphone contact, SMS log, and call log, and etc.

We also can use user personal data for unique purposes such as to know the user happiness, mood and stress. Smartphone log can be used for happiness identification done by [6], stress identification done by [17], user mood identification done by [7], or we also can develop an application which can help human to do their daily routines [18]. [6] This paper provides the evidence that we can predict the happiness of human based on their phone log. In this paper, the authors proposed approach using Random Forest classifier to recognize daily happiness of person which obtained from the mobile phone usage data (call log, SMS, and Bluetooth proximity data), and background noise. They can achieve 80.81% of accuracy to classify 3-class daily happiness (happy, neutral, and unhappy). [17] This paper proposed new approach for daily stress recognition based on human behavior metrics derived from the mobile phone activity (call log, SMS log, and Bluetooth interaction). Their approach based on Random Forest and Gradient Boosted Machine algorithms. They use two class classification problem (stressed and unstressed) and with their approach, they can achieved 72.39% of accuracy, it is could be proof that individual daily stress can be predicted from smartphone data. [7] This research proof that by using phone log, we can predict the user mood. The authors develop smartphone service called *MoodSense*. They observe 25 iPhone users and using only six information features from mobile log (SMS, email, phone call, application usage, web browsing, and location). By using simple clustering classifier can achieved 61% accuracy on average and improved to 91% when inference is based on the same participant's data.

Smartphone data log also can be used for personality classification. [19] They develop conceptual model that explains about relationship between user Big Five personality (Extraversion, Agreeableness, Conscientiousness, Emotional Stability and Openness to Experience) and their satisfaction with basic mobile phone services such as call, message, and 3G services. The main propose of this paper is several implications for design of mobile phone

services. Another research done by [20]. They said by using smartphone log and their approach, they can predict Big five personality types of users. The authors said, by using their approach they can achieved 42% better than random and on this research they found that Extraversion and Neuroticism were the traits that were best predicted in their study. The last example proves that smartphone log can be used for personality classification done by [8]. This paper shows the evidence that any relationship between Big Five user personality traits and users smartphone data log. They collected data from 117 Nokia N95 smartphone users during 17 months period in Switzerland, they use statistical and machine learning approach to classify the user's smartphone data log based on personality.

6. CONCLUSIONS

In this thesis, we proposed two approaches of gait authentication using PR-ML algorithms and biometric cryptosystem, respectively. In the PR-ML based authentication system, although the quality of built-in sensors is low (the sampling rate is only 27Hz), the achieved results are very considerable. It reflects high potentials to deploy our mechanism to support current active mobile authentications such as PIN or password in reality. Since there is currently no public dataset in this field, the comparison between related works is only relative. Therefore, a more realistic dataset is also constructed to evaluate our mechanism fairly. Nevertheless, many environment factors such as human emotion, time effect, disease and ground materials which could be affected to the human gait is not explored yet. Hence, such issues will be considered deeper in future.

Looking at the case of the biometric cryptosystem, we introduce a novel system using gait combined with fuzzy commitment scheme. The achieved performance in terms of FAR, FRR as well as the key length and the security level are relatively comparative with other state of the art BCSs. The results show the potentials to construct an effective BCS especially on

mobile devices since we use mobile sensors to acquire biometric gait and a lightweight model which only require low storage capability and computational complexity. Moreover, gait could be considered as a new modality for multi-modal BCSs. The drawbacks of our work are that the FRR is still rather high which could causes inconvenient for users. Hence, our further work will focus on reducing the rate of FRR by constructing higher discriminant templates as well as finding an optimal quantization scheme for binarization.

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