**Summary:**

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

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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 |