

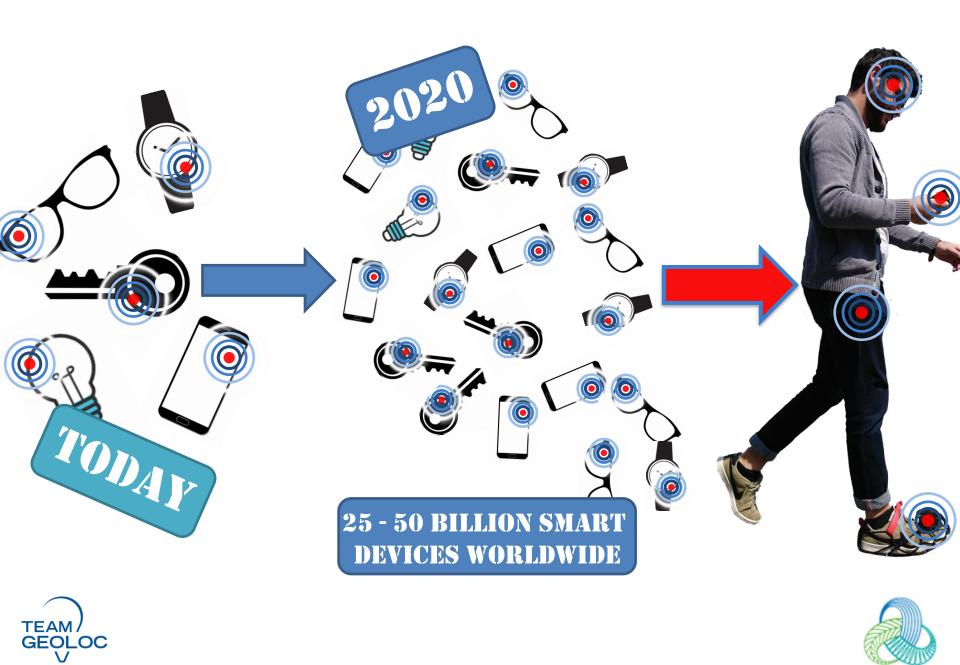
Integrating human dimension in the development of pedestrian navigation





15 November 2018, Toulouse, France





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



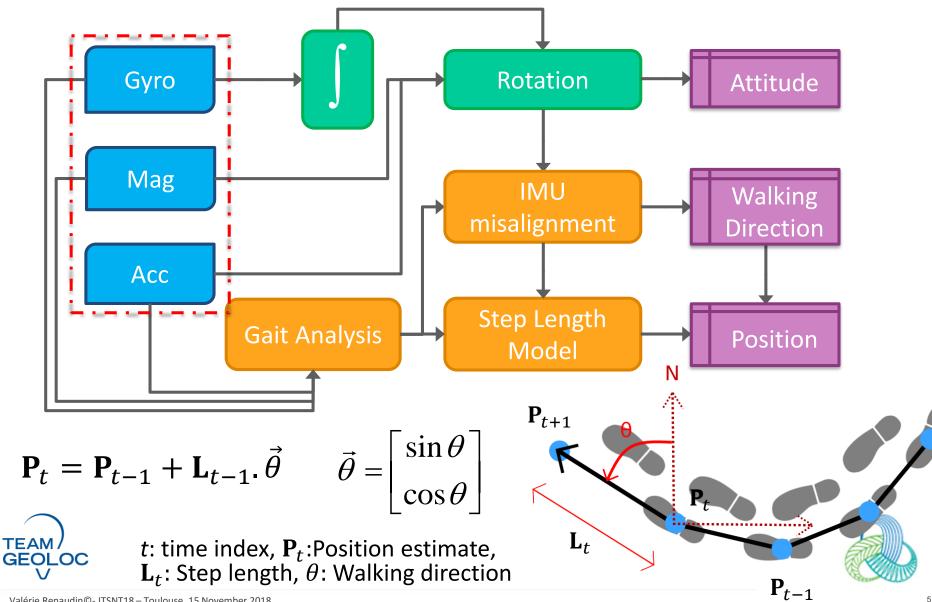
Expand the prescription sports-health program to integrate the practice of walking and cycling in the treatment of patients





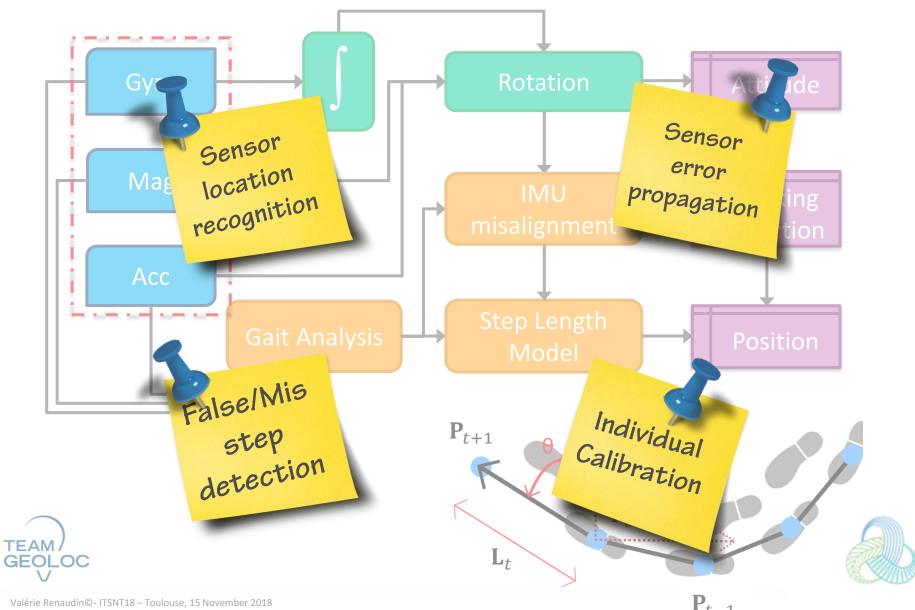


Pedestrian Dead Reckoning



Valérie Renaudin©- ITSNT18 – Toulouse, 15 November 2018

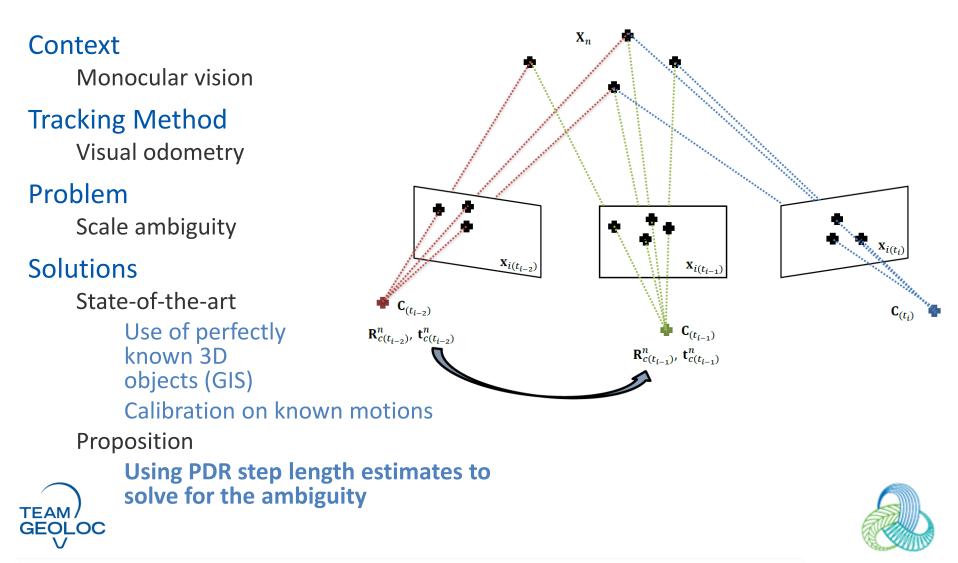
Pedestrian Dead Reckoning



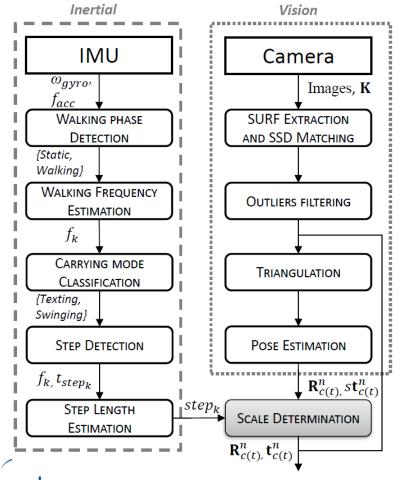


Monocular Visual Odometry Assisted by Step Length

Assisted Monocular Visual Odometry



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

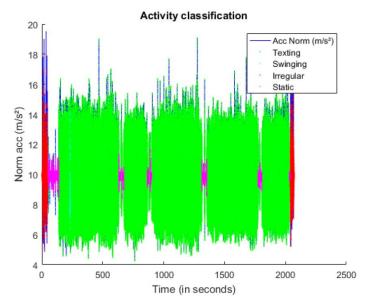
 $s_{t_{im}} = \frac{D_{PDR}(t_{im})}{D_{VO}(t_{im})}$





Review of visual odometry: types, approaches, challenges, and applications, M. O. A. Aqel et al, SpringerPlus vol. 5, 2016,

Step Length Model



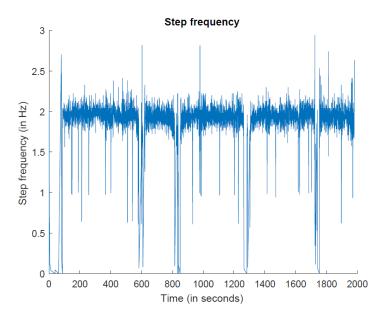
Activity classification

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



Mode Recognition and Step Detection Algorithms for Mobile Phone Users, *M. Susi et al.* Sensors, 2013.



Step Length Estimation Using Handheld Inertial Sensors, V. Renaudin et al., Sensors, 2012.

Experimentation

Scenarios

800 m walk in urban environmentStops in front of 2 reference objects3 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

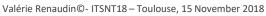
Differential GNSS (handheld helicoidal antenna + Septentrio)

Foot mounted **PERSY** (PEdestrian Reference SYstem) : positionning error 0,3% traveled distance

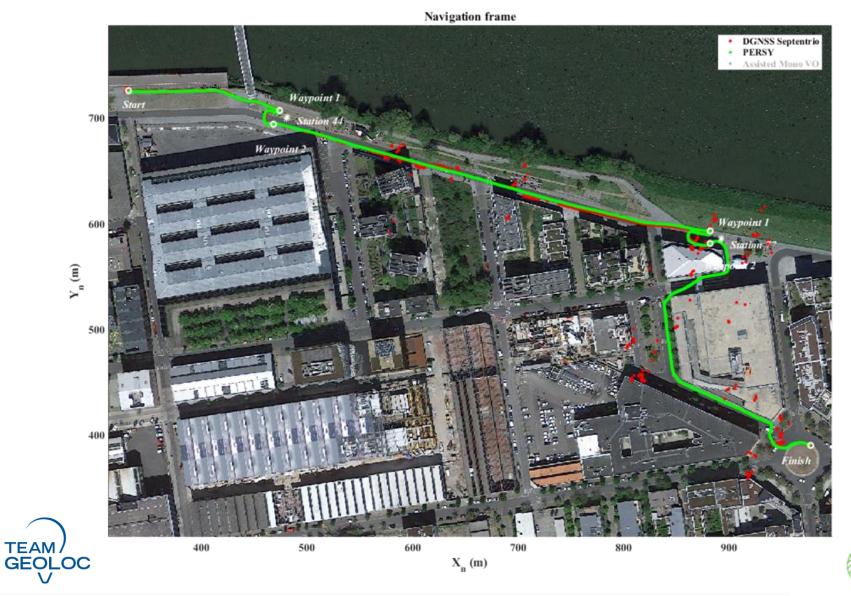




A new PDR navigation device for challeng. urban environments, M. Ortiz et al., Sensors, 2017 Foot-mounted pedestrian navigation reference with tightly coupled GNSS carrier phases, inertial and magnetic data, J. Le Scornec et al., IEEE Proceedings IPIN 2017

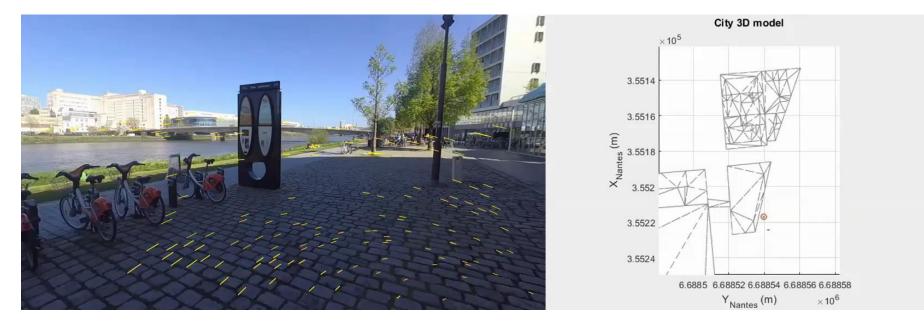


Pedestrian path in urban environment





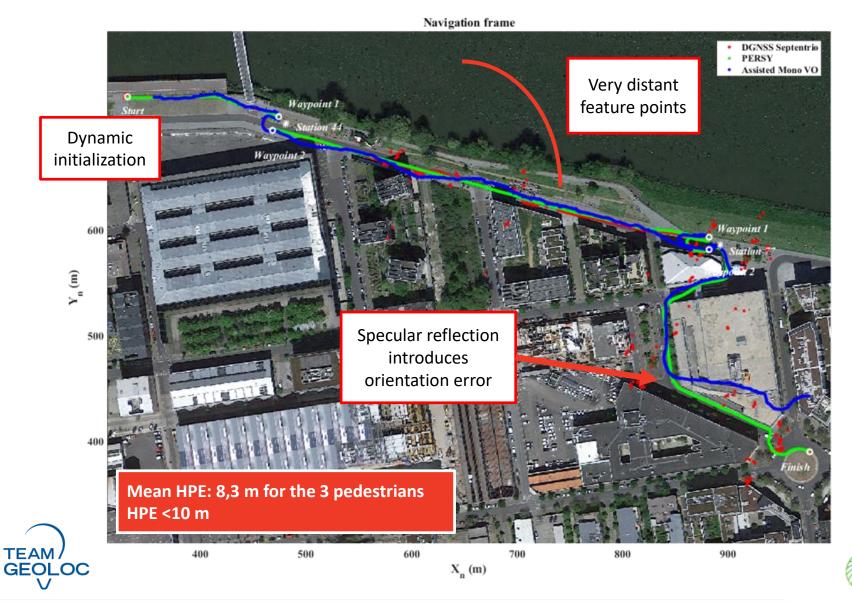
Accurate Vision/PDR PVT Estimates







Pedestrian path in urban environment

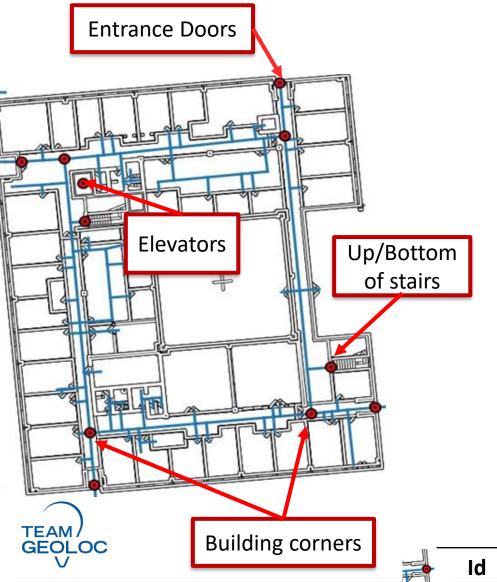


TEAM) GEOLOC

> 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 bulding directions/corners Position correction with lift locations Adjust dynamic model to motion context (staircase, lift, ...)

Proposition

Ν

Ε

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

Type



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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

Positioning



Supervised Learning

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PDR error mitigation

Particle Filter Design

Graph design

Correction of step length estimates

Correction of over/mis-step

detection

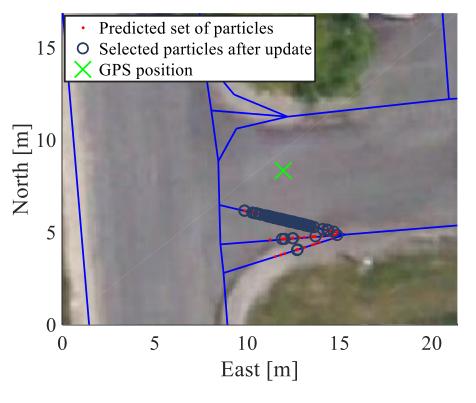
Correction of heading misalignment

Mechanization

PDR

Updates

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



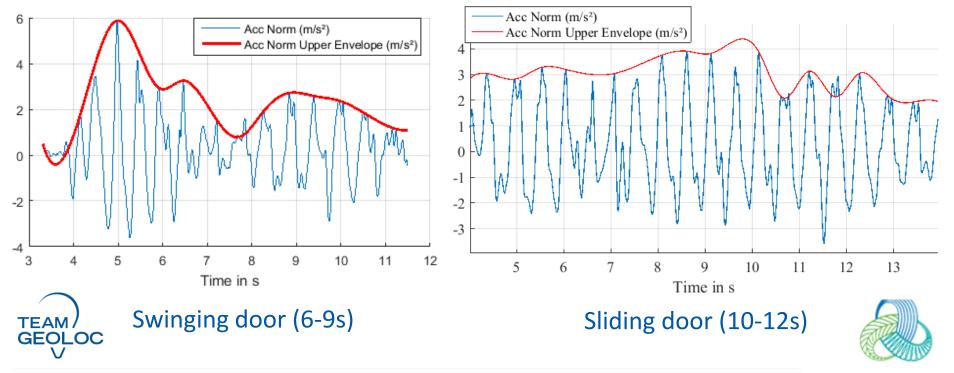




Pedestrian dead reckoning navigation with the help of A* -based routing graphs in large unconstrained spaces, F. T. Alaoui et al, Wirel. Commun. Mob. Comput., 2017

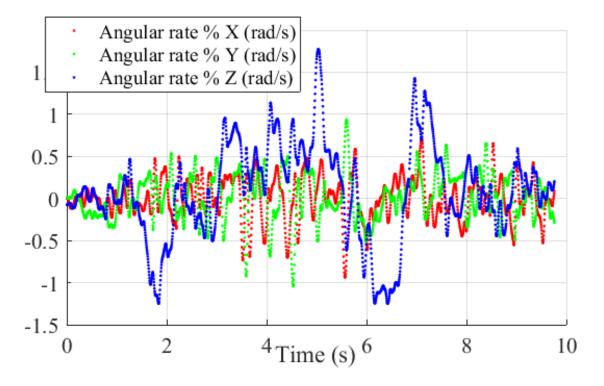
Signal patterns: indoor/outdoor transition (1/2)

- 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



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

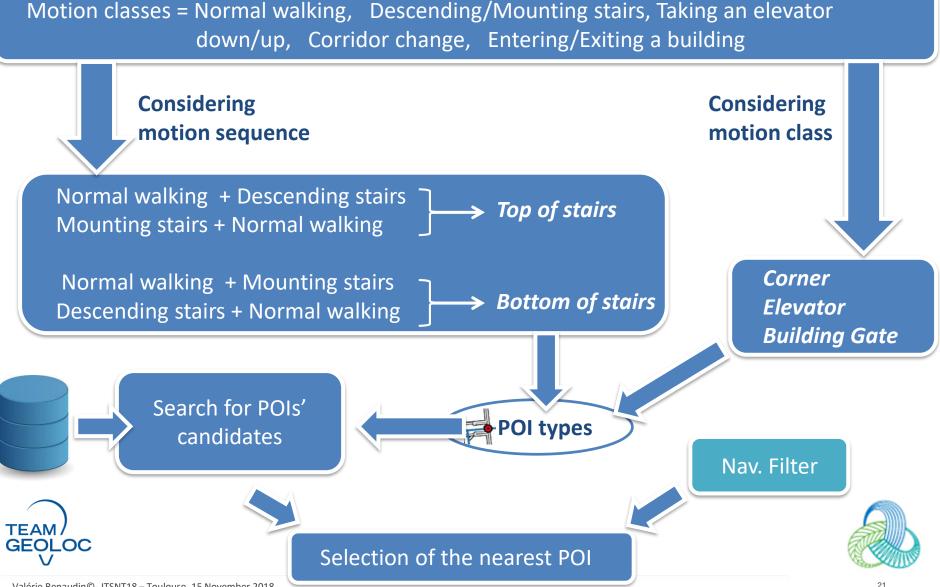


Swinging doors (4-6 s)





Finding the Right POI Using Signal Pattern



Supervised Learning Perf. Assessment

Features selected using Mutual Information

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

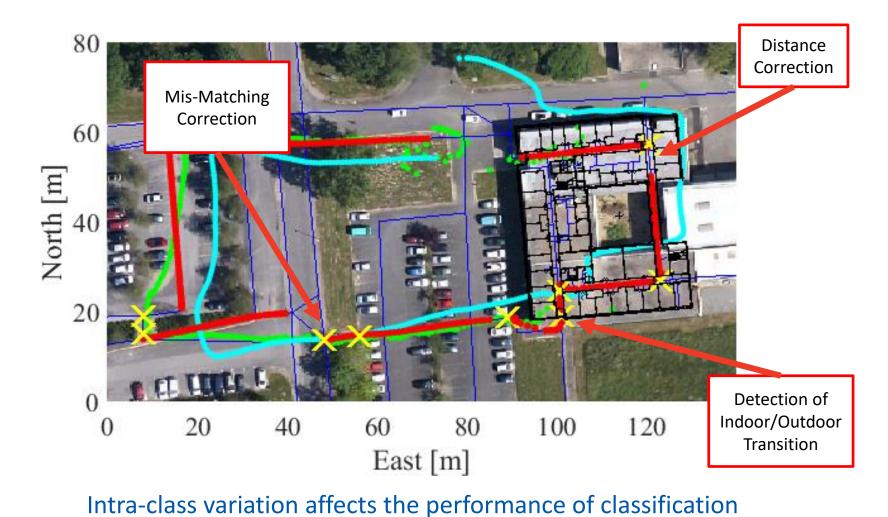
Corner	Entry / Exit	Down Stairs	Elevator Down / Up	Normal Walk.	Up Stairs
91.67	100	96.84	100	98.71	98.13
100	96.36	97.87	100	98.71	97.22

Precision: True positive / (True Positive + False Positive)
Sensitivity: True positive / (True Positive + False Negative)
Overall Detection/CLassification Accuracy: 98.41M



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Experimental Assessment





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

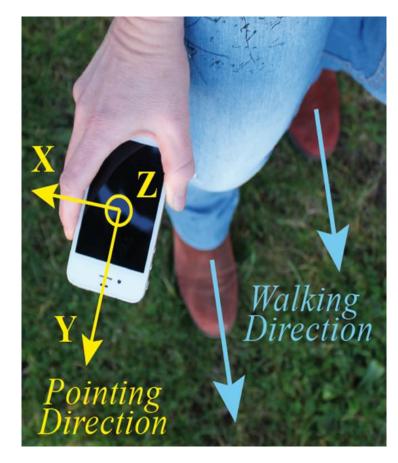


TEAM) GEOLOC

> 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

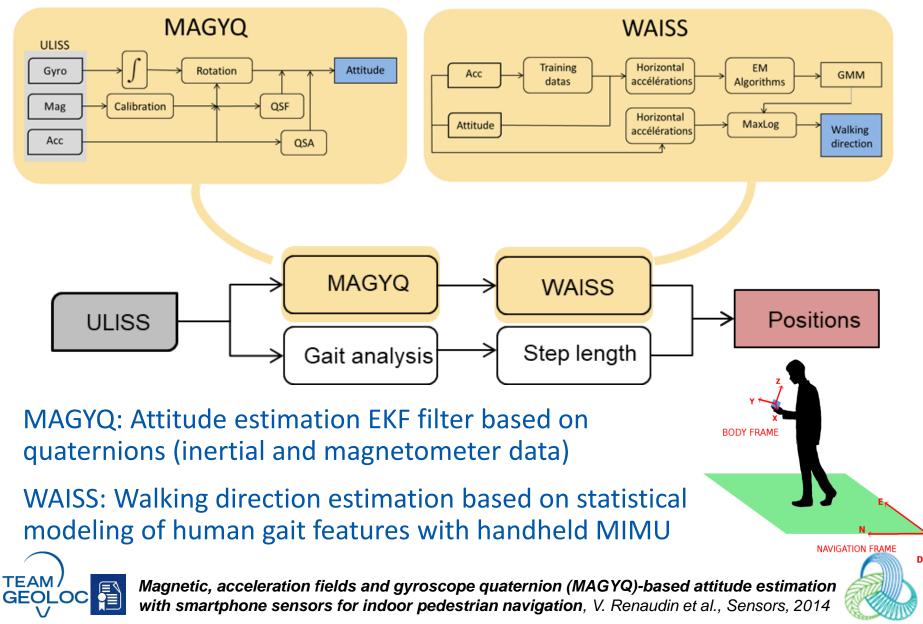
Calibration by fusing multiple signals Calibration on known paths

Proposition

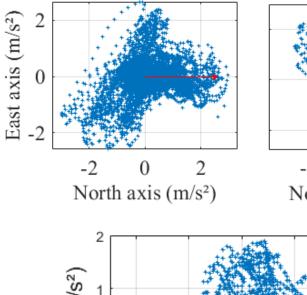
Modeling personal way of holding the sensor in hand to construct navigation filters

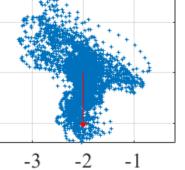


Attitude Estimation

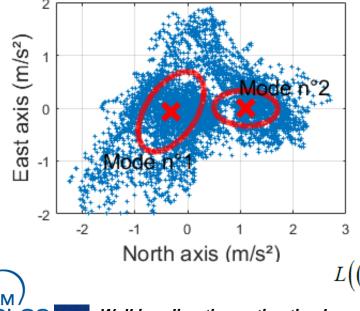


WAISS Method: Building Individual Models





North axis (m/s²)



Distribution of horizontal accelerations depends on the walking direction

Distribution modeling with a Gaussian Mixture

$$f_{acc}\left(\mathbf{x}\right) = \sum_{k=1}^{q} \tau_{k} \mathcal{N}\left(\mathbf{x}, \mathbf{m}_{k}, \mathbf{P}_{k}\right)$$

Straight-line data set with 0° walking direction

Expectation Maximization algorithm

$$\left(Z_{i} | \mathbf{x}_{i}, \left(\tau_{k}^{c}, \mathbf{m}_{k}^{c}, \mathbf{P}_{k}^{c}\right)\right) = \frac{\tau_{k}^{c} \mathcal{N}\left(\mathbf{x}_{i}, \mathbf{m}_{k}^{c}, \mathbf{P}_{k}^{c}\right)}{\sum_{j=1}^{p} \tau_{j}^{c} \mathcal{N}\left(\mathbf{x}_{i}, \mathbf{m}_{j}^{c}, \mathbf{P}_{j}^{c}\right)}$$

$$L\left(\left(Z_{i}\right)_{1\leq i\leq n},\left(\mathbf{x}_{i}\right)_{1\leq i\leq n},\boldsymbol{\Psi}\right) = \sum_{i=1}^{n}\sum_{k=1}^{p}t_{ik}\log\left(\tau_{k}\mathcal{N}\left(\mathbf{x}_{i},\mathbf{m}_{k},\mathbf{P}_{k}\right)\right)$$



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

$$L((\mathbf{x}_{i})_{1 \le i \le n}, \theta) = \sum_{i=1}^{n} \log(f_{accM}(\mathbf{x}_{i}, \theta))$$
$$\theta_{w} = \arg\max_{\theta} \left(L((\mathbf{x}_{i})_{1 \le i \le n}, \theta)\right)$$

Experimental Assessment

Use of PERSY as angular reference

$$\alpha = \operatorname{atan}\left(\frac{Y_{P2} - Y_{P1}}{X_{P2} - X_{P1}}\right) | \qquad \operatorname{R=} \begin{bmatrix} \cos(\alpha) & -\sin(\alpha) & 0\\ \sin(\alpha) & \cos(\alpha) & 0\\ 0 & 0 & 1 \end{bmatrix}$$

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

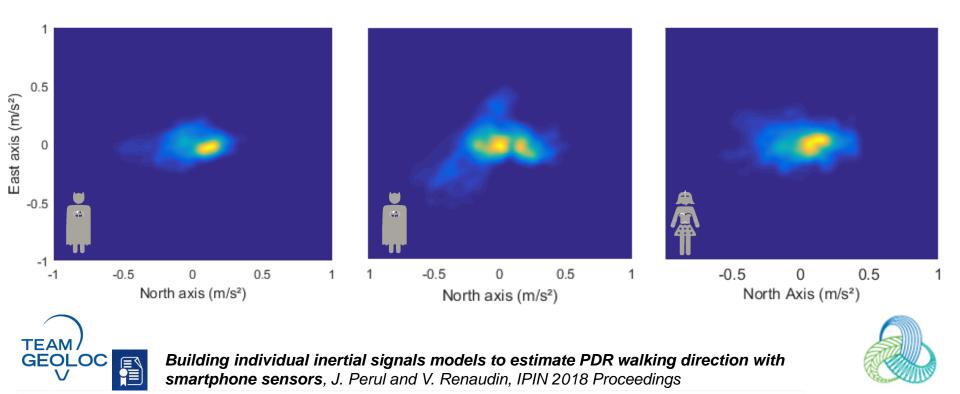
GEOLOC

PERS

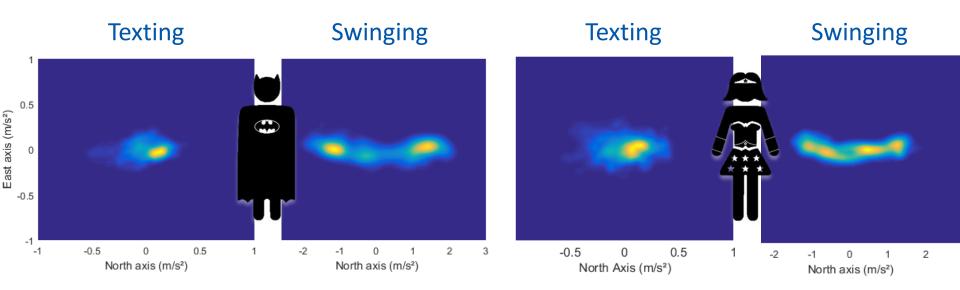
ULISS

Choosing the right GMM

Different distributions for different persons Need to adapt the number of GMM modes for each individual Use of criterions



Impact of the Carrying Mode on Modeling



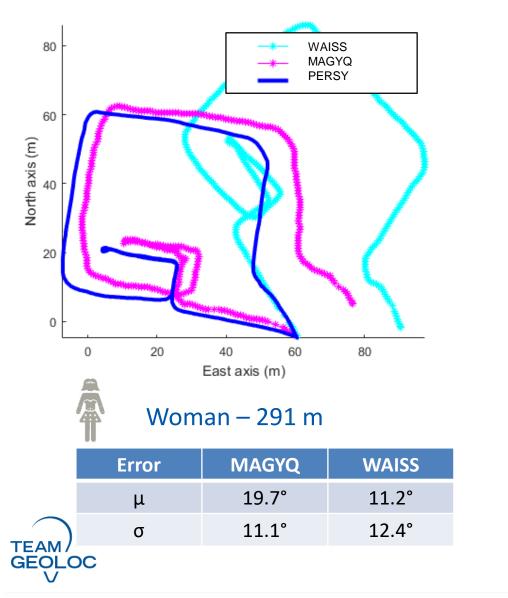
Different distributions for the same person

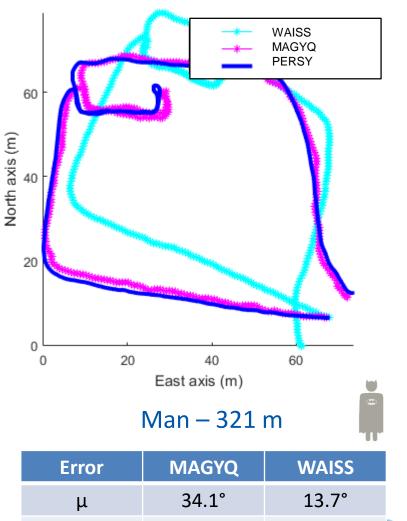
Need to adapt the number of modes for each individual and for each carrying mode





Assessment: Texting Mode with Misalignment



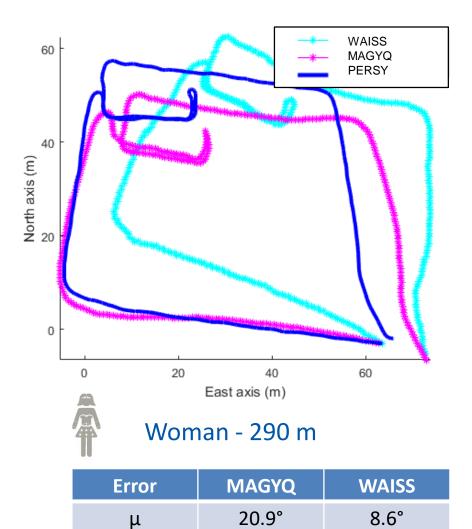


14.6°

σ

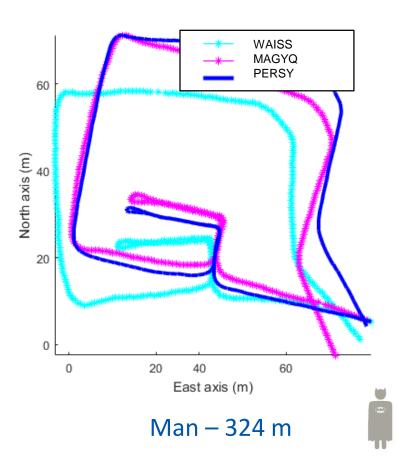
17.3°

Assessment: Swinging Arm



16.7°

9.9°



Error	MAGYQ	WAISS
μ	16.1°	8.8°
σ	13.1°	10.3°

σ

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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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