



# Integrating human dimension in the development of pedestrian navigation

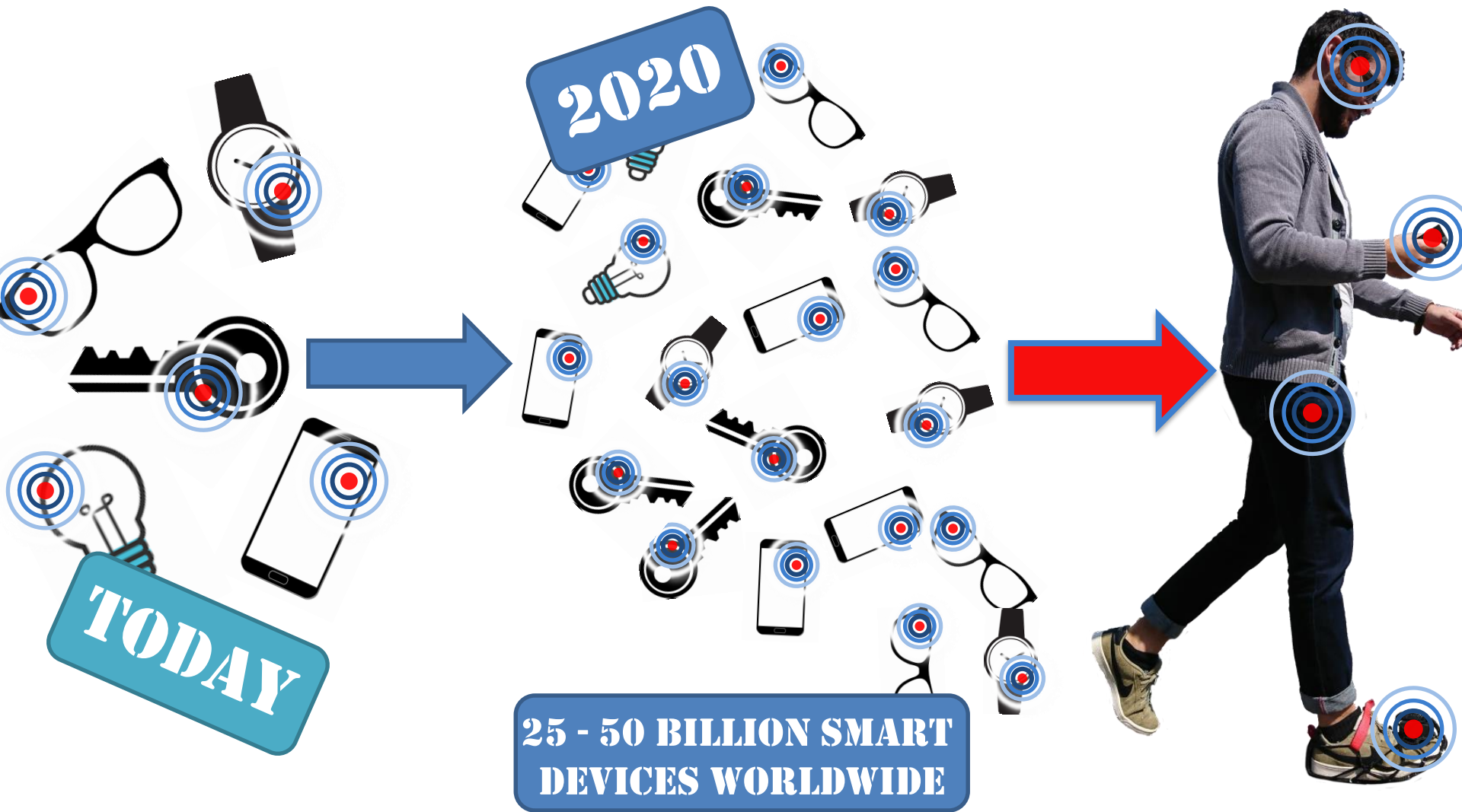


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15 November 2018, Toulouse, France



IFSTTAR



# Development driven by market needs



Promote multimodal transport with the following priority rules : at first pedestrians, then cyclists, then motorists



Use crowdsourced data collected by a wide range of stakeholders to produce accessibility maps



Expand the prescription sports-health program to integrate the practice of walking and cycling in the treatment of patients

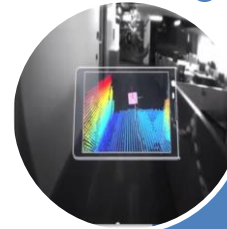
# Technology Push & Sensors' Location on Human Body



Light Fidelity



Infrastructure based motion detection



Camera, mono, stereo, depth, ...



Sounds, radiowave, ...



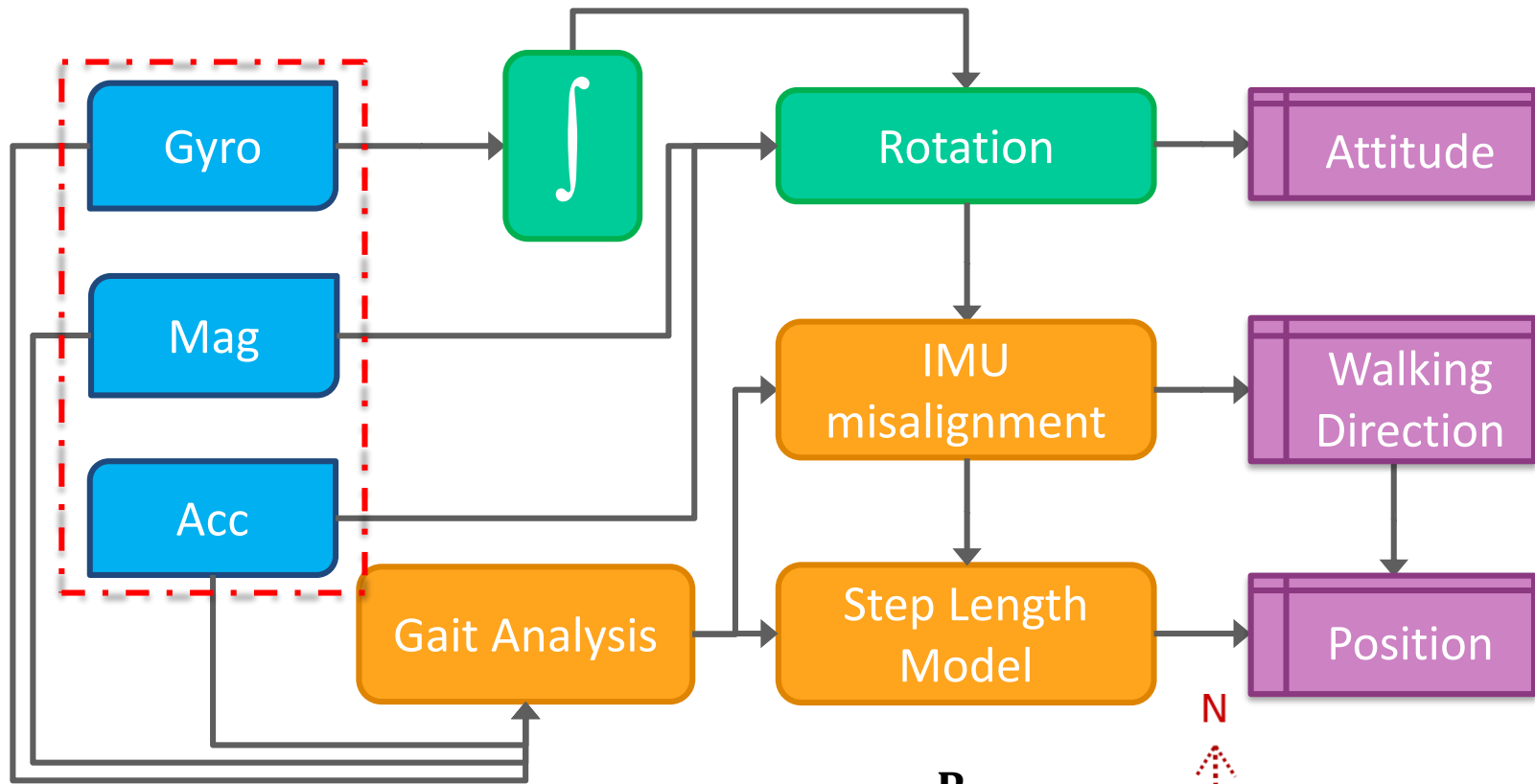
Inertial Sensors, Atomic, 3D glass shell



GNSS, lower consumption, multi-freq

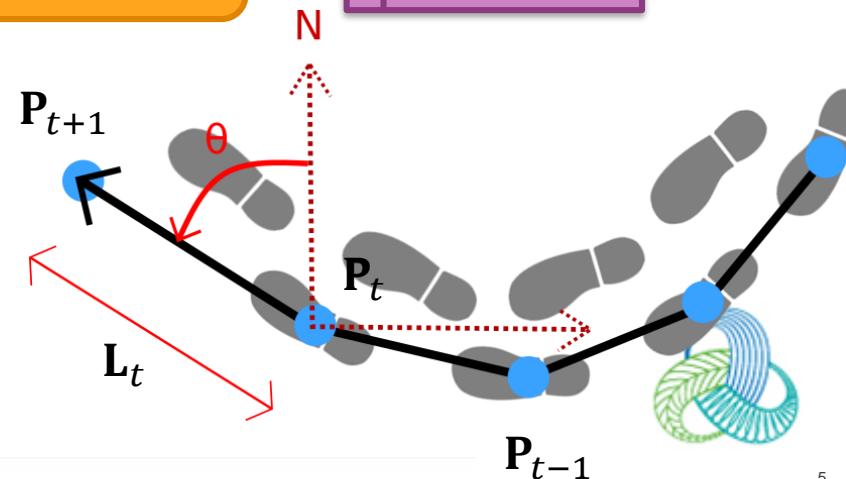


# Pedestrian Dead Reckoning



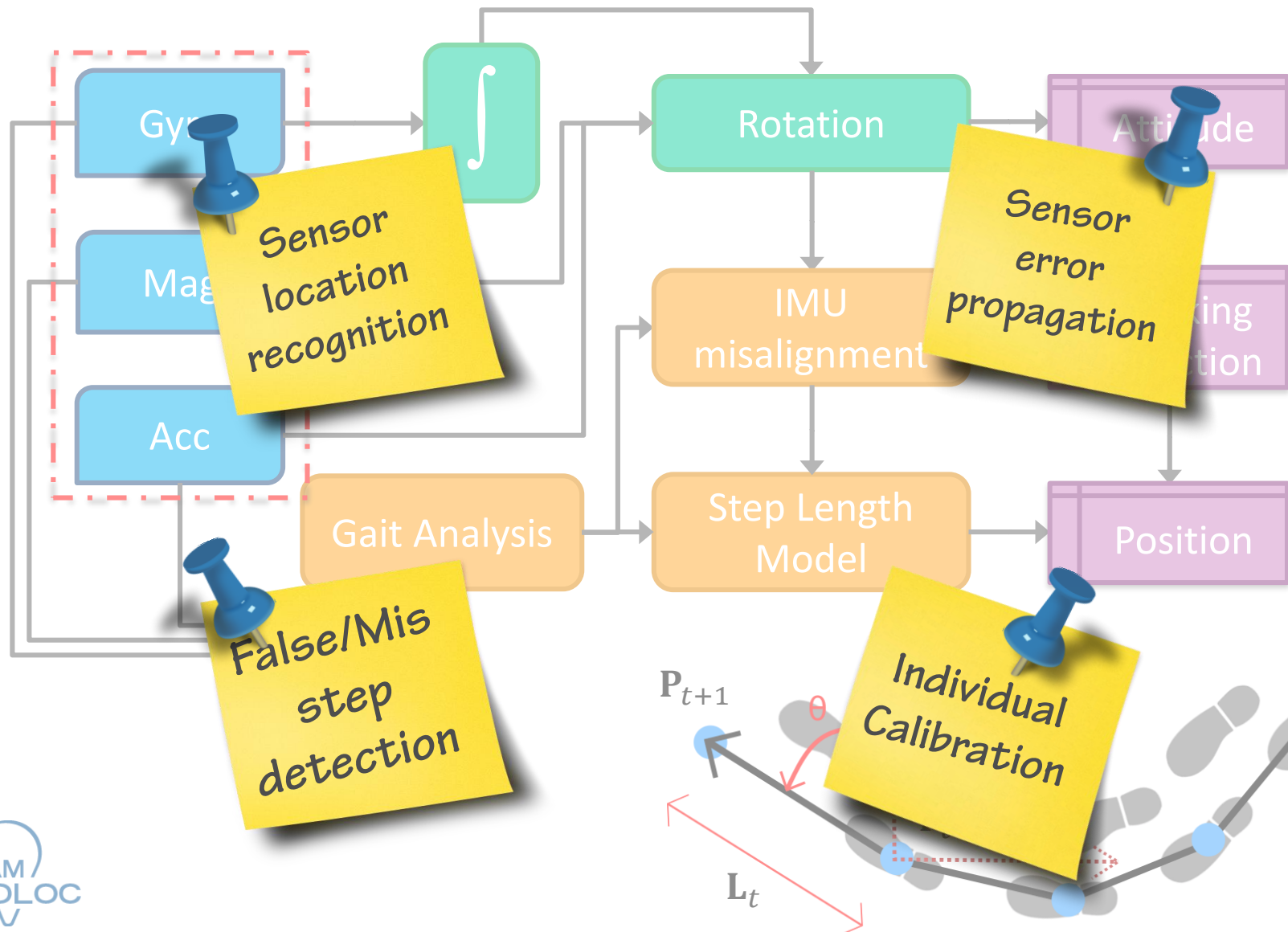
$$\mathbf{P}_t = \mathbf{P}_{t-1} + \mathbf{L}_{t-1} \cdot \vec{\theta} \quad \vec{\theta} = \begin{bmatrix} \sin \theta \\ \cos \theta \end{bmatrix}$$

$t$ : time index,  $\mathbf{P}_t$ : Position estimate,  
 $\mathbf{L}_t$ : Step length,  $\theta$ : Walking direction





# Pedestrian Dead Reckoning





**Monocular  
Visual  
Odometry  
Assisted by  
Step Length**

# Assisted Monocular Visual Odometry

## Context

Monocular vision

## Tracking Method

Visual odometry

## Problem

Scale ambiguity

## Solutions

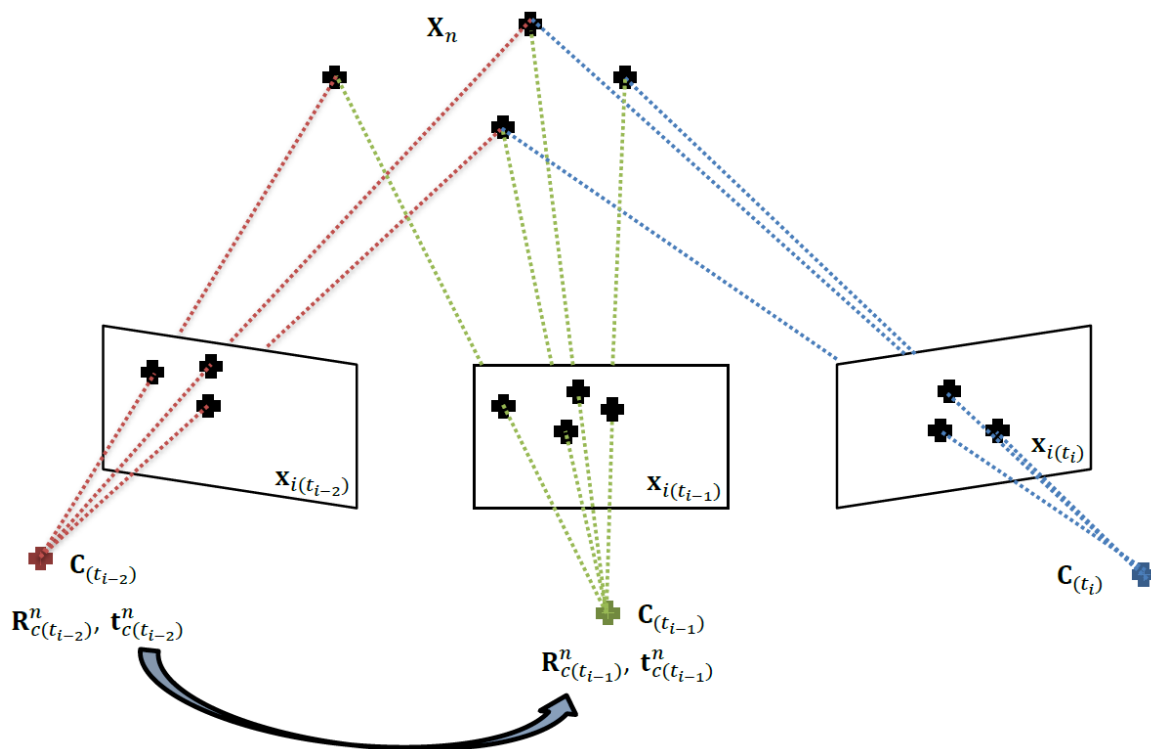
State-of-the-art

Use of perfectly  
known 3D  
objects (GIS)

Calibration on known motions

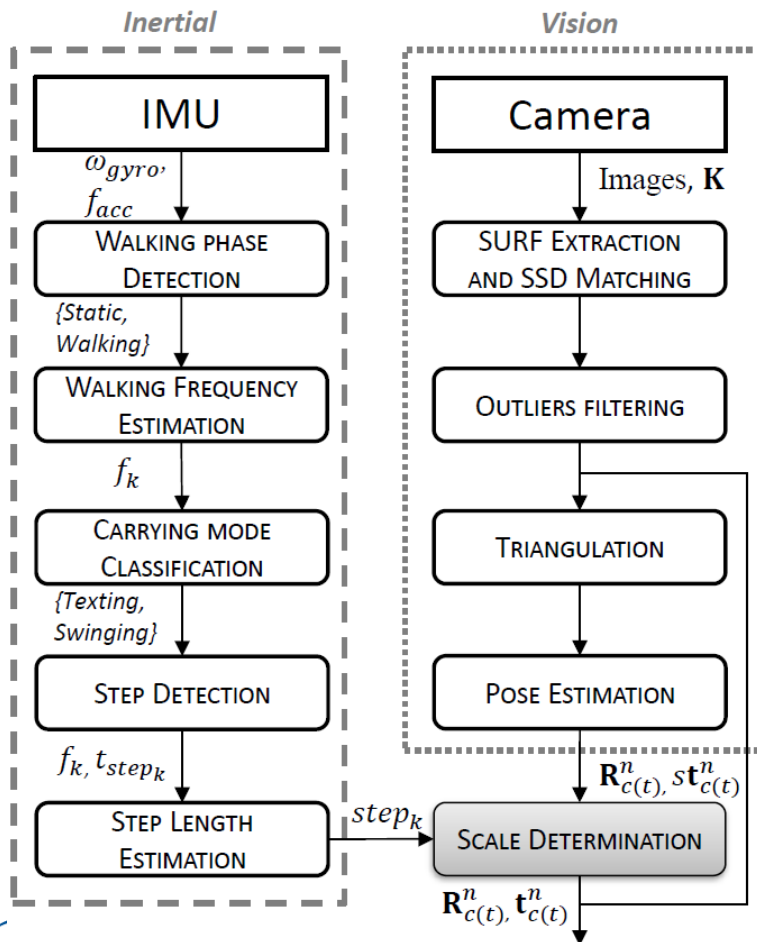
Proposition

Using PDR step length estimates to  
solve for the ambiguity





# Monocular Visual Odometry



## Vision (VO)

SURF features extraction

Matching with SSD between  $x_i(t_{i-2})$ ,  $x_i(t_{i-1})$  and  $x_i(t_i)$

Outliers filtering with MSAC

Triangulation

Relative pose estimation

## Inertial (PDR)

PDR processing

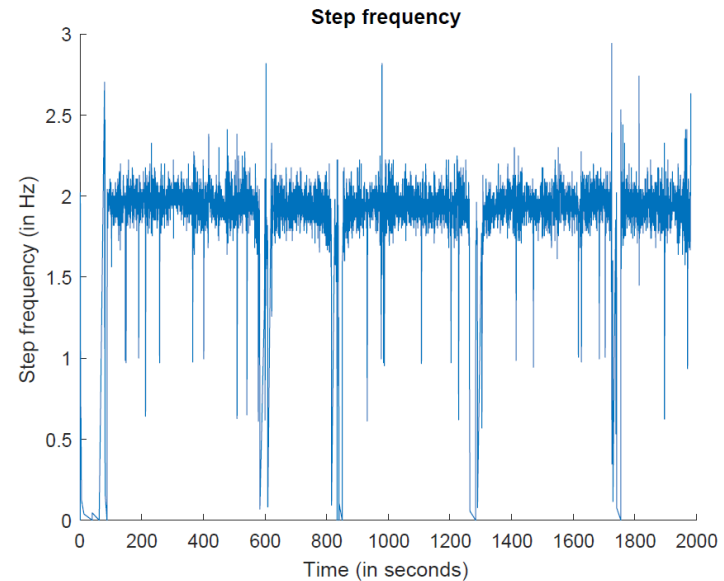
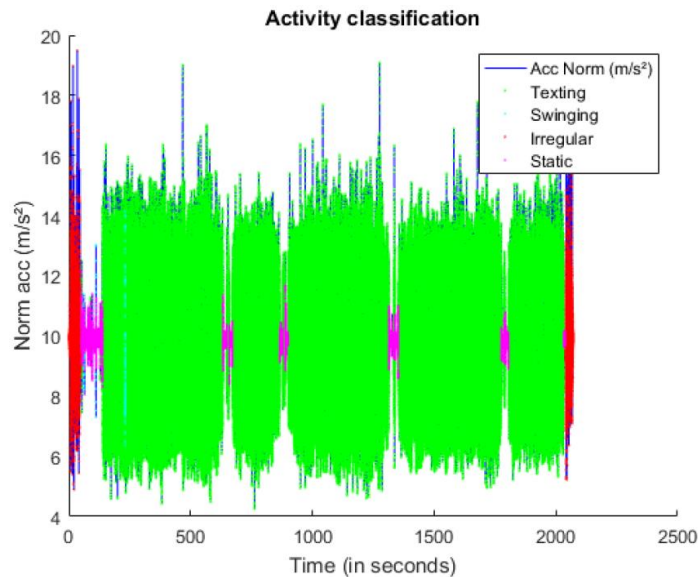
## Fusion Vision/Inertial

Scale Determination

$$s_{tim} = \frac{D_{PDR}(t_{im})}{D_{VO}(t_{im})}$$



# Step Length Model



Activity classification

Step frequency estimation (STFT, Energy in sub-bands):  $f_k$

Step detection:  $t_{step_k}$

Step length modeling:

$$step_k = h_{ped} * (a * f_k + b) + c$$

Synchronization between step events and visual odometry is important

Height changes extracted from Digital Terrain Model considering a fixed height of the hand

# Experimentation

## Scenarios

800 m walk in urban environment  
Stops in front of 2 reference objects  
3 pedestrians

## Hardware

Handheld IMMU: **ULISS** (Ubiquitous Localization with Inertial Sensors and Satellites) at 200 Hz  
1920\*1080 visual measurements at 10 Hz with a Garmin monocular **Camera**

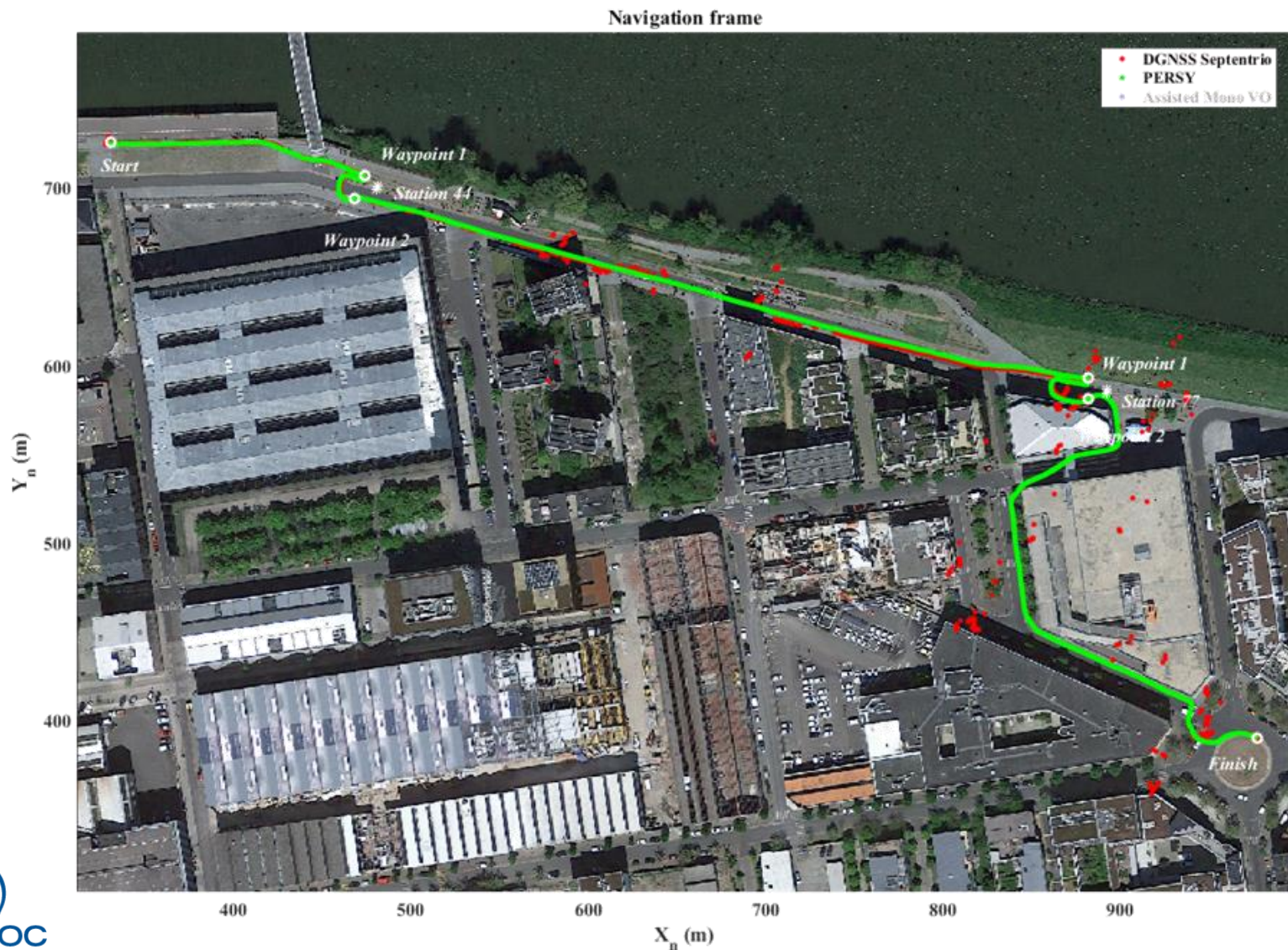
## Reference

Differential GNSS (handheld helicoidal antenna + Septentrio)  
Foot mounted **PERSY** (PEdestrian Reference SYstem) : positionning error 0,3% traveled distance

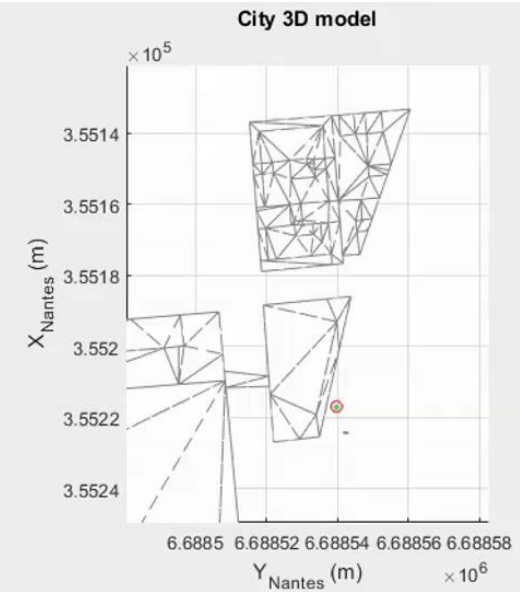




# Pedestrian path in urban environment

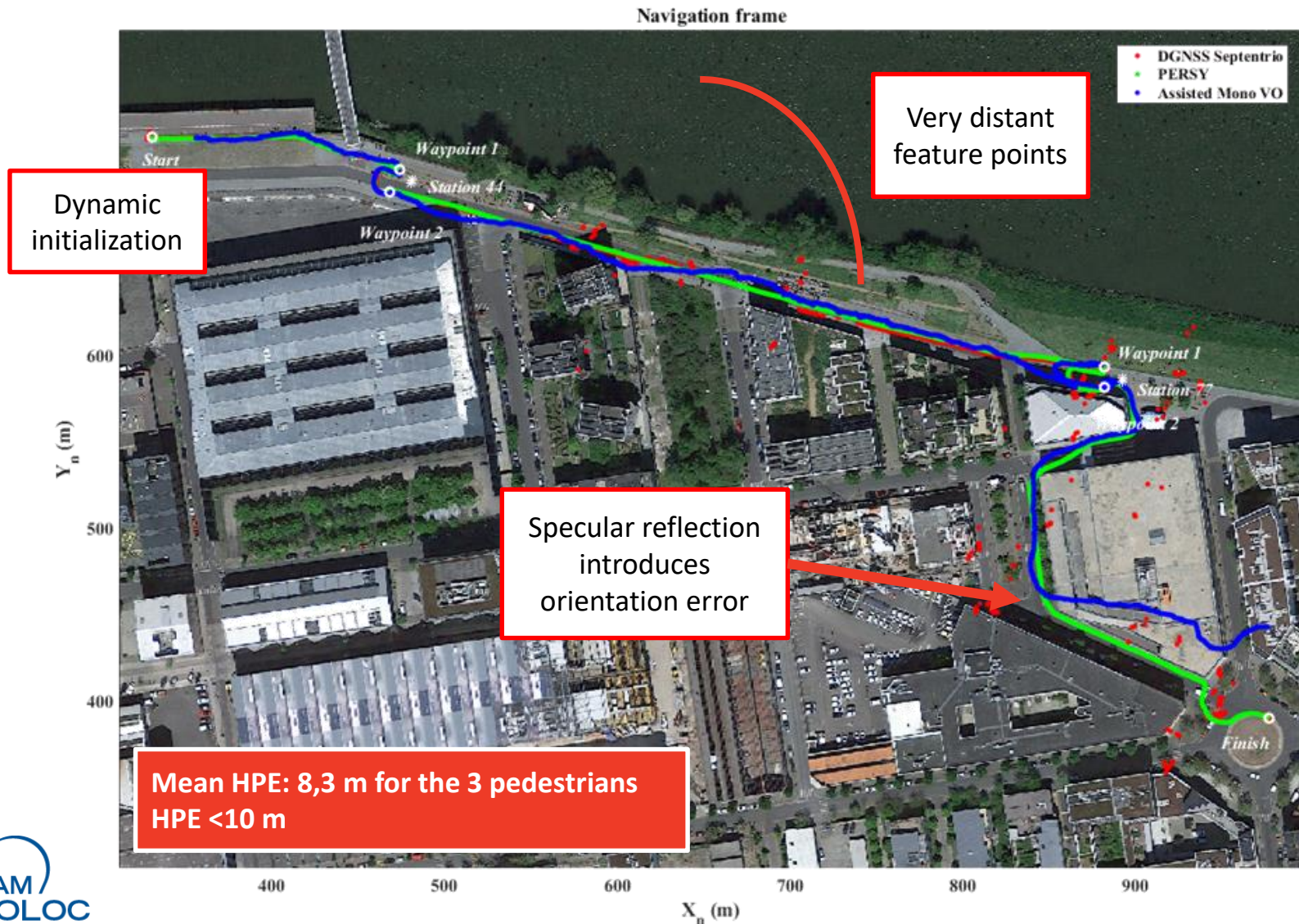


# Accurate Vision/PDR PVT Estimates





# Pedestrian path in urban environment

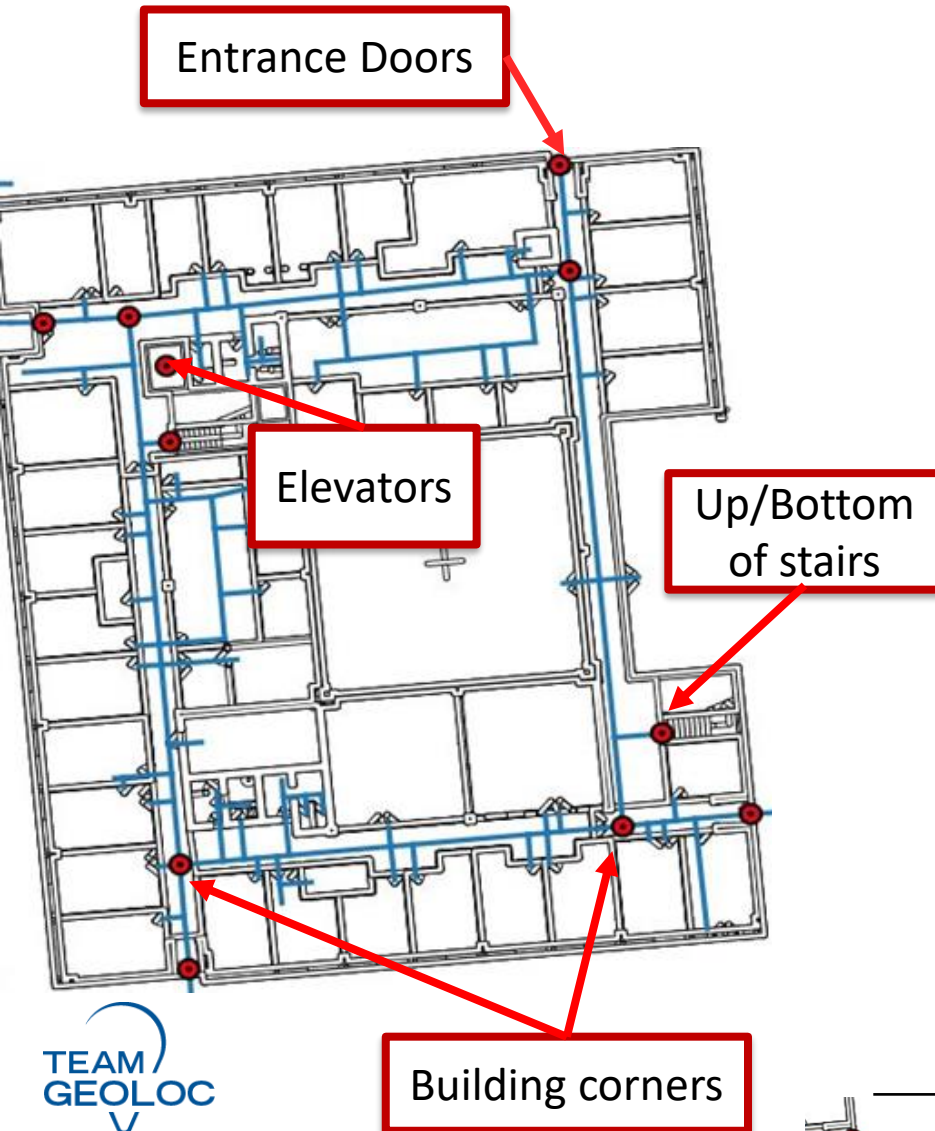


**Linking Human  
Motion and  
Map Locations**



**Monocular  
Visual  
Odometry  
Assisted by  
Step Length**

# Position updates by means of human motion signal patterns recognition



## Context

Pedestrian navigation with GIS content

## Tracking Method

Particle Filter combined with topological graph

## Problems

Graph mis-matching  
PDR error mitigation

## Solutions

State-of-the-art

Heading correction with principal building directions/corners

Position correction with lift locations

Adjust dynamic model to motion context (staircase, lift, ...)

Proposition

**Associate recognized human motions with map regions (Point of Interest)**



Id

E

N

Type





# Graph Mis-Matching Mitigation

Collect data

Learn signal patterns

Link POIs to the map

- 4 women & 4 men
- Different motion speeds
- Six Buildings

- Feature Selection
- Different dataset for test and validation
- SVM, Random Forest, Neural Network

- 5 POI types
- Online signal segmentation & classification
- Online POI detection

Supervised Learning

Positioning



# PDR error mitigation

## Particle Filter Design

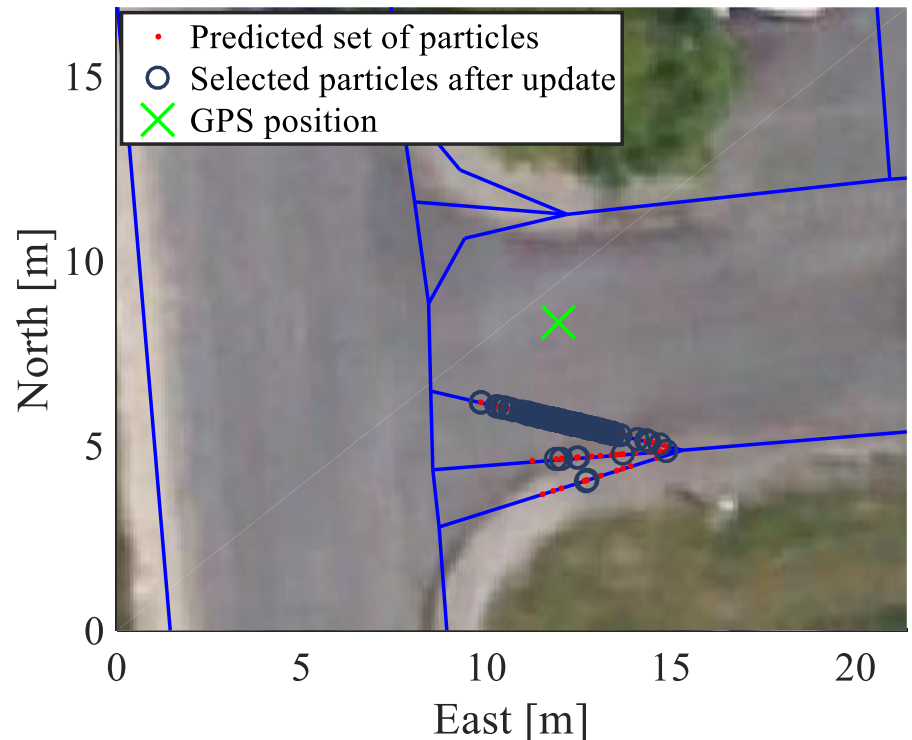
- Graph design
- Correction of step length estimates
- Correction of over/mis-step detection
- Correction of heading misalignment

## Mechanization

PDR

## Updates

- Proximity distance between POI/GPS positions and graph
- Likelihood between PDR heading and graph

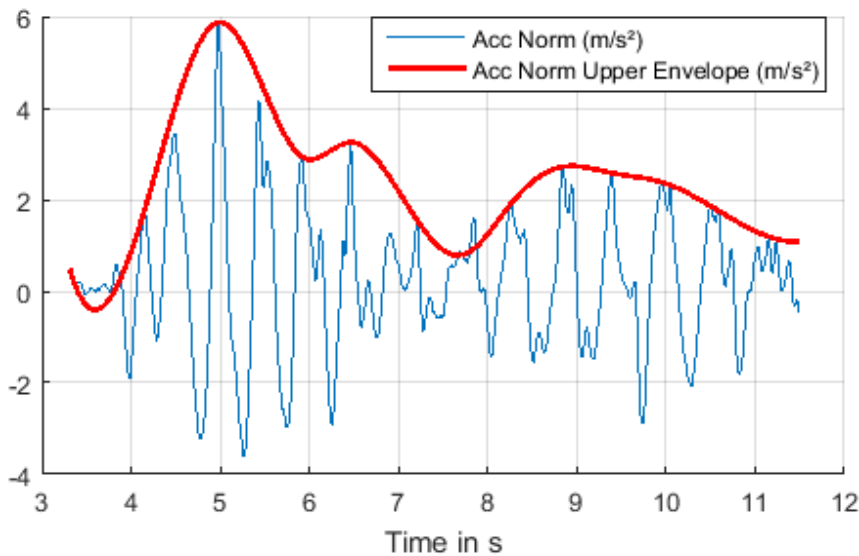




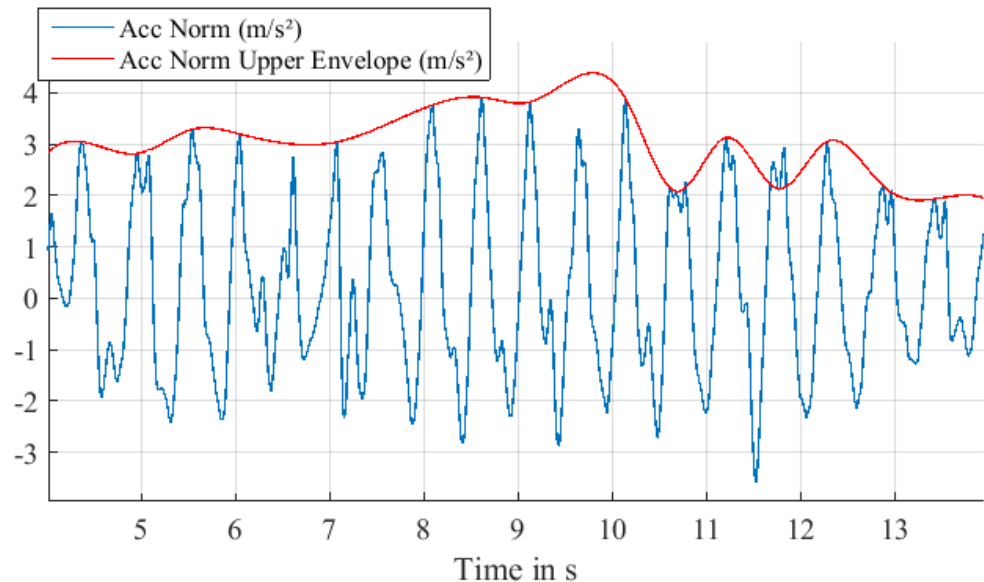
# Signal patterns: indoor/outdoor transition (1/2)

IO transition event is marked by a parabolic form of the acc. norm upper envelope: deceleration - quasi-static phase - acc.

The duration of pattern depends on doors' type: shorter for sliding doors



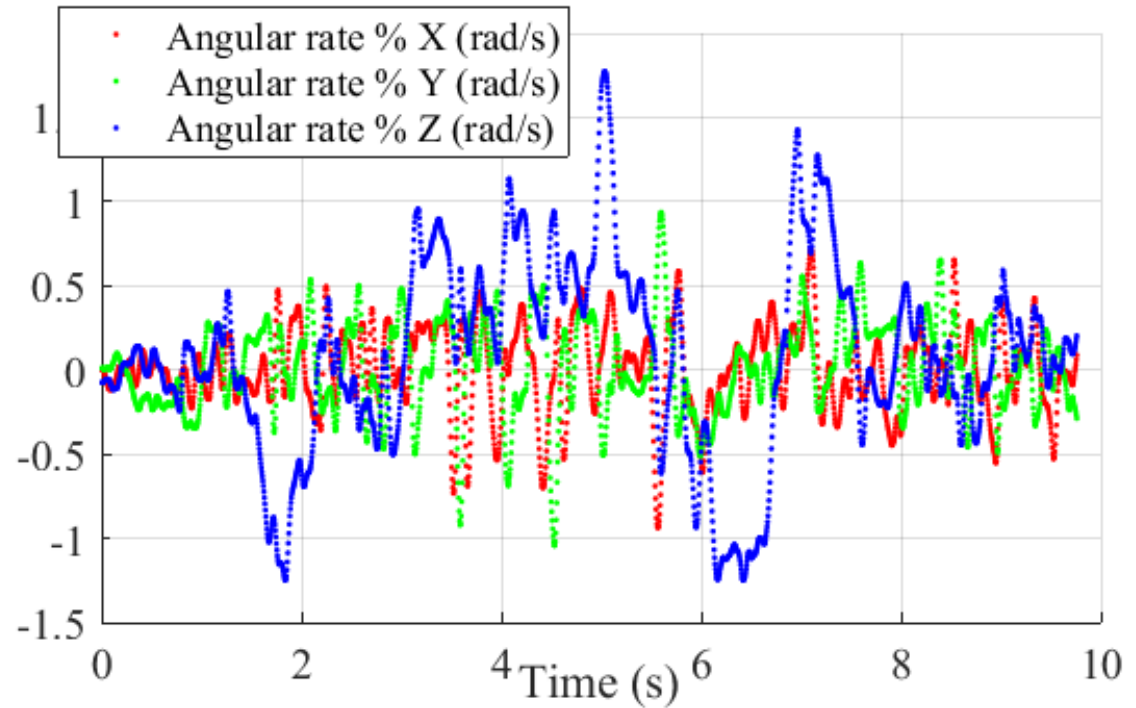
Swinging door (6-9s)



Sliding door (10-12s)

# Signal patterns: indoor/outdoor transition (2/2)

In a texting mode, the vertical component of the angular rate has a greater variance during the indoor/outdoor transition



Swinging doors (4-6 s)

# Finding the Right POI Using Signal Pattern

Motion classes = Normal walking, Descending/Mounting stairs, Taking an elevator down/up, Corridor change, Entering/Exiting a building

Considering  
motion sequence

Considering  
motion class

Normal walking + Descending stairs  
Mounting stairs + Normal walking } → *Top of stairs*

Normal walking + Mounting stairs  
Descending stairs + Normal walking } → *Bottom of stairs*

*Corner  
Elevator  
Building Gate*

Search for POIs'  
candidates

POI types

Nav. Filter

Selection of the nearest POI



# Supervised Learning Perf. Assessment

Features selected using Mutual Information

Best performance obtained with Random Forest, especially for the indoor/outdoor transition case

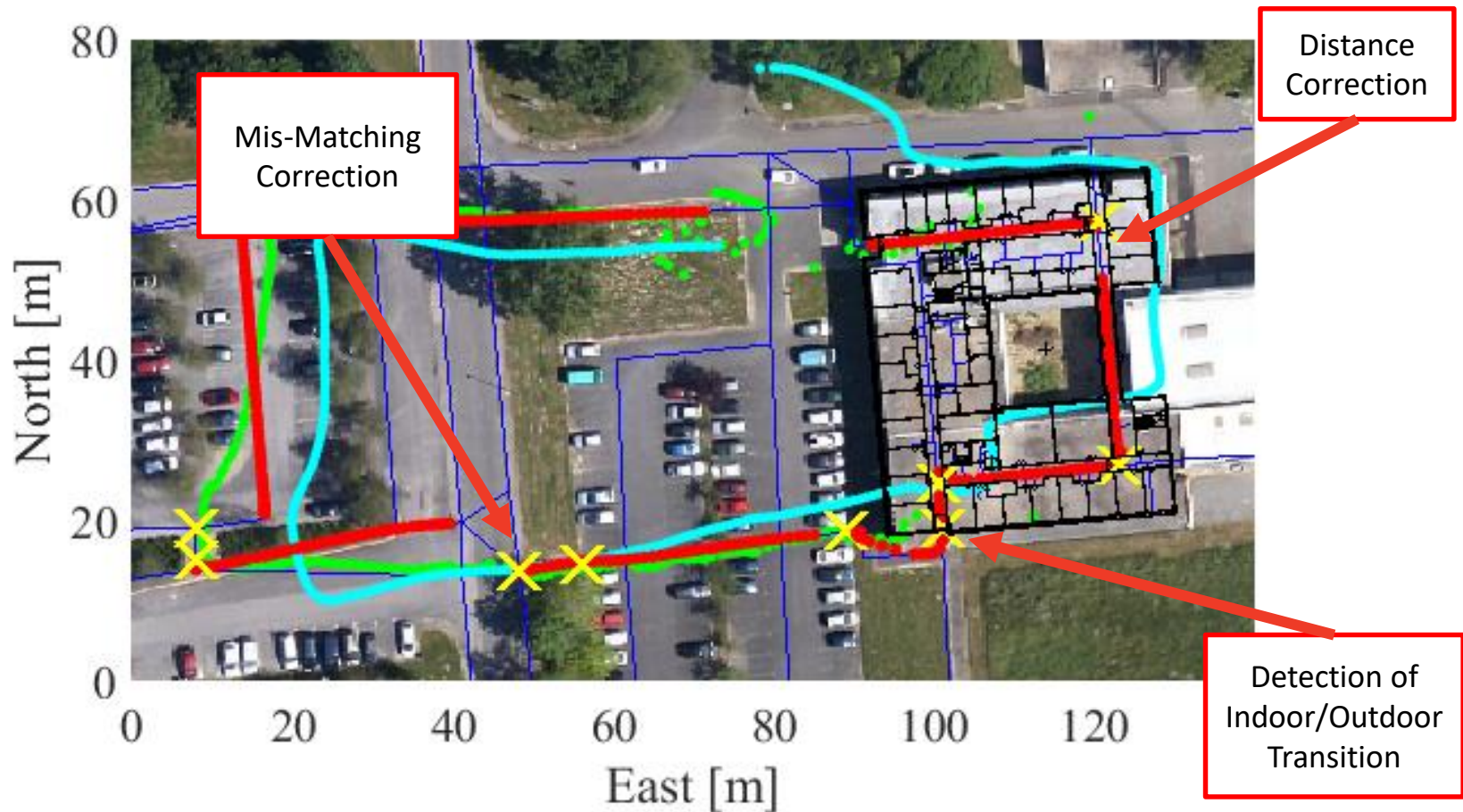
Corner	Entry / Exit	Down Stairs	Elevator Down / Up	Normal Walk.	Up Stairs
91.67	100	96.84	100	98.71	98.13
100	96.36	97.87	100	98.71	97.22

**Precision:** True positive / (True Positive + False Positive)

**Sensitivity:** True positive / (True Positive + False Negative)

Overall Detection/Classification Accuracy: 98.41M

# Experimental Assessment



Intra-class variation affects the performance of classification

Intra-class variation is significantly related to cross-individual dispersion (Speed, Gait patterns, etc.)



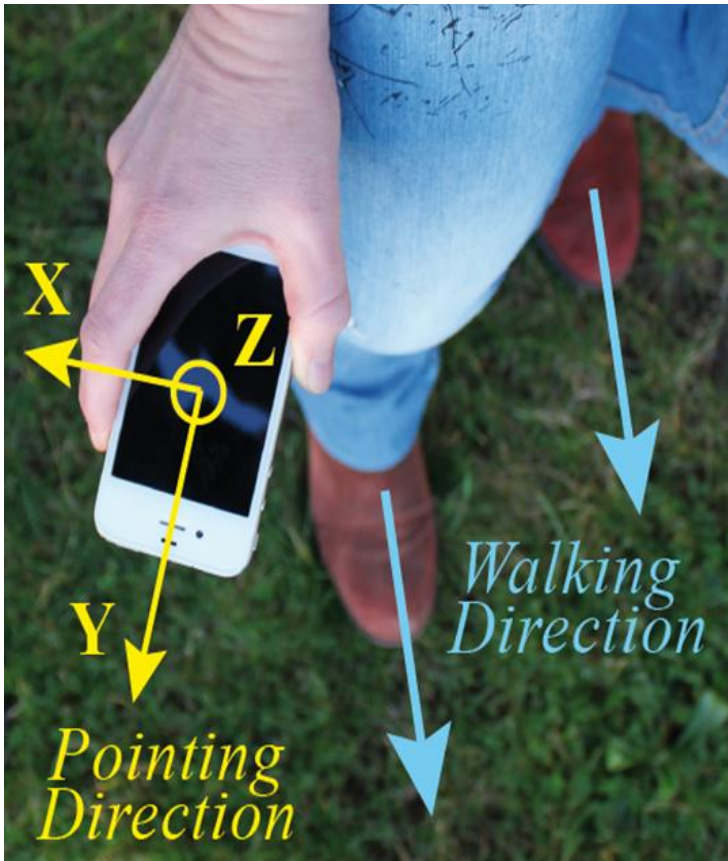
**Linking Human  
Motion and  
Map Locations**

**Building on  
Modeling  
Personal  
Dynamic  
Profile**

**Monocular  
Visual  
Odometry  
Assisted by  
Step Length**



# Embedding Personal Dynamics Pattern in the Navigation Filters



## Context

Improving personal mobility (transport)  
with mass market devices

## Tracking Method

Kalman Filter, Complementary Filter,  
Machine Learning aiding

## Problems

Varying physiological features  
Impact of environmental changes (ground  
slopes)

## Solutions

State-of-the-art

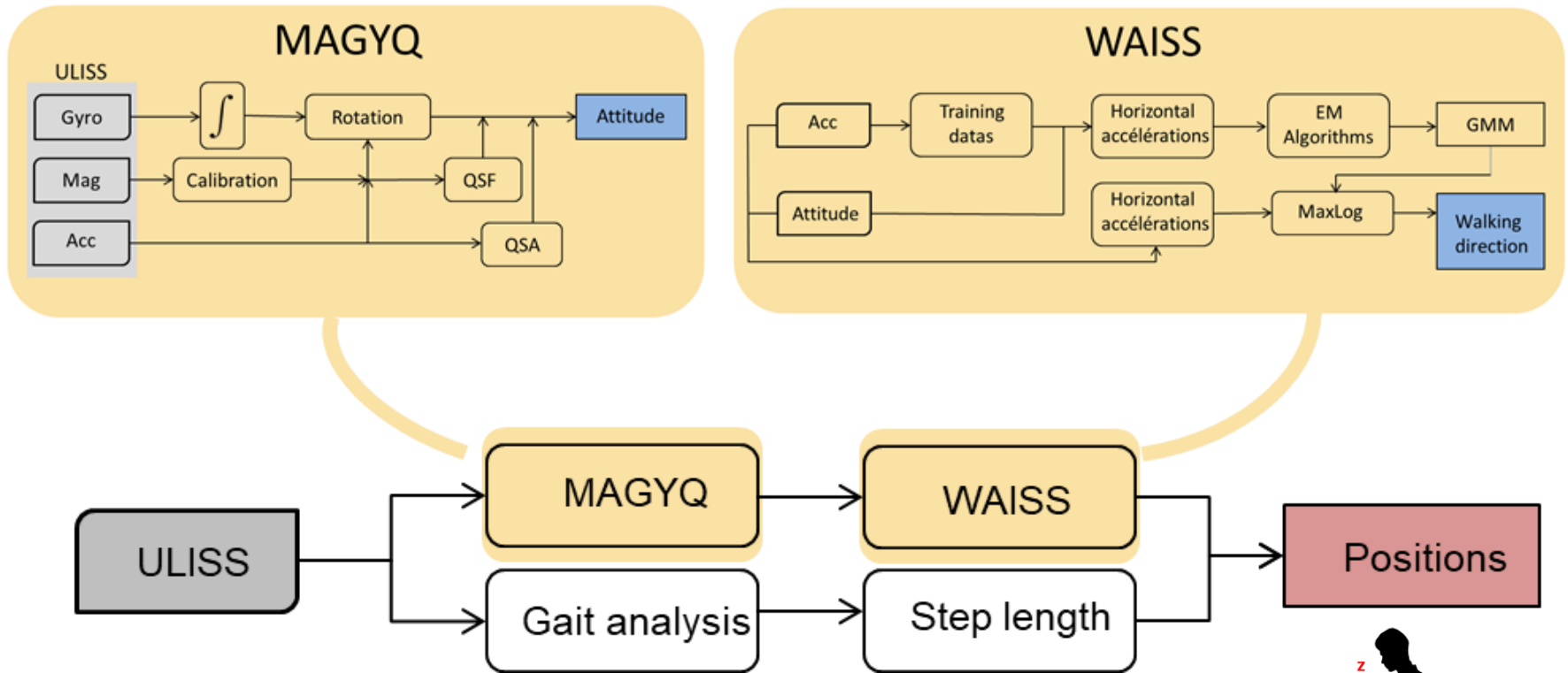
Calibration by fusing multiple signals  
Calibration on known paths

Proposition

**Modeling personal way of holding  
the sensor in hand to construct  
navigation filters**

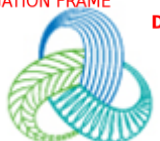
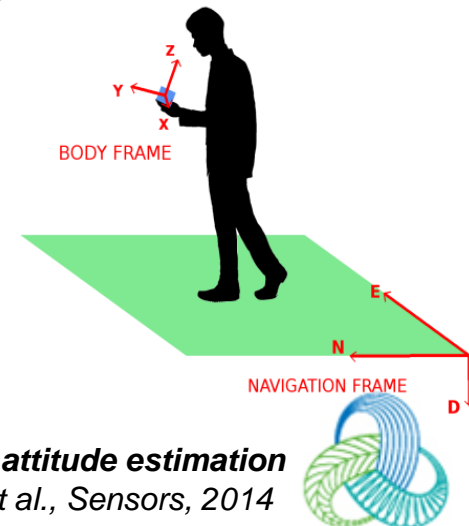


# Attitude Estimation

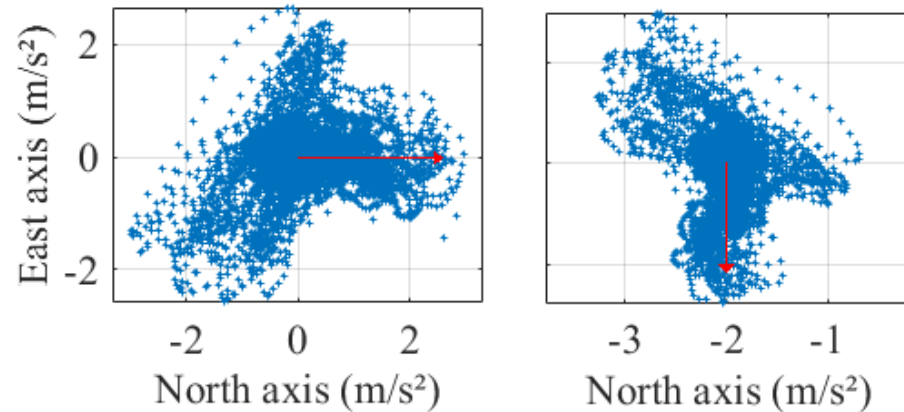


**MAGYQ:** Attitude estimation EKF filter based on quaternions (inertial and magnetometer data)

**WAISS:** Walking direction estimation based on statistical modeling of human gait features with handheld MIMU



# WAISS Method: Building Individual Models



Distribution of horizontal accelerations depends on the walking direction

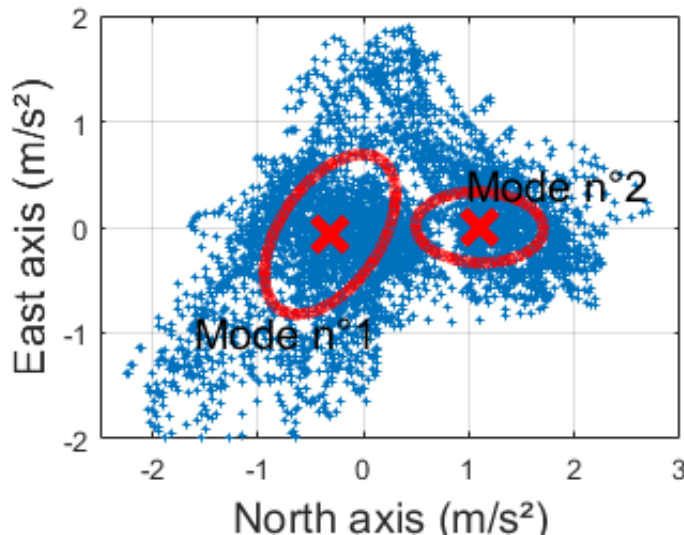
Distribution modeling with a Gaussian Mixture

$$f_{acc}(\mathbf{x}) = \sum_{k=1}^q \tau_k \mathcal{N}(\mathbf{x}, \mathbf{m}_k, \mathbf{P}_k)$$

Straight-line data set with 0° walking direction

Expectation Maximization algorithm

$$(Z_i | \mathbf{x}_i, (\tau_k^c, \mathbf{m}_k^c, \mathbf{P}_k^c)) = \frac{\tau_k^c \mathcal{N}(\mathbf{x}_i, \mathbf{m}_k^c, \mathbf{P}_k^c)}{\sum_{j=1}^p \tau_j^c \mathcal{N}(\mathbf{x}_i, \mathbf{m}_j^c, \mathbf{P}_j^c)}$$



$$L((Z_i)_{1 \leq i \leq n}, (\mathbf{x}_i)_{1 \leq i \leq n}, \Psi) = \sum_{i=1}^n \sum_{k=1}^p t_{ik} \log(\tau_k \mathcal{N}(\mathbf{x}_i, \mathbf{m}_k, \mathbf{P}_k))$$

**Walking direction estimation based on statistical modeling of human gait features with handheld MIMU**, C. Combettes et al., IEEE/ASME Trans. Mechatronics, vol. 22, 2017

# WAISS Method: Walking Direction Estimation

Maximization of model likelihood with observations corresponding to one stride



$$L((\mathbf{x}_i)_{1 \leq i \leq n}, \theta) = \sum_{i=1}^n \log(f_{accM}(\mathbf{x}_i, \theta))$$
$$\theta_w = \arg \max_{\theta} (L((\mathbf{x}_i)_{1 \leq i \leq n}, \theta))$$

## Experimental Assessment

Use of PERSY as angular reference

$$\alpha = \text{atan}\left(\frac{Y_{P2} - Y_{p1}}{X_{P2} - X_{p1}}\right) \quad R = \begin{bmatrix} \cos(\alpha) & -\sin(\alpha) & 0 \\ \sin(\alpha) & \cos(\alpha) & 0 \\ 0 & 0 & 1 \end{bmatrix}$$

Test different types of carrying modes: texting / swinging  
Create individual models appropriate to the person's walking style

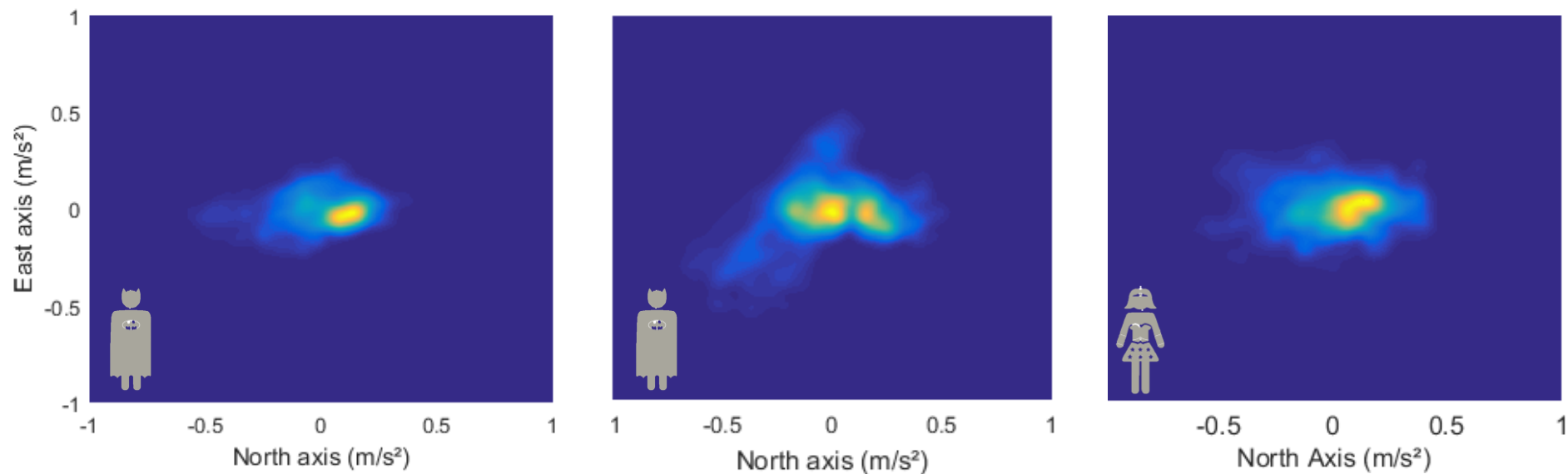


# Choosing the right GMM

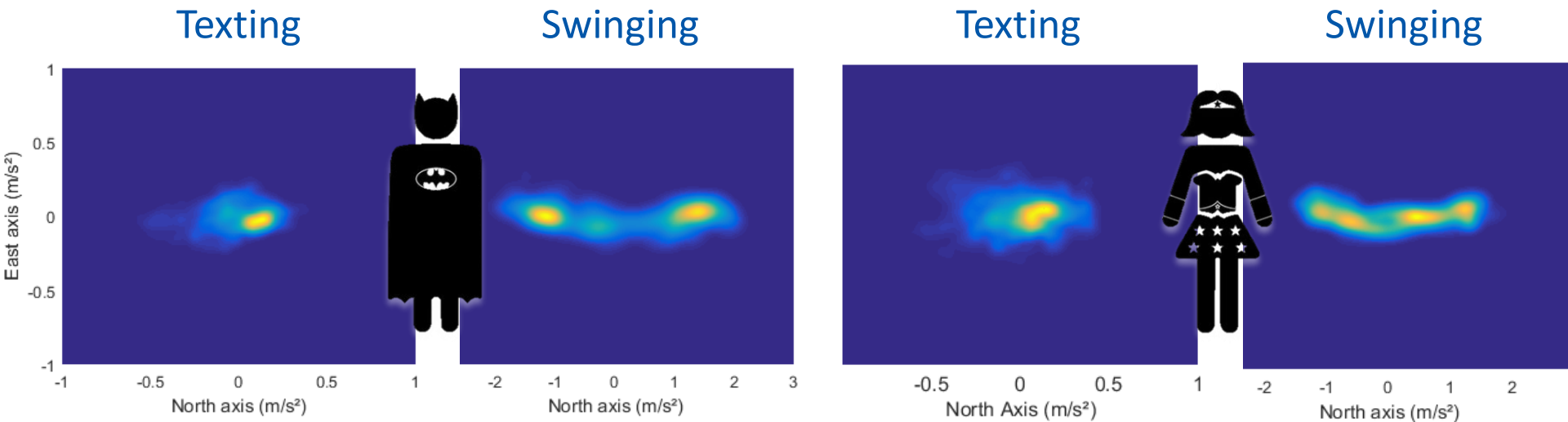
Different distributions for different persons

Need to adapt the number of GMM modes for each individual

Use of criteria



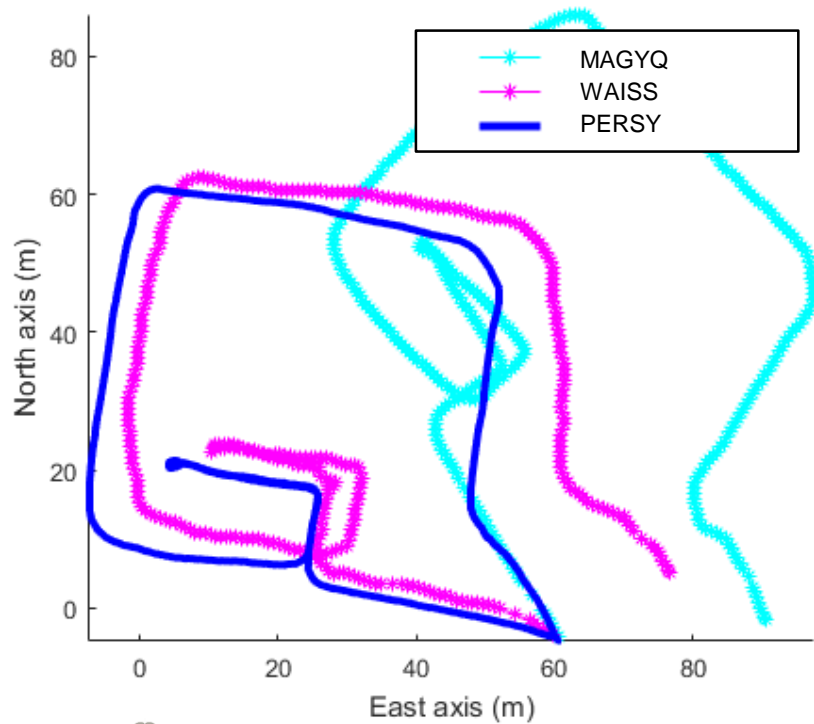
# Impact of the Carrying Mode on Modeling



Different distributions for the same person

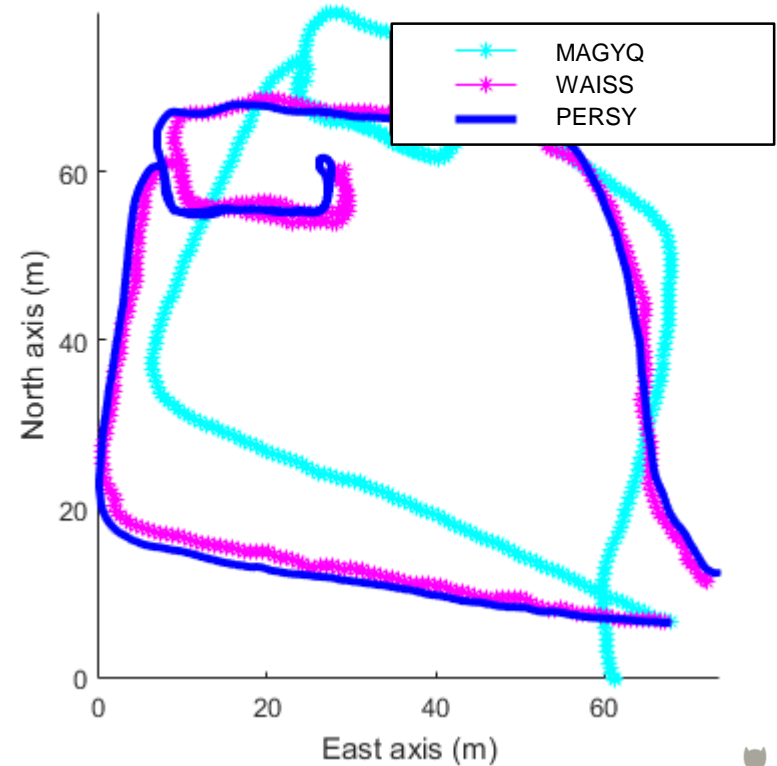
Need to adapt the number of modes for each individual and for each carrying mode

# Assessment: Texting Mode with Misalignment



Woman – 291 m

Error	MAGYQ	WAISS
$\mu$	19.7°	11.2°
$\sigma$	11.1°	12.4°

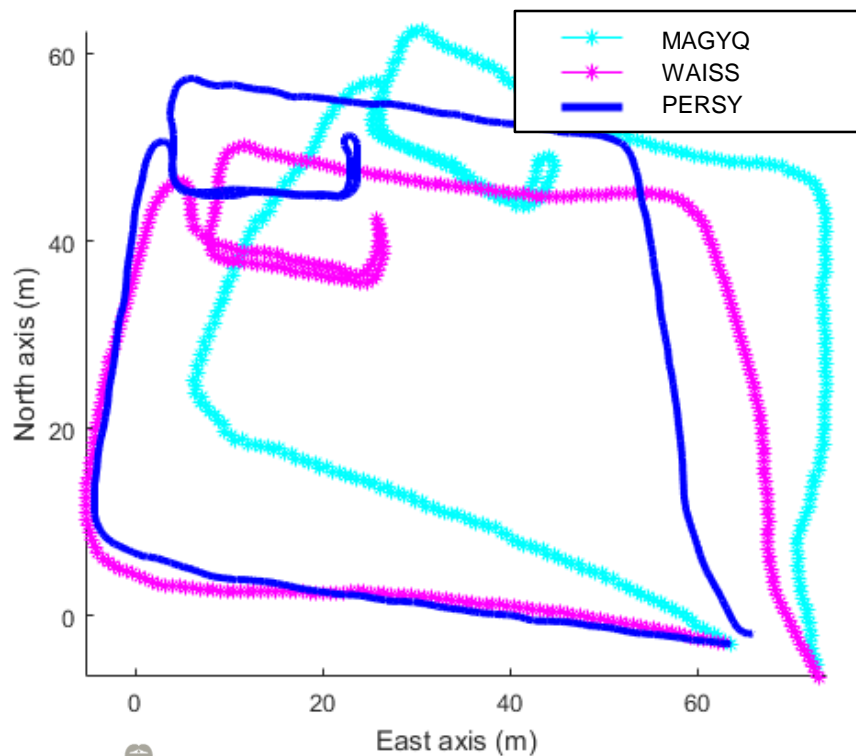


Man – 321 m

Error	MAGYQ	WAISS
$\mu$	34.1°	13.7°
$\sigma$	14.6°	17.3°

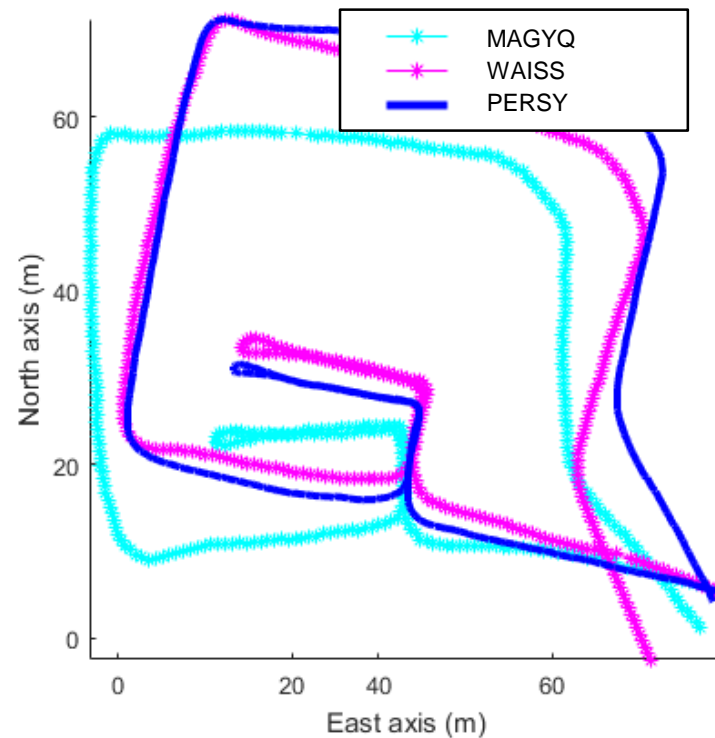


# Assessment: Swinging Arm



Woman - 290 m

Error	MAGYQ	WAISS
$\mu$	20.9°	8.6°
$\sigma$	16.7°	9.9°



Man - 324 m

Error	MAGYQ	WAISS
$\mu$	16.1°	8.8°
$\sigma$	13.1°	10.3°

# CONCLUSIONS



Human diversity challenges personal navigation technology



What scientific approach can solve it?  
Modeling, artificial intelligence, ...?



Is the hypothesis of an average human being possible?



Inventing navigation for the new forms of mobility?



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