Mobility Detection Using Everyday GSM Traces

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Mobility Detection

- High level activity discerned from course Grained GSM Data provides immediate opportunities to applications that do not require high definition of mobility.
- In a one month study with three participants the author was able to predict within an 85% accuracy in activity categories and accurate step counts.

Primary Premise

- **Detail not required for many applications**

Computer-Supported Coordinated Care

- **Authors identify immediate applications to the CSCC space where 50% of Americans aged 65 to 74 and 30% aged 75 to 94 have mobile phones.**

Step Counts

- **Authors Identify immediate need in healthcare for ubiquitous step counting capabilities in their fight against heart disease, diabetes and obesity.**

Common Usages not Cost effective

Course and Fine Grained

- **Smart Spaces**
- **RFID tags**
- **Lester belt-worn sensor clusters**

GPS vs GSM

- 5% Coverage in a typical persons Day to Day life
- Paper demonstrates certain high grained activities can be identified on GSM alone

Proved

- Statistical Classification and Boosting Techniques detects
  - Walking
  - Driving
  - Remaining in Place
- Without overhead of additional sensors

Step Counter

- **Using their method they predicated comparative step counts to commercial step counters.**

Their System

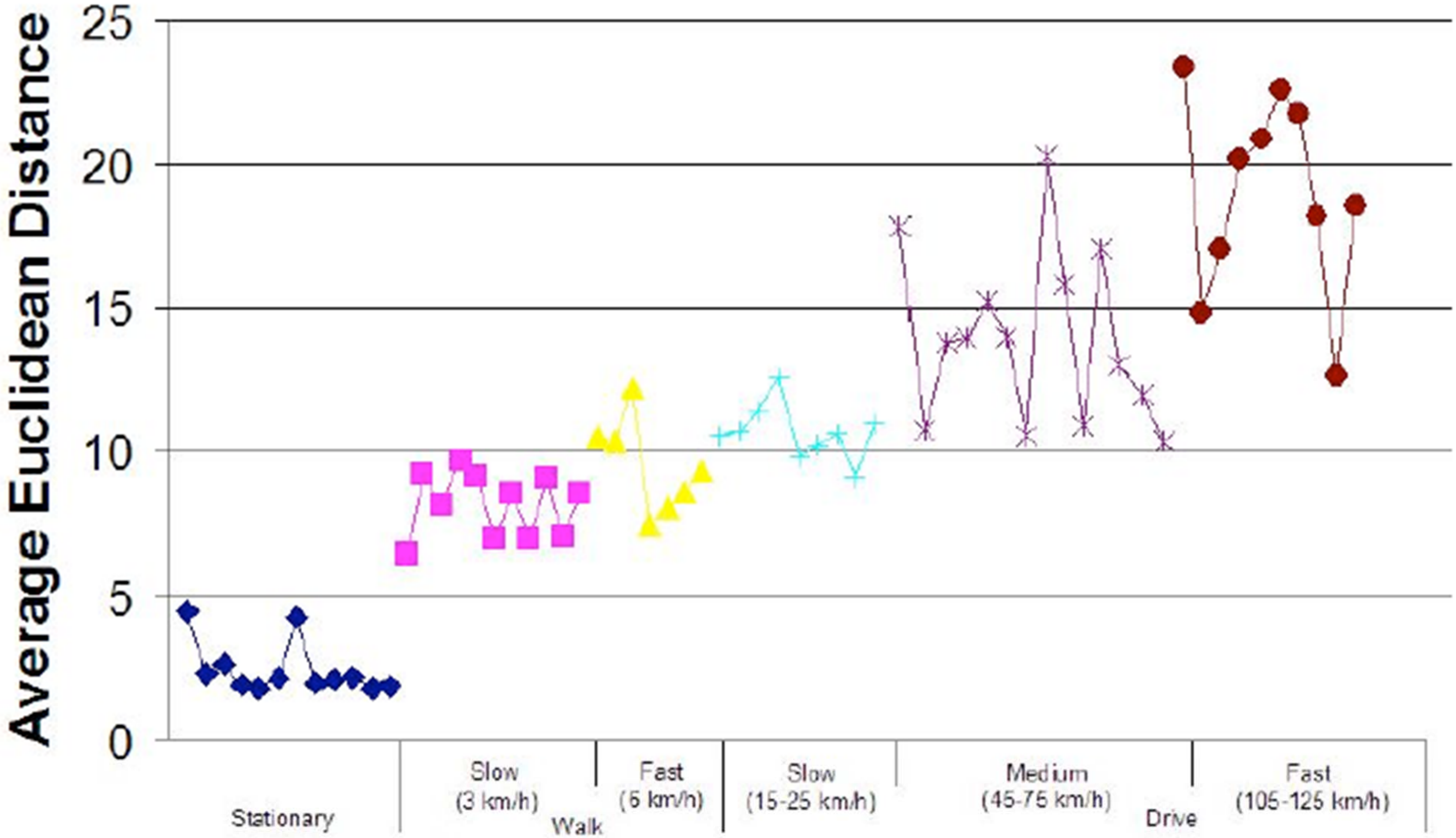
- **Application on Audiovox SMT 5600**
  - **Measure and Record Surrounding GSM radio environment (every second)**
  - **Each reading accounts for seven towers**
    - **Signal Strength Values**
    - **Cell IDs**
    - **Channel Numbers**
  - **15 additional reads**
    - **Signal Strength**
    - **Channel Numbers**

Inferring User Mobility Modes

- "Extract a set of features that indicate proportional levels of movement"
- Basically, If the set of towers and signal strengths change, then the phone is moving.

Euclidean Distance Values

- They can differentiate between walking, driving and being still
- Slow Driving and Fast Walking may look the same
- Focus is on the magnitude of the change



Average Euclidean Distance
25
20
15
10
5
0
Stationary
Slow
(3 km/h)
Walk
Fast
(6 km/h)
Slow
(15-25 km/h)
Medium
(45-75 km/h)
Drive
Fast
(105-125 km/h)

7 Feature Classification System

1. Euclidean distance between two consecutive measurements
2. Spearman rank correlation coefficient [33] between two consecutive measurements. (This number represents how closely the signal strengths from common cell towers were ranked. A more similar ranking indicates less movement.)
3. The number of common cell towers between two consecutive measurements.
4. Mean Euclidean distance over a window of measurements where the values are calculated between consecutive measurements and then averaged together.
5. Variance in Euclidean distance values over a window of measurements where the values are calculated between consecutive measurements.
6. The variance in signal strengths for each tower seen within a given window. (The variance values for each tower are averaged together to produce a single number representing the signal strength "spread" over the entire window.)
7. Euclidean distance value between the first and last measurement of a window.

Two Stage Classification System

- Stage One
  - Moving of not moving
- Stage Two
  - If not moving then walking or driving

Trained Classification System

- Boosted Logistics Regression Technique
- All aglo were provided by the weka machine learning toolkit
- Steps: total the number of waling periods and multiply by an appropriate step rate

Evaluation : Ground Truth

- 3 people 1 month
- Audiovox SMT 6500 App to record doing what and when correlated with written log
- Calibrated Pedometer: Omron Healthcare HJ-112 (between the three 50 days of step counts)

Inferring Mobility Modes

- **Infer One of Three States**
- **Issues with training for non-moving state as non-moving state includes movement (TV room to kitchen)**
- **Compromise data dropped that wasn't between 2 and 5 am**

Overall 85% accuracy

Precision

Ground Truth	Predicted Movement: Stationary	Walking	Driving
Stationary	95.4%	12.6%	6.9%
Walking	2.5%	70.2%	8.8%
Driving	2.1%	17.2%	84.3%

Recall

Ground Truth	Predicted Movement: Stationary	Walking	Driving
Stationary	92.5%	4.5%	3.0%
Walking	7.7%	80.0%	12.2%
Driving	4.5%	13.8%	81.7%

Figure 2. Precision and recall confusion matrices for all GSM network traces aggregated over all data collectors. Overall accuracy is 85%

Inferring Steps

- No need to exclude data, pedometer always counting no matter the activity and location, same with GSM.
- GSM Step counter not calibrated
- Drove data through linear regression with a 5 forked cross validation on their data set to get formula
  - Daily step count = 25* (minutes of walking)

Steps not so bad

- 1500 to 12000 steps with average of 5000 from GSM
- Differed from Omron
  - 1400 steps per day
- Ran second experiment with similar results against different models of pedometers.

CSCC Applications

- **Seeks to improve the qualify of care while reducing the burden on the members in the care network of the individual**
- **This mobility detection method can use GSM driven activity inference to convey care and wellness information**

Social Media Applications

- http://socialight.com
- http://www.textamerica.com

Related Work

- SHARP – Fine grained activity sensing with RFID
- Wearable Sensors (think cyborg)
- Reality Mining: Bluetooth capable phone for inferring relationships

Conclusions

- Demonstrated Feasibility
- Demonstrated value to such applications as CSCC and social-mobile applications
- Evaluated Effectiveness
- Demonstrated recognition of mobility patterns
- No special Devices required