# 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

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| *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

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| *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)

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| *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

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| *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

## ITRC Data

# How to Describe the Data: Level 2

## About Data Collection

## About Data Itself