Presented by Chuong Ngo

Using Mobile Phone Barometer for Low-Power Transportation Context Detection

By Kartik Sankaran, Minhui Zhu, Xiang Fa Guo, Akkihebbal L. Ananda, Mun Choon Chan, and Li-Shiuan Peh

Smart in Smartphones

- Intelligent behavior
  - Context aware apps
- Sensors = context
  - Increased power consumption
  - Specialized hardware

Transportation-mode Detection

- Useful for many things
  - Personal tracking
  - Regional data/planning
- Usually accelerometers
  - Low power
  - 10+ Hz sampling
  - Complex ML model

Is there a better way?

A Flash

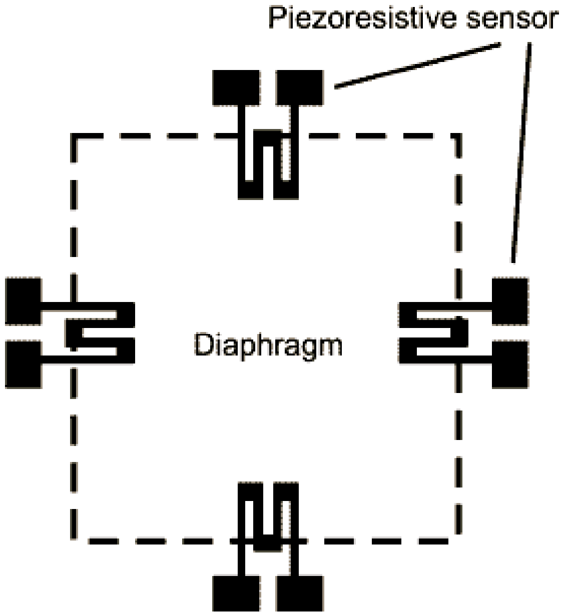
- Terrain is not perfectly flat
- Faster transportation = faster traversal of terrain
- More vertical movement for faster modes of transporation

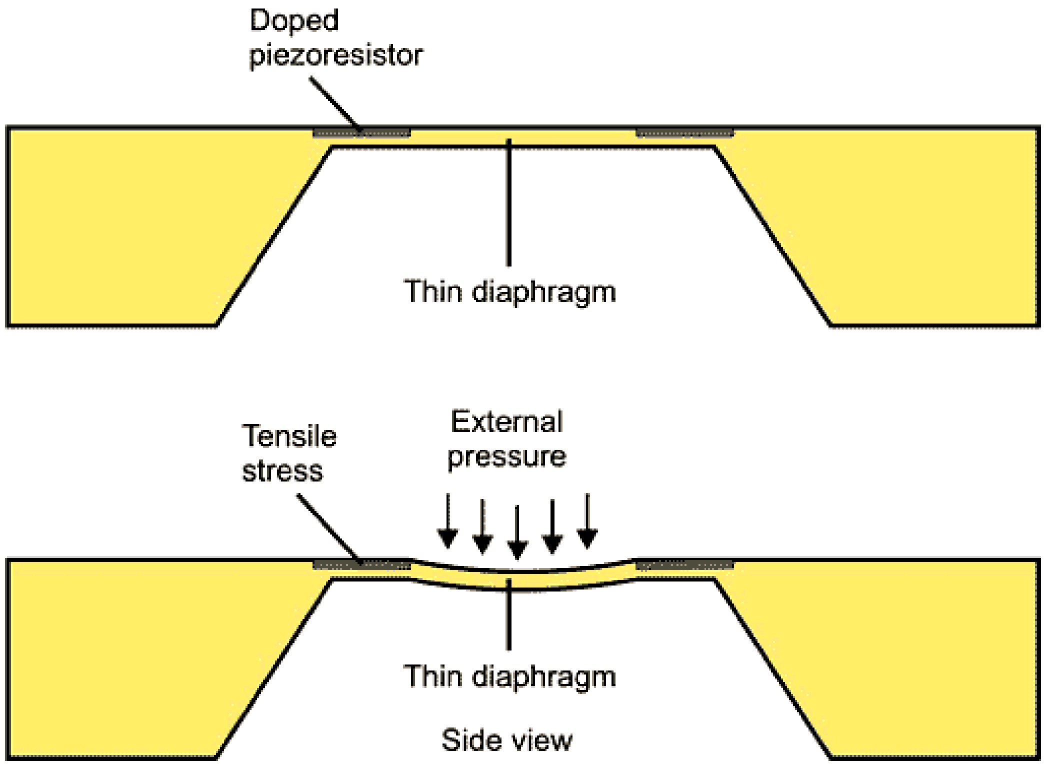
Barometer Background

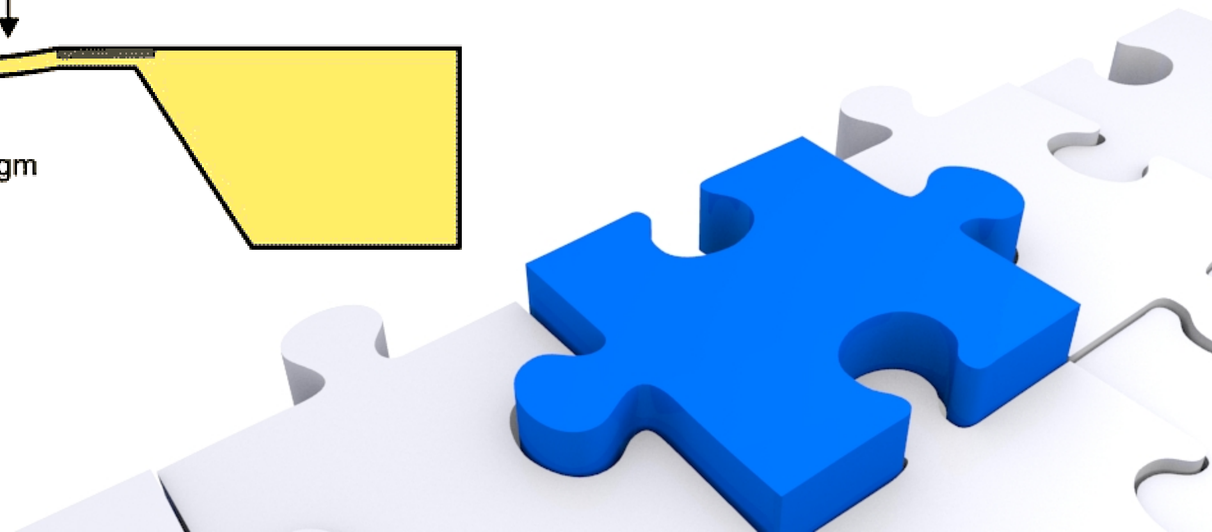
- Orientation and position independent
- Simpler calibration
- Better WAIT detection
- Lower necessary sampling rate

- Barometric pressure unstable
  - Altitude
  - Weather
  - Temperature
- Installation bias
- Aging drift

Barometer Breakdown







Methodology Comparisons

Sensor	Power	Limitations	Barometer advantage
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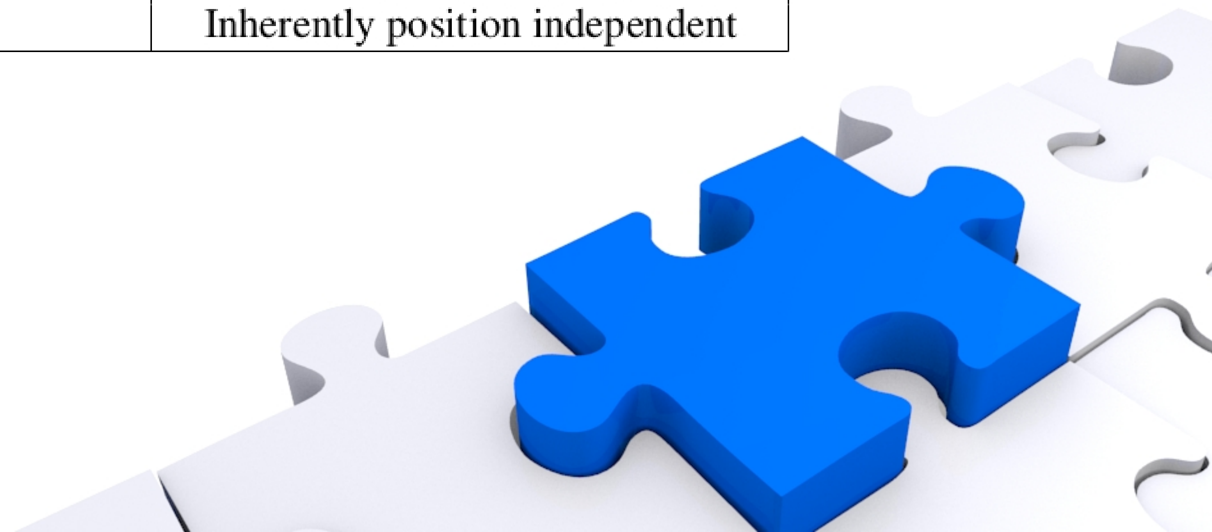

Power Play

	Power (mW)	Increase over base power
Accl (20 Hz)	230	112%
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The Grand Idea

Method Behind the Madness

- 3 detected states: Idle, Walking, and Vehicle
  - Rate of height changes in a given time frame
  - States are less sensative than with accelerometer
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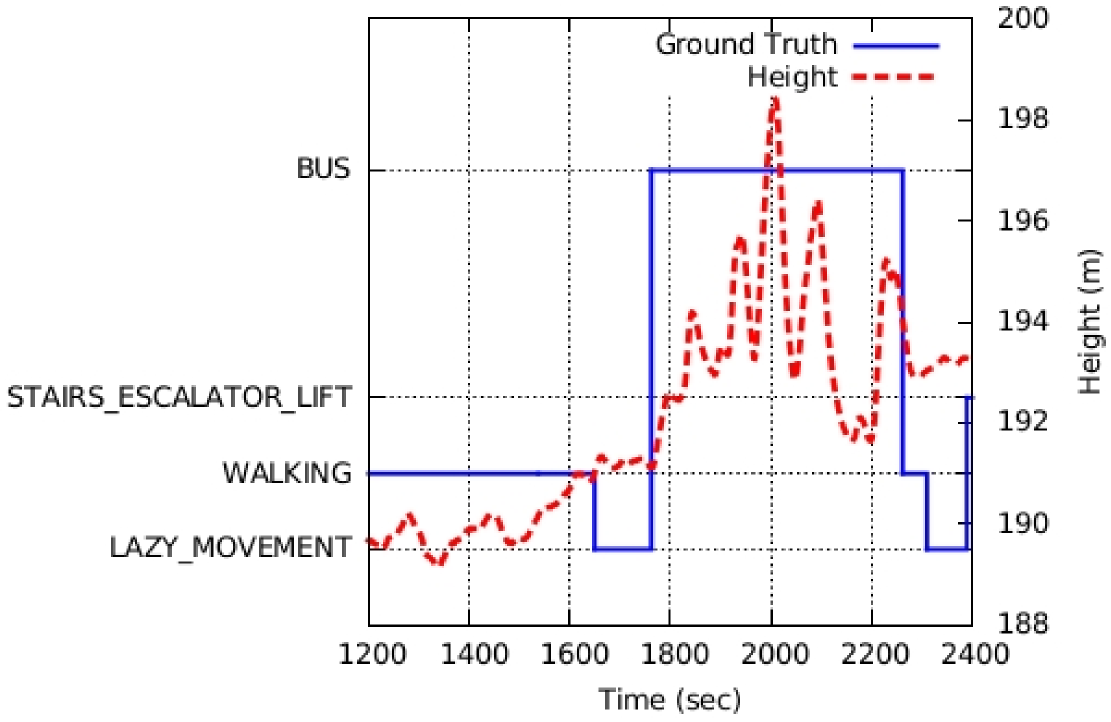

(a) Commute on a bus in Boston

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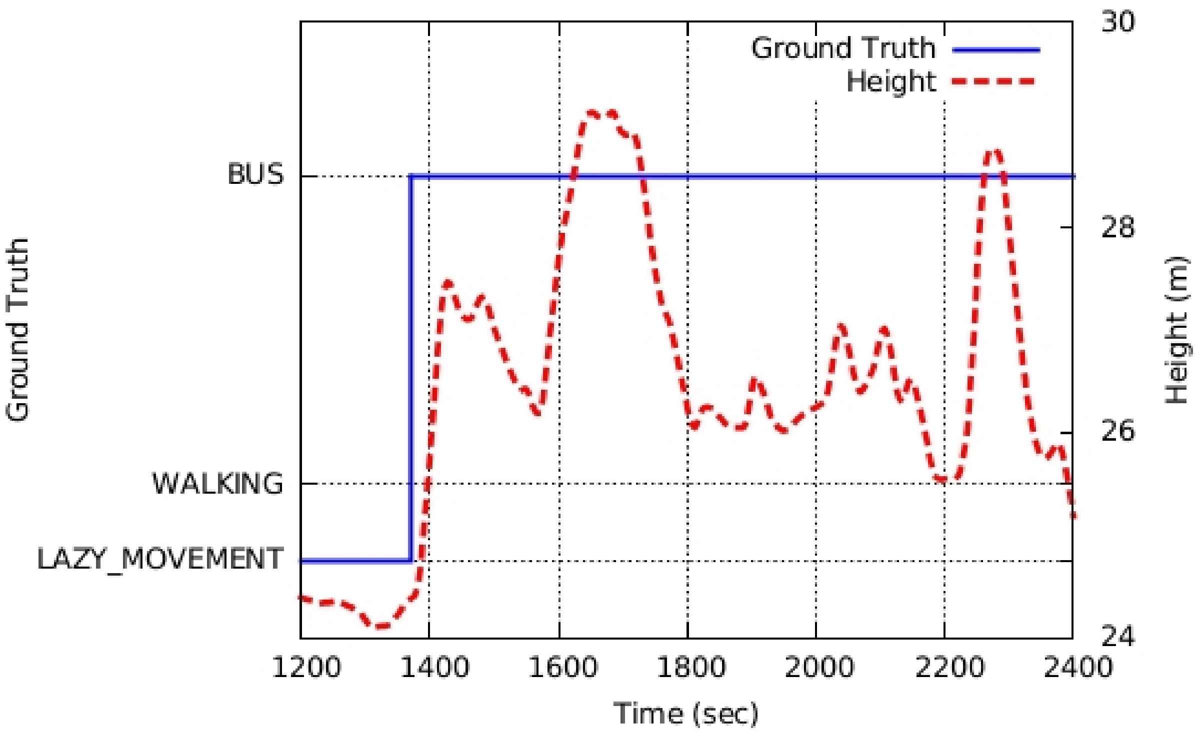

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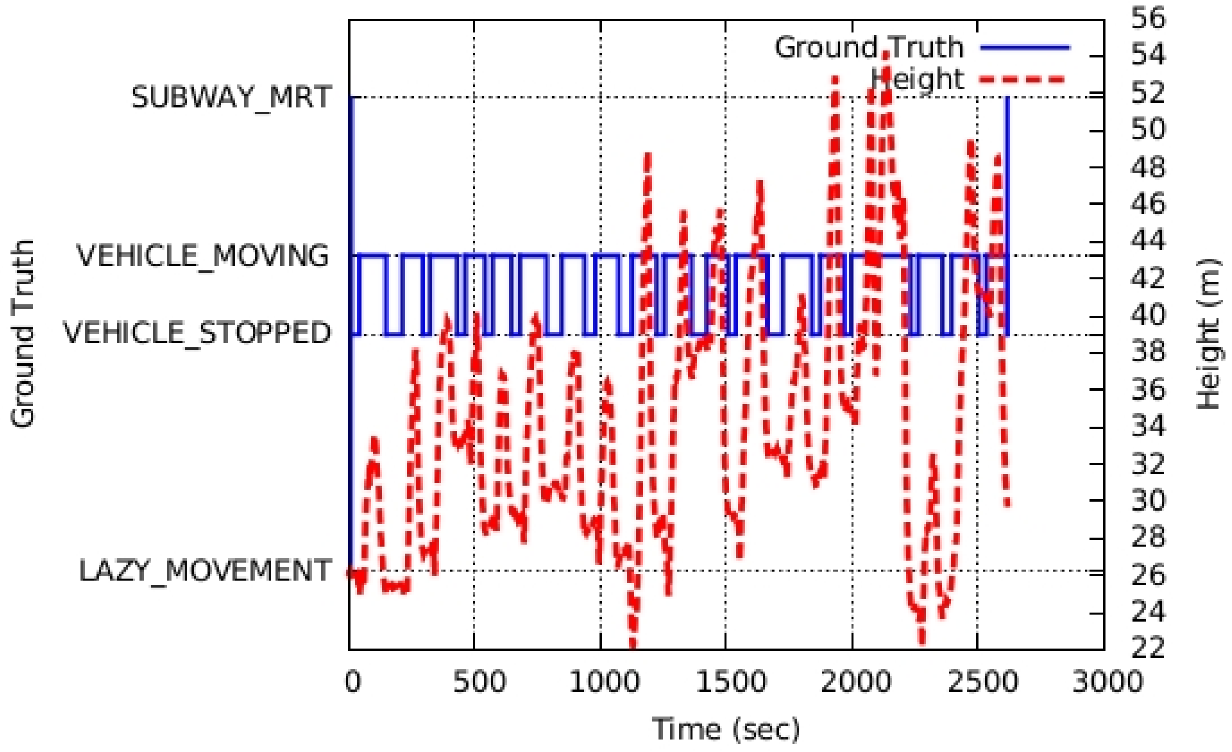

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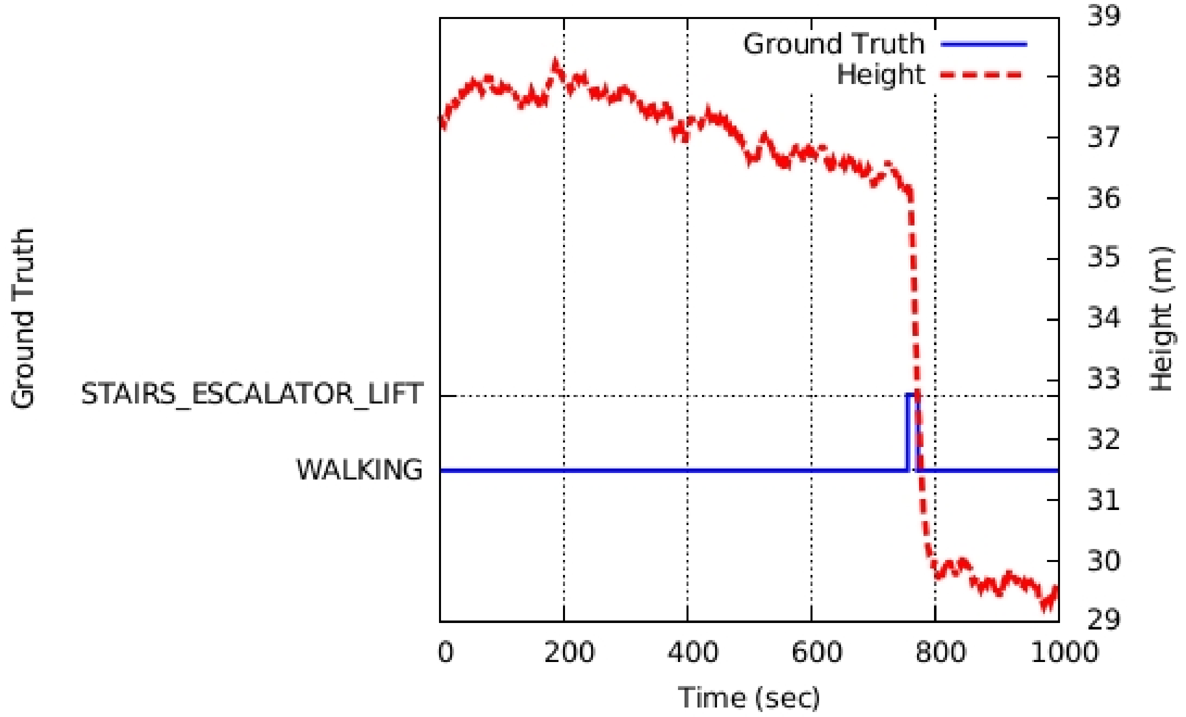

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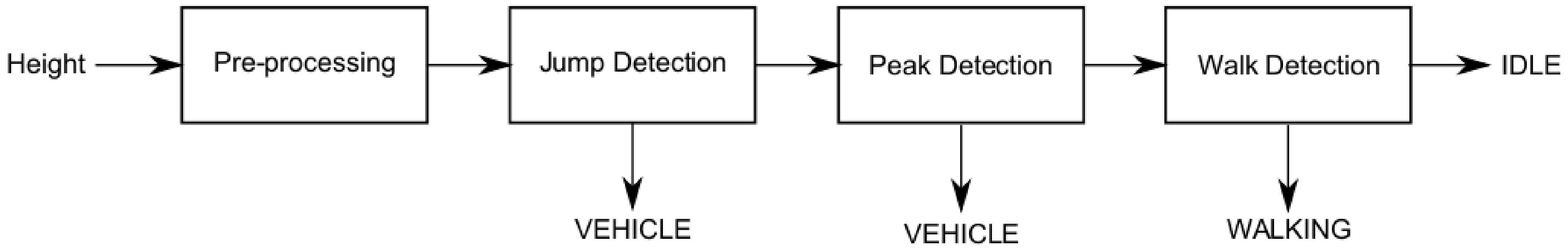
An Idea Made Real

System Overview



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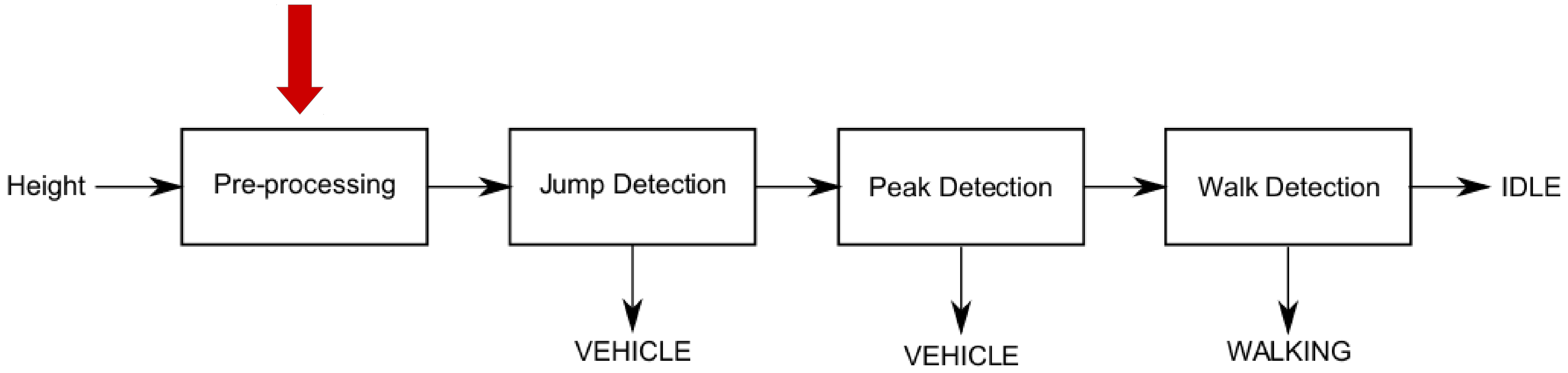

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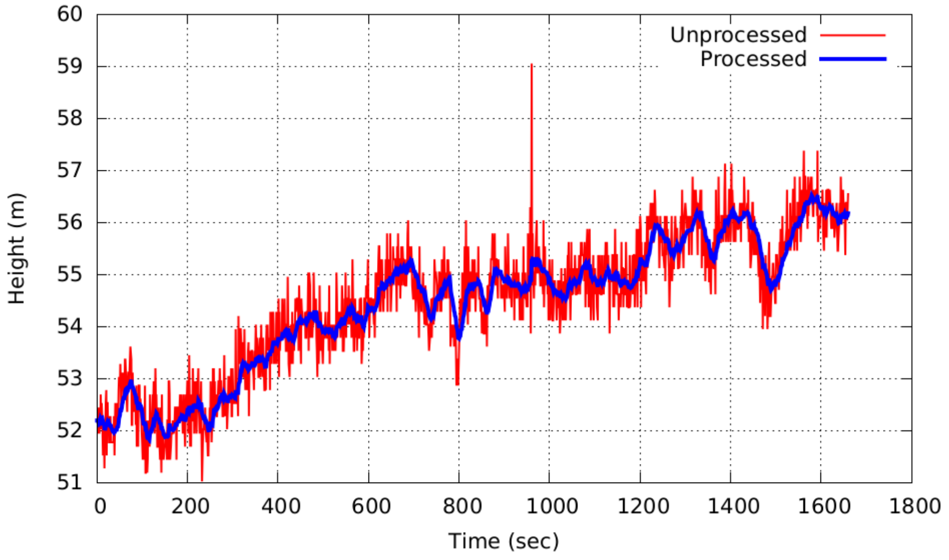

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- Data is noisy
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- Jumps occur at high speeds or when traversing highly sloped roads.
  - > 0.8 m per 5 sec
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- 30% - 70% ratio
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Walking and Idle Detections

- Default state: Idle
- Calculate standard deviation of height values in time window
  - Sliding 200 sec window
  - > 0.3 m is walking state
- Algorithm unaffected by weather drift.

Evaluation

The Arena

Country	Volunteers	Total hours	Vehicle hours	Walking hours	Idle hours
Singapore	7	15	6.5	6.4	2.1
Boston (USA)	6	55.95	3.75	7.8	44.4
China	1	108.5	22	1.5	85

- Phones used: Nexus 4/5, Galaxy S3/S4
  - Android Jellybean (4.1 – 4.3)
- Special barometer traces for weather
- Barometer detection simulated

Accuracy

	Baro	FMS	Google	GoogleSmooth
Idle	76%	33%	76%	76%
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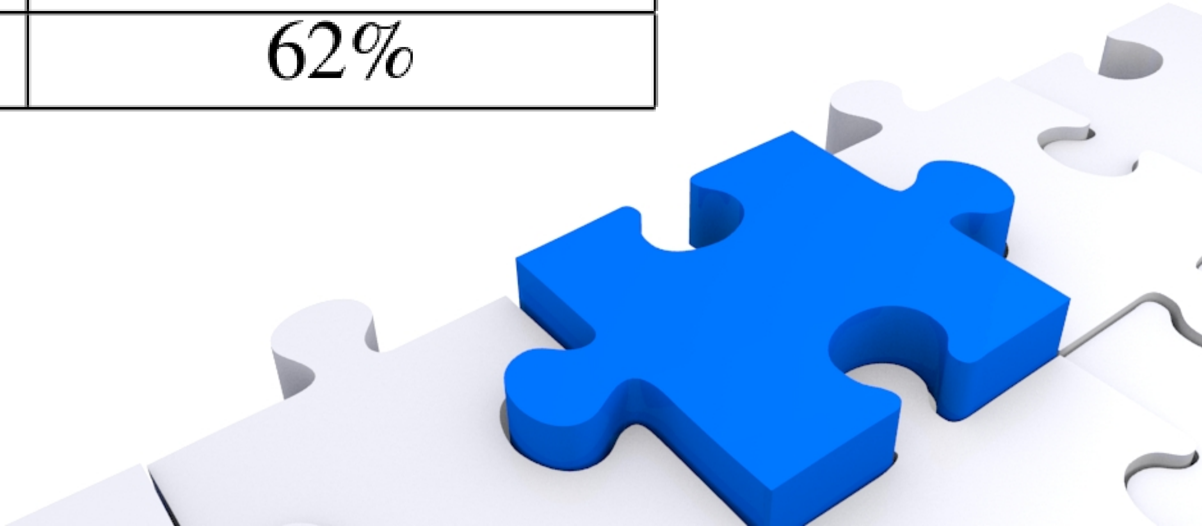

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Accuracy by Location

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Confusion Matrix

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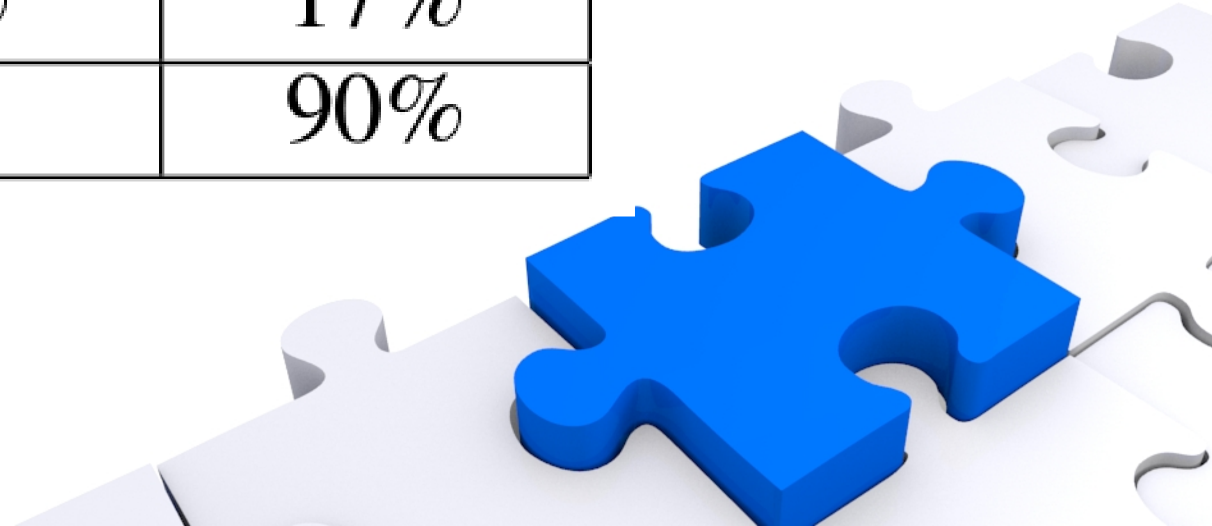

Latency

Table 13: Latency (sec) for each user state for barometer and Google algorithms (stddev in brackets)

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Power Usage

Table 14: Power usage

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Google	120
Baro	88

Comparing the Power Levels

(a) Power profile of barometer-based context detection

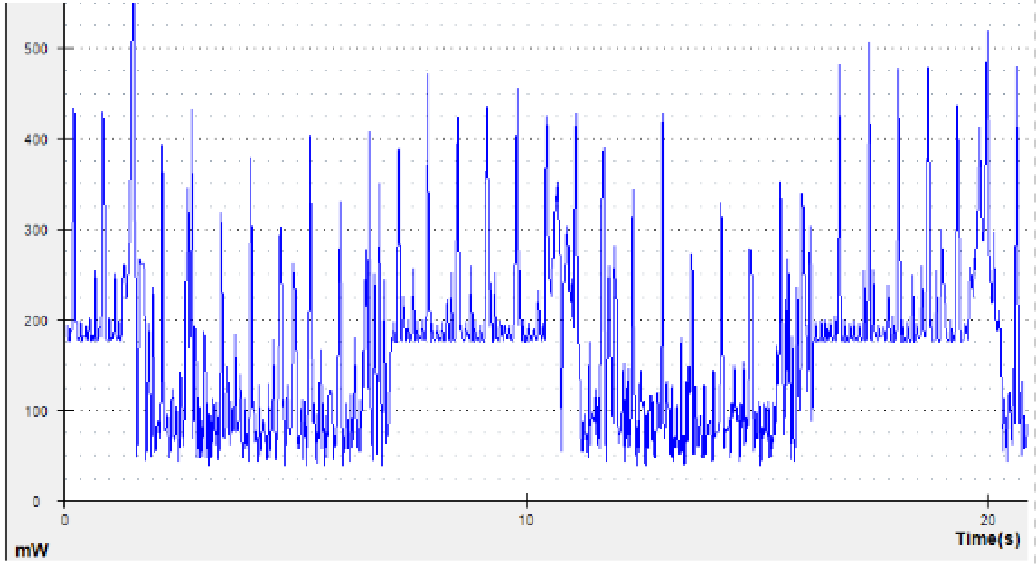

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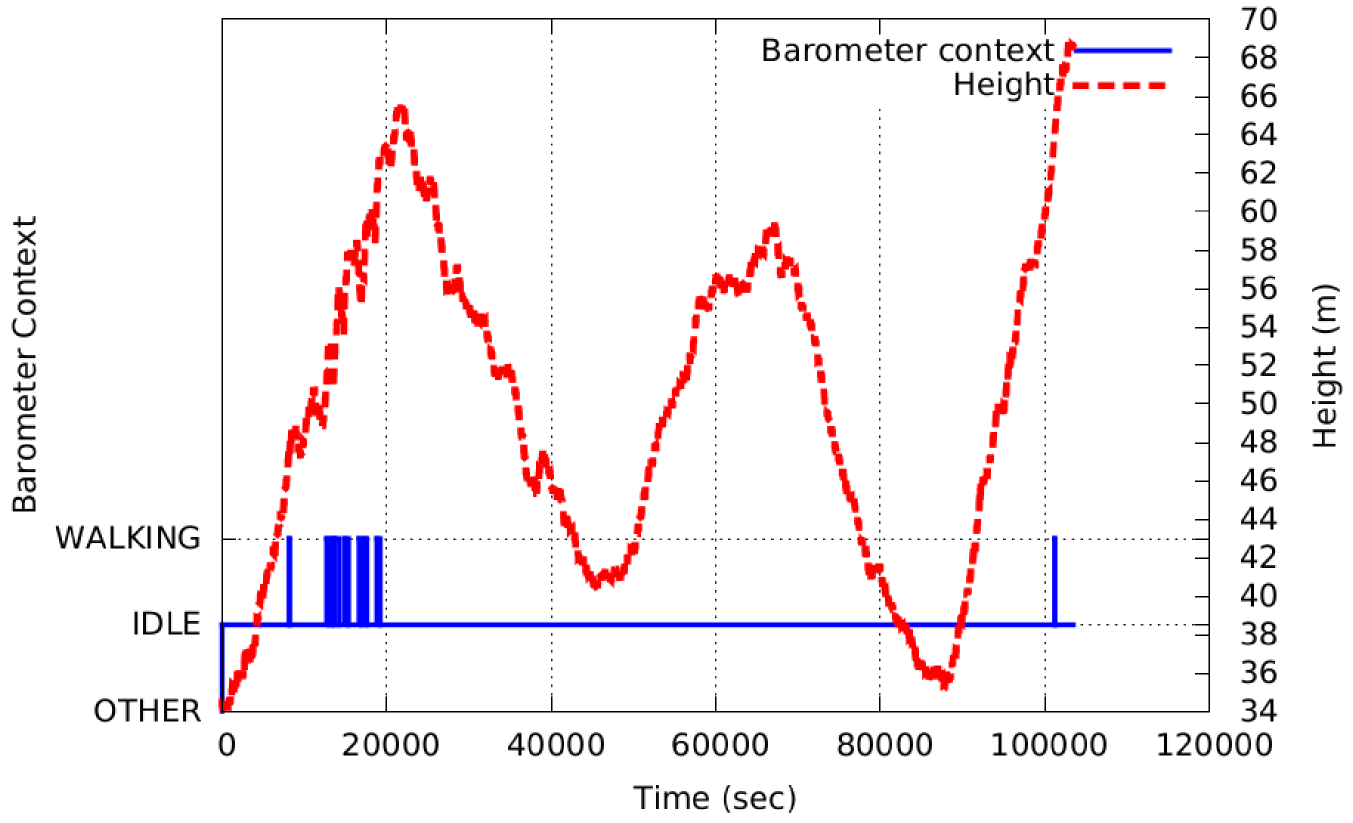
Figure 10: Power profile of Google and barometer algorithms

Taking a Closer Look

Weathering Heights



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	Vehicle (50 kmph)	Vehicle (35 kmph)	Vehicle (25 kmph)	Walk (5 kmph)	Walk (8 kmph)
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Coming Together

A Meeting of the Minds

- Barometer
  - IDLE and certain VEHICLES
  - WALKING

- Google Activity Recognition
  - WALKING
  - IDLE and certain VEHICLES

Two Minds Are Better Than One

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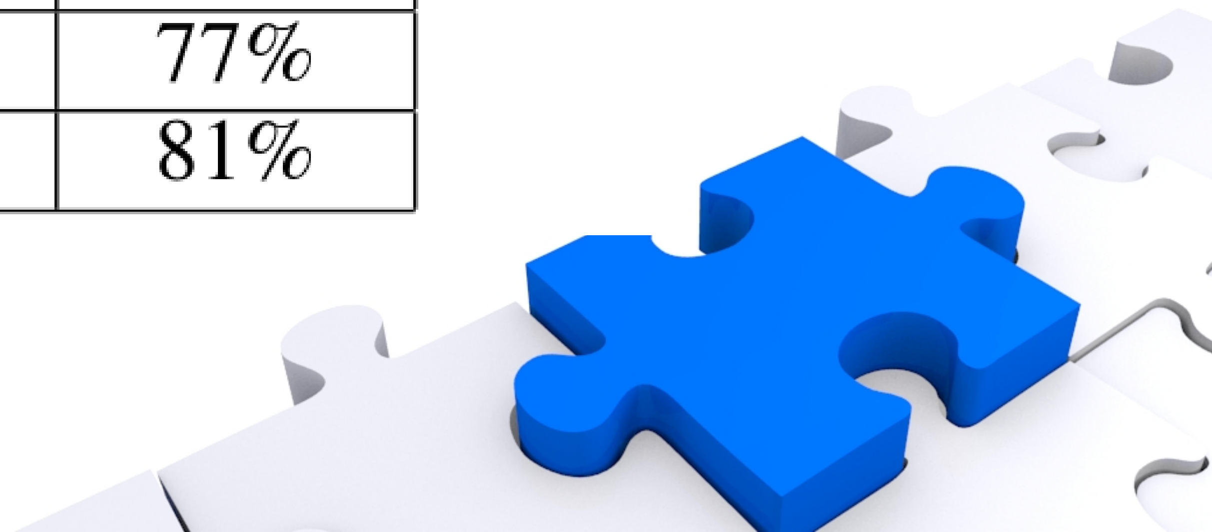

Conclusion

- Allows for activity detection with lower power usage compared to accelerometer.
- Classifies three kinds of movement states: IDLE, WALKING, and VEHICLE.
- A good method for detecting IDLE states and fast vehicle movement.
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Discussion

- What are some other ways to correct the issue with the barometer's WALKING detection?
- Are the three categories of IDLE, WALKING, and VEHICLE enough?
- Does this approach have any real value?

Android application – Cover
- needs context to make is possible.
Context for location readings.

Hardware:
M7/M8 Co-processor
- Collects and process from accelerometer, gyroscope, and compasses
- IOS
Step counter
- Android
- Coprocessor

Transportation-mode Detection

- Useful for many things
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- Usually accelerometers
  - Low power
  - 10+ Hz sampling
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Android Move
- First to use Google's Activity Recognition API.

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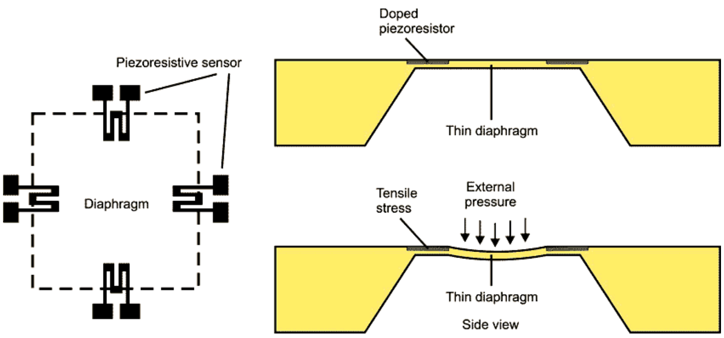

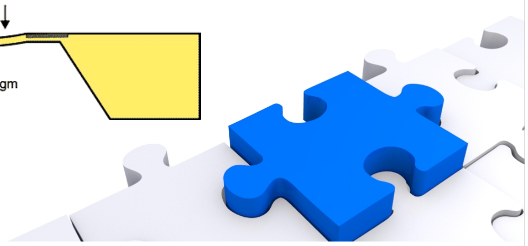

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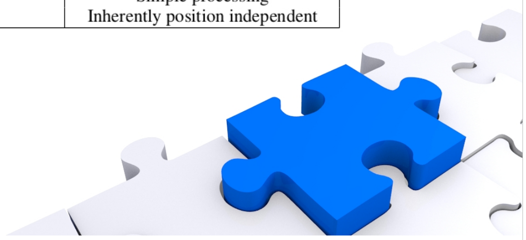

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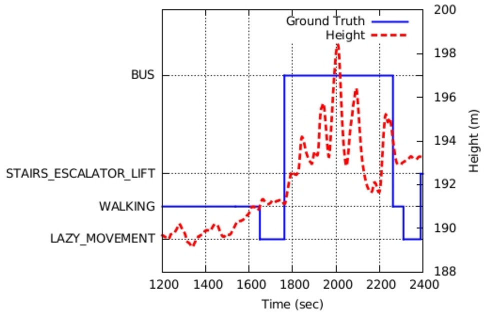

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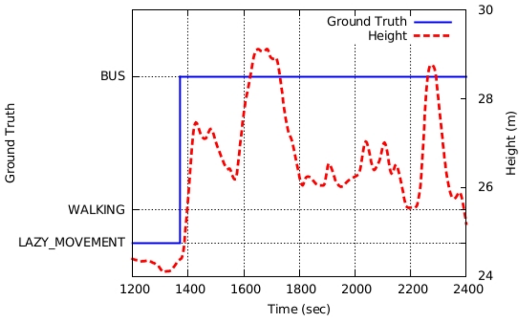

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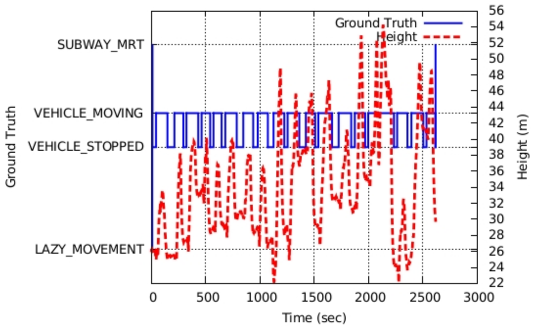

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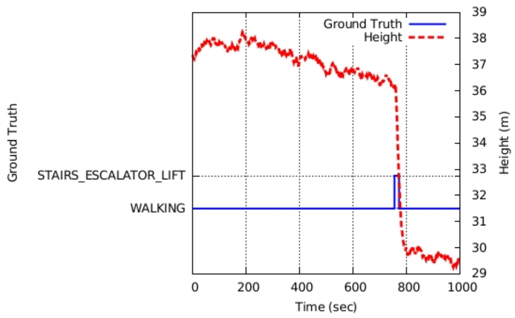

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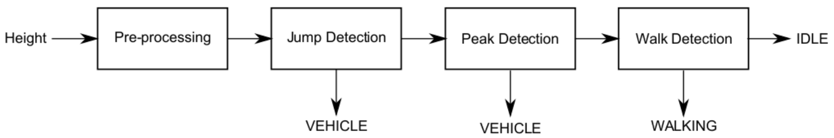

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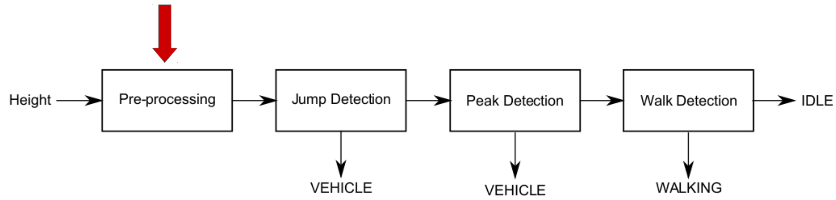

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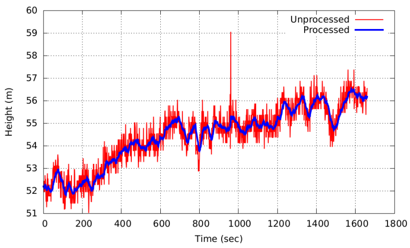

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- Special barometer traces for weather
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178 hours of traces (47 transportation)
Galaxy x3 samples at 5 Hz
Nexus 4 samples at 4 Hz
Nexus 5 (internal smoothing) value every 2 sec

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China
– cross country train ride
- walking ground truth possibly inaccurate

Boston and Singapore
- inaccurate traces disregarded

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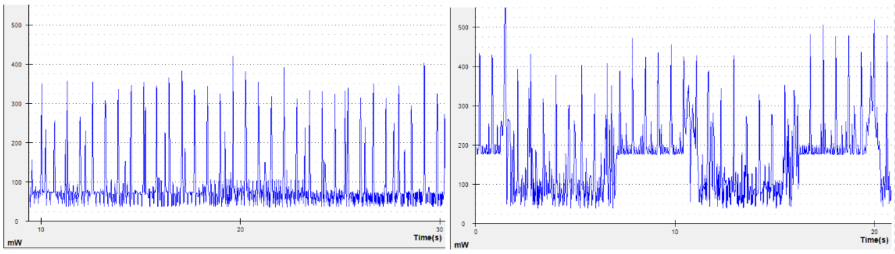

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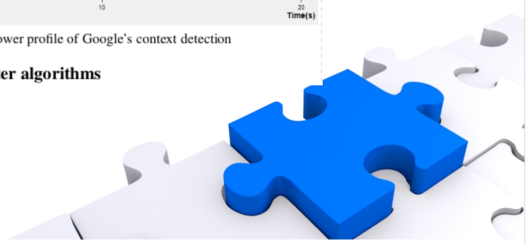

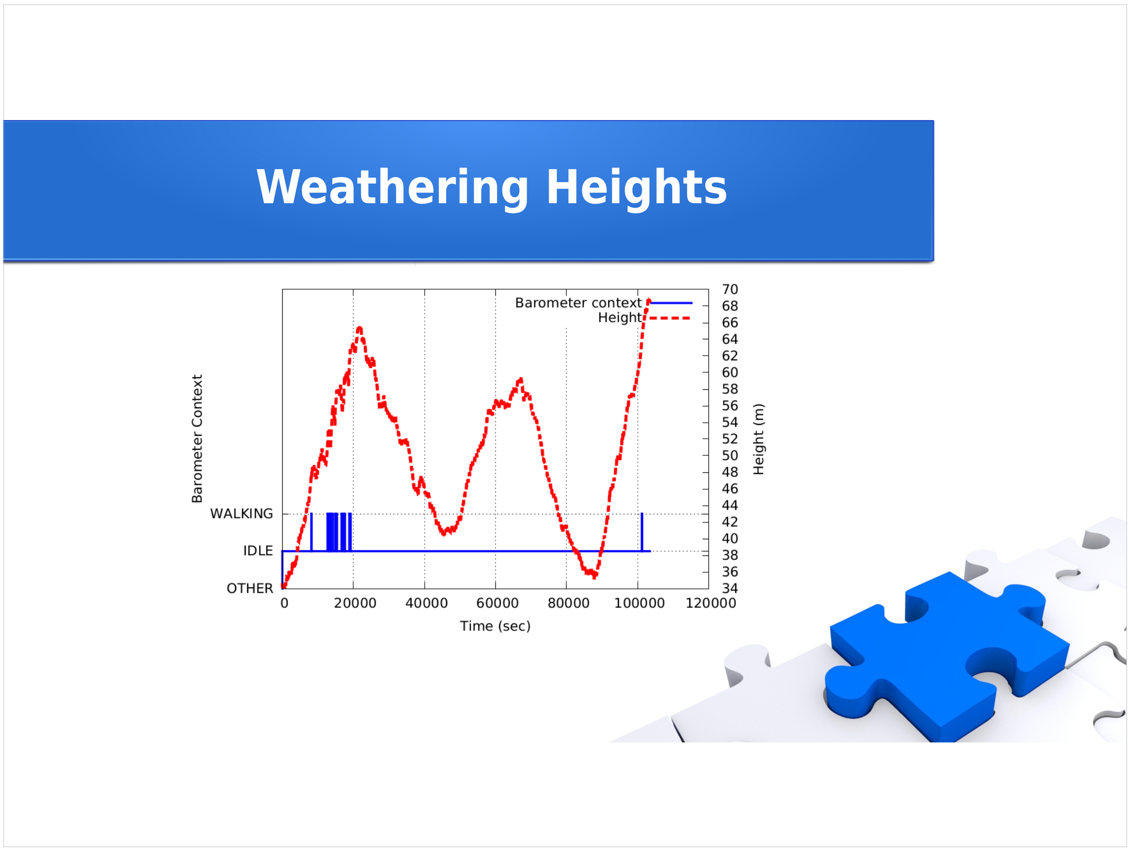

Weather variance during eval traces in Boston and Singapore

Tested only against IDLE

Collected in Singapore for rainy and windy days

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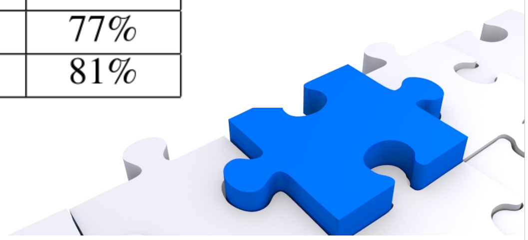

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