Personal Sensing
Continued

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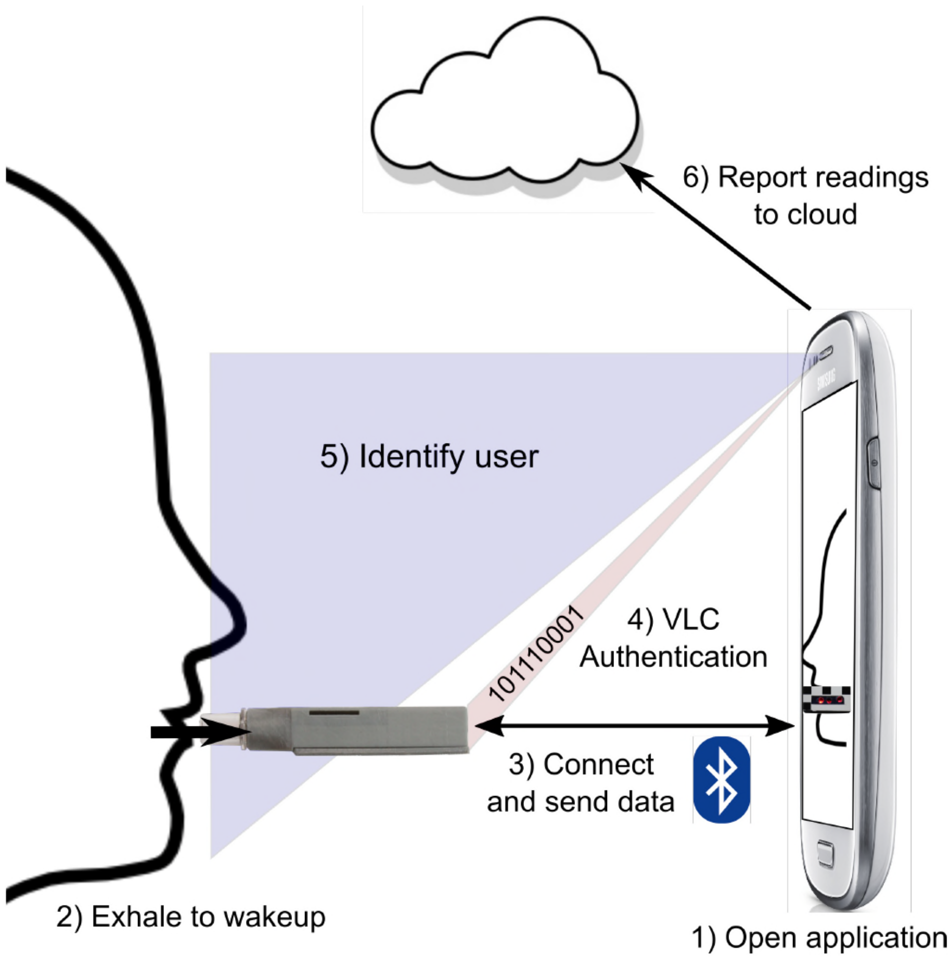
Reminders

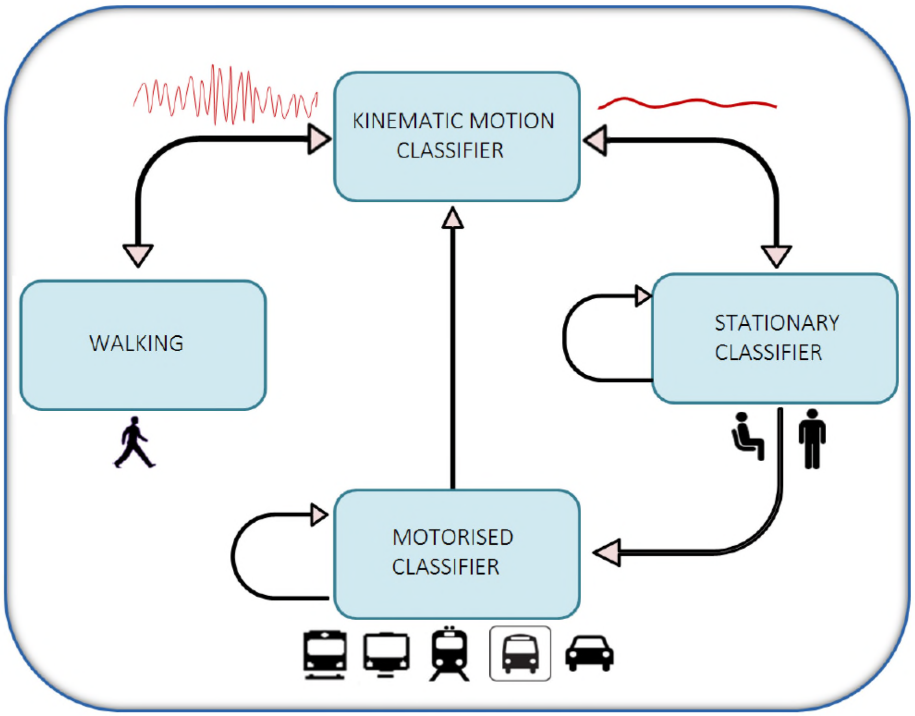
- Project Title and Abstract: Due Today.
- We have a critique due tomorrow evening (for Friday).

Smoking Detection Did You Beat It?



Transportation Mode Detection

- Based on phone accelerometers



Samuli Hemminki, Petteri Nurmi, and Sasu Tarkoma, "Accelerometer-based Transportation Mode Detection on Smartphones," ACM SenSys, November 2013

Challenge: Gravity Estimation

- Accelerometers measure the superposition of two forces:
  - Forces due to acceleration along each axis
  - Forces due to gravity along each axis
- Since accelerometer orientation is unknown, it is hard to separate the two.
  - What is the gravity component of the measurements read along each axis?

Solution #1

- Insight: Gravity is fixed. Other forces come and go.
- Solution: Average the acceleration measurements over a long enough time window
  - Transient forces will tend to cancel out
  - Constants (i.e., gravity) will remain
- Pros/cons?

Solution #2

- If there are intervals of relatively low accelerometer variance, it means that the accelerometer is not "moving".
  - Acceleration measurements during those intervals are mostly attributed to gravity.
  - Remember current measurements and set them as the "gravity components"
- Reset measured gravity components when significant motion is detected.

Features

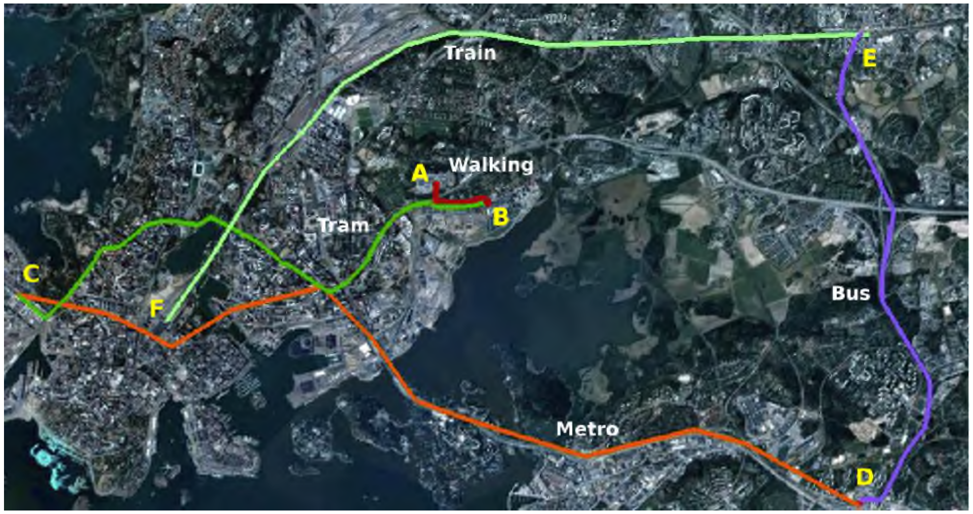
- Mean, variance, kurtosis, integral, auto-correlation, zero crossings, energy, entropy, FFT coefficients, etc.
  - Frame-based
  - Peak-based
  - Segment-based
- Standard classifier from prior work

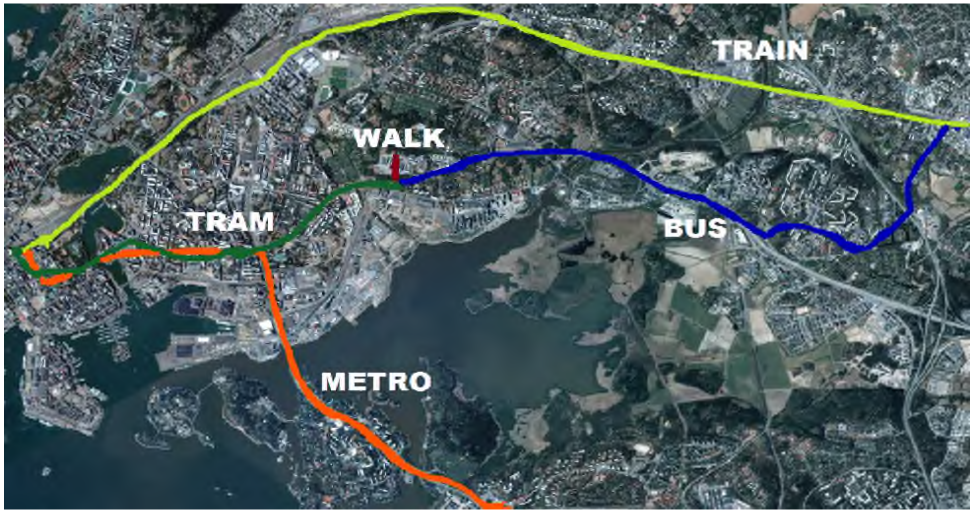
Features

Domain	Features
Statistical	Mean, STD, Variance, Median, Min, Max, Range, Interquartile range Kurtosis, Skewness, RMS
Time	Integral, Double integral, Auto-Correlation, Mean-Crossing Rate,
Frequency	FFT DC,1,2,3,4,5,6 Hz, Spectral Energy, Spectral Entropy, Spectrum peak position, Wavelet Entropy, Wavelet Magnitude
Peak	Volume (AuC), Intensity, Length, Kurtosis, Skewness
Segment	Variance of peak features (10 features), Peak frequency (2 features), Stationary duration, Stationary frequency

Evaluation

- 150 hour of transportation
- 16 individuals
- 4 countries
- Multiple scenarios (walk, train, tram, metro, bus, …)





Evaluation Results

- Better accuracy than competition

	Precision			Recall		
	Peaks	Wang	Reddy	Peaks	Wang	Reddy
Stationary	96.1 (0.5)	57.3 (4.5)	81.6 (1.0)	70.0 (2.1)	59.5 (2.3)	70.6 (2.9)
Walk	93.1 (0.1)	87.2 (0.2)	97.7 (0.1)	95.9 (0.1)	89.1 (0.2)	95.9 (0.1)
Bus	78.2 (4.2)	71.1 (1.4)	67.3 (1.6)	78.0 (3.3)	70.4 (1.4)	86.2 (6.4)
Train	68.2 (5.0)	32.1 (0.8)	7.7 (4.4)	80.1 (4.0)	31.6 (0.7)	55.4 (11.9)
Metro	64.5 (5.9)	54.4 (0.6)	70.1 (8.8)	82.0 (2.6)	51.4 (0.9)	56.6 (3.5)
Tram	84.0 (2.1)	58.1 (0.8)	82.8 (7.5)	86.1 (2.1)	58.2 (0.8)	64.5 (7.0)
Mean	80.1 (2.9)	60.0 (1.4)	68.0 (3.9)	82.1 (2.4)	60.2 (1.1)	71.6 (5.3)

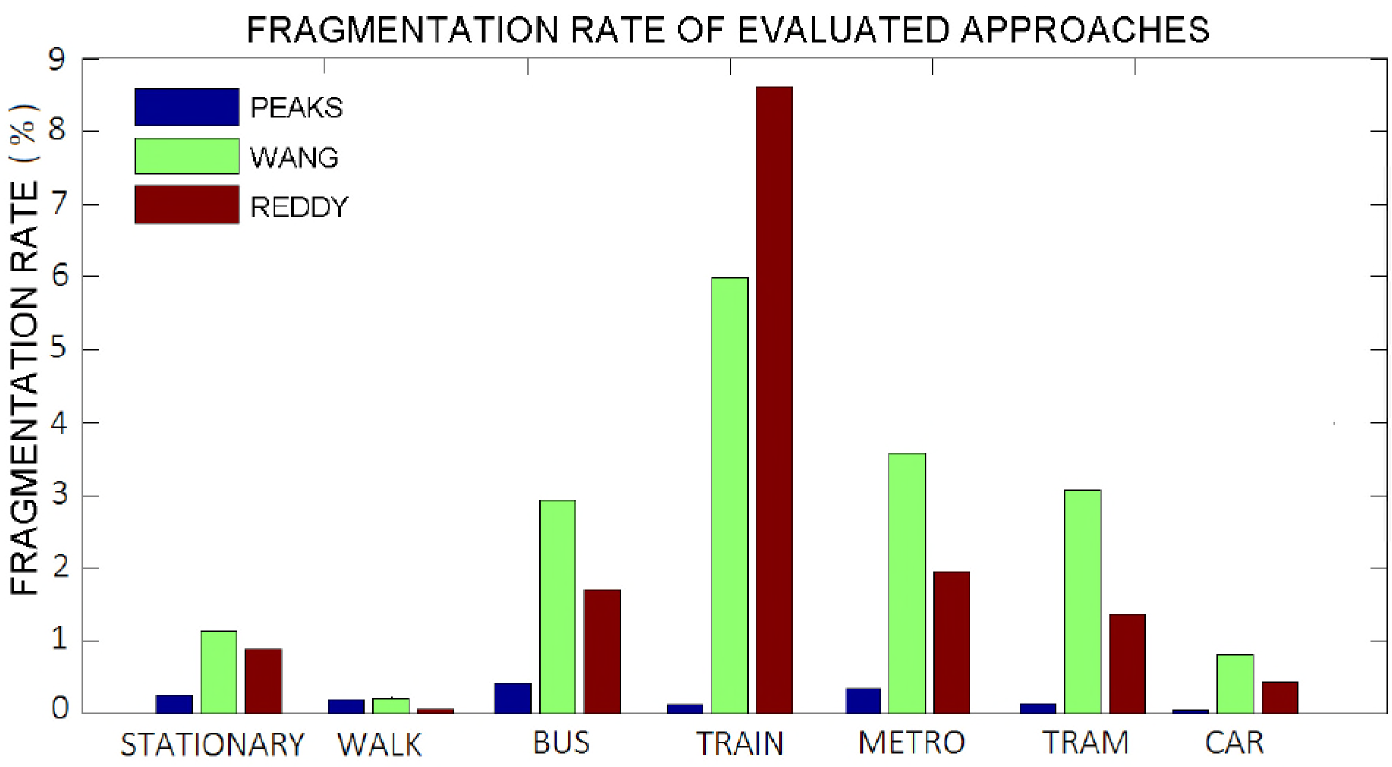
Evaluation Results

- Confusion matrix

Stationary	Walk	Bus	Train	Metro	Tram
62733	755	135	58	302	361
1549	63664	456	650	723	805
3976	647	32400	18	104	8118
6730	330	874	31921	5907	1894
5057	711	2961	10879	41203	2682
4341	318	10123	87	2067	77715

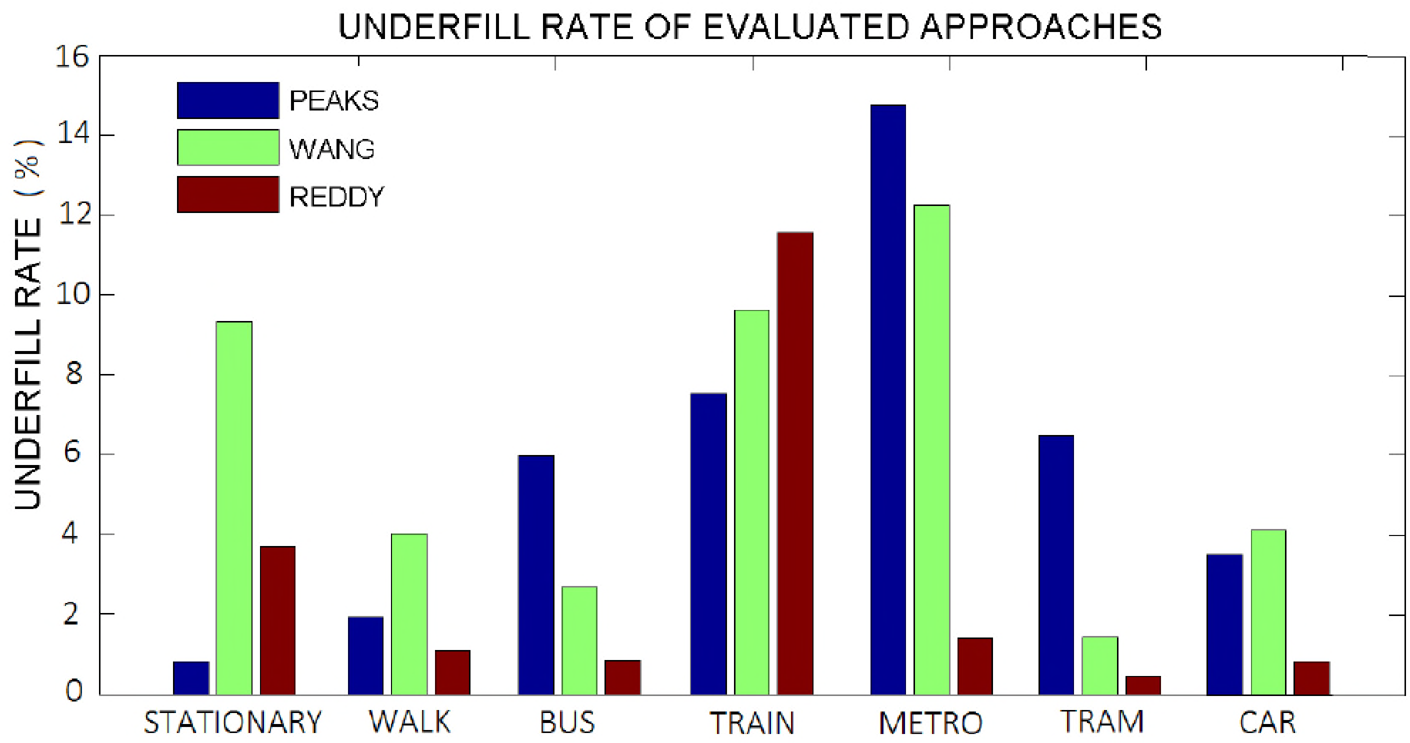
Evaluation Results

- Fragmentation: Fraction of ground truth events recognized as multiple events



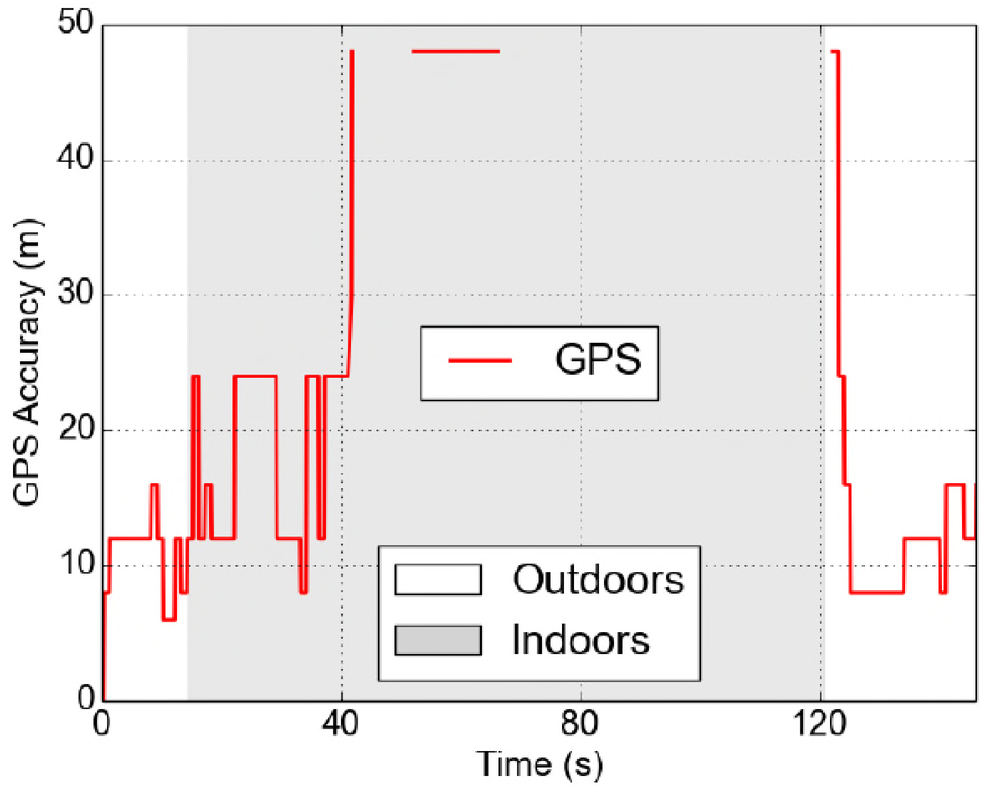
Evaluation Results

- Under-fill: Percentage of time missing from an event due to detection latency



Indoor/Outdoor Detection

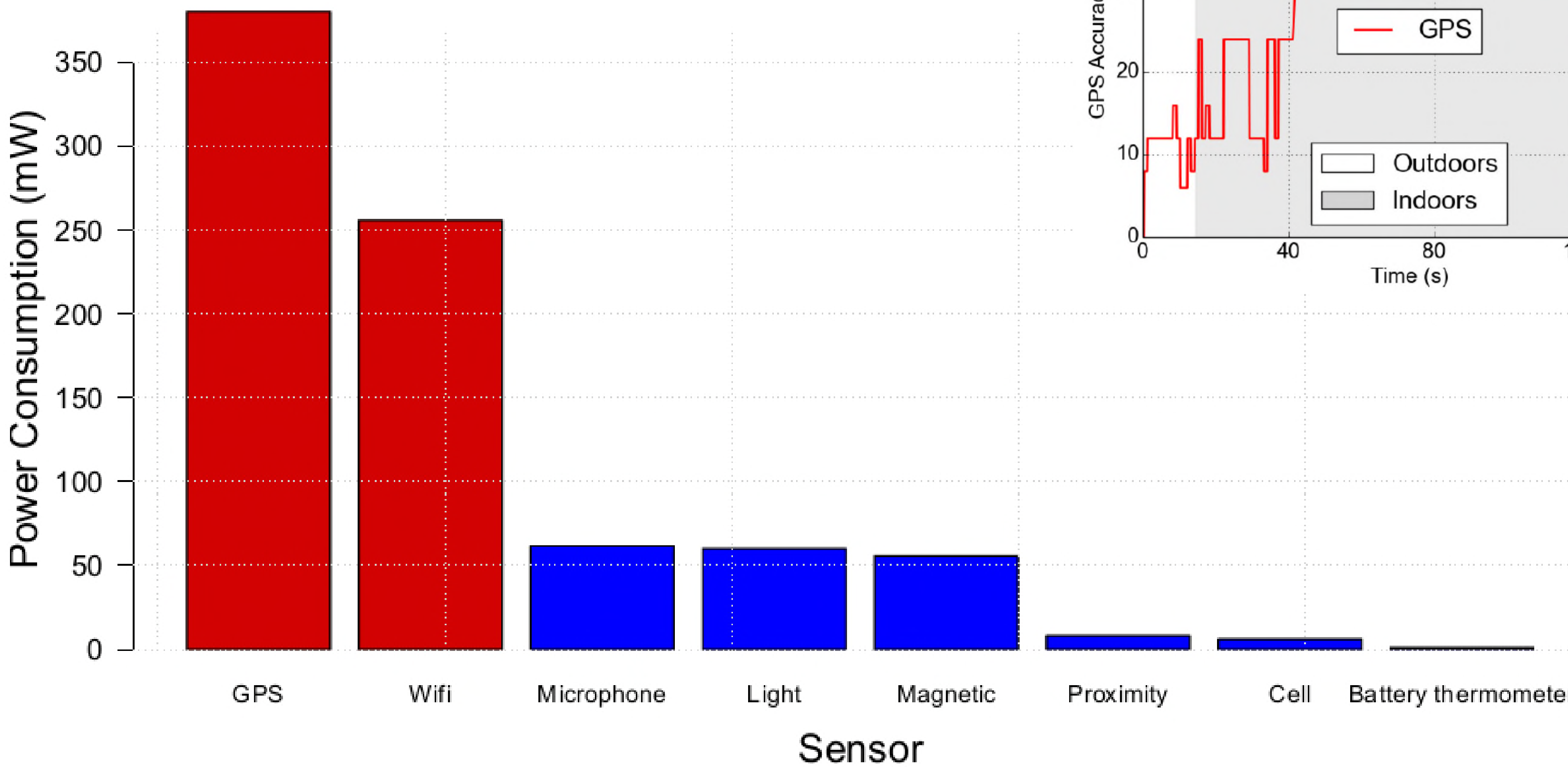
- Possible solution: GPS?

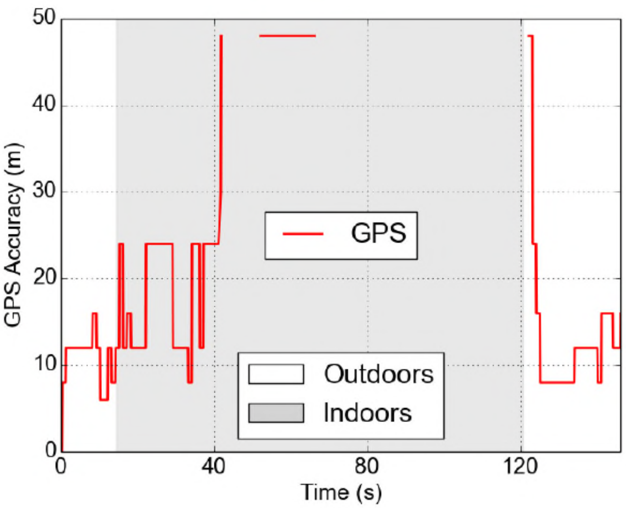


Valentin Radu, Panagiota Katsikouli, Rik Sarkar, Mahesh K. Marina, "A Semi-Supervised Learning Approach for Robust Indoor-Outdoor Detection with Smartphones," ACM Sensys, November 2014

Indoor/Outdoor Detection

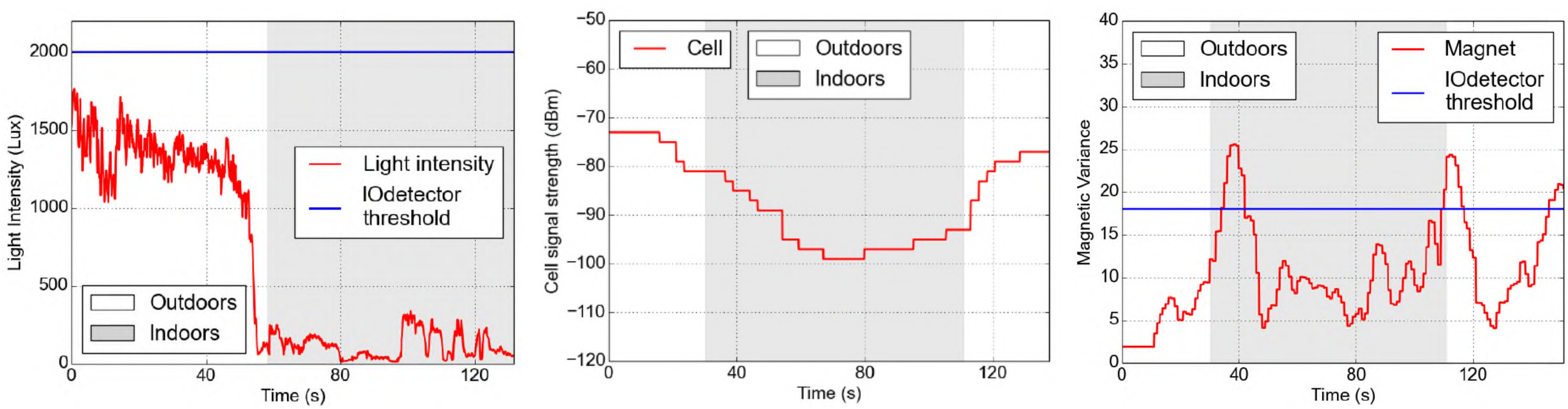
- Possible solution: GPS?





Indoor/Outdoor Detection

- Possible solution: IO-Detector
  - Light sensor (higher-intensity outdoors)
  - Cell signal (stronger outdoors)
  - Magnetometer (higher fluctuations indoors)



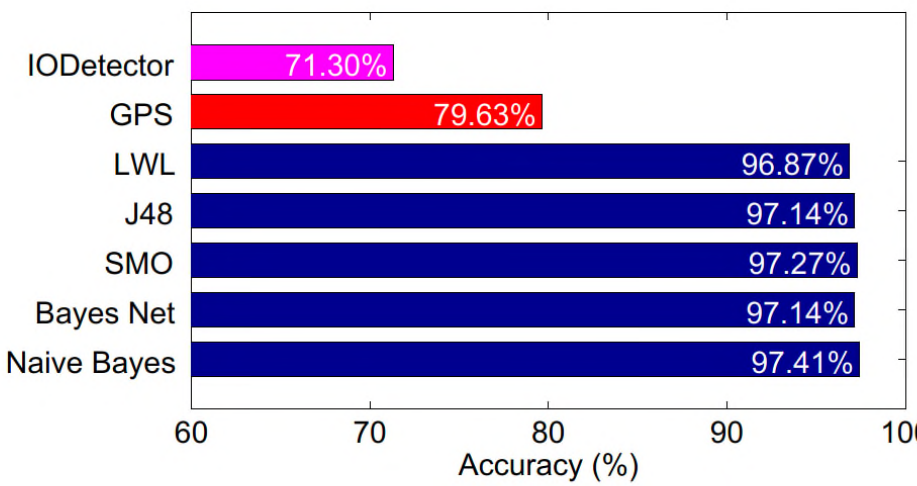
Supervised Classification

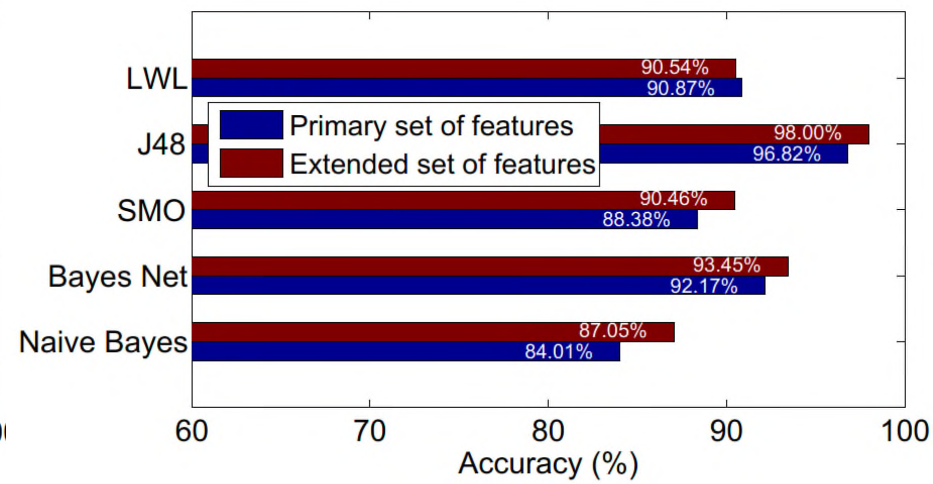
- Sensors: light, proximity, magnetic, microphone, cell, WiFi, GPS, battery thermometer, etc.
- Multiple classifiers selected from WEKA library
- Primary feature set
  - Light intensity, cell strength, magnetic variance
- Extended feature set
  - Light intensity, sound intensity, temperature, magnetic variance, cell strength, proximity

Supervised Classification

1. **Primary features:** Light intensity, Cellular signal strength and magnetic variance. (This is analogous to IOdetector, but we use cell signal strength instead of its derivative.)
2. **Extended feature set:** light intensity, sound intensity from microphone, temperature from battery thermometer, magnetic variance, cellular signal strength and proximity sensor value.

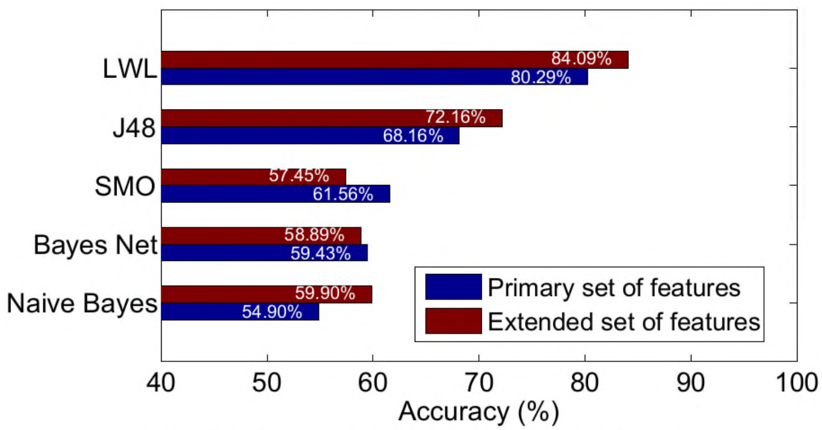
- Single-area data set (trained and tested on one area)
- Multiple-area data set (trained on all areas, tested using cross validation)



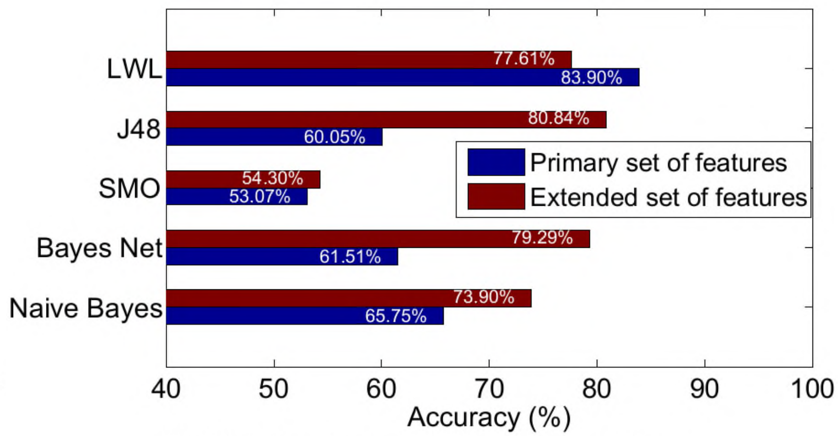


Supervised Classification

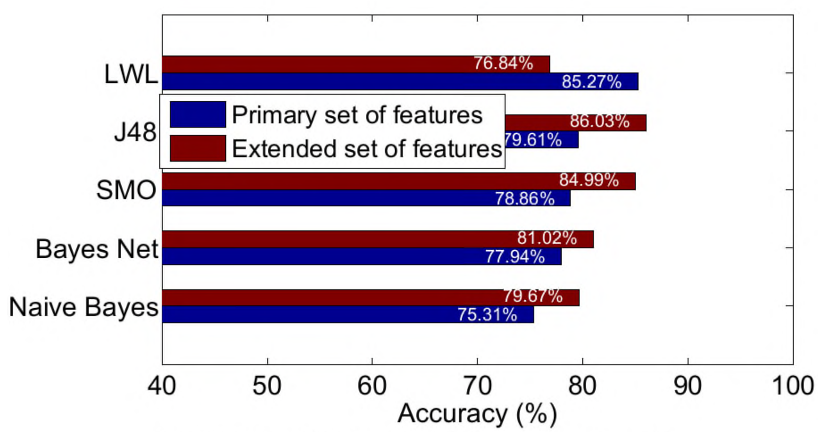
- Trained on one area and tested on another



(a) Training: campus; evaluation: city + home



(b) Training:city; evaluation: campus + home



(c) Training: home; evaluation: campus + city

Results show inadequate performance

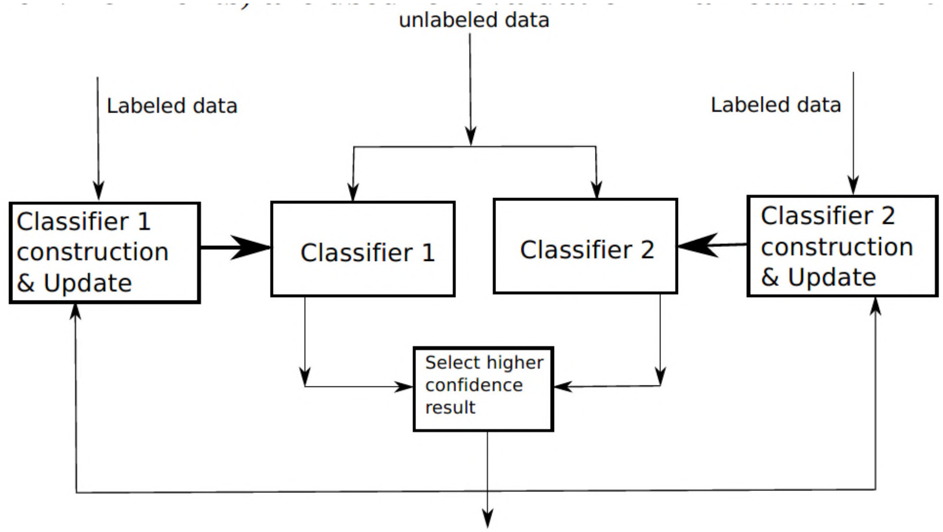
Semi-supervised Classification

- Clustering (with partial labeling)
- Self-learning
- Co-training

Co-training

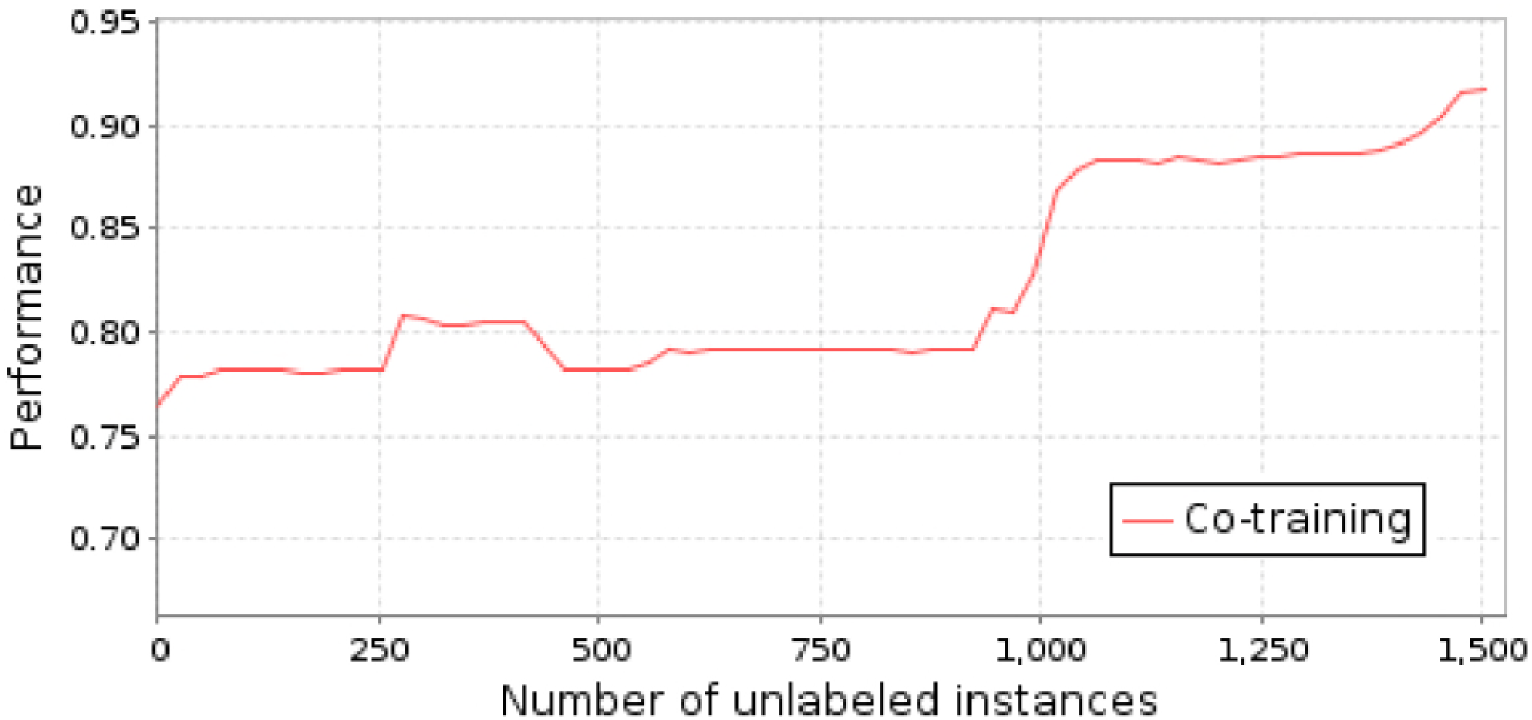
- Small amount of labeled data is used to train two classifiers. Unlabeled samples are then classified. The output with higher confidence is used to train both classifiers

Naive Bayes based selection	
Classifier 1	Classifier 2
light intensity, time of the day, proximity value, battery temperature	sound amplitude, cell signal strength, magnetic variance
SVM based selection	
Classifier 1	Classifier 2
cell signal strength, light intensity, time of day, proximity value	battery temperature, sound amplitude, magnetic variance



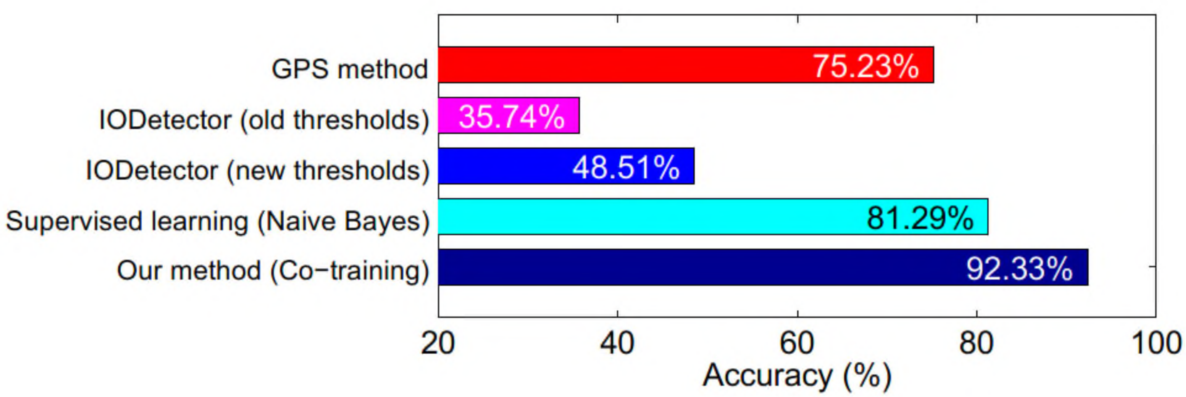
Co-training Performance

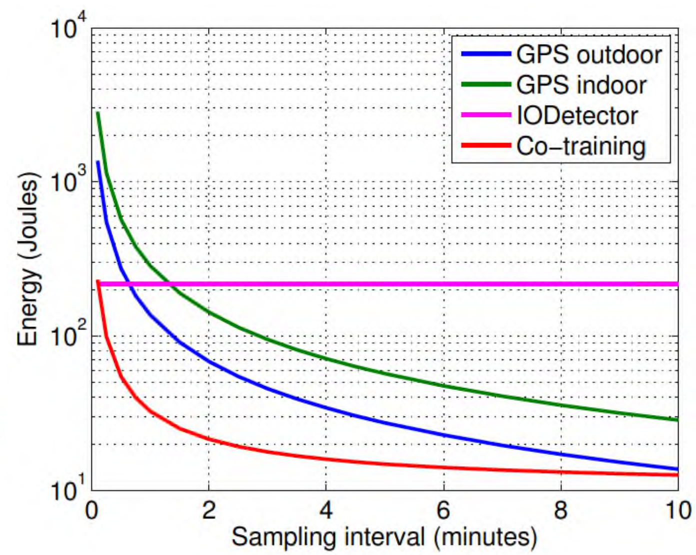
- Accuracy gradually improves as new unlabeled data is introduced



Co-training Performance

- Improves accuracy of detection in unknown environments compared to other approaches





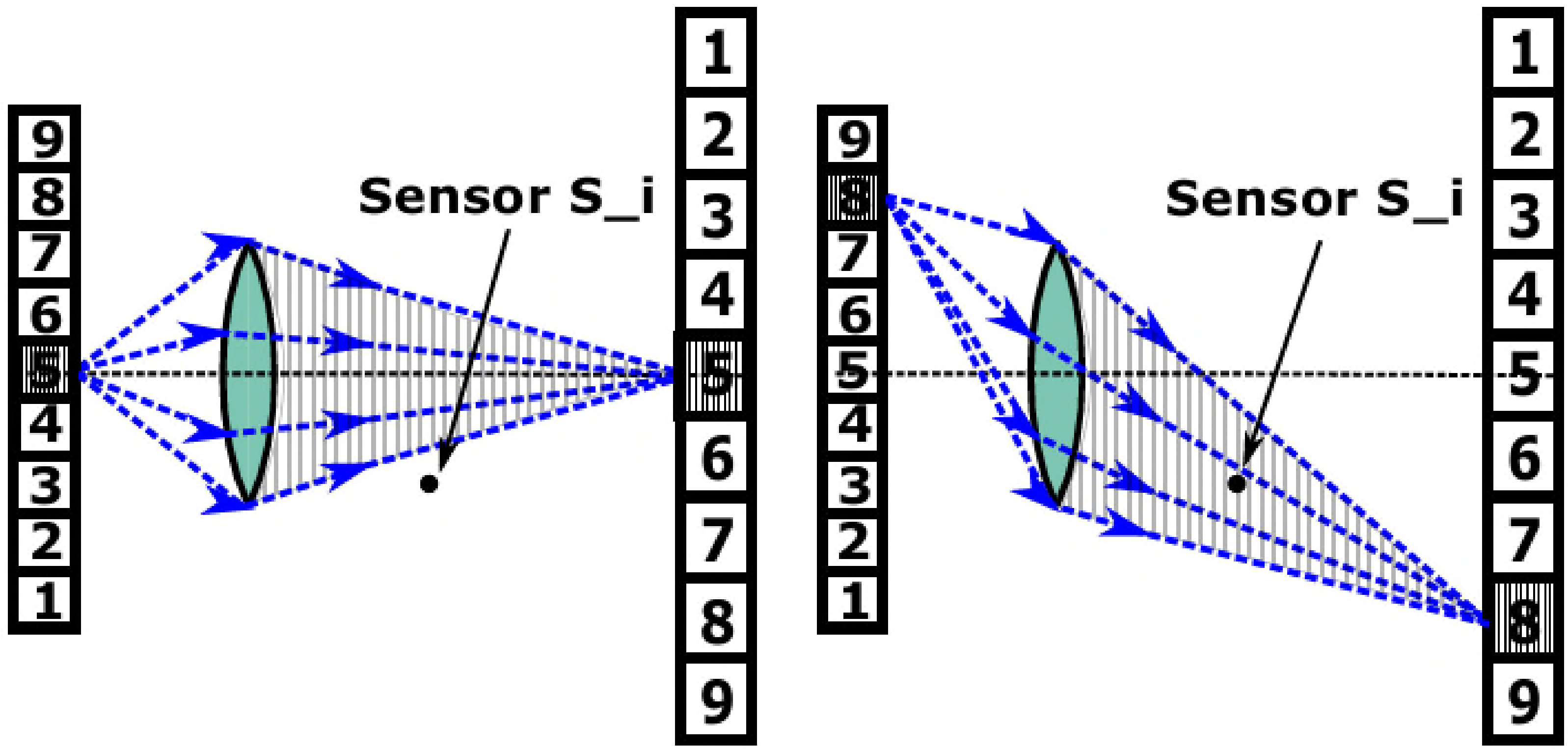
Localization with a Single LED

- Can you simultaneously localize a large number of optical receivers using a single "smart" LED?

Song Liu and Tian He, "SmartLight: Light-weight 3D Indoor Localization Using a Single LED Lamp," ACM Sensys, Delft, The Netherlands, November 2017

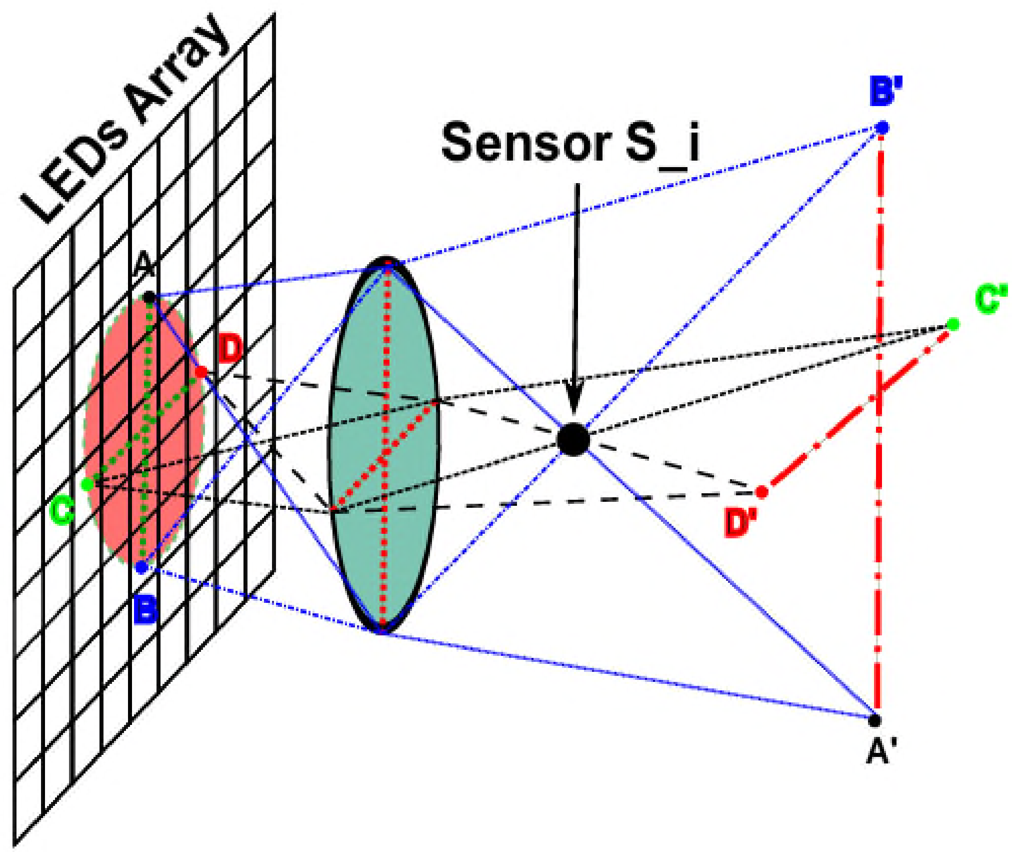
Idea #1

- Your location determines what you see:

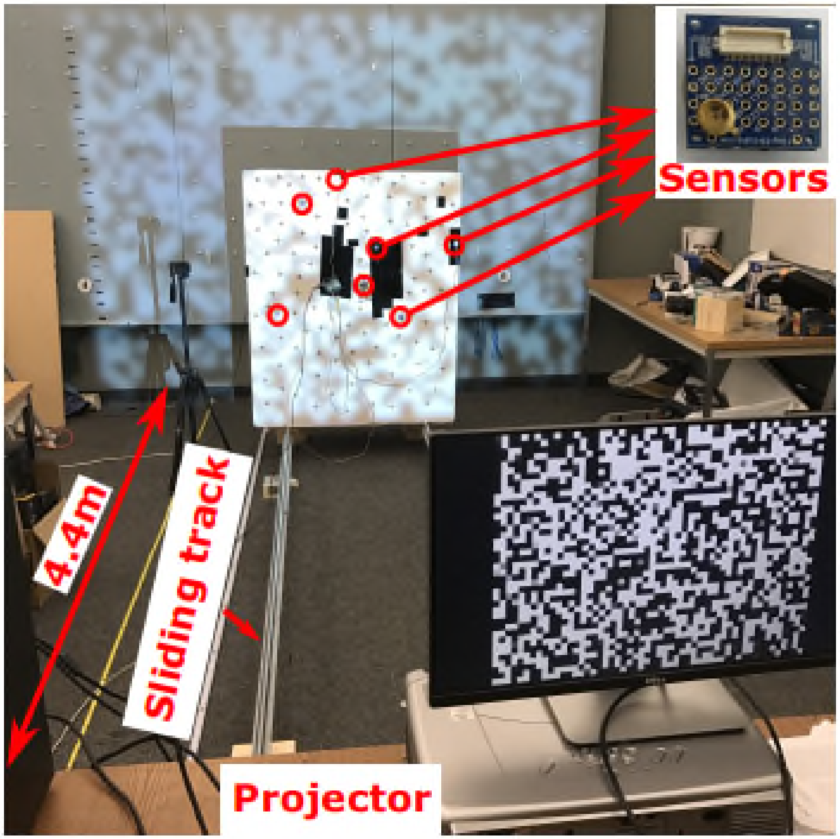


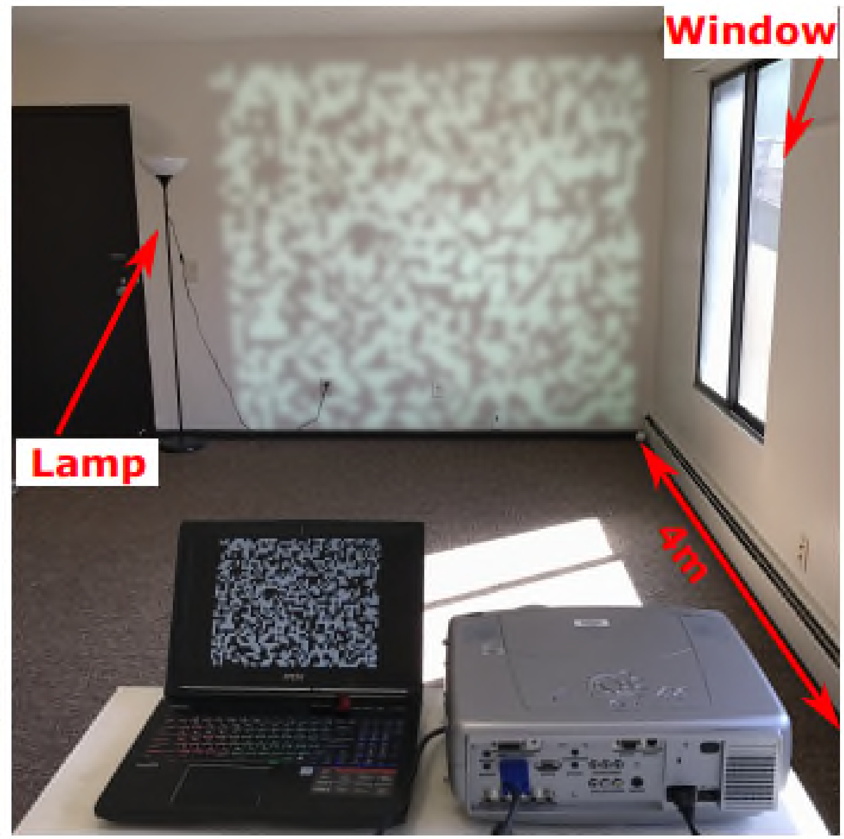
Idea #2

- Distance determines size of visible area

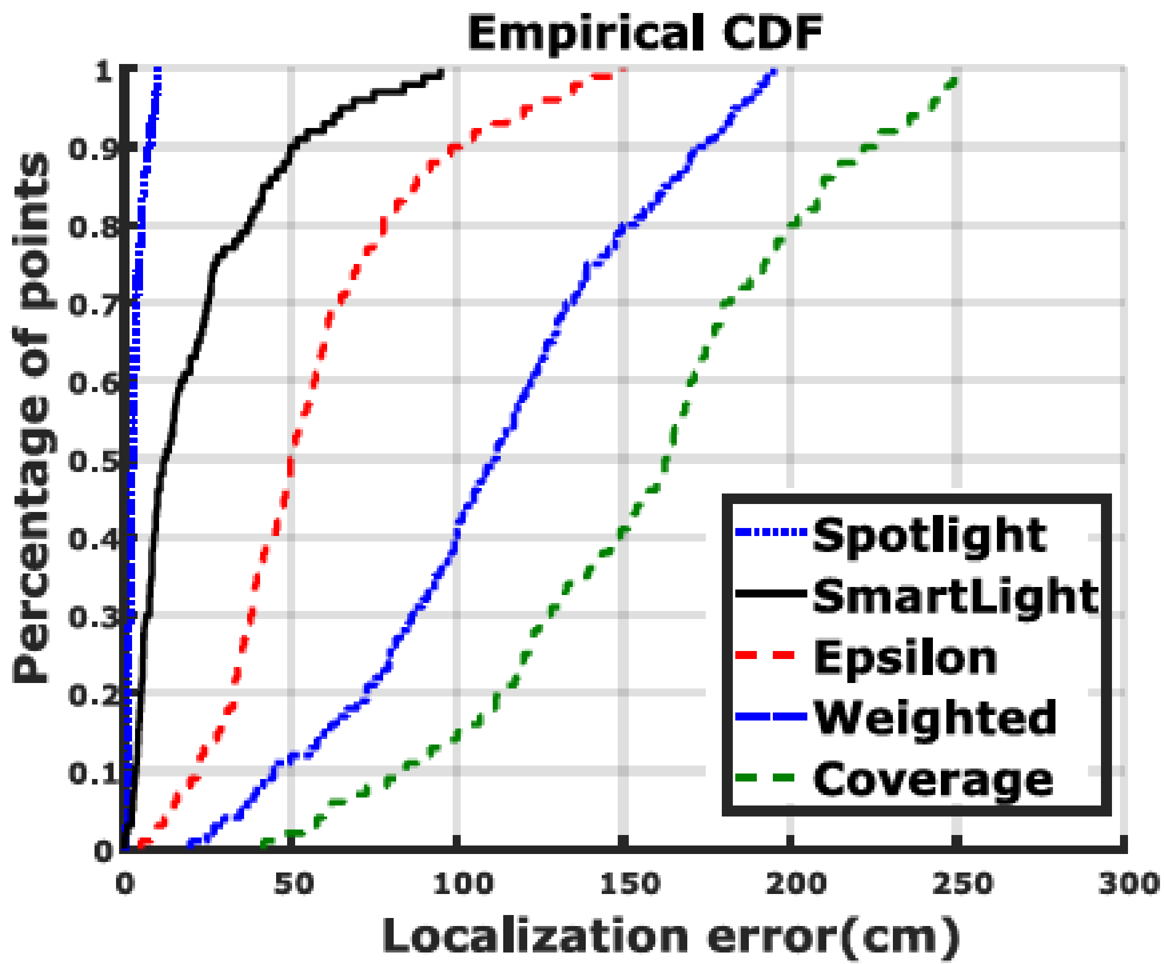


Testbed





Evaluation



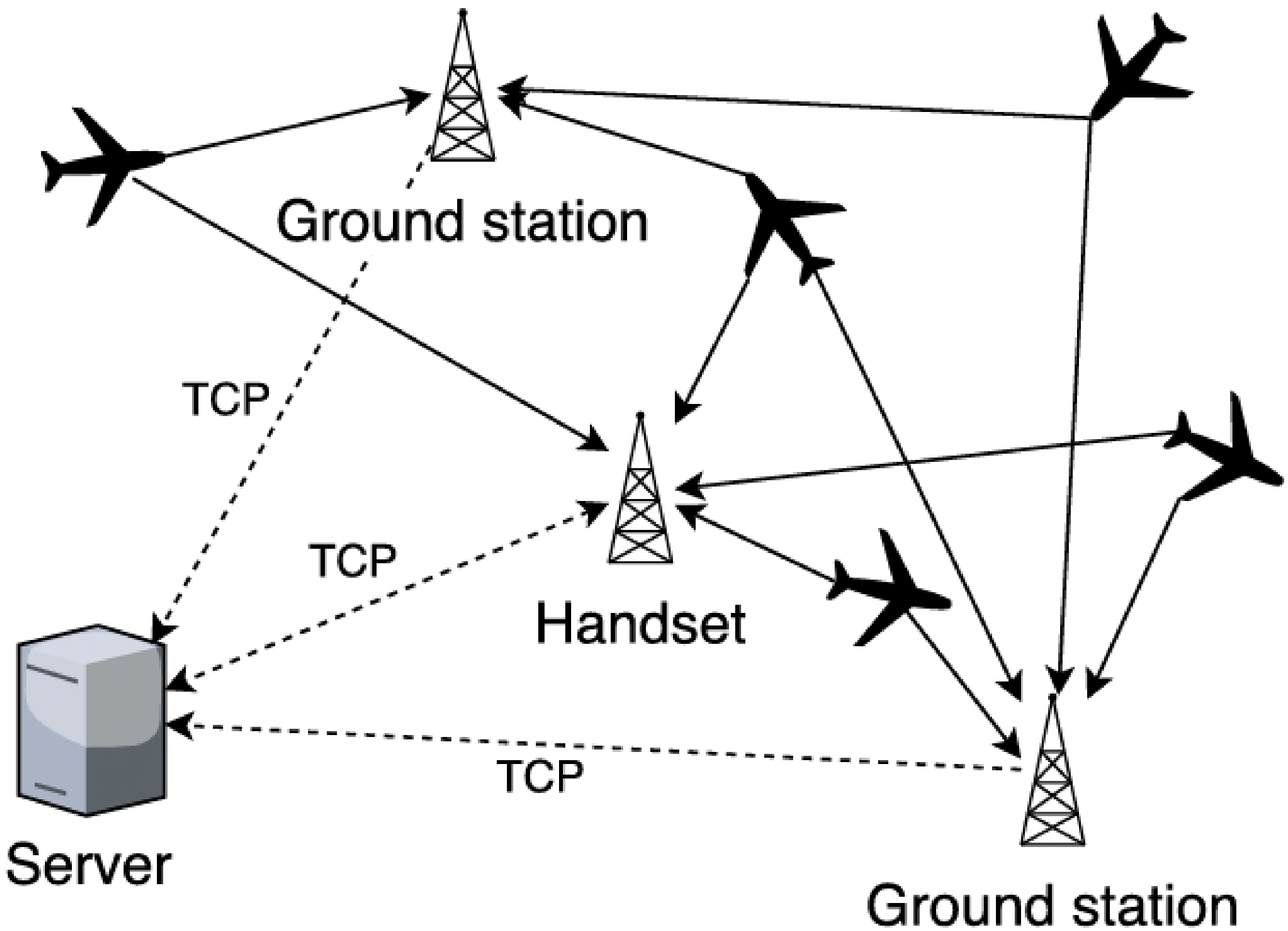
Empirical CDF
Percentage of points
Localization error(cm)
0
0.1
0.2
0.3
0.4
0.5
0.6
0.7
0.8
0.9
1
0
50
100
150
200
250
300
Spotlight
SmartLight
Epsilon
Weighted
Coverage

Localization with Aircraft Signals

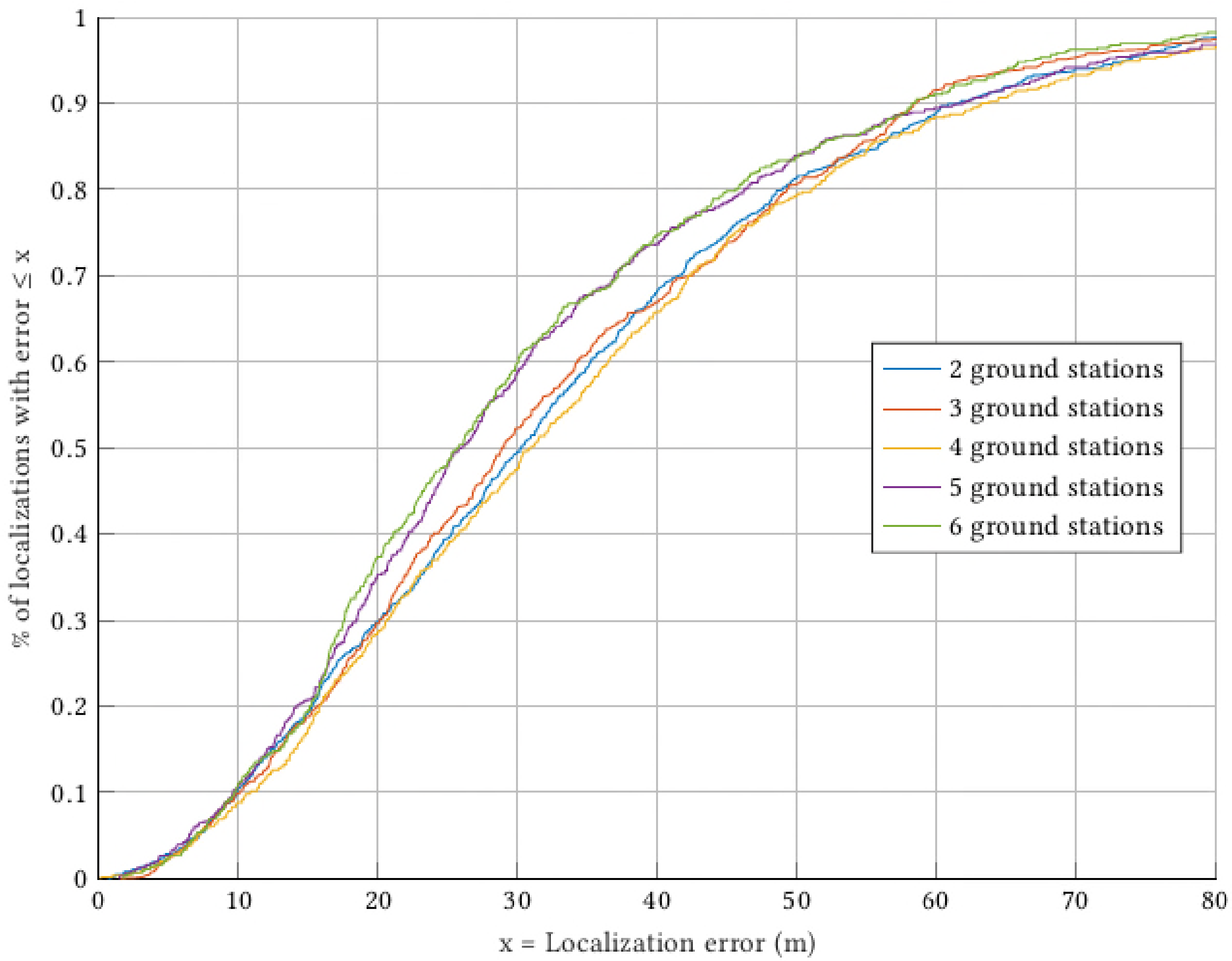
- Can we use aircraft signals to localize mobile devices even in-doors (where there is no GPS)?

Manuel Eichelberger, Kevin Luchsinger, Simon Tanner, and Roger Wattenhofer, "Indoor Localization with Aircraft Signals," ACM Sensys, Delft, The Netherlands, November 2017

Localization with Aircraft Signals



Evaluation



1
0.9
0.8
0.7
0.6
0.5
0.4
0.3
0.2
0.1
0
0
10
20
30
40
50
60
70
80
x = Localization error (m)
% of localizations with error ≤ x
2 ground stations
3 ground stations
4 ground stations
5 ground stations
6 ground stations

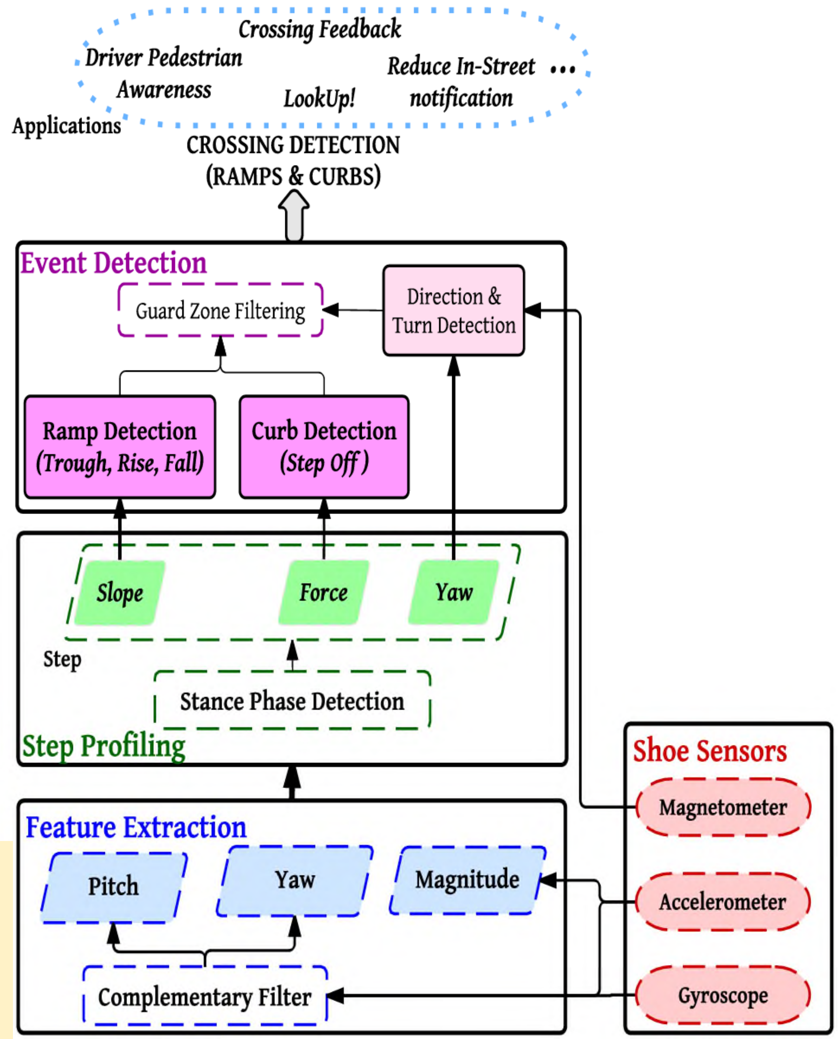
The “Bonus Track”

“Look up!”

A Pedestrian Safety App

Step Detection

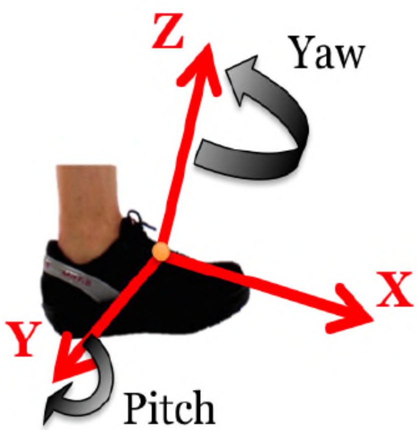
- Detects when people step down from sidewalk to street

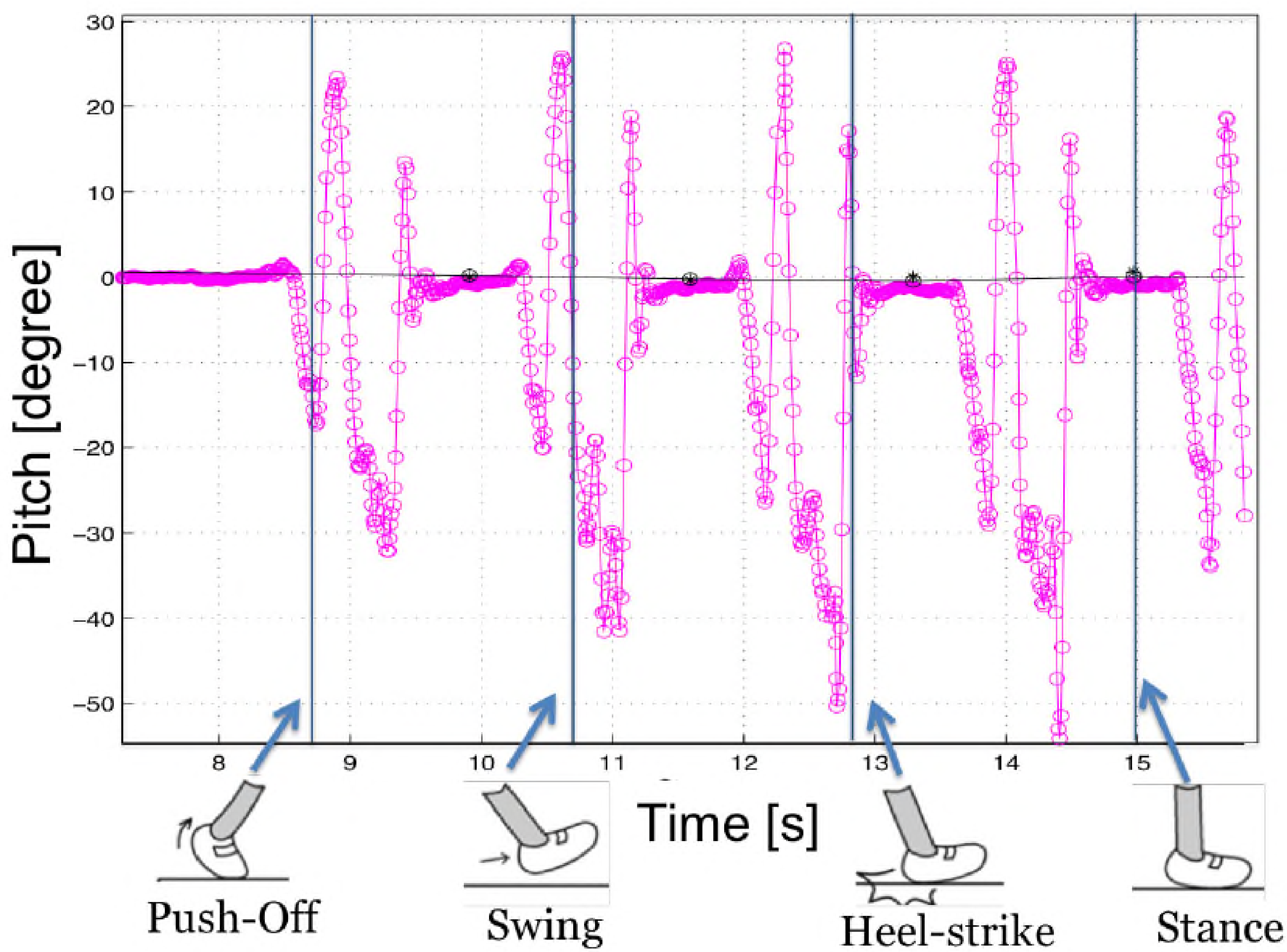


Shubham Jain, Carlo Borgiattino, Yanzhi Ren, Marco Gruteser, Yingying Chen, and Carla Fabiana Chiasserini, "LookUp: Enabling Pedestrian Safety Services via Shoe Sensing," ACM MobiSys, May 2015

Step Detection

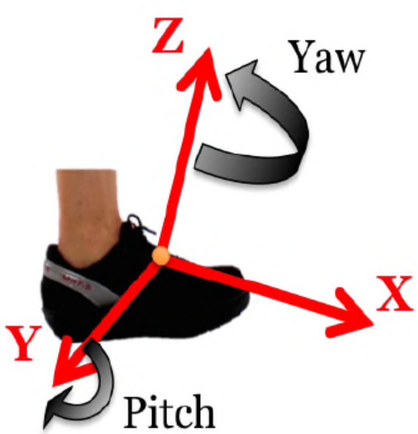
- Detects phases of walking

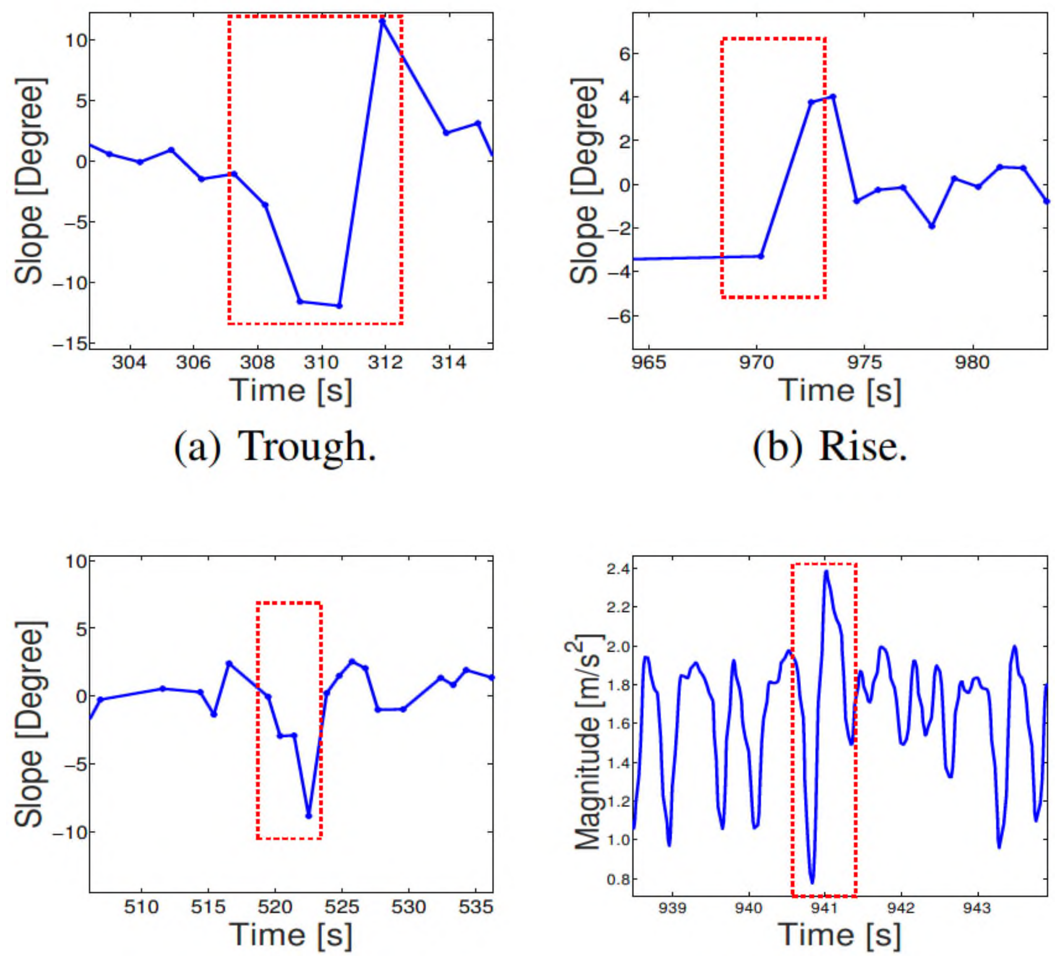




Step Detection

- Detects slope changes across steps





(a) Trough. (b) Rise.

(c) Fall. (d) Step Off.

Performance Evaluation

- High detection accuracy