Lab Research Documentation and Direction

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# General Overview Document: Level 0

## Research Description

## History of Our Research

### Vo Viet

**Mobile-based Activity Recognition System Using Sensory Data**

1. **Overview:**
   1. Data acquisition using built-in sensors (accelerometer) of mobile devices;
   2. Data preprocessing (time interpolation, noise filtering, segmentation on Y-axis);
   3. Feature extraction in both time domain and frequency domain;
   4. Personalized Activity recognition: Combine clustering algorithm and Support Vector Machine (SVM) classifier
2. **Problems and solutions:**
3. Balance accuracy and power consumption for feature extraction

|  |  |
| --- | --- |
| *Paper title* | Balancing Precision and Battery Drain in Activity Recognition on Mobile Phone |
| *Appeared in* | 18th IEEE International Conference on Parallel and Distributed Systems (ICPDS), 2012 |
| *Dataset* | * ***SCUTT-NAA***   + 31/44 subjects with activities fully provided   + *Sensor:* ADXL 330 accelerometer, sampling rate = 100Hz * ***Self-constructed data***   + *Mobile device:* Google Android HTC Nexus One   + *Sensor:* Bosch Sensortec’s 3-axis BMA 150 accelerometer   + *Sampling rate:* 30Hz   5 volunteers, 5 categories of activity (bicycling, downstair, jogging, upstair, walking) |
| *Data Preprocessing* | * *Linear interpolation:* 100Hz (SCUTT-NAA) and 32Hz (self-constructed data) * *Noise elimination:* Daubechies orthogonal wavelet (Db6) decomposition at level 2 |
| *Data analysis* | * ***Classifier approach (SVM):***   + *Segmentation:* 256-sample length (8 seconds) per window, overlapping 50% * ***Matching approach (DTW):***   + *Segmentation:* peak detection on Y-axis, 8 gait cycles per window, overlapping at 4th peak |
| *Feature extraction* | * ***Time domain feature (TF):***   + Time gap peaks: average gap values between two consecutive peaks   + Mean and Variance Acceleration   + Accelerometer Energy: amount of change on a physical activity   + Hjorth Mobility (signal mean frequency) and Complexity (deviation of the signal from the sine shape) * ***Frequency domain feature (FFT):***   + The first 40 FFT coefficients |
| *Classification* | * ***Classifier approach: SVM*** * ***Matching approach: DTW*** |
| *Results* | * ***SCUTT-NAA:***   + FFT feature yields better prediction accuracy than TF   + SVM performs better than DTW * ***Self-constructed data:***   + TF yields better prediction accuracy and more effective computational complexity   + SVM performs better than DTW |

1. Balance accuracy and power consumption for feature extraction and classification: select appropriate sampling rate and feature set for deploying on mobile phones

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| --- | --- |
| *Paper title* | Adaptive Energy-Saving Strategy for Activity Recognition on Mobile Phone |
| *Appeared in* | IEEE International Symposium on Signal Processing and Information Technology (ISSPIT), 2012 |
| *Dataset* | * ***SCUTT-NAA***   + 31/44 subjects with activities fully provided   + *Sensor:* ADXL 330 accelerometer, sampling rate = 100Hz * ***Self-constructed data***   + *Mobile device:* Samsung Galaxy Note   + *Sensor:* 3-axis K3DH accelerometer   + *Sampling rate:* {50Hz, 17Hz, 5Hz}   4 volunteers, 5 categories of activity (bicycling, downstair, jogging, upstair, walking) |
| *Data Preprocessing* | * *Linear interpolation:* to acquire fixed interval length signals * *Noise elimination:* Daubechies orthogonal wavelet (Db6) decomposition at level 3 (SCUTT-NAA) and 2 (self-constructed data) |
| *Data analysis* | * Gait cycle partition using peak detection on the Y-dimensional signal * Segment length:   + *SCUTT-NAA:* 512-sample length, no overlapping   + *Self-constructed data:* 256-sample length, overlapping of 128 data points |
| *Feature extraction* | * ***Time domain feature (TF):***   + Time gap peaks: average gap values between two consecutive peaks   + Mean and Variance Acceleration   + Accelerometer Energy: amount of change on a physical activity   + Hjorth Mobility (signal mean frequency) and Complexity (deviation of the signal from the sine shape) * ***Frequency domain feature (FFT):***   + The first 40 FFT coefficients |
| *Classification* | * SVM classifier with RBF kernel |
| *Adaptive strategy* | * + *Walking:* 17Hz, TF   + *Bicycling:* 17Hz, TF   + *Down Stair:* 17Hz, TF   + *Jogging:* 5Hz, TF   + *Up Stair:* 5Hz, FFT |
| *Results* | * High sampling rates normally give better prediction * FFT coefficients perform more effective classification than TF * Adaptive method saves a value of 28% of energy consumption compared with non-adaptive method (50Hz, TF+FFT) |

1. Personalization in mobile activity recognition system: individual model needs huge training data => improve cross-people prediction scheme

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| --- | --- |
| *Paper title* | Personalization in Mobile Activity Recognition System Using K-Medoids Clustering Algorithm |
| *Appeared in* | International Journal of Distributed Sensor Networks, 2013 |
| *Dataset* | * ***SCUTT-NAA***   + 44 subjects, totally 1278 samples   + *Sensor:* ADXL 330 accelerometer, sampling rate = 100Hz * ***Self-constructed data***   + *Mobile device:* Google Android HTC Nexus One   + *Sensor:* Bosch Sensortec’s 3-axis BMA 150 accelerometer   + *Sampling rate:* 30Hz   + 6 volunteers, 5 categories of activity (bicycling, downstair, jogging, upstair, walking) |
| *Data Preprocessing* | * ***SCUTT-NAA****:* to acquire fixed interval length (100 Hz and 32Hz) signal   + *Linear interpolation:* 100Hz   + *Noise elimination:* Daubechies orthogonal wavelet (Db6) decomposition at level 3 * ***Self-constructed data****:*   + *Linear interpolation:* 32Hz   + *Noise elimination:* Db6 at level 2 |
| *Data analysis* | * Gait cycle partition using peak detection on the Y-dimensional signal * Segment length:   + *SCUTT-NAA:* 512-sample length, no overlapping   + *Self-constructed data:* 256-sample length, overlapping of 128 data points |
| *Feature extraction* | * ***Time domain feature (TF):***   + Time gap peaks: average gap values between two consecutive peaks   + Mean and Variance Acceleration   + Accelerometer Energy: amount of change on a physical activity   + Hjorth Mobility (signal mean frequency) and Complexity (deviation of the signal from the sine shape) * ***Frequency domain feature (FFT):***   + The first 40 FFT coefficients |
| *Activity recognition* | Combine clustering algorithm with SVM classifier   1. Generate model for person ; 2. Classify unlabelled samples of person by using model ; 3. Cluster the labelled samples of person B by iteratively relocating the centroids by using the Euclidean distance; 4. Extract from each cluster a number of confident samples where is given and is the number of classes; 5. Update model by using these confident samples. |
| *Results* | * *Mobile AR system:*   + Computational complexity on time domain is more effective than frequency domain ( , where is the signal length) * *Personalization in predefined activities:*   + **K-means:** yields optimal result in cross-people prediction, 8% accuracy increased   + **K-medoids:** better than K-means in small sample groups (because it is more robust than K-means in the presence of noise and outliers); accuracy decreases when the number of test samples increases except for the value * *Update new activities:* K-medoids performs better than K-means |

### Ali Fahmi

**Multimodal Biometrics for Usable Authentication System Using a Smartphone**

1. **Overview:**
   1. Singlemodal biometric for user authentication system
      * Arm’s flex when responding call
      * Ear biometrics
   2. Multimodal biometrics for user authentication system: arm’s flex and ear shape
2. **Problems and solutions:**
   1. User authentication using arm’s flex biometric

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| --- | --- |
| *Paper title* | Arm’s Flex when Responding Call for Implicit User Authentication in Smartphone |
| *Appeared in* | International Journal of Security and Its Applications 6(3), 2012 |
| *Data acquisition* | * *Mobile phone:* Pantech Sky Vega Racer * *Sensor:* accelerometer * 6 volunteers, 20 patterns of two categories ((1) phone picked from desk, and (2) phone picked from pocket) for each person |
| *Classification* | * *Template Matching method:* measuring similarity and thresholding * *Similarity =* (Euclidean distance score) / (Cosine similarity score) |
| *Result* | * ***Category 1:***   + *Classification accuracy = 87.8%*   + *False Match Rate (FMR) = 14%*   + *False Non-Match Rate (FNMR) = 3.3%* * ***Category 2:***   + *Classification accuracy = 90%*   + *False Match Rate (FMR) = 11.3%*   + *False Non-Match Rate (FNMR) = 3.3%* |

* 1. User authentication using ear biometric

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| --- | --- |
| *Paper title* | Implicit Authentication based on Ear Shape Biometrics using Smartphone Camera during a Call |
| *Appeared in* | International Conference on Systems, Man, and Cybernetics, IEEE, 2012 |
| *Data acquisition* | * *Mobile phone:* Samsung Galaxy S2 * 20 subjects, totally 80 images of size 1600x1200, cropped to 100x165 grayscale images |
| *Data preprocessing* | * Split each image into 4 quadrantal parts |
| *Feature extraction* | * Combining histogram resulted from Local Binary Pattern (LBP) and Geometric Analysis * 61 features are obtained |
| *Classification* | * kNN classifier |
| *Result* | * Classification rate = 92.5% |

* 1. Multimodal biometrics for authentication: arm’s flex and ear

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| --- | --- |
| *Paper title* | A Study on Multibiometrics derived from Calling Activity Context using Smartphone for Implicit User Authentication System |
| *Appeared in* | International Journal of Contents 9(2), 2013 |
| *Idea for combination* | First use arm’s flex, then use ear image when the phone is put near the ear in picking a call activity |
| *Data acquisition* | * *Mobile phones:* Samsung Galaxy S3, LG Optimus II, Pantech Sky Vega Racer * *Data source:* accelerometer, gyroscope, front camera |
| *Data preprocessing* | * **Arm flex:**   + Linear interpolation, noise filtering (2n+1-moving average filter) * **Ear image:**   + Divide ear image into four subregions |
| *Feature Extraction* | * **Arm flex:**   + Segmentation: fixed length of 250 * **Ear image:**   + Divide ear image into four subregions   + Combining histogram resulted from Local Binary Pattern (LBP) and Geometric Analysis |
| *Classification* | * **Arm flex:**   + *Template Matching* by using Dynamic Time Warping (DTW) distance measure (score in [0;1]) * **Ear image:**   + kNN classifier with Euclidean distance from histogram (score in [0;1])   + Summation of two distance score (in [0;2]) and thresholding with values |
| *Result* | * *Accuracy:*   + : 95%   + : 92.5%   + : 87.5% |

* 1. Thesis: Multimodal biometrics for authentication: arm’s flex and ear

|  |  |
| --- | --- |
| *Title* | Multimodal Biometrics for Usuable Authentication System Using a Smartphone |
| *Idea for combination* | First use arm’s flex, then use ear image when the phone is put near the ear in picking a call activity |
| *Data acquisition* | * *Mobile phones:* Samsung Galaxy S3, LG Optimus II, Pantech Sky Vega Racer * *Accelerometer, gyroscope:* 30 persons, 300 data in total * *Front camera:* 30 persons, 300 images in total |
| *Data preprocessing* | * **Arm flex:**   + Linear interpolation, noise filtering (2n+1-moving average filter) * **Ear image:**   + Divide ear image into four subregions |
| *Feature extraction* | * **Arm flex:**   + Segmentation: fixed length of 250 * **Ear image:**   + Divide ear image into four subregions   + Combining histogram resulted from Local Binary Pattern (LBP) and Geometric Analysis, and Monogenic Local Binary Pattern (M-LBP) |
| *Classification* | * **Arm flex:**   + *Template Matching* by using Dynamic Time Warping (DTW) distance measure (score in [0;1]) * **Ear image:**   + kNN classifier with Euclidean distance from histogram (score in [0;1])   + Summation of two distance score (in [0;2]) and thresholding with values |
| *Result* | * *Accuracy:* 95% () * *Receiver Operating Characteristics (ROC) analysis:* calculate area under curve (AUC)   + AUC = 0.8731 for arm flex only   + AUC = 0.9218 for ear only   + *AUC* = 0.9301 when combined |

### Thang Hoang

**Gait Authentication on Mobile Phone Using Pattern Recognition and Biometric Cryptosystem**

1. **Overview:**
   1. Data acquisition using built-in sensors (accelerometer,magnetometer) of mobile devices;
   2. Data preprocessing (time interpolation, noise filtering);
   3. Data analysis (gait cycle detection, pattern extraction);
   4. Feature extraction in both time domain and frequency domain;
   5. Classification: Machine Learning method
      * Support Vector Machine (SVM) classifier
2. **Problems and solutions:**
3. Data acquisition, preprocessing and classification method selection (Template Matching method vs. Machine Learning method)

|  |  |
| --- | --- |
| *Paper title* | Gait identification using accelerometer on mobile phone |
| *Appeared in* | International Conference on Control, Automation and Information Sciences (ICCAIS), IEEE, 2012 |
| *Data acquisition* | * *Mobile device:* Google Android HTC Nexus One * *Sensor:* Bosch Sensortec’s 3-axis BMA 150 accelerometer * *Sampling rate:* 27Hz * 11 volunteers (24 year-old), 12 laps with 26 seconds each lap for each person |
| *Data Preprocessing* | * *Linear interpolation:* to acquire fixed interval length (32Hz) signal * *Noise elimination:* Daubechies orthogonal wavelet (Db6) decomposition at level 2 |
| *Data analysis* | * Gait cycle partition using peak detection on the Z-dimensional signal |
| *Feature extraction* | * ***Time domain feature****:* average gait cycles (AGCs) is a sequence of values where one value is an average distance between one gait cycle to others (calculated by using DTW) * ***Frequency domain features:*** the first 40 FFT coefficients form a feature vector |
| *Classification* | * ***Template Matching method:*** DTW is performed to match two AGCs templates * ***Machine Learning method:*** SVM with feature vector is first 40 FFT coefficients |
| *Results* | * *Identification accuracy:*   + *DTW:* 79.1%   + *SVM:* 92.7% , additional validation is needed |

1. Examining the impact of different sampling rates (from different devices) on the preprocessing steps

|  |  |
| --- | --- |
| *Paper title* | Adaptive Cross-Device Gait Recognition Using a Mobile Accelerometer |
| *Appeared in* | Journal of Information Processing Systems 9(2), 2013 |
| *Data acquisition* | * *Mobile devices:* Google Android HTC Nexus One and LG Optimus G * *Sensor:* accelerometer * *Sampling rates:* 27Hz (Google HTC) and 100HZ (LG Optimus) * 14 volunteers (23~28 year-old), 12 laps with 36 seconds each lap for each person |
| *Data preprocessing* | * *Linear interpolation:* to acquire signals with fixed interval length at 32Hz and 100Hz * *Noise elimination:* Db6 decomposition at level ( for 32Hz signal and for 100Hz signal) |
| *Data analysis* | * *Data segmentation* by using autocorrelation |
| *Feature extraction* | * ***Time domain features:***   + Average maximum acceleration   + Average minimum acceleration   + Average absolute difference   + Root mean square   + 10-bin histogram distribution   + Standard deviation   + Waveform length   + Time of a gait cycle   + Gait cycle frequency * ***Frequency domain features:***   + First 40 FFT coefficients   + First 40 DCT coefficients |
| *Classification* | SVM with Radial Basis Function (RBF) kernel |
| *Classification result* | 99.81% (Google HTC, Db6 at level 2) and 97.53% (LG Optimus, Db6 at level 3) |
| *Feature validation* | * *Measure:* Average Error Rate (AER) and Intra-class Correlation Coefficients (ICC) * ***Time domain features:***   + High ICC values (0.7~0.996) => time domain features are high reliable regardless of sampling rate   + Low AER => not influenced by the sampling rate * ***Frequency domain features:***   + Fair to good values of ICC (0.666~0.804) => reliable   + High AER => very sensitive to the sampling rate |
| *Sampling rate examination* | * *Sampling rate =* {16+4k} with k = 1,2,...,21 * *Result:* best classification result with sampling rate of 32~36Hz, noise filtering at level 2 |
| *Noise filtering* | Higher levels of decomposition will eliminate noise better   * *Level 1:* 12~48Hz * *Level 2:* 12~100Hz (accuracy rate decreases when the sampling rate increases, best classification achieved at sampling rate 32~36Hz) * *Level 3:* best accuracy rate of 97.53% at the sampling rate of 100Hz |

1. Preprocessing step: Handling mobile installation issues: disorientation and misplacement of mobile phone in side the trouser’s pocket

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| --- | --- |
| *Paper title* | A Lightweight Gait Authentication on Mobile Phone Regardless of Installation Error |
| *Appeared in* | Security and Privacy Protection in Information Processing Systems 405:83-101, 2013 (SEC 2013) |
| *Data acquisition* | * *Mobile phone:* Google Android HTC Nexus One (sampling rate of 27Hz) * *Sensor:* accelerometer, magnetometer * 38 volunteers (24~28 year-old), 18 laps with 36 seconds each lap for each person, three types of footwear (sleeper, sandal and shoe) |
| *Data preprocessing* | * *Signal transformation:* rotation by using magnetometer to detect the roll, pitch and yaw angles * *Linear interpolation:* to acquire fixed interval length (32Hz) signal * *Noise filtering:* DB6 wavelet decomposition at level 2 |
| *Data analysis* | * *Segmentation:* based on gait cycles (2,4,8) |
| *Feature extraction* | * Feature extraction in both time domain and frequency domain * Feature subset selection by using Sequential Forward Selection (SFS) algorithm and Sequential Floating Forward Selection (SFFS) algorithm |
| *Classification* | * SVM with RBF kernel |
| *Result* | * *Accuracy:* 94.93% (SFFS) * False-Match-Rate (FMR): 0% * False-Not-Match-Rate (FNMR): 3.89% * Authentication time: <4 seconds |

1. System security and privacy concerns

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| --- | --- |
| *Paper title* | Secure and Privacy Enhanced Gait Authentication on Smart Phone |
| *Appeared in* | The Scientific World Journal, 2014 |
| *Data acquisition* | * *Mobile phone:* Google Nexus One (sampling rate of Hz) * *Sensor:* accelerometer * 34 volunteers (24~28 year-old), 18 laps for each person with different types of footwear and clothes |
| *Data preprocessing* | * *Linear interpolation:* to acquire fixed interval length (32Hz) * *Noise filtering:* Db6 wavelet decomposition at level 2 |
| *Data analysis* | * Gait cycle based segmentation |
| *Feature extraction* | * Feature extracted in both time domain and frequency domain. Feature vector is of length 290. * Binary feature vector extraction by using quantization. * Extract reliable bits by integrating Gaussian distribution to each components of the feature vector. Feature vector’s length is reduced. |
| *Key binding* | * Randomly generate a binary secret key * Calculate a the value by using a cryptographic hash function * Encoding using Bose-Chaudhuri-Hocquenghem (BCH) scheme * Binding using exclusive-OR operator |
| *Authentication* | * Decoding using BCH algorithm to obtain the secret key * Calculate the hash value using the equivalent cryptographic hash function * Matching between the two hash values |
| *Result* | Key length = 50 bits:   * False Acceptance Rate (FAR) = 3.92% * False Rejection Rate (FRR) = 11.76% |

## Tentative Direction

## Facilities

### Smartphone

### Applications

### Server

# Data Description: Level 1

## Individual Data

### Vo Voiet Dataset

### Ali Fahmi Dataset

### Thang Dataset

## ITRC Data

### First Data Collected by ITRC

1. **Collecting data configuration**
   1. Event Types : A(App), B(Broadcast), G(GPS), N(Network), S(Sensor)
   2. Monitoring Period : GPS/duration of collecting data : 15minutes, uploading period: 60 minutes
2. **[Application Event]**

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| Event Type | Event | Value 1 | Value 2 | Value 3 |
| A | Name of application | Usage duration |  |  |

1. **[Broadcast Event]**

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| Event Type | Event | Value 1 | Value 2 | Value 3 |
| B | INCOMING\_CALL\_END | Phone Number | Duration (sec) |  |
| B | OUTGOING\_CALL\_END | Phone Number | Duration (sec) |  |
| B | SMS\_RECEIVED | Phone Number | Text len |  |
| B | SMS\_SENT | Phone Number | Text Len |  |
| B | RINGER\_MODE\_CHANGED | Mode(NORMAL/SILENT/VIBRATE) | Ring Vol | Music Vol |
| B | CONFIGURATION\_CHANGED | Mode(LANDSCAPE/PORTRAIT) |  |  |
| B | bluetooth.ACL\_CONNECTED | BT Name | BT Address |  |

1. **[GPS Event]**

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| --- | --- | --- | --- | --- |
| Event Type | Event | Value 1 | Value 2 | Value 3 |
| G | GPS | Provider(network/gps) | Latitude | Longitude |

1. **[Network Event]**

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| Event Type | Event | Value 1 | Value 2 | Value 3 |
| N | SIG | Net Type(GSM/CDMA) | Signal Strength |  |

1. **[Sensor Event]**

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| Event Type | Event | Value 1 | Value 2 | Value 3 |
| S | ACCELEROMETER | value 1 | value 2 | value 3 |
| S | AMBIENT\_TEMPERATURE | value 1 | value 2 | value 3 |
| S | GAME\_ROTATION\_VECTOR | value 1 | value 2 | value 3 |
| S | GRAVITY | value 1 | value 2 | value 3 |
| S | GYROSCOPE | value 1 | value 2 | value 3 |
| S | GYROSCOPE\_UNCALIBRATED | value 1 | value 2 | value 3 |
| S | LIGHT | value 1 | value 2 | value 3 |
| S | LINEAR\_ACCELERATION | value 1 | value 2 | value 3 |
| S | MAGNETIC\_FIELD | value 1 | value 2 | value 3 |
| S | MAGNETIC\_FIELD\_UNCALIBRATED | value 1 | value 2 | value 3 |
| S | PRESSURE | value 1 | value 2 | value 3 |
| S | PROXIMITY | value 1 | value 2 | value 3 |
| S | RELATIVE\_HUMIDITY | value 1 | value 2 | value 3 |
| S | ROTATION\_VECTOR | value 1 | value 2 | value 3 |
| S | SIGNIFICANT\_MOTION | value 1 | value 2 | value 3 |

1. **[WebBrowser Event]**

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| --- | --- | --- | --- | --- |
| Event Type | Event | Value 1 | Value 2 | Value 3 |
| W | Web History | URL | The number of access |  |

1. Android Sensor Description

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| --- | --- | --- | --- |
| Sensor | Type | Description | Common Uses |
| TYPE\_ACCELEROMETER | Hardware | Measures the acceleration force in m/s2 that is applied to a device on all three physical axes (x, y, and z), including the force of gravity. | Motion detection (shake, tilt, etc.). |
| TYPE\_AMBIENT\_TEMPERATURE | Hardware | Measures the ambient room temperature in degrees Celsius (°C). See note below. | Monitoring air temperatures. |
| TYPE\_GRAVITY | Software or Hardware | Measures the force of gravity in m/s2 that is applied to a device on all three physical axes (x, y, z). | Motion detection (shake, tilt, etc.). |
| TYPE\_GYROSCOPE | Hardware | Measures a device's rate of rotation in rad/s around each of the three physical axes (x, y, and z). | Rotation detection (spin, turn, etc.). |
| TYPE\_LIGHT | Hardware | Measures the ambient light level (illumination) in lx. | Controlling screen brightness. |
| TYPE\_LINEAR\_ACCELERATION | Software or Hardware | Measures the acceleration force in m/s2 that is applied to a device on all three physical axes (x, y, and z), excluding the force of gravity. | Monitoring acceleration along a single axis. |
| TYPE\_MAGNETIC\_FIELD | Hardware | Measures the ambient geomagnetic field for all three physical axes (x, y, z) in μT. | Creating a compass. |
| TYPE\_ORIENTATION | Software | Measures degrees of rotation that a device makes around all three physical axes (x, y, z). As of API level 3 you can obtain the inclination matrix and rotation matrix for a device by using the gravity sensor and the geomagnetic field sensor in conjunction with the getRotationMatrix() method. | Determining device position. |
| TYPE\_PRESSURE | Hardware | Measures the ambient air pressure in hPa or mbar. | Monitoring air pressure changes. |
| TYPE\_PROXIMITY | Hardware | Measures the proximity of an object in cm relative to the view screen of a device. This sensor is typically used to determine whether a handset is being held up to a person's ear. | Phone position during a call. |
| TYPE\_RELATIVE\_HUMIDITY | Hardware | Measures the relative ambient humidity in percent (%). | Monitoring dewpoint, absolute, and relative humidity. |
| TYPE\_ROTATION\_VECTOR | Software or Hardware | Measures the orientation of a device by providing the three elements of the device's rotation vector. | Motion detection and rotation detection. |
| TYPE\_TEMPERATURE | Hardware | Measures the temperature of the device in degrees Celsius (°C). This sensor implementation varies across devices and this sensor was replaced with theTYPE\_AMBIENT\_TEMPERATURE sensor in API Level 14 | Monitoring temperatures. |

### Second Data Collected by ITRC

Our research focus on opportunistic sensing which is we develop application which does not need user’s intervention. To analyze the result, because of the data that we collected does not have any label so we prefer to use unsupervised learning.

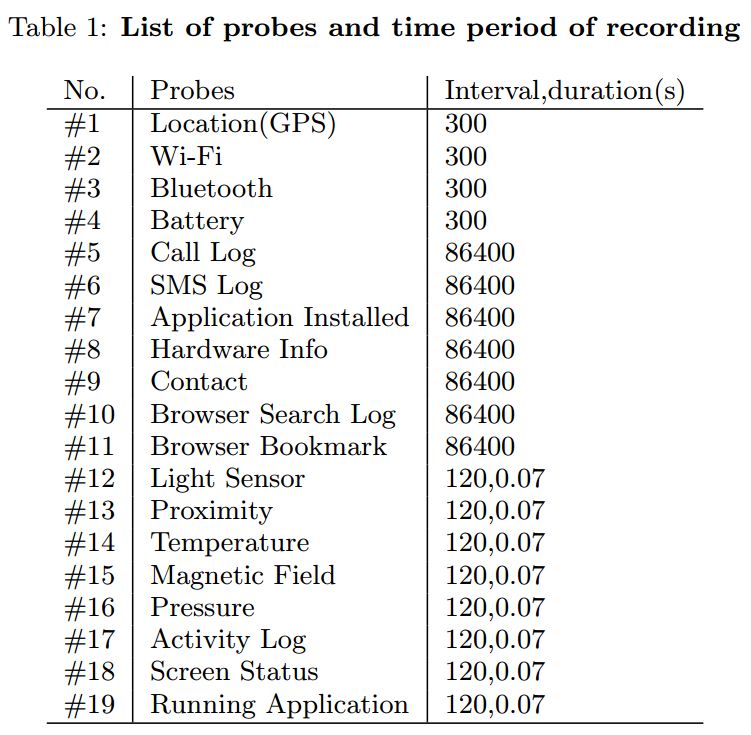
In this research we develop two systems are:

1. Application data collector
2. Data extraction and visualization

Application data collector is application that we used for collecting user’s personal data. This application is android application. After we have all of data from the user, we have to extract and visualize, and also analyze it. To extract, visualize, and analyze the data, we use R programing language.

#### Application Data Collector

To develop application data collector, we do not develop 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 1 shows Funf framework can collect many of sensing from smartphone such location, movement, communication and usage, social proximity, and many more. In this document, we do not describe details about Funf architecture but we describe about the data that we have collected and how to extract, visualize and analyze it. More details about Funf architecture can be seen in the main site of Funf[[1]](#footnote-1) and also Funf developer site[[2]](#footnote-2).



#### Data Description

Our application follows opportunistic sensing because we do not want to bothering user much. To do that we must define the time (interval and duration), when the application will request the data from the smartphone. Interval means how many times in second system will send data request to the smartphone. The example, we set interval 300 seconds means 5 minutes, so application will request and store the data for every 5 minutes. Duration is used in sensor data because without duration is useless to collect the sensors data. The example of duration, when we set interval 120 seconds and duration 0.07 s so 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 1.shows the interval and duration from each probes. Those interval and duration already tested and we thought those setting was optimum one but we can change those setting by change the value on the string.xml in android project. Figure 2a shows the string.xml file in the directory of android project and Figure 2b shows inside the string.xml file, we can change value of interval and duration in that file.

|  |  |
| --- | --- |
| C:\Users\rischan\Music\funf.png | D:\Dropbox\thesis\figures\dataviewinsmartphone.png |
| Figure 1. Funf Open Sensing Framework | Figure 3. Personal data in user’s smartphone |

To make easy for remembering, we classify the data to three of data categorization, are:

1. On Request Data (Current Data)
2. Historical Data (Saved in Android db)
3. Continuous Data (Sensor data)

On request data means we try to ask current values from android system such as location, battery, nearby Bluetooth and etc. Historical data means the data that already store in android database so we try to access and collect it, 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). Another important thing is because we are living in time dimension space so every data has timestamp. Funf already has features to collect time, 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.

|  |  |
| --- | --- |
| D:\Dropbox\thesis\figures\ppt2\pptdata\sstringxml.JPG | D:\Dropbox\thesis\figures\ppt2\pptdata\funfsettingxml.JPG |
| (a) | (b) |
| Figure 2. (a) strings.xml file in project directory, (b) inside the string.xml file | |

Data that we collected using our application will be store in SQLite database format with (\*.db) extension, the view of data can be seen in Figure 3. To open those database, we can use SQLite browser that can be download in SQLite browser main site[[3]](#footnote-3).

Table 2. On Request Data Table

|  |  |  |  |
| --- | --- | --- | --- |
| **\_id** | **name** | **timestamp** | **value (JSON)** |
|  | SimpleLocationProbe | Unix UTC |  |
|  | WifiProbe |  |  |
|  | BluetoothProbe |  |  |
|  | BatteryProbe |  |  |

##### On Request Data

Table 2.shows the table of On Request Data. The table 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. On request data has four of probes are location, nearby Wi-Fi, nearby Bluetooth, and battery.

###### Simple Location Probe

Location is one of the most important information from the user. In this research, we try to get the location information from the users. The value that returned by system is like this:

{"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 representing a geographic location. A location can consist of a latitude, longitude, timestamp, and other information such as bearing, altitude and velocity. 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. In general, usually we only use latitude and longitude to define the human location, but in this data we have many of data, another data such as accuracy, bearing, altitude, and elapse real time are explained below.

**Accuracy**

Get the estimated accuracy of this location, in meters. We define accuracy as the radius of 68% confidence. In other words, if you draw a circle centered at this location's latitude and longitude, and with a radius equal to the accuracy, then there is a 68% probability that the true location is inside the circle.

**Altitude**

Get the altitude if available, in meters above the WGS 84 (World Geodetic System) reference ellipsoid. If this location does not have an altitude then 0.0 is returned. The coordinate origin of WGS 84 is meant to be located at the Earth's center of mass; the error is believed to be less than 2 cm.

**Bearing**

Get the bearing, in degrees. Bearing is the horizontal direction of travel of this device, and is not related to the device orientation. If this location does not have a bearing then 0.0 is returned.

**Elapsed Real Time**

Note that the UTC time on a device is not monotonic: it can jump forwards or backwards unpredictably. So always use *getElapsedRealtimeNanos()* when calculating time deltas. On the other hand, *getTime()* is useful for presenting a human readable time to the user, or for carefully comparing location fixes across reboot or across devices.

More details about the key and values from the location probes can be seen in Android API documentation through this link.

http://developer.android.com/reference/android/location/Location.html#

###### Nearby Wi-Fi Probe

One of important information about the user is nearby Wi-Fi. This probes will collect all of Wi-Fi information which is near with user. This data also can be collected by using our application data collector. Returned value from the system is looks like:

{"BSSID":"b0:c7:45:7d:0f:7c"**,"SSID":"rischan"**,"capabilities":"[WPA2-PSK-CCMP+TKIP][ESS]","frequency":5180,**"level":-46**,"timestamp":1403476993.05}

We have 6 couple of keys and values, BSSID, SSID (Access Point name), capabilities, frequency, level, and timestamp.

**Capabilities**

Describes the authentication, key management, and encryption schemes supported by the access point.

**Frequency**

The frequency in MHz of the channel over which the client is communicating with the access point.

**Level**

The detected signal level in dBm, also known as the RSSI. Use *calculateSignalLevel(int, int)* to convert this number into an absolute signal level which can be displayed to a user.

###### Nearby Bluetooth Probe

Beside of nearby Wi-Fi, one of important information related with human is nearby Bluetooth. This probes will collect all of Wi-Fi information which is near with user. The value that we get from our application looks like:

{android.bluetooth.device.extra.DEVICE":{"mAddress":"74:F0:6D:E8:ED:67"},"android.bluetooth.device.extra.NAME":"RRI-ITMS PC","android.bluetooth.device.extra.RSSI":-79,"timestamp":1404128054.397}

We have information about the device, in this case Bluetooth device address, also Bluetooth name, RSSI, and timestamp.

**android.bluetooth.device.extra.RSSI**

Used as an optional short extra field in ACTION\_FOUND intents. Contains the RSSI value of the remote device as reported by the Bluetooth hardware. Constant Value: "android.bluetooth.device.extra.RSSI“. More details about Bluetooth documentation can be seen in Android API documentation through this link

http://developer.android.com/reference/android/bluetooth/BluetoothDevice.html

###### Battery Probe

Battery Probe will collect battery information from the user’s smartphone such as charging or discharging, health condition, level, and etc. The value that returned by system looks like:

{**"charge\_type":0**,**"health":2**,"icon-small":17303540, "level":89,"online":1, "scale":100,**"status":3**,"technology":"Li-ion","temperature":305,"timestamp":1403476991.281,"voltage":4138}

We have 11 couple of keys and values from those data. The description about the meaning of values of charge\_type, health, status, and voltage can be seen below:

Charge Type value meaning

* BATTERY\_PLUGED\_AC =1
* BATTERY\_PLUGGED\_USB =2
* BATTERY\_PLUGGED\_WIRELESS=4

Status value meaning

* BATTERY\_STATUS\_CHARGING =2
* BATTERY\_STATUS\_DISCHARGING =3
* BATTERY\_STATUS\_FULL =5
* BATTERY\_STATUS\_NOT\_CHARGING =4
* BATTERY\_STATUS\_UNKNOWN =1

Health values meaning

* BATTERY\_HEALTH\_COLD =7
* BATTERY\_HEALTH\_DEAD =4
* BATTERY\_HEALTH\_GOOD =2
* BATTERY\_HEALTH\_OVERHEAT =3
* BATTERY\_HEALTH\_OVER\_VOLTAGE =5
* BATTERY\_HEALTH\_UNKNOWN =1
* BATTERY\_HEALTH\_UNSPECIFIED\_FAILURE =5

**Voltage**

Integer containing the current battery voltage level. Constant Value: "voltage".

More details about Battery documentation can be seen in Android API documentation in this link http://developer.android.com/reference/android/os/BatteryManager.html

##### Historical Data

Table 3.shows the table of historical data. The table 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. Historical data are the call log data, SMS log, the list of installed application in user’s smartphone, user’s smartphone device (hardware) info, bookmark in smartphone browser, Log search (history) in smartphone browser, and contact in user’s smartphone.

To protect user privacy we use SHA to hash the privacy information such as user name in contact, phone number, name of caller, and etc.

Table 3. Historical Data Table

|  |  |  |  |
| --- | --- | --- | --- |
| **\_id** | **name** | **timestamp** | **value (JSON)** |
|  | CallLogProbe | Unix UTC |  |
|  | SmsProbe |  |  |
|  | ApplicationsProbe |  |  |
|  | HardwareInfoProbe |  |  |
|  | BrowserBookmarksProbe |  |  |
|  | BrowserSearchesProbe |  |  |
|  | ContactProbe |  |  |

###### Call Log Probe

The data from Call log probes looks like:

{"\_id":2172,"date":1403874310514,"duration":160,"name":"{\"ONE\_WAY\_HASH\":\"d5c7034c3a03ea8ec287f7e8f082d6ec8c07ffb1\"}","number":"{\"ONE\_WAY\_HASH\":\"d4f6776ca772a1d8fadb157ef323e906d78d8d9a,"timestamp":1403874310.514,"type":2}

We have 7 couple of JSON keys and values, date is the date when user call (incoming/outgoing) the date in UNIX timestamp format, duration is the duration of user when he/she make call, name and number are hashed, timestamp, and type. The value of type explained below:

Type value meaning

* INCOMING\_TYPE = 1
* OUTGOING\_TYPE = 2
* MISSED\_TYPE = 3

###### Sms Log Probe

The returned data from user’s smartphone of the SMS log probes looks like:

{"address":"dad42137da1fcasdsaga54d6c0f0dc8cd1d42e7a3","body":"{\"ONE\_WAY\_HASH\":\"c1f3942137da1fca36554d6c0f0dc8cd1d42e7a3\"}","body-byte-len":90,"body-token-byte-len":"3-52-16-16-","body-token-count":4,"date":1403316814524,"read":true,"thread\_id":215,"timestamp":1403316814.524,"type":1}

Similar with call log, the address, body text are hashed because this information is related to user privacy. Even though we encrypted some of information but we do not lose the pattern of information. If the address (phone number) is same the output of SHA hash also same. In this probe, we also collect the pattern of body token count, based on that data we know the length of message, the number of letters in each words, and etc.

In SMS log probes data we have key “type”, the meaning of type value explained below:

Type value meaning

* MESSAGE\_TYPE\_ALL =0
* MESSAGE\_TYPE\_INBOX =1
* MESSAGE\_TYPE\_SENT =2
* MESSAGE\_TYPE\_DRAFT =3
* MESSAGE\_TYPE\_OUTBOX =4
* MESSAGE\_TYPE\_FAILED =5
* MESSAGE\_TYPE\_QUEUED =6

If the type message (SMS) is SENT, the data have key “status”, and the meaning of the value in key “status” explained below:

Status value meaning

* STATUS\_NONE =-1
* STATUS\_COMPLETE =0
* STATUS\_PENDING =32
* STATUS\_FAILED =64

###### Installed Application probe

The data from Installed application probes can be seen below, this data is only from one application data:

{"dataDir":"**/data/data/com.lifevibes.trimapp**”,"enabled":true,"enabledSetting":0,"icon":2130837526, "installed":true,"installedTimestamp":null,"isTrusted":0,"nativeLibraryDir":"/data/data/com.lifevibes.trimapp/lib","packageName":"**com.lifevibes.trimapp**","processName":"**com.lifevibes.trimapp**”,"sourceDir":"/system/app/TrimApp\_phone\_J.apk","targetSdkVersion":17,"taskAffinity":"com.lifevibes.trimapp”,"timestamp":1403476969.264,"uid":10142}

Installed application probes collect the list of installed applications in user’s smartphone. The data above is an example of one data from one application. Based on that data we can determine the name of application using the name of package and that data also provides the information about the directory that used by application.

###### Hardware Info Probe

To know user’s smartphone specification, we can use this probes. The data from this probes looks like:

{"androidId":"5a0d4221916c50ce","bluetoothMac":"08:D4:2B:2A:05:3D","brand":"samsung","deviceId":"354257050990298","model":"SHV-E250K","timestamp":1403489373.257,"wifiMac":"08:D4:2B:2A:05:3E"}

Based on data from hardware info probes we can know the information about device Bluetooth mac, device brand, phone model, and Wi-Fi mac.

###### Bookmark and Log Search Probe

This application also provides the bookmark probes and log search probes. Bookmark probes will collect all of bookmark data from user’s smartphone browser. Search log probes will collect all of history (search log) from user’s smartphone browser. The data from bookmark probes looks like:

{"\_id":999,"bookmark":0,"created":0,"date":1403860944022,"timestamp":1403860944.022,"title":"홈 - 내학사행정","url":"http://portal.jnu.ac.kr/Education/Webservice\_S/Default.aspx","visits":125}

Based on that data we have information about the date in UNIX timestamp format, the title of bookmark, url, and how many user visit those bookmark.

The data from search log probes looks like:

{"\_id":2,"date":1383925223295,"search":"facebook","timestamp":1383925223.295}

We have date in UNIX timestamp, the log search, and also timestamp.

###### Contact Probe

The data from contact probes can be seen below:

{"contactData":"contact\_id":3,"custom\_ringtone":"{\"ONE\_WAY\_HASH\":\"\"}","display\_name":"{\"ONE\_WAY\_HASH\":\"50bf609648d98370521094b6b724d240bd469610\"}","in\_visible\_group":1,"last\_time\_contacted":0, photo\_id":0,"send\_to\_voicemail":0,"starred":0,"times\_contacted":0,"timestamp":1404296933.626}

Similar with Call and SMS log, the data which related with user privacy were hashed. From the contact data we can know the information about the name of people in contact (hashed), group, last time contacted, and many more. Even though the name of contact was hashed but we still can analyze the pattern. When the user try to contact one of person, if the name is same the output of hash also same, so we still have the pattern data, even we do not know exactly the name of people whom contacted by user.

##### Continuous Data

Table 4.shows the table of continuous data. The table 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 4. Continuous Data Table

|  |  |  |  |
| --- | --- | --- | --- |
| **\_id** | **name** | **timestamp** | **value (JSON)** |
|  | LightSensorProbe | Unix UTC | {"accuracy":1,"lux":**121.0**,  "timestamp":**1402725082**.124436} |
|  | ProximitySensorProbe |  | {"accuracy":0,"distance":**8.0**,  "timestamp":**1402725082**.030173} |
|  | TemperatureSensorProbe |  |  |
|  | MagneticFieldSensorProbe |  | {"accuracy":2,"timestamp":**1402725082**.028829,"x":-**26**.939999,"y":**-8**.5199995,"z":**-24**.06} |
|  | PressureSensorProbe |  | {"accuracy":0,"pressure":**999**.82,  "timestamp":**1402725083**.016377} |
|  | ScreenProbe |  | {"screenOn":**true**,"timestamp":**1402725416**.351} |
|  | RunningApplicationsProbe |  |  |
|  | ActivityProbe |  |  |

###### Android Sensors Data

The Sensor Probes that we used are light sensor, proximity sensor, temperature sensor, magnetic field sensor, and pressure sensor. Table 4. Shows the table of continuous data and on the last column, we can see the example value from each sensor probes. The data which came from android sensor have accuracy the meaning of accuracy are described below:

**Accuracy**

Meaning of accuracy values in sensors data, are:

* SENSOR\_STATUS\_ACCURACY\_HIGH means this sensor is reporting data with maximum accuracy, return value = 3.
* SENSOR\_STATUS\_ACCURACY\_LOW means this sensor is reporting data with low accuracy, calibration with the environment is needed, return value = 1
* SENSOR\_STATUS\_ACCURACY\_MEDIUM means this sensor is reporting data with an average level of accuracy, calibration with the environment may improve the readings, return value = 2.
* SENSOR\_STATUS\_UNRELIABLE means the values returned by this sensor cannot be trusted, calibration is needed or the environment doesn't allow readings, return value = 0.
* SENSOR\_STATUS\_NO\_CONTACT means the values returned by this sensor cannot be trusted because the sensor had no contact with what it was measuring (for example, the heart rate monitor is not in contact with the user), return value = -1.

The details information about android sensors can be seen in Table 5.

Table 5. Android Sensors Explanation

|  |  |  |  |
| --- | --- | --- | --- |
| Sensor | Type | Description | Common Uses |
| TYPE\_ACCELEROMETER | Hardware | Measures the acceleration force in m/s2 that is applied to a device on all three physical axes (x, y, and z), including the force of gravity. | Motion detection (shake, tilt, etc.). |
| TYPE\_LIGHT | Hardware | Measures the ambient light level (illumination) in lx.  values[0]: Ambient light level in SI lux units | Controlling screen brightness. |
| TYPE\_MAGNETIC\_FIELD | Hardware | Measures the ambient geomagnetic field for all three physical axes (x, y, z) in μT. | Creating a compass. |
| TYPE\_PRESSURE | Hardware | Measures the ambient air pressure in hPa or mbar. | Monitoring air pressure changes. |
| TYPE\_PROXIMITY | Hardware | Measures the proximity of an object in cm relative to the view screen of a device. This sensor is typically used to determine whether a handset is being held up to a person's ear.  values[0]: Proximity sensor distance measured in centimeters | Phone position during a call. |
| TYPE\_TEMPERATURE | Hardware | Measures the temperature of the device in degrees Celsius (°C). This sensor implementation varies across devices and this sensor was replaced with theTYPE\_AMBIENT\_TEMPERATURE sensor in API Level 14.  values[0]: ambient (room) temperature in degree Celsius. | Monitoring temperatures. |

###### Running Application Probe

We have installed application probes which can collect the list of installed application in user’s smartphone. To know user interest we also try to collect the current applications which user used or running application.

The data from running application probes looks like:

{"duration":6.143,"taskInfo":{"baseIntent":{"mAction":"android.intent.action.MAIN","mCategories":["android.intent.category.LAUNCHER"],"mComponent":{"mClass":"kr.ac.jnu.netsys.MainActivity","mPackage":"edu.mit.media.funf.wifiscanner"}, "mPackage":"edu.mit.media.funf.wifiscanner","mWindowMode":0},"id":30,"persistentId":30},"timestamp":1402725116.144}

We have information about the name of application package which is in current running also the time usage (duration).

###### Activity Probe

In our application we do not collet the accelerometer value directly but we use algorithm to determine the status of activities which are none, low, or high. We use sum of variance to detect the user activity based on accelerometer value. The details algorithm can be seen in Figure 4.

|  |
| --- |
| D:\Dropbox\thesis\figures\ppt2\activity.JPG |
| Figure 4. Activity log algorithm |

The value of activity probes that we get from the application looks like:

{"activityLevel":"none","timestamp":1402725083.715}

# How to Describe the Data: Level 2

## About Data Collection and Data Itself

### Individual Data

#### Vo Viet Dataset

|  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- |
| No. | Name of Dataset | When (in duration) | How many people participated | Who was in charge | Data location |
|  |  |  |  |  |  |
|  |  |  |  |  |  |

#### Ali Fahmi Dataset

|  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- |
| No. | Name of Dataset | When (in duration) | How many people participated | Who was in charge | Data location |
|  |  |  |  |  |  |
|  |  |  |  |  |  |

#### Thang Dataset

|  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- |
| No. | Name of Dataset | When (in duration) | How many people participated | Who was in charge | Data location |
|  |  |  |  |  |  |
|  |  |  |  |  |  |

### ITRC Data

#### ITRC First Data Collection

|  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- |
| No. | Name of Dataset | When (in duration) | How many people participated | Who was in charge | Data location |
|  |  |  |  |  |  |
|  |  |  |  |  |  |

#### ITRC Second Data Collection

We have finished to collect user personal data. The all of data stored in Rischan PC using path C:\ITRC\_DATA. The data has been archived in zip format with name “itrc 2014 userdata finalpoint 20140903.zip” with size 4.25 GB. The extracted data can be accessed in path C:\ITRC\_DATA\itrc 2014 userdata finalpoint 20140903\. The size of all of data after extracted is 28.7 GB. Extracted data contain 47 directories in different name for each student data. We have tied to looking information about those data such as the size of data from each student and starting point also ending point of data recording. The result of data summarization which contain with name of directories, size, starting point, and ending point can be seen in Table 6.

Table 6. 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 |

1. http://www.funf.org/ [↑](#footnote-ref-1)
2. https://code.google.com/p/funf-open-sensing-framework/wiki/FunfArchitecture [↑](#footnote-ref-2)
3. http://sqlitebrowser.org/ [↑](#footnote-ref-3)