Online Pose Classification and Walking Speed Estimation using Handheld Devices

Jun-geun Park
MIT CSAIL

Joint work with: Ami Patel (MIT EECS), Jonathan Ledlie (Nokia Research), Dorothy Curtis (MIT CSAIL), Seth Teller (MIT CSAIL)

Massachusetts Institute of Technology
CSAIL
Nokia Research Center

Speed Estimation: Motivation

- Accurate indoor positioning and navigation using smartphones require precise speed estimate.

J. Battat, "A Fine-grained Geospatial Representation and Framework for Large-Scale Indoor Environments", MEng thesis, MIT, 2010

Pose Classification: Motivation

- Device pose (location relative to user body) is an important input for high-level situational inference.

On hand? In bag? At Ear? In Pocket?

System Design Summary

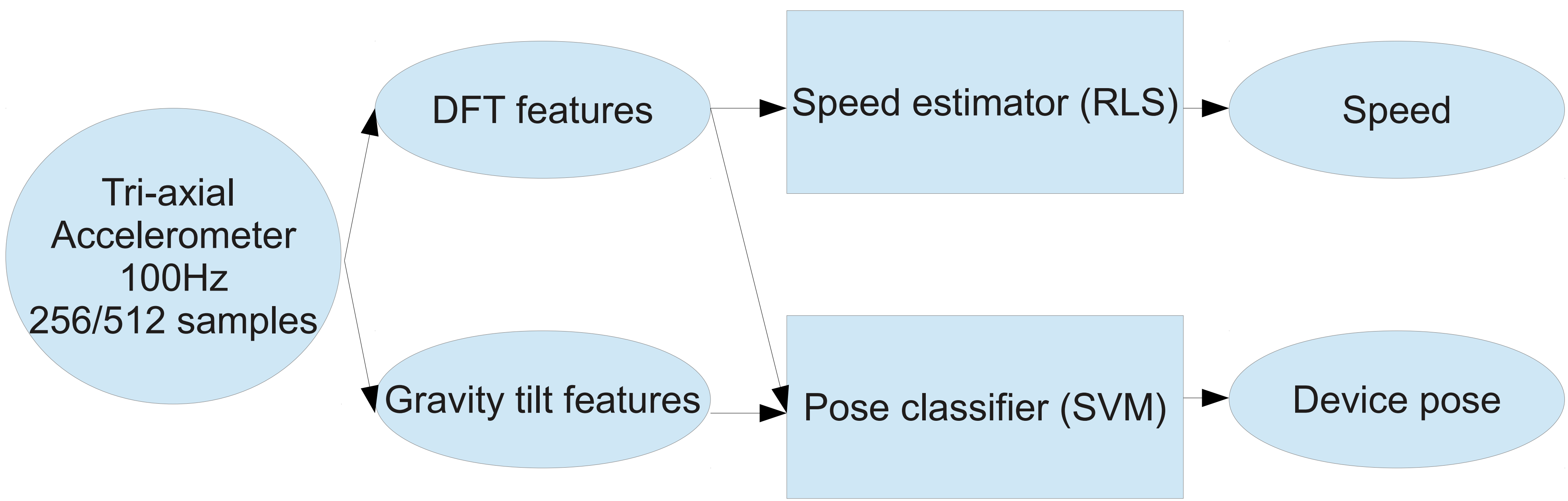
- Target application: indoor navigation/context awareness using smartphone sensors
- Input: acceleration signal from a single triaxial accelerometer
- Output:
  - Device pose: ear / hand / pocket / bag
  - Walking speed: in m/s
- Design assumptions
  - Handheld device – no fixed device position
  - Normal indoor walking – no treadmill evaluation
  - Different speed / device pose / path characteristics
  - Moving user
- Approach: machine-learning based

Nokia N900

Nokia Sensorbox

System Overview

- C++ implementation on Nokia N900
- Training done on a desktop offline
- Speed estimator and pose classifier are decoupled.



Machine Learning Based Pose/Speed Inference

- Previous work often relied on heuristics and explicit models.
  - Device pose: tilt angle (Kawahara, 2007)
  - Speed: (AutoGait, 2010)(Weinberg, 2002)
    - Speed = frequency x stride length
    - Stride length = proportional to height / frequency / acceleration range
- Our approach: Direct mapping from input features to a target variable, pose or speed, using machine learning methods
  - Robust under noise / individual variations

Regularized Kernel Methods

- Regularized kernel methods are a powerful class of machine learning algorithms that finds a stable model from non-linear data under presence of noise.
  - Speed estimation: Regularized Kernel Least Squares
  - Pose classification: Support Vector Machines

Regularized Kernel Methods

- Kernel methods: transform input space to (high-dimensional) feature space, allowing using linear models on non-linear data.

“Representer's theorem”

$$f(\mathbf{x}') = \sum_{i=1}^{n} c_i^* K(\mathbf{x}', \mathbf{x}_i)$$

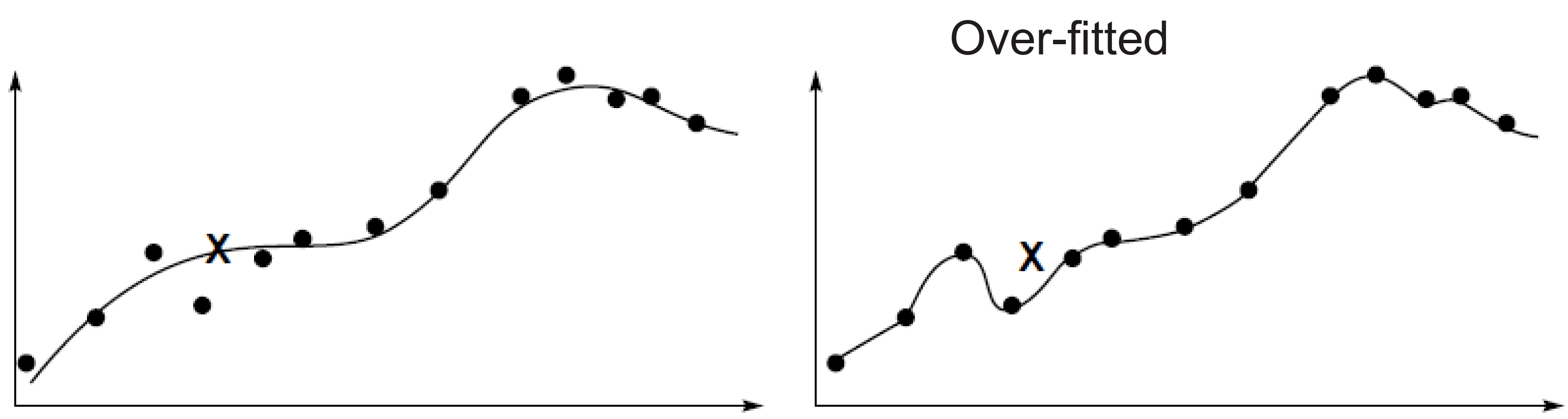
K(x', xi) encodes “similarity” between test input x' and training input xi

$$K(x', x) = \exp(-\frac{\|x' - x\|^2}{2\sigma^2})$$

Linear sum of kernels, or similarities, between x' and training inputs.

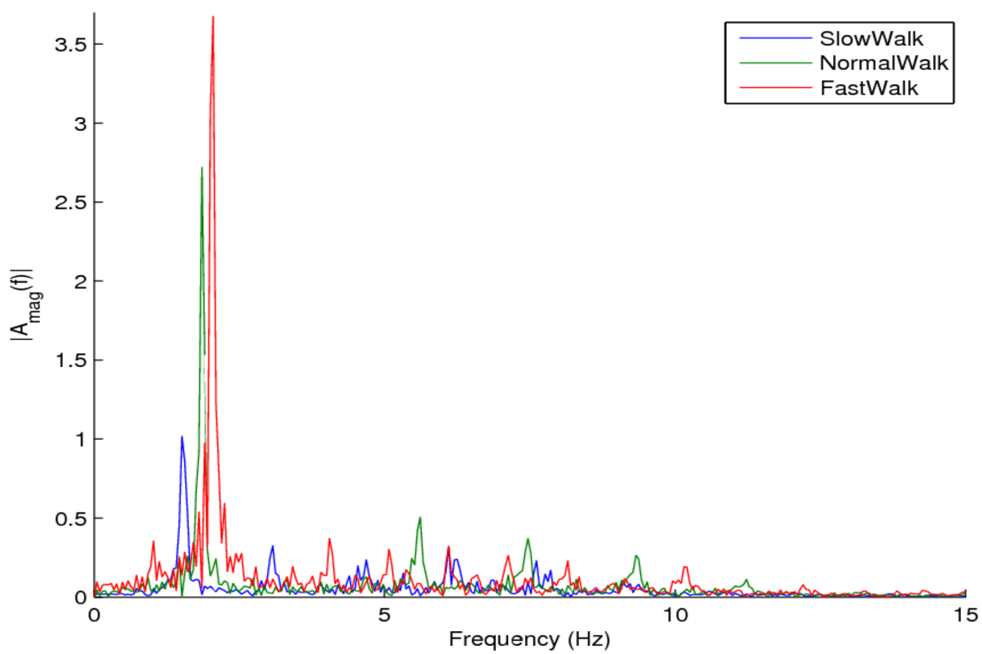
Regularized Kernel Methods

- Regularization: prevent overfitting
  - Overfitting to a specific user/pose/circumstance is undesirable.



Primary Feature: Acceleration Signal Spectrum

- Sliding window of 256 or 512 samples with 50% overlap.
- Primary feature: spectrum of the acceleration signal obtained by DFT, up to first 60 components (11.7Hz)



Kernel: RBF kernel

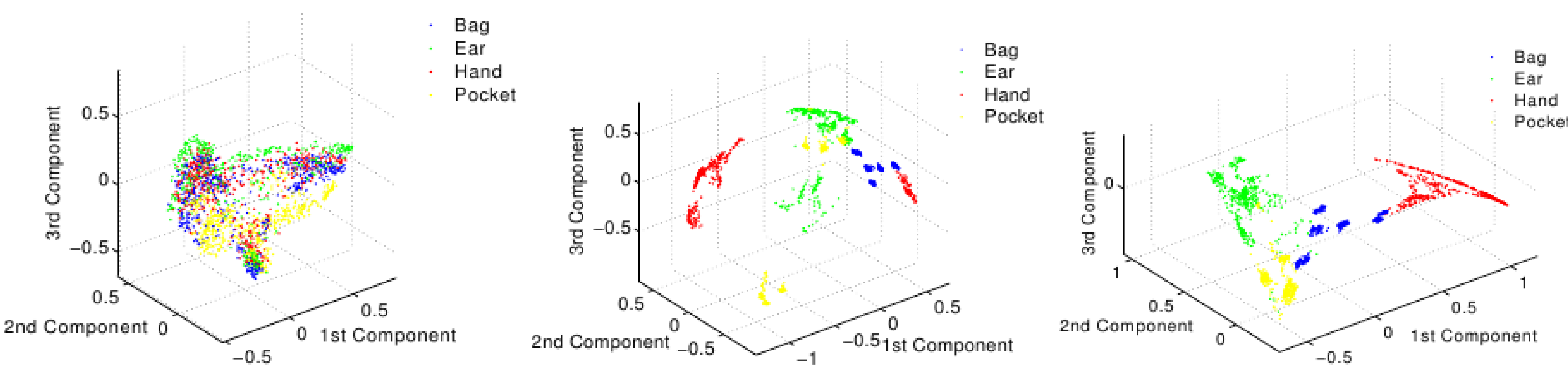
$$K(x', x) = \exp\left(-\frac{\|x' - x\|^2}{2\sigma^2}\right)$$

Additional Features for Pose Classification

- (Reparametrized) gravity tilt feature

$$\mathbf{x}_G = \left(|g_x|, |g_y|, |g_z|, \sqrt{g_x^2 + g_y^2}, \sqrt{g_x^2 + g_z^2}, \sqrt{g_y^2 + g_z^2} \right)$$

  – At least two of six dimensions are invariant under a rotation along an axis ($|g_z|, \sqrt{g_x^2 + g_y^2},$ under z-axis rotation)



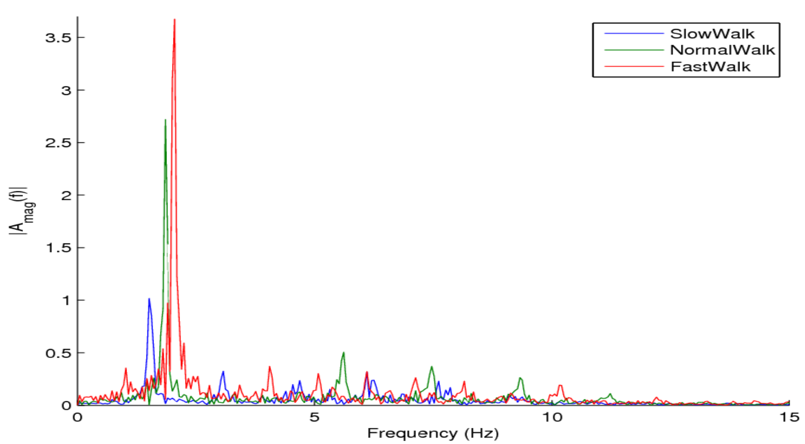
(a) Horizontal/vertical DFT vector (b) Raw gravity vector (c) Gravity tilt feature vector (Equation (9))

Additional Features for Speed Estimation

- Energy shows a good correlation with walking speed.
- Separation of spectral distribution and energy

Normalized FFT spectrum vector

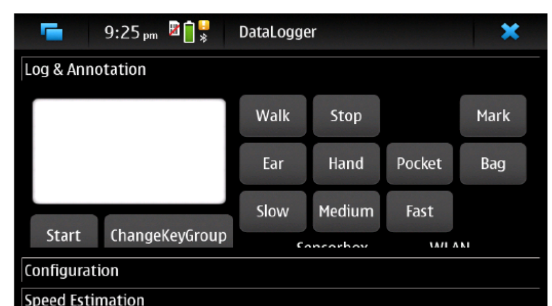
$$K_S(\mathbf{x},\mathbf{x}') = \exp\left(-\frac{\|\mathbf{x}_M - \mathbf{x}'_M\|^2}{2\sigma_M^2}\right) + \exp\left(-\frac{(x_E - x'_E)^2}{2\sigma_E^2}\right)$$



“Energy” (= squared sum of DFT magnitudes)

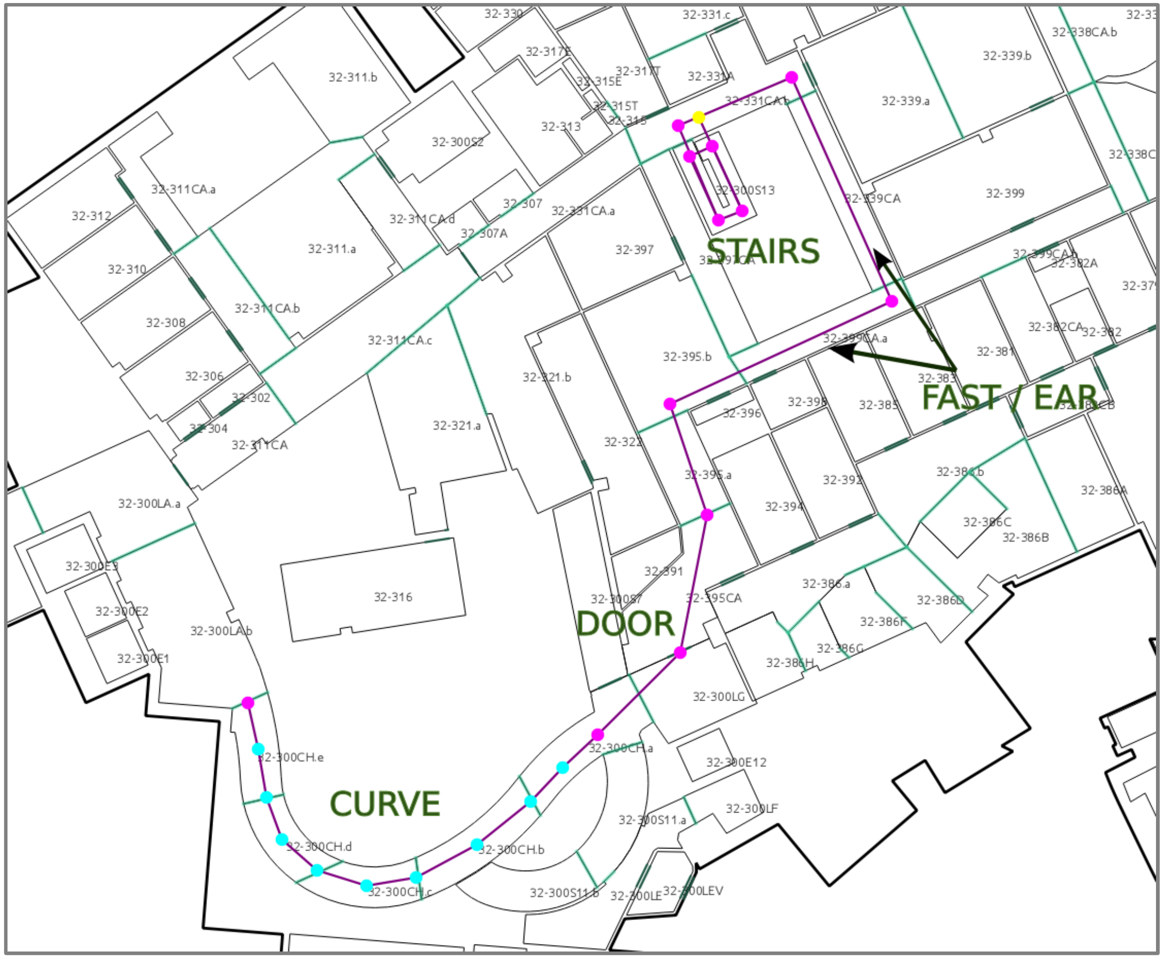
Evaluation Methodology

- Non-interrupted free-walking in indoor environments
  - A participant carried a sensorbox while walking.
  - An experimenter followed the participant with N900 connected to the sensorbox via bluetooth.
  - Four poses (ear/hand/pocket/bag) x three speed regimes
  - Two experiment scenarios
  - Hand (button) / video annotation
  - 14 participants, 3.5 person-hours data



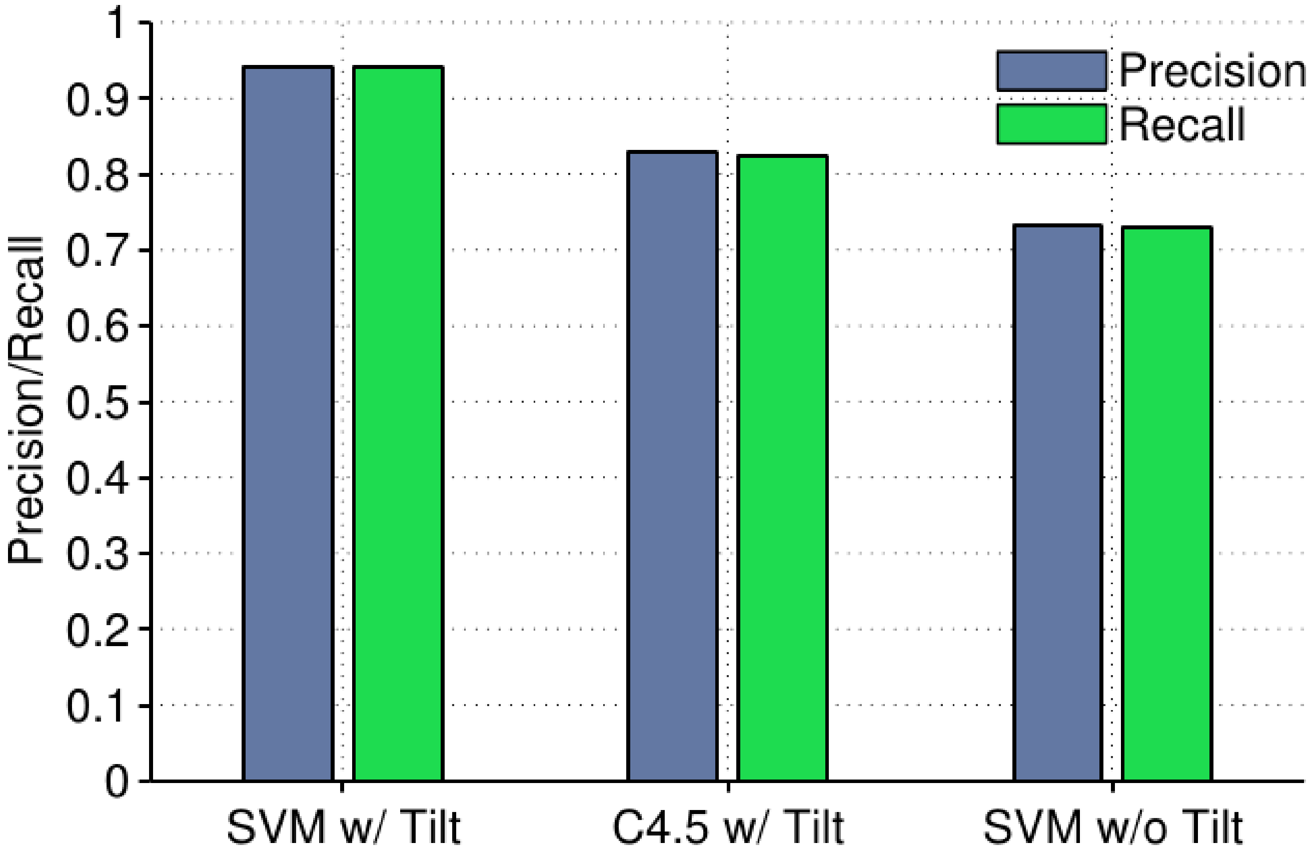
Evaluation Scenario: Natural Walking in Indoor Environments

- The experiment path contains curves, doors, turns, stairs, “special” intervals.



Result: Pose Classification

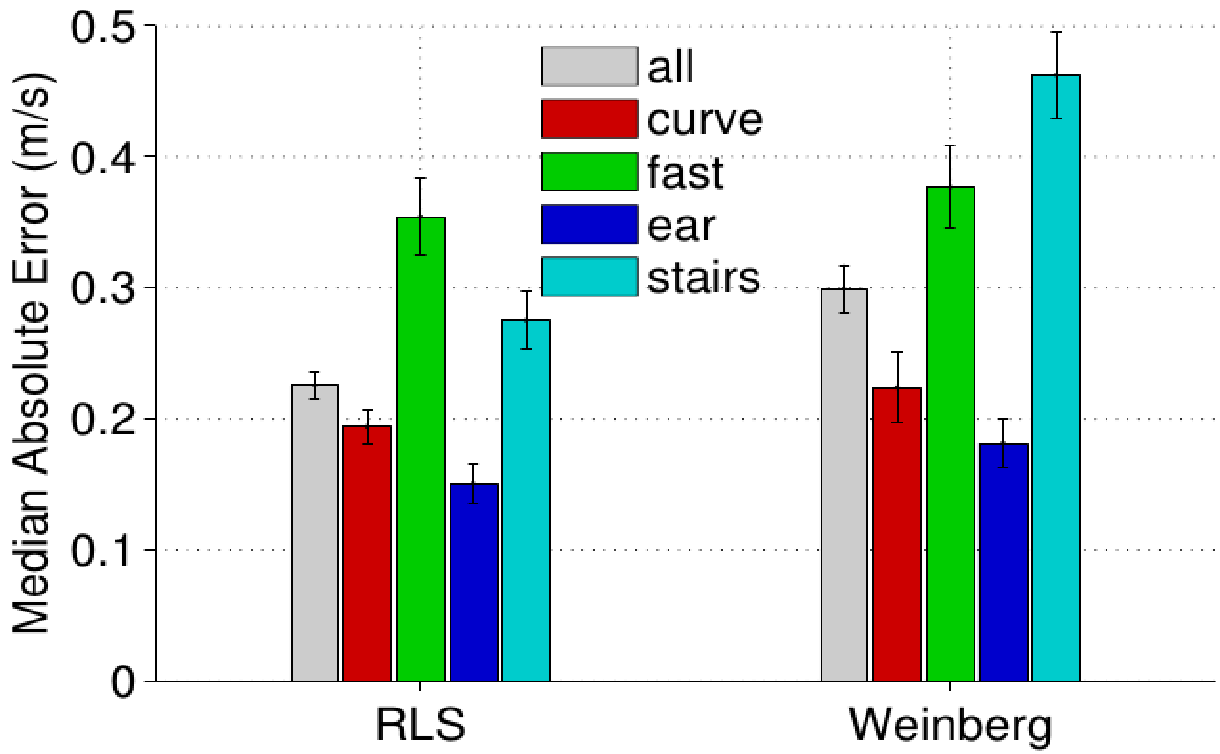
- Gravity tilt feature combined with kernel methods (SVM) improves pose-classification significantly.



C4.5: Kunze et al., 2005

Result: Walking Speed Estimation

- Regularized kernel methods predicts walking speeds consistently better then model-based step-counting methods under different scenarios.



Weinberg method:
Stride length =

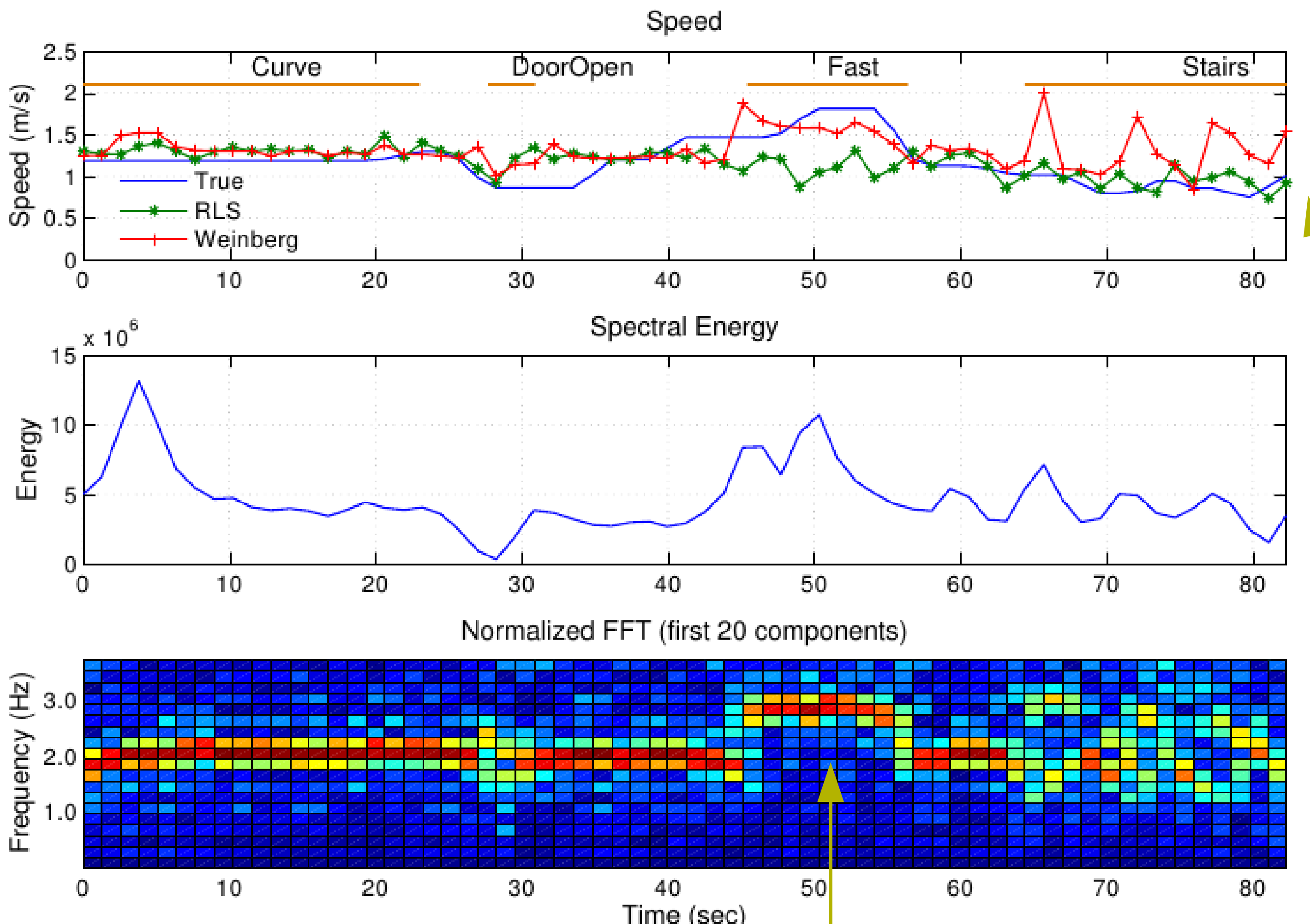
$$k_4 \cdot \sqrt[4]{a_{max} - a_{min}}$$

Online Computation Performance

- C++ implementation on Nokia N900
- Average end-to-end computation time for prediction (given 512 samples = 5.12 sec as input)

Pose classification	10.46 ms
Speed estimation	9.37 ms

An Example Showing Strengths/Weaknesses of Our Approach



Weakness: Participant was running at 3Hz (higher than most of frequencies in our dataset)

Strength: Step lengths are confined on stairs, but our ML-based method worked well.

Conclusion

- Device pose classification and walking speed estimation from a single triaxial accelerometer in a handheld device.
- Machine learning algorithms (regularized kernel methods) with suitable choice of features achieve high performance.
- These algorithms can be efficiently executed online.
- ML-based methods are not free from limitations – They may perform poorly when presented an unseen pattern.
- Data will be available at: http://rvsn.csail.mit.edu/location