

# Parameter Estimation for Mobile Positioning Applications

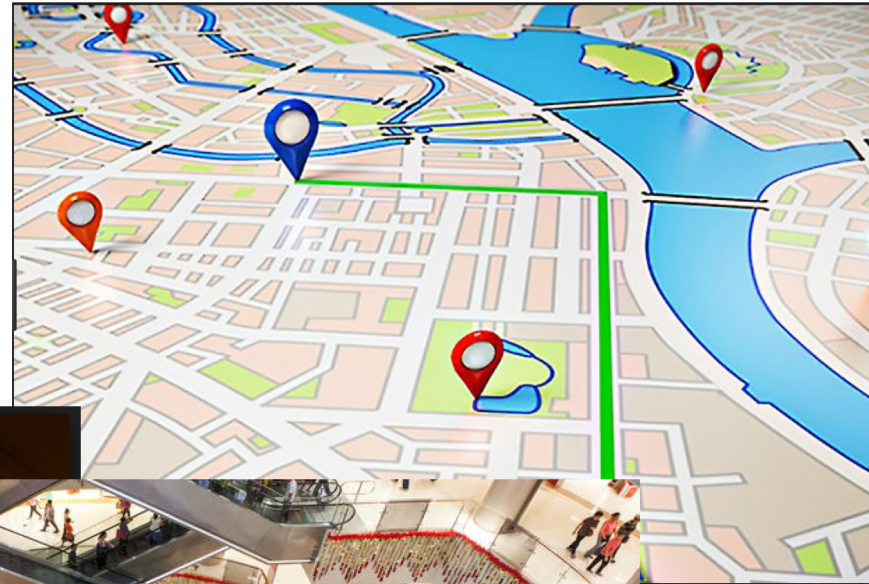
Parinaz Kasebzadeh

# Parameter Estimation For Mobile Positioning Application

# Positioning

- ~~GPS~~

GPS Signal Lost!!



<http://www.radio.cz/en/section/courts/massive-blanka-tunnel-has-been-completed-after-years-of-delays>

# Positioning in GPS Denied Environments

- **Wireless networks systems**
  - Outdoors Assisting GNSS signals with information from other wireless networks
    - Cellular networks
  - Indoors
    - Existing infrastructure (WLAN)
- **Micro-electromechanical systems (MEMS)**  
Inertial Measurement Units (IMUs)

What is the suitable device for processing these signals?



<https://www.newegg.com/>



<http://www.sztozed.com/>



<https://www.sensa.com/>  
<https://www.pinterest.co.uk/camronpr/technology/>

# Mobile Positioning Applications

Introduction

Challenges

Proposed Solution

Results

# Mobile Positioning Applications

- **Wireless networks systems**

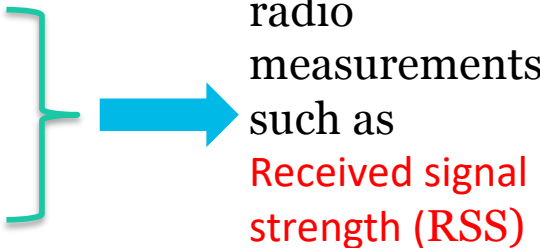
- P. Kasebzadeh, C. Fritsche, E. Özkan, F. Gunnarsson, F. Gustafsson. **Joint Antenna and Propagation Model Parameter Estimation using RSS measurements.** In Proceedings of the 18th International Conference on Information Fusion , pages 98–103, Washington D. C., USA, July 2015.

- **Inertial Measurement Units (IMUs)**

- P. Kasebzadeh, C. Fritsche, G. Hendeby, F. Gunnarsson, F. Gustafsson. **Improved Pedestrian Dead Reckoning Positioning With Gait Parameter Learning.** In Proceedings of the 19th International Conference on Information Fusion , pages 379–385, Heidelberg, Germany, July 2016.
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# Antenna Gain Parameter Estimation Challenges

- Cellular radio networks poor coverage
  - Excessive interference
- 
- Positioned radio measurements such as **Received signal strength (RSS)**
- The changes of channel and antenna parameters based on the instantaneous propagation condition are neglected.
  - When a detailed propagation model calibration is ruled out, the applicability of the RSS measurements for ranging is subject to significant uncertainty.

# Antenna Gain Parameter Estimation

## Proposed solution

- A semi-empirical propagation model for the RSS measurement.
  - Combination of an empirical distance-dependent path loss model and a deterministic antenna gain model.
  - A Least-squares estimator is proposed to jointly estimate the path loss and antenna gain model parameters.
  - The approach is verified with both simulated and real data.
-



# Antenna Gain Parameter Estimation

## Propagation and antenna models

- Semi-empirical propagation model for the RSS measurement

$$Y = P_T - \{L(d) - G_{\text{ant}}(\phi, \psi)\} + e,$$

Empirical distance-dependent propagation path loss model  $L(d)$

$$L(d) = A + 10B \log_{10}\left(\frac{d}{d_0}\right)$$

Deterministic antenna gain model  $G_{\text{ant}}(\phi, \psi)$   
 $G_{\text{ant}}(\phi, \psi) = G_h(\phi) + G_v(\psi)$

# Antenna Gain Parameter Estimation

Antenna models

$$G_h = G_{max} - \min \left( 12 \left( \frac{\phi - \phi_0}{\phi_h} \right)^2, G_{h,min} \right)$$

$$G_v = \max \left( -12 \left( \frac{\psi - \psi_{etilt}}{\psi_v} \right)^2, G_{v,min} \right)$$

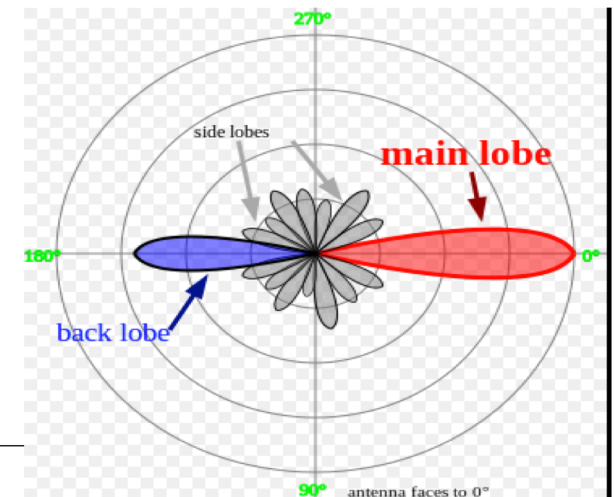
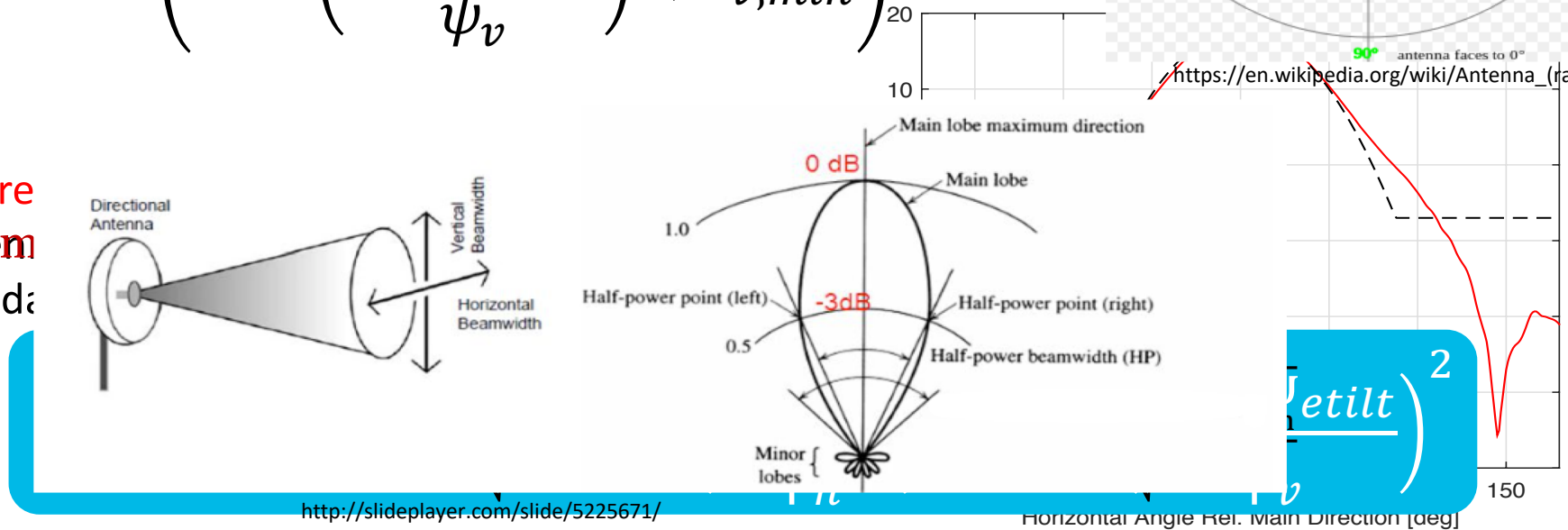


Figure  
Antenna  
real data



# Antenna Gain Parameter Estimation

## Parameter estimation

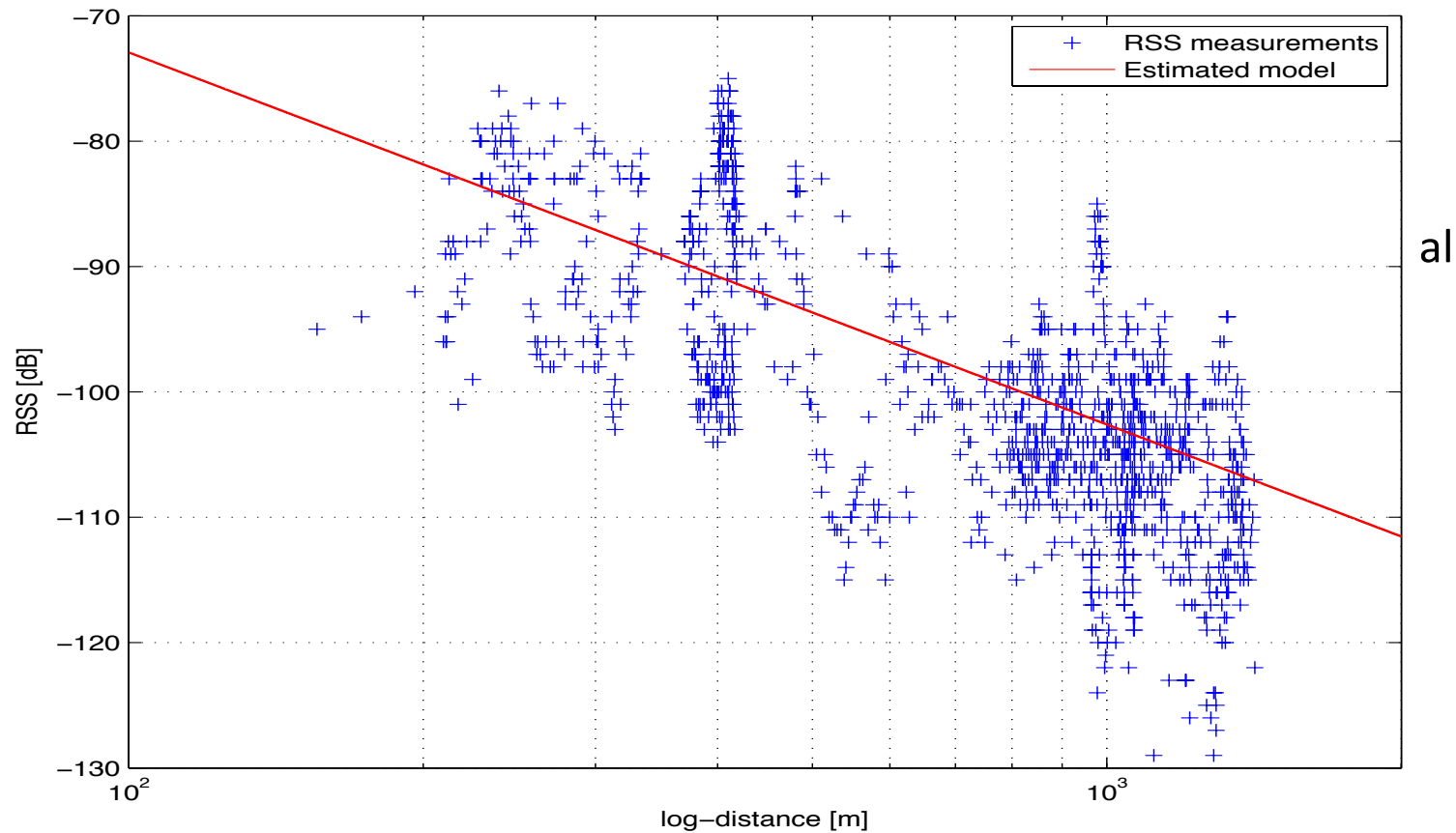
With this simplification, the maximum likelihood estimate of the parameters becomes tractable, and can be found according to

$$\hat{\theta} = \arg \max_{\theta \in \Theta} p(Y|\theta) \quad \theta = [A, B, \phi_h^{-2}, \psi_v^{-2}]^T$$

under the Gaussian noise assumption the maximum likelihood solution is equivalent to the least squares estimator.

# Antenna Gain Parameter Estimation

## Experimental Results



**Figure:** RSS measurements together with estimated path loss model

# Mobile Positioning Applications

- **Wireless networks systems**

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# Gait Parameter Estimation

## Challenges and Solution

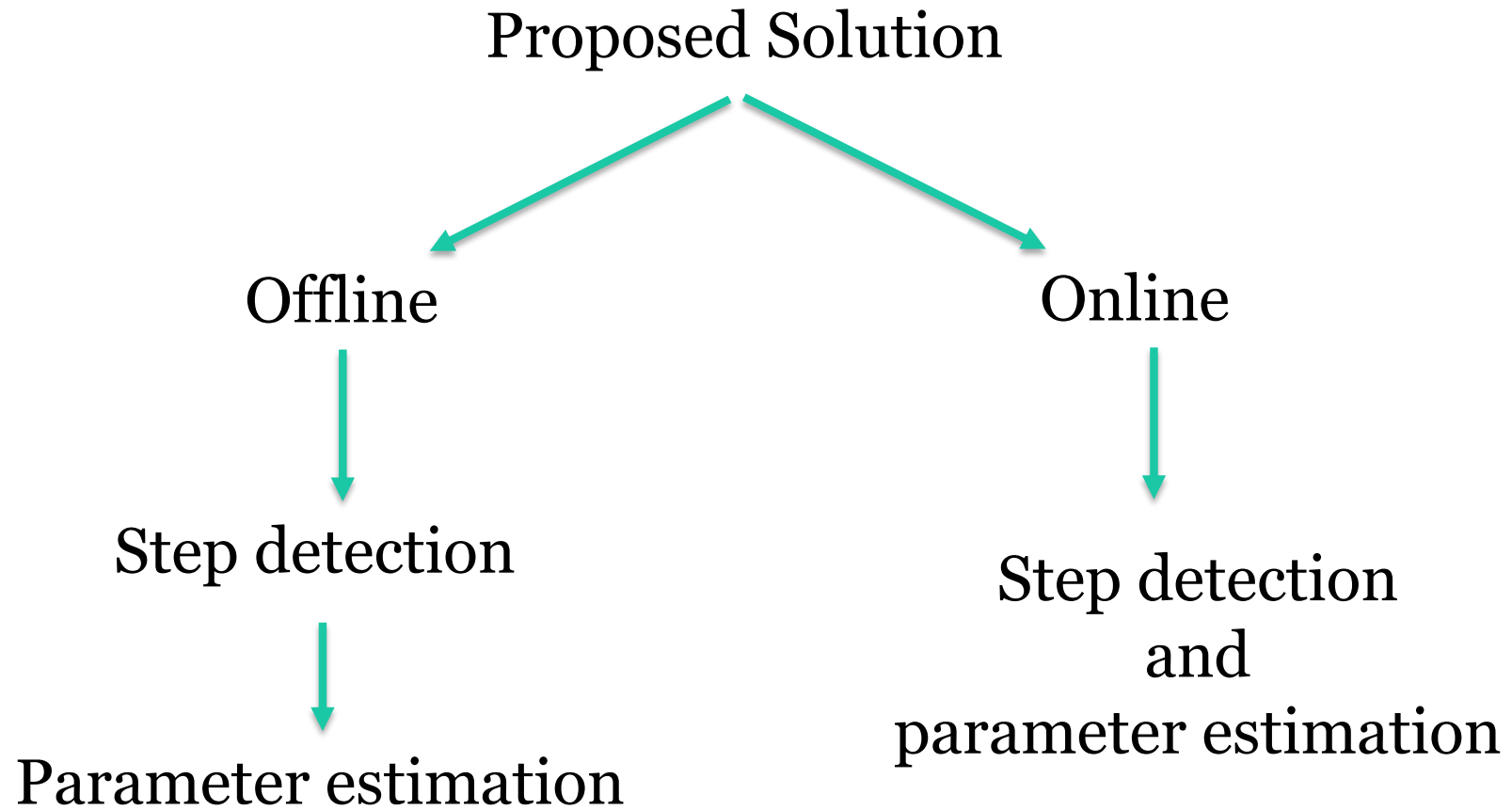
### Challenges

### Proposed Solution

IMUs are not self-contained navigation systems. The reason comes from the positioning error caused by gyroscopes and accelerometers in a rapid drift algorithm, such as the step length and the step detection threshold.

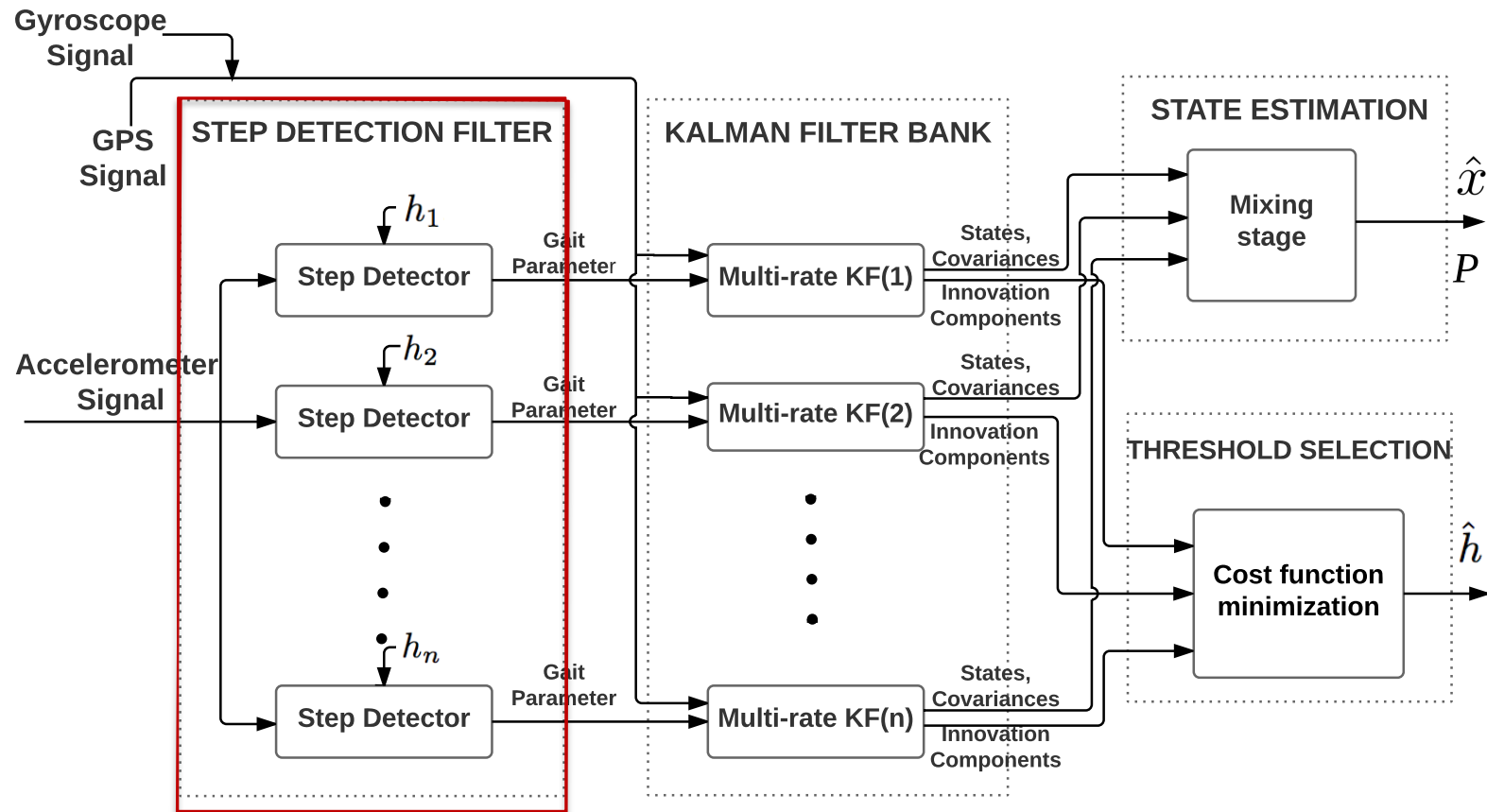
# Gait Parameter Estimation

Proposed solution



# Gait Parameter Estimation

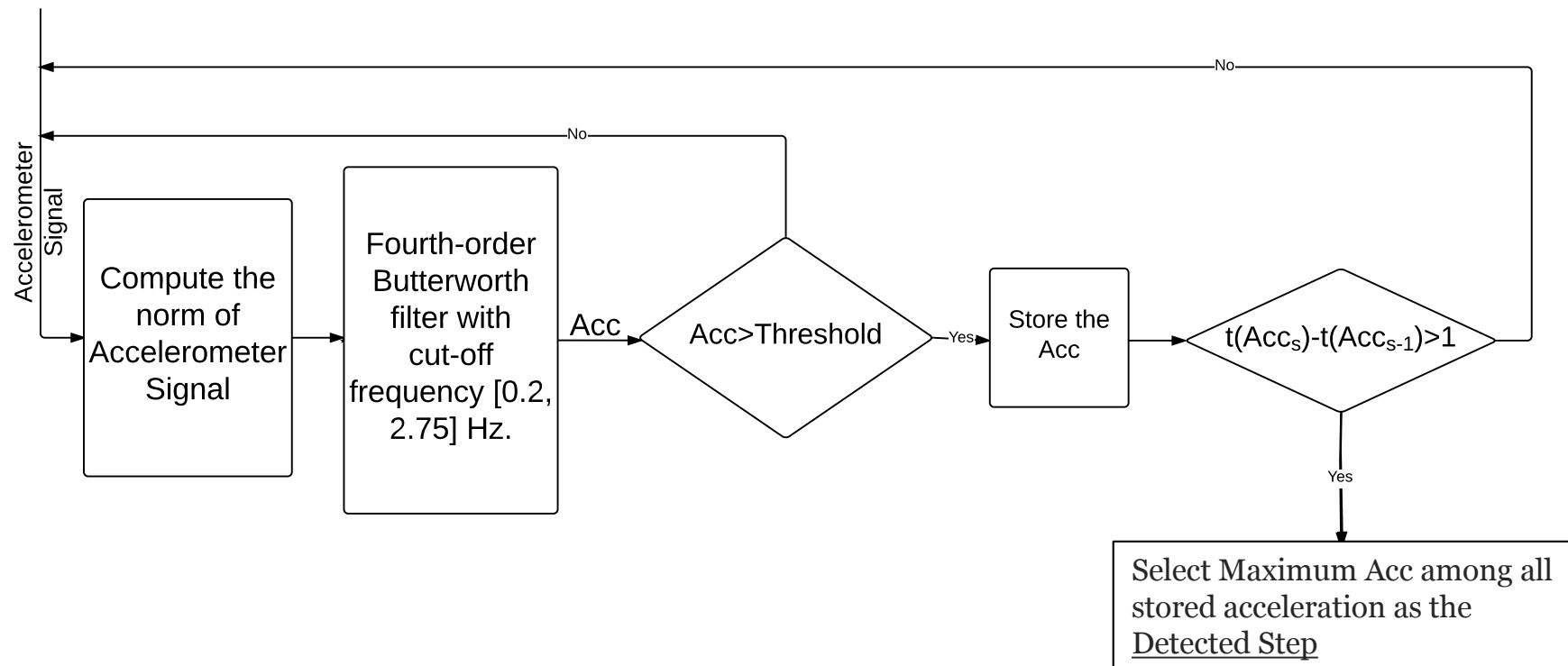
## Offline Solution





# Gait Parameter Estimation

## Step detection algorithm



# Gait Parameter Estimation

## Experimental results for step detection algorithm

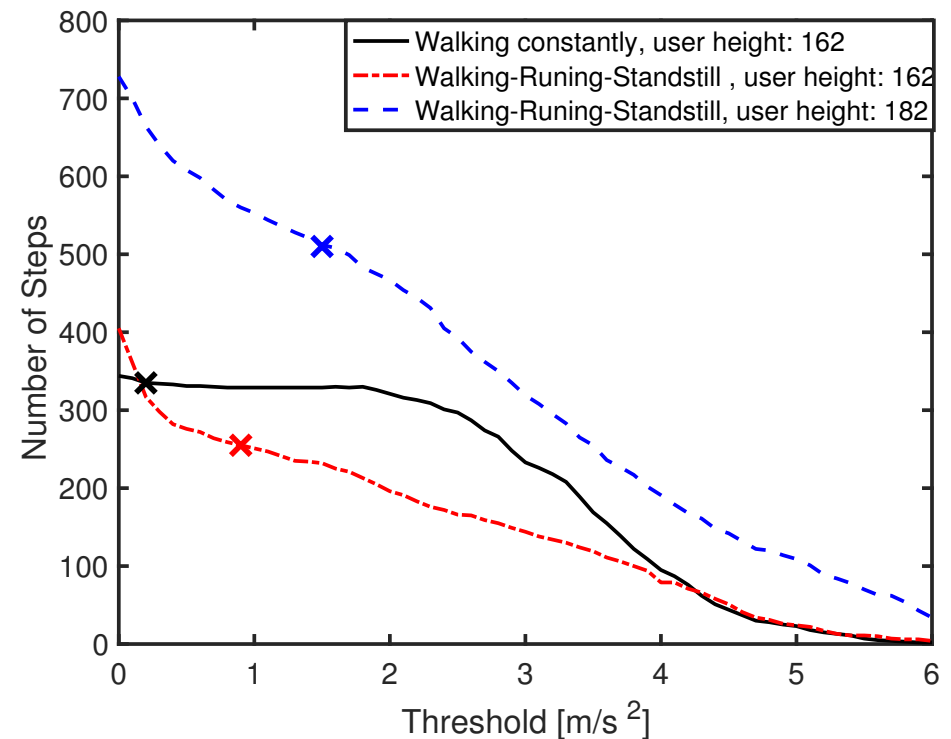
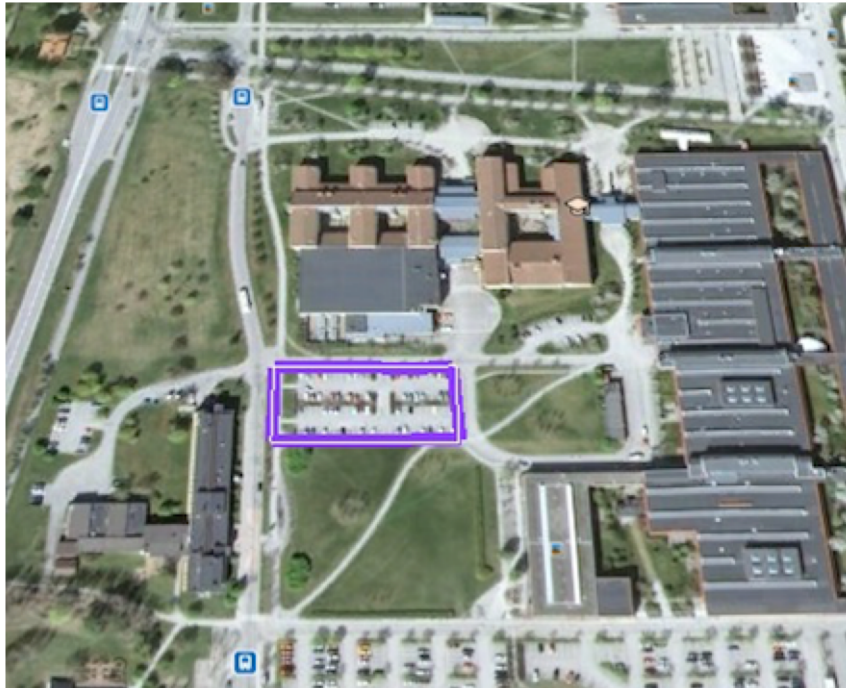
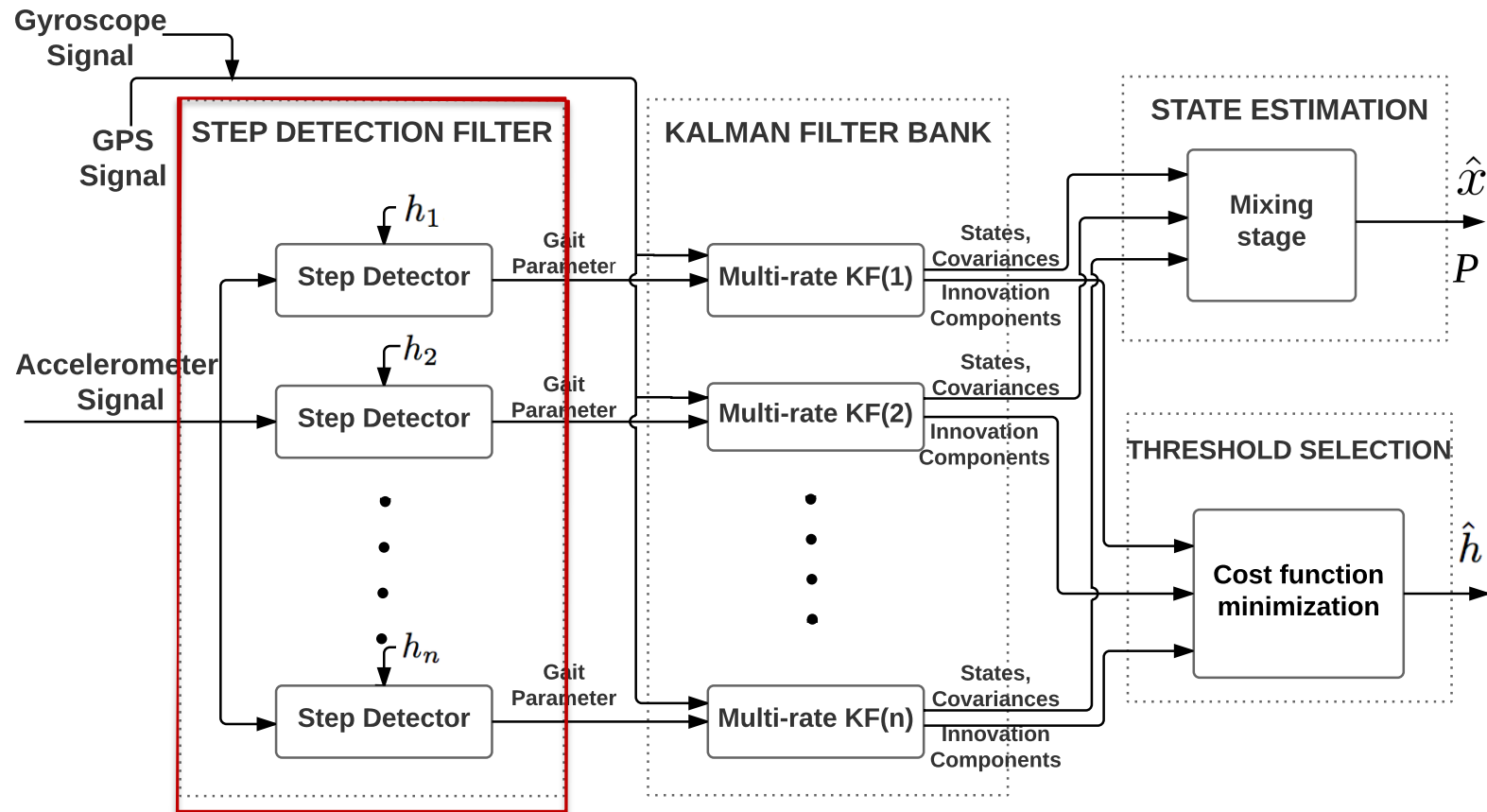


Figure: [Left] Measurement trajectory. [Right] Number of steps detected vs. step detection threshold for different users with different walking paces.

# Gait Parameter Estimation

## Offline Solution



# Gait Parameter Estimation

## Pedestrian Odometric Model

### Basic Model

PDR algorithms detect gait parameters to determine the traveled distance. The basic longitudinal model is given by

$$d_{s+1} = d_s + L + n_s,$$

### Extended Pedestrian Odometric Model

#### **A longitudinal multi-rate model**

- Updated each time a step is detected or a GPS position estimate becomes available.
- The underlying motion model is the standard constant velocity (CV) model extended with step length.

State vector :  $x = [d, v, L]^T$

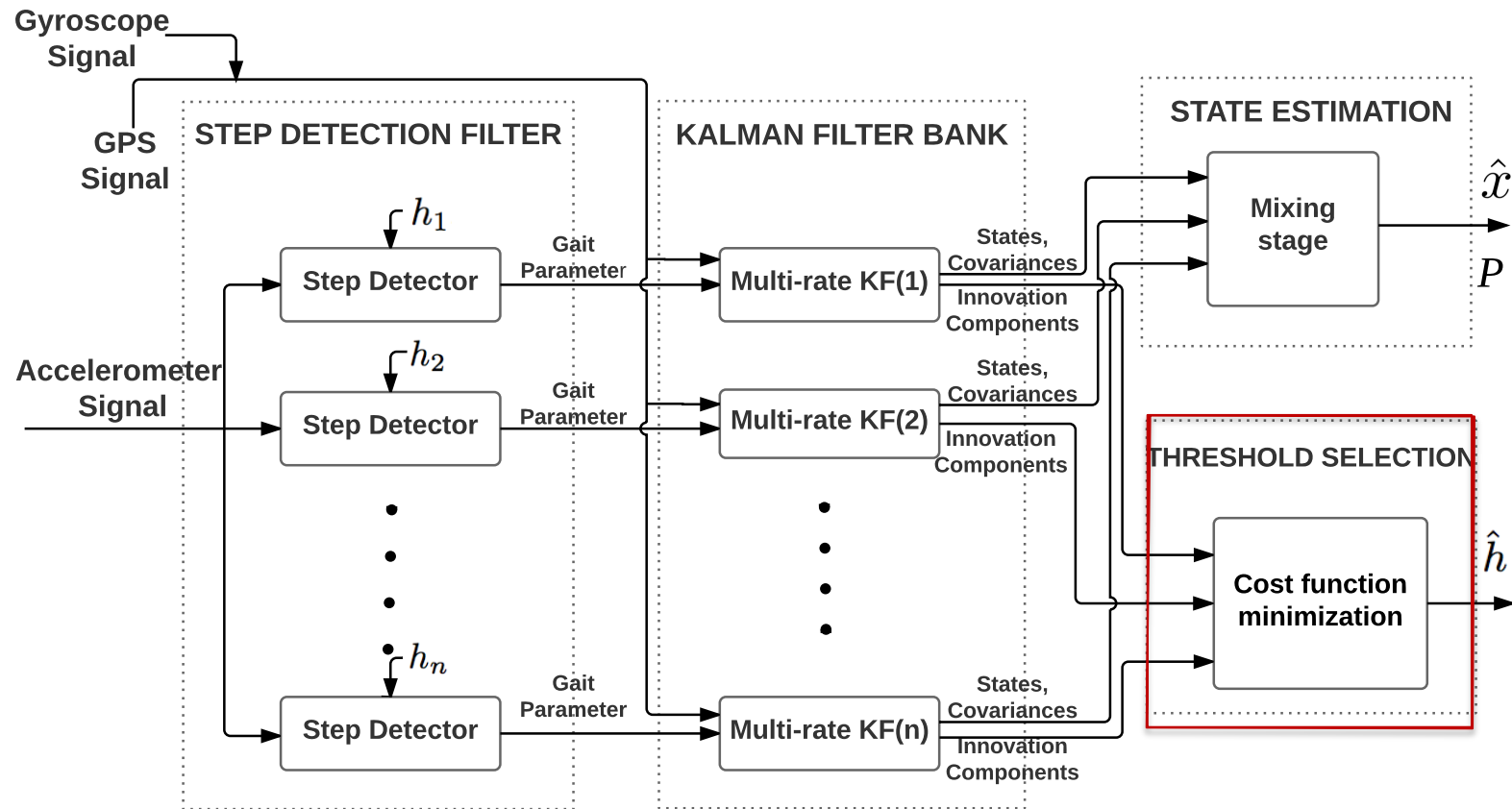
#### **A 2-D multi-rate horizontal model**

- It is a Coordinated Turn (CT) model with polar velocity extended with step length.
- The nonlinear CT allows for a varying turn rate and also a varying target speed.

State vector :  $x = [X, Y, v, h, \omega, b, L]^T$

# Gait Parameter Estimation

## Offline Solution



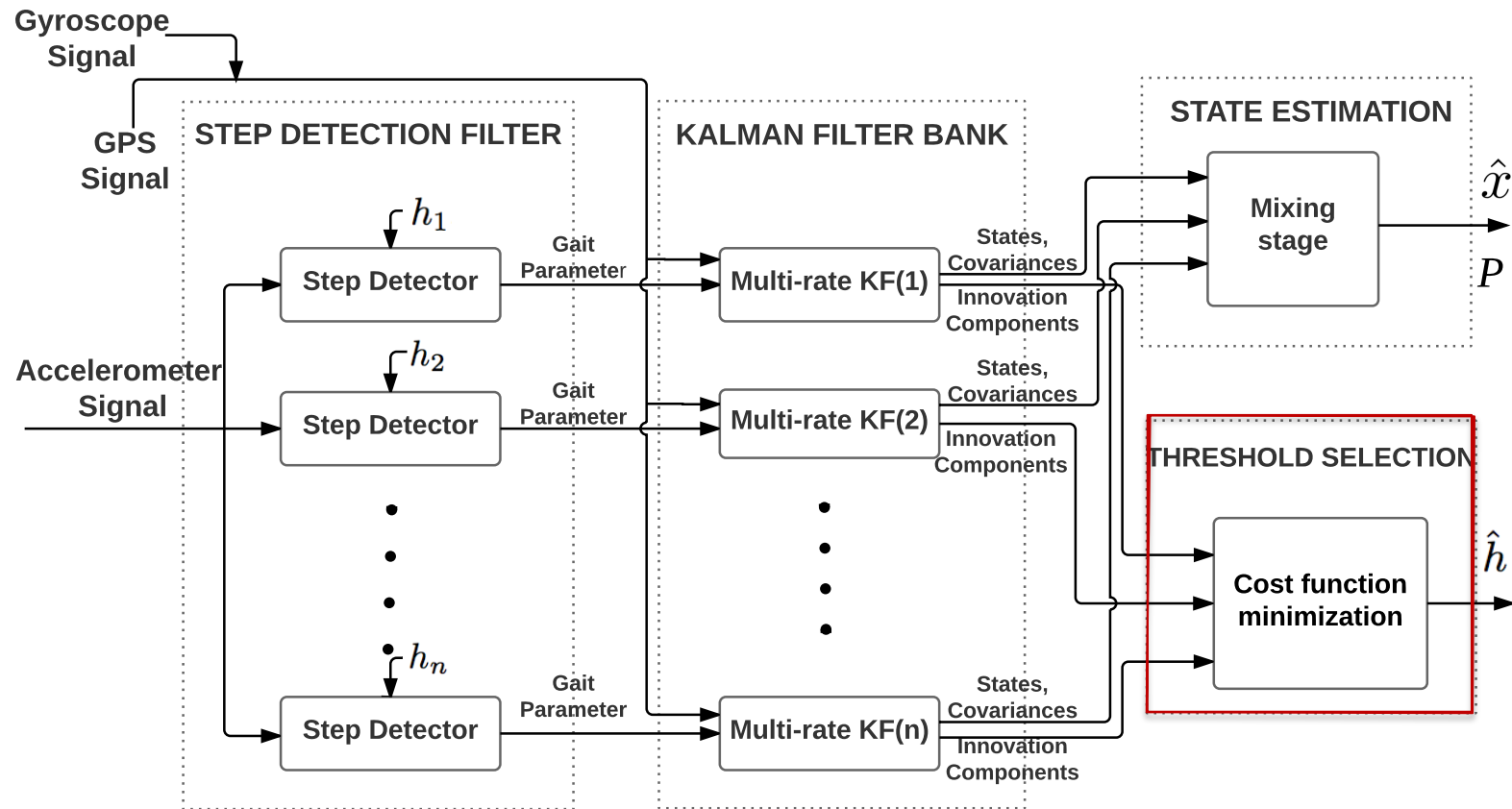
# Gait Parameter Estimation

Results for the threshold selection block

		True Threshold $\left[\frac{m}{s^2}\right]$	Estimated Threshold $\left[\frac{m}{s^2}\right]$
Different attributes	User 1	2.06	2.0
	User 2	0.81	0.8
	User 3	0.61	0.4
Same user, Different paces	Slow pace	0.51	0.6
	Moderate pace	3.46	3.4
	Fast pace	1.56	1.4

# Gait Parameter Estimation

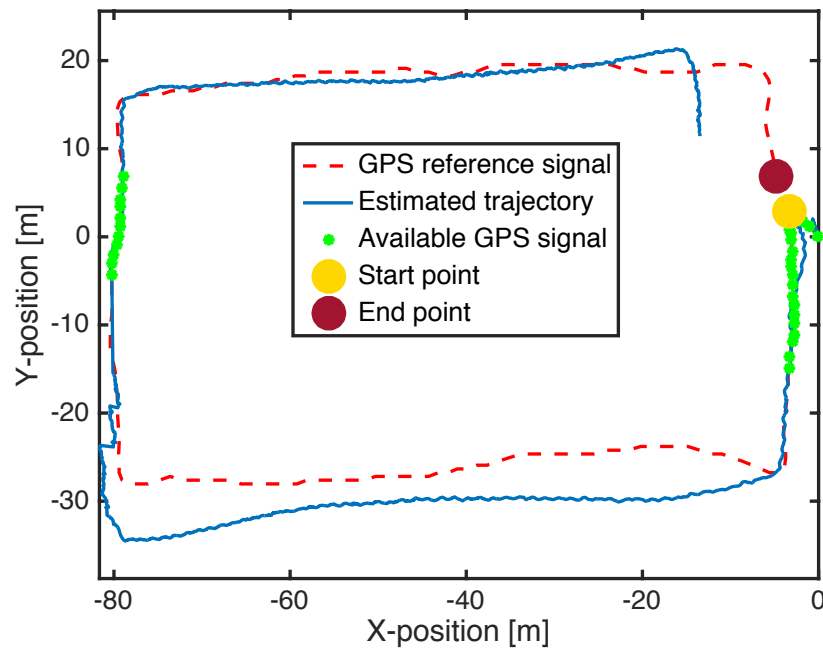
## Offline Solution



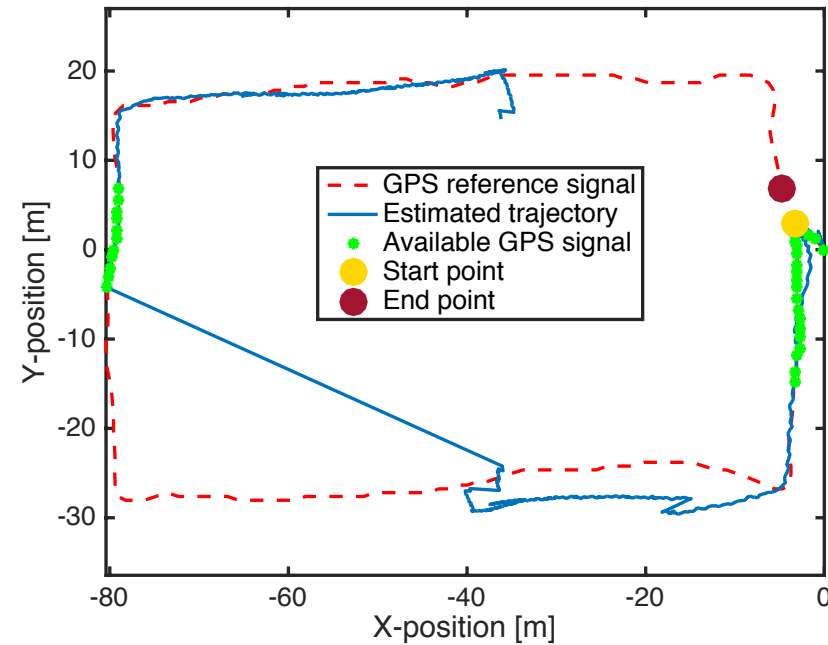
# Gait Parameter Estimation

## Results for horizontal model

### Adaptive Threshold



### Fixed Threshold

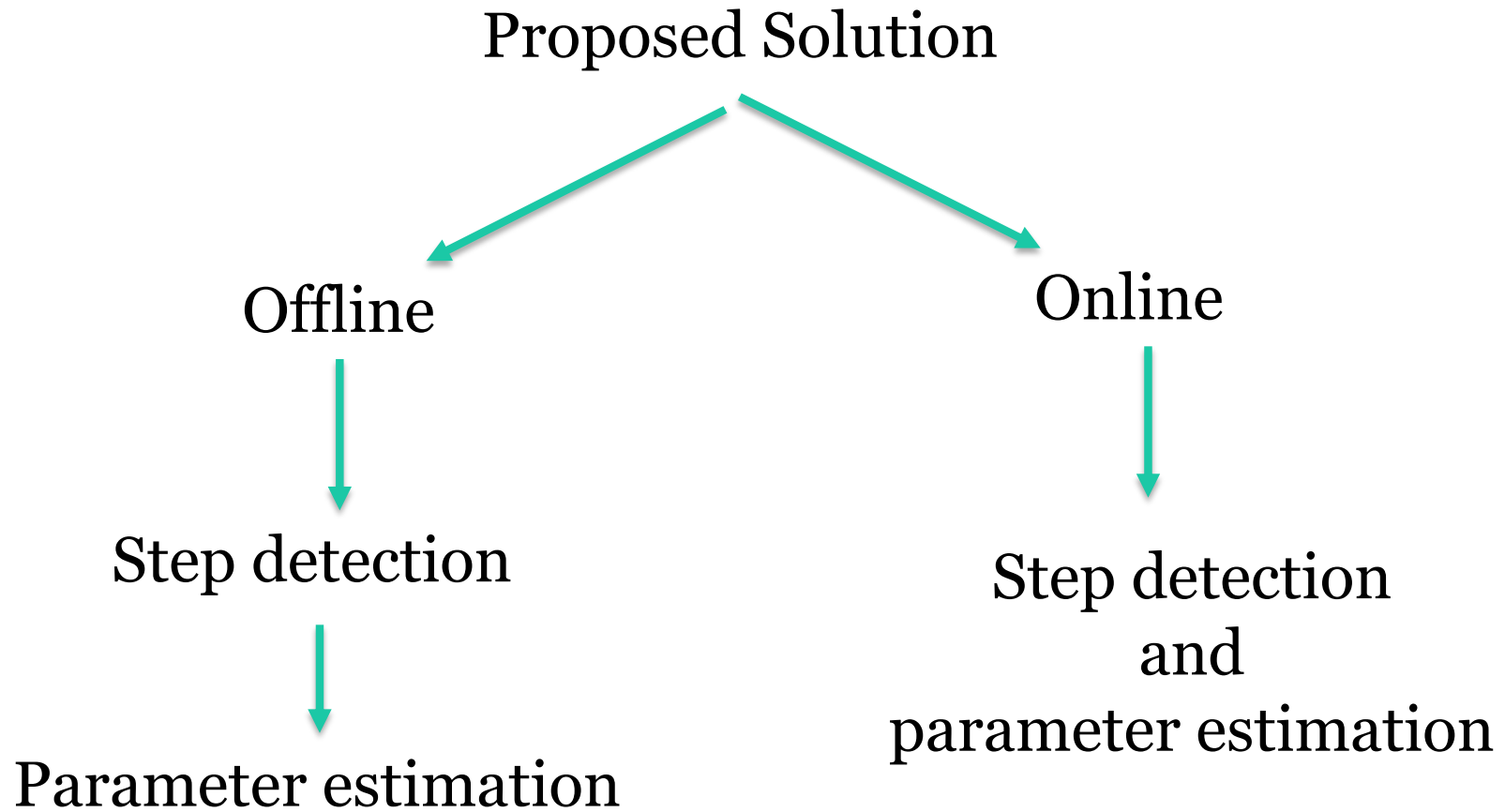


Same reference trajectory but with adaptive and fixed parameters.



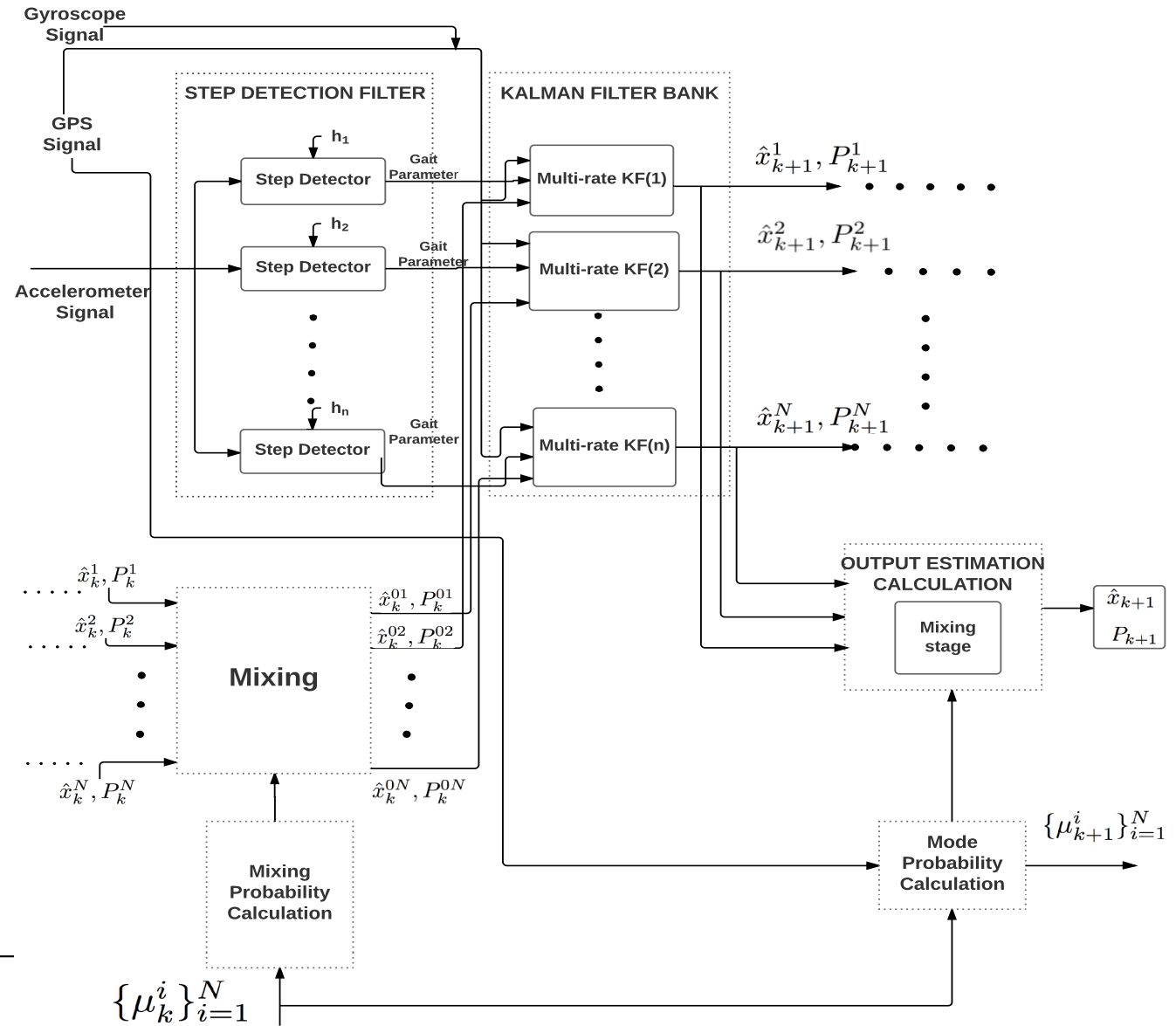
# Gait Parameter Estimation

Proposed solution



# Gait Parameter Estimation

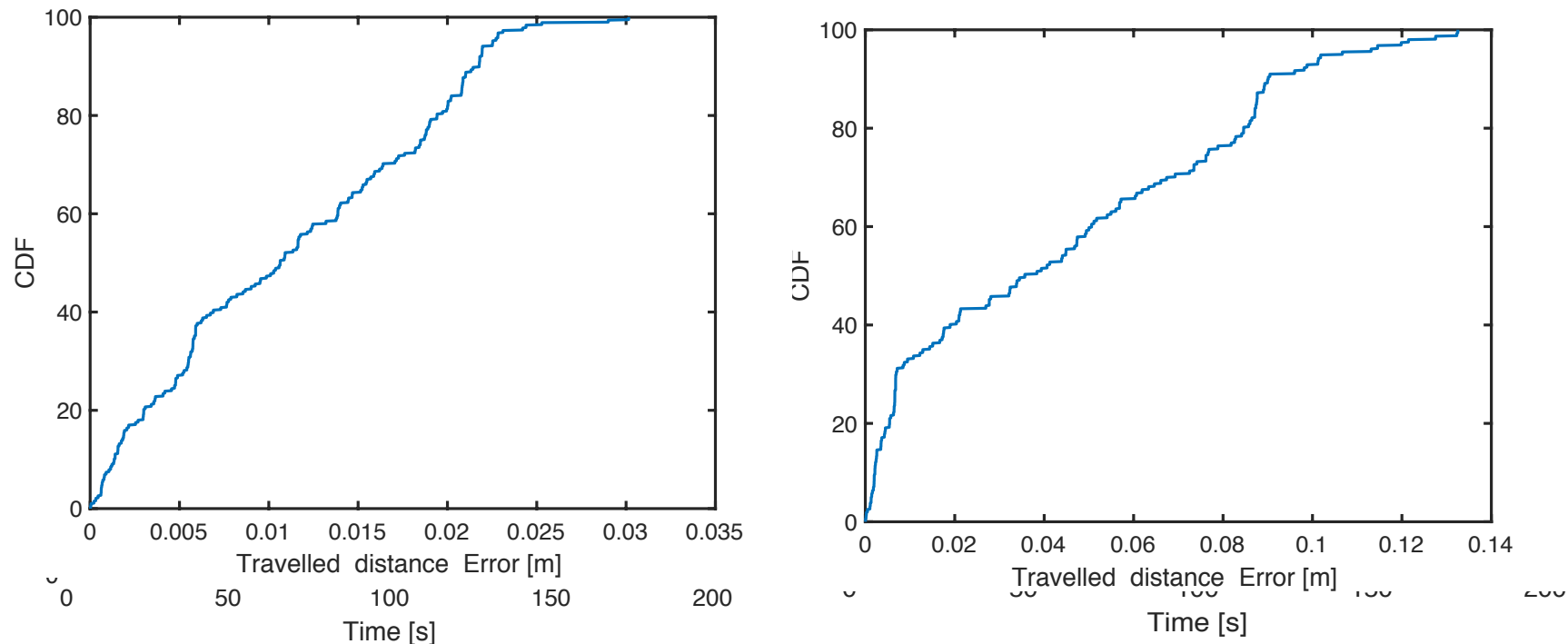
## Online model



# Gait Parameter Estimation

## Online model, Results for Longitudinal model

The CDF of root-mean-square error for estimated travelled distance. Mode Probability threshold

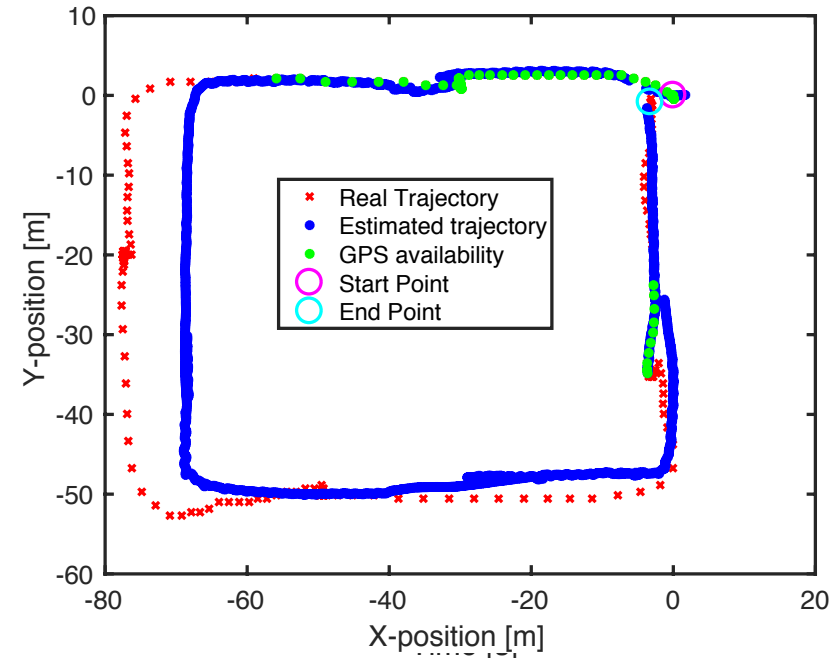
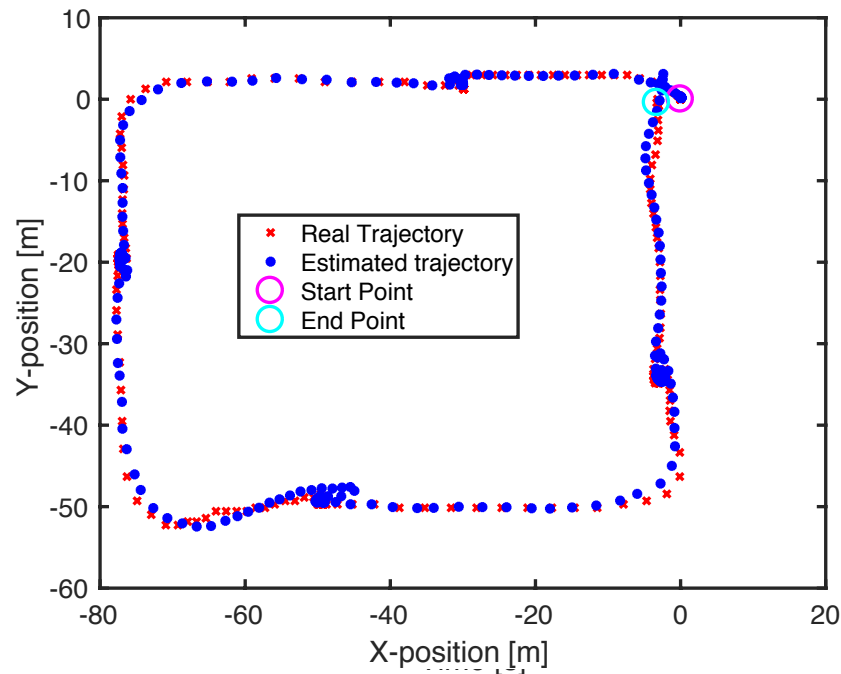


**Figure:** Results for longitudinal model with real data for complex walking pattern. **[Left]** GPS is available during entire experiment. **[Right]** GPS denied environment.

# Gait Parameter Estimation

## Online model , Results for horizontal model

The estimated trajectory is compared with the real trajectory. The estimated trajectory is shown in blue dots and the real trajectory is shown in red crosses. The start and end points are marked with pink and cyan circles respectively.



**Figure:** Results for horizontal model with real data for complex walking pattern. **[Left]** GPS is available during entire experiment. **[Right]** GPS denied environment.

# Gait Parameter Estimation

## Constraints / Challenges

- **Motion mode:** Walking (both model), Running (only online model), Standing still (only online model),
- **Device mode:** handheld in view

How we can improve the accuracy of our proposed model!  
What about other mode?

# IMU Dataset For Motion and Device Mode Classification

# IMU dataset

## Mode Classification

- Supervised learning of classifiers requires labeled training data.
- Training data must be extensive and cover
  - various physical attributes.
  - various motion and device modes.
  - different environmental situations.

# IMU dataset

## Motion-Device mode Classification

**TABLE:** Motion-Device mode Classification

Motion mode Device mode	Standing Still (SS)	Walking (W)	Running (R)
Fixed hand(1)	Class SS	Class W1	Class R1
Swinging hand(2)		Class W2	Class R2
Pocket(3)		Class W3	Class R3
Backpack(4)		Class W4	Class R4

- **Motion mode:** can select a set of appropriate internal parameters in the PNS; step length and step detection thresholds.
- **Device mode:** can be used to better utilize the sensor.



# IMU dataset

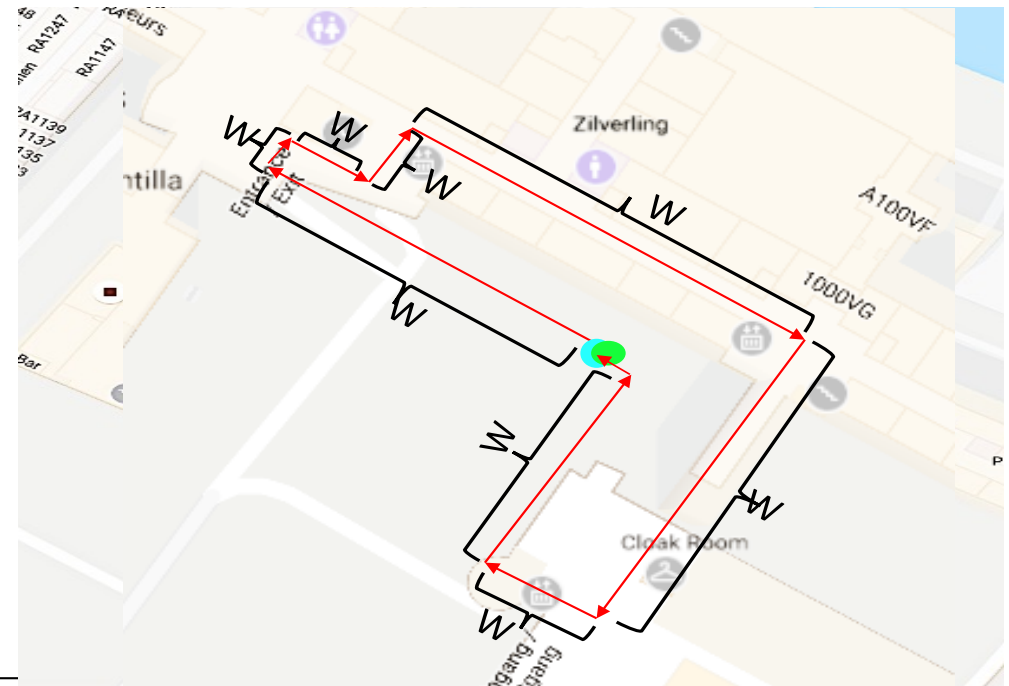
## Experiment Description

## Measurement scenarios

- Case 1: (Outdoor-only) Standing Still, Walking and Running.
- Case 2: (Outdoor-indoor) Walking.
- Case 3 & Case 4: (Outdoor-indoor) Standing Still, Walking and Running.

## Participants

- 6 Male
- 2 Female



# IMU dataset

## Motivation

## Sensors

- Xsens MVN Motion Capture,
- Smartphone Nexus 5

## Measurement specifications

- Accelerometer(Both)
- Gyroscope(Both)
- Magnetometer(Both)
- Barometer (Both, Not processed in MVN)
- GPS (Phone)

## Measurement types

- Raw sensory data (Both)
- Virtual IMU data from Body model (MVN)



# IMU dataset

## Dataset description

- The dataset containing all the introduced scenarios.
- The logged data from the phones and the MVN are extracted with 100 Hz and 60 Hz.
- All data are merged into one '.mat'-file
- File contains the data structure and attributes corresponding to each subject.
- Data is labeled.
- Example, measurements for Case 4 are in Case4
- and Case4.Subject(1) provides the all data for subject 1.
- The dataset is available from
- <http://users.isy.liu.se/en/rt/parka23/research.html>

# IMU dataset

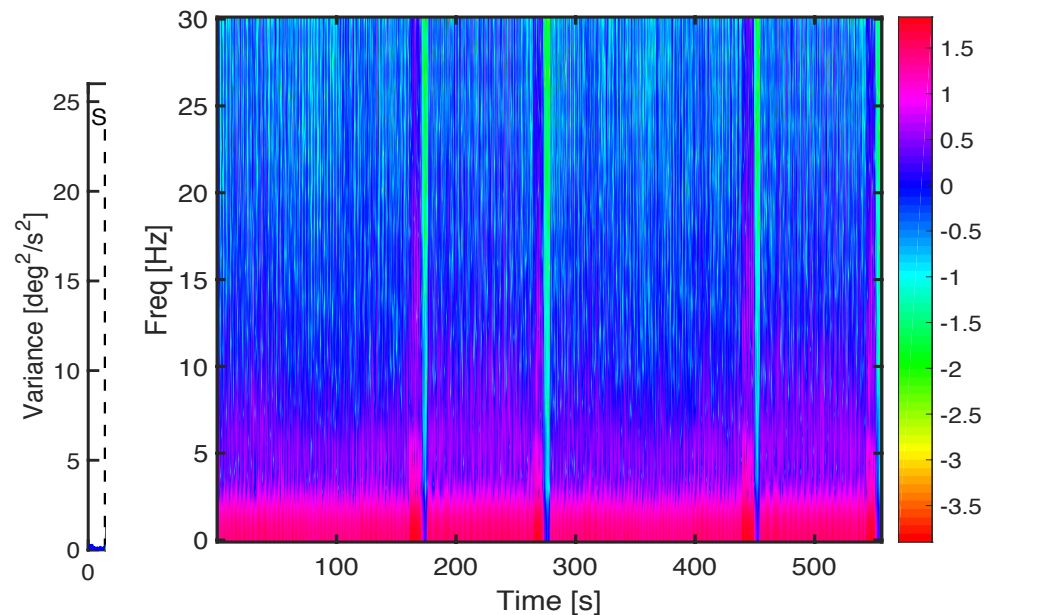
## Classification Evaluation

### Classification Steps

- Feature extraction on the raw signals; A way to bring out the inherent information in the available data in better way, and reduce the dimensionality of the raw data to be able to apply classification algorithms.
- Classification; As a final step in characterizing the data, a classifier is applied to the features to try extract the motion and device modes.

### Feature extraction

**Figure 1** Gyroscope signals for 4 different foot and hand motion tracks together with the signal from the smartphones.



# IMU dataset

## Classifier evaluation

- Two datasets, are formed for phone and motion tracker signals, separately.
- Each set contains eight features constructed from four signal attributes for both gyroscope and accelerometer.
- A supervised learning approach is applied.
- A multivariate decision tree classifier is trained
- Using MATLAB; Machine learning toolbox.
- The classifier is validated with 10-fold cross-validation.

# IMU dataset

## Classification results

TABLE : Confusion matrix of the modes classification represented in Table I using the binary decision tree classifier using cross-validation with 10 folds. The table shows how different annotated activities are classified in [%].

(a) Data from 4 different motion trackers

		Recognised activity								
		R1	R2	R3	R4	SS	W1	W2	W3	W4
Annotated activity	R1	83	8	0	6	0	0	0	0	0
	R2	5	72	1	0	0	0	0	1	0
	R3	0	2	96	0	0	0	0	0	0
	R4	5	0	0	85	1	0	0	0	1
	SS	0	2	0	1	79	2	0	0	1
	W1	0	0	1	1	5	78	1	0	13
	W2	0	8	0	0	0	1	84	6	0
	W3	7	8	1	3	2	1	13	92	0
	W4	0	0	1	4	13	17	1	0	84

(b) Data from phones.

		Recognised activity								
		R1	R2	R3	R4	SS	W1	W2	W3	W4
Annotated activity	R1	58	3	0	0	0	0	0	2	0
	R2	1	60	4	4	0	0	1	2	0
	R3	0	13	83	0	1	0	0	0	0
	R4	20	3	0	56	0	0	0	2	0
	SS	1	0	6	0	84	4	3	2	1
	W1	3	0	0	7	7	83	3	1	8
	W2	1	3	6	7	2	1	77	14	0
	W3	14	17	2	22	1	1	16	75	0
	W4	0	0	0	4	5	11	1	0	90

# Summary

- Developed models for different measurements and investigate how their parameters can be estimated.
- Given that the parameters are known, the position of the mobile user can be estimated.
- Radio-based RSS, GPS, and inertial measurements are considered.
- Unknown parameters of the models are then estimated using a least square estimator or in a filtering framework.
- To address the reliability issue of GNSS methods, while taking advantage of their accuracy, they were used upon availability of strong satellite signals.
  - Positioned RSS signals are used to estimate the unknown parameters of the RSS model in an offline phase. Then RSS-based positioning methods use these estimated parameters.
  - A gait model is developed in which the gait parameters and the position of the mobile users are estimated using inertial sensor measurements.
- The performance of the developed methods were evaluated on simulated as well as real data and the results were presented.

Thanks for your attention!

[www.liu.se](http://www.liu.se)