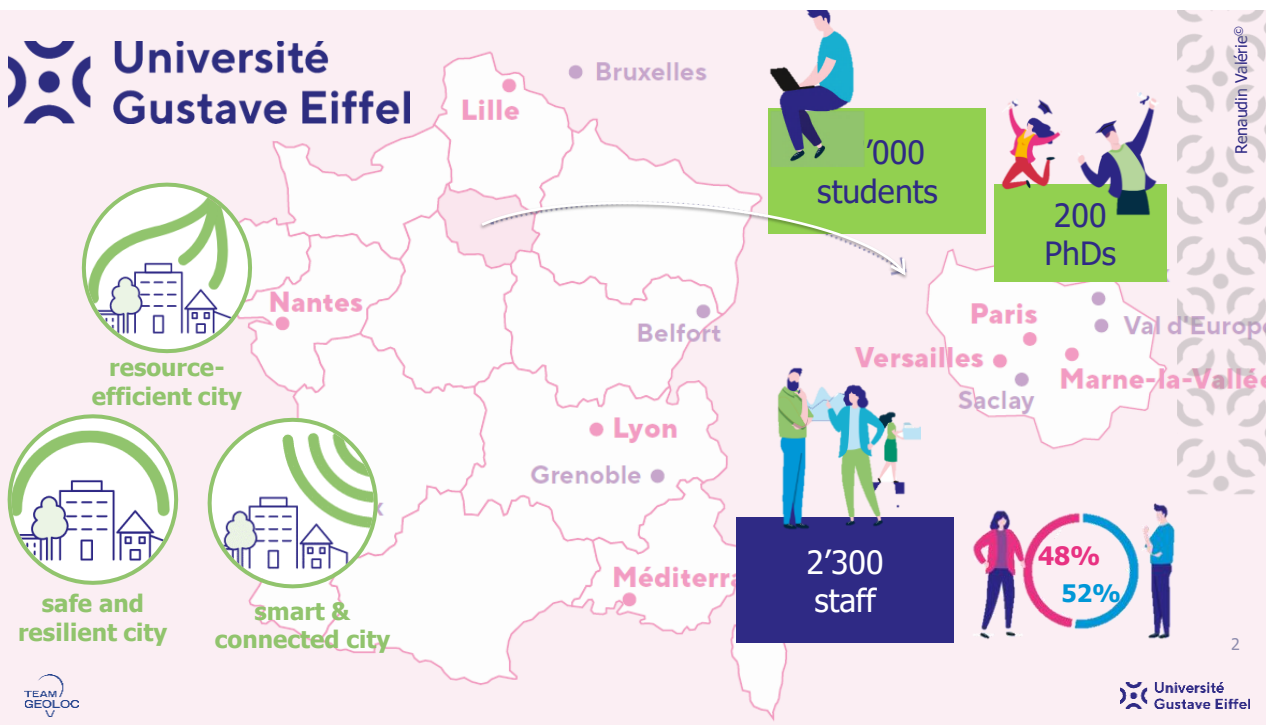


25 January 2023
RENAUDIN Valérie

Smart Processing with Wearable Devices: Shall We Consider the Human Influence?



POSITIONING AND NAVIGATION: A CATALYST FOR NEW FORMS OF MOBILITY

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V

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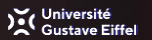
Interaction between humans & wearables

- a source of electricity from
- footstep kinetic energy
- body's thermal energy



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INDOOR & INFRASTRUCTURE-FREE POSITIONING AND NAVIGATION: AN R&D DRIVER OF NEW WEARABLES



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Earing aids, bone conduction headphones

Armworn trackers, patches, fitness

Smartwatches, emergency bracelets

Head: immersive infotainment

Smartglass, AR, VR

Smartclothing, health tracker

Sport apparel, mobility

Smartinsole, military

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CURRENT AVAILABLE SOLUTIONS

Radio Beacon Network

Learning from Signal Characteristics

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RADIO BEACON NETWORK

Installation of beacons in a specific infrastructure

Measurements of signal propagation for trilateral or passing by a landmark

Technologies in use: UWB, BLE, RFID, ultrasound, light

Benefit

- Absolute location in the indoor maps
- Scalable

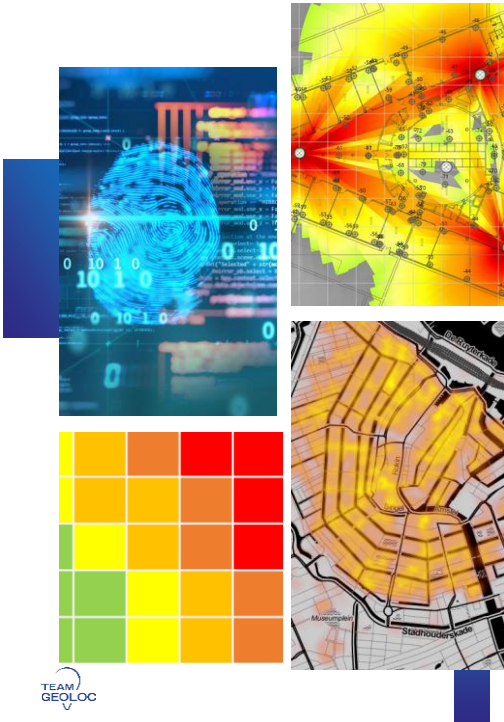
Drawback

- Costly
- Obstruction
- Numerous calibration needed
- Accuracy versus density

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LEARNING FROM SIGNAL CHARACTERISTICS

Fingerprinting Method

- Offline: Gridding of space and geotag signals prints
- Operational: minimization of the "any" distance

Technologies in use: any signals of interest, Wifi/Magnetic Fields being popular

Benefit

- Absolute location in the indoor maps
- Use geometrical constrains to increase accuracy (Bayesian Approach)

Drawback

- Main assumption - *static radio signals patterns* - is rarely true
- Difficulties in updating the database
- Attenuation of high frequencies by the human body: what about the crowd?
- Cost of establishing the database (urgency?)

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INERTIAL NAVIGATION SYSTEMS: BEACON-FREE

1st and 2nd Newton's laws applied to acceleration and angular rates

Time based evolution of the...

...speed & position ($\dot{\mathbf{x}}, \mathbf{x}$), $\forall u \in [t, \Delta t]$

$$\dot{\mathbf{x}}_{t+\Delta t}^n = \int_t^{t+\Delta t} \ddot{\mathbf{x}}^n du = \dot{\mathbf{x}}_t^n + \ddot{\mathbf{x}}^n \Delta t$$

$$\mathbf{x}_{t+\Delta t}^n = \int_t^{t+\Delta t} \dot{\mathbf{x}}^n du = \mathbf{x}_t^n + \dot{\mathbf{x}}_t^n \Delta t + \frac{1}{2} \ddot{\mathbf{x}}^n \Delta t^2$$

...attitude angles (\mathbf{q}_ω^n) using angular rates to create the rotational increment (\mathbf{q}_ω^b)

$$\mathbf{q}_\omega^n(t + \Delta t) = \mathbf{q}_\omega^n(t) \circ \mathbf{q}_\omega^b(t)$$

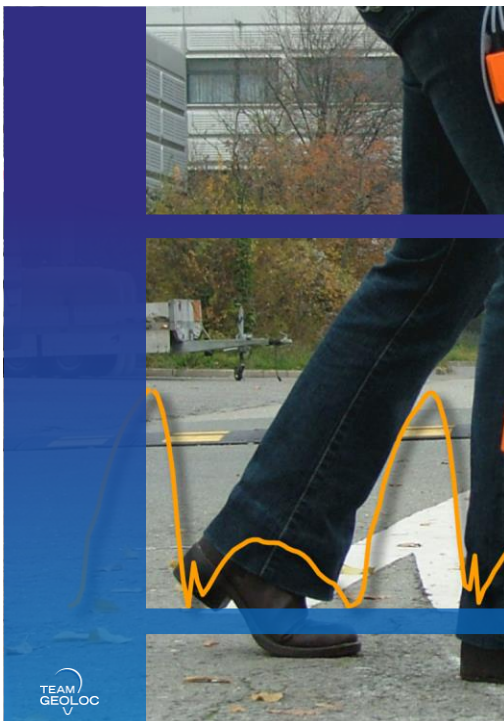
Benefit

- No infrastructure deployment
- No knowledge of the map
- Functional without mobile cellular network coverage
- Accessible to a larger population
- Private by design: General Data Protection Regulation (GDPR)

Drawback

- Propagation of measurement errors: t^2 for acceleration errors, t^3 for angular rate errors

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KEEP YOUR ORIENTATION WITH THE INERTIAL SENSORS

Positioning error larger than 10 km after a 2 minutes walk with handheld inertial sensors

“ I am lost! ”

Backbone of pedestrian navigation...

1. Search for continuous calibration tricks to mitigate the error of low cost sensors
2. Fusion with other measures to compensate for the errors
3. Use kinematic and contextual information to model the motion
4. Learn from the human interaction with wearables



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PEDESTRIAN DEAD RECKONING APPROACH

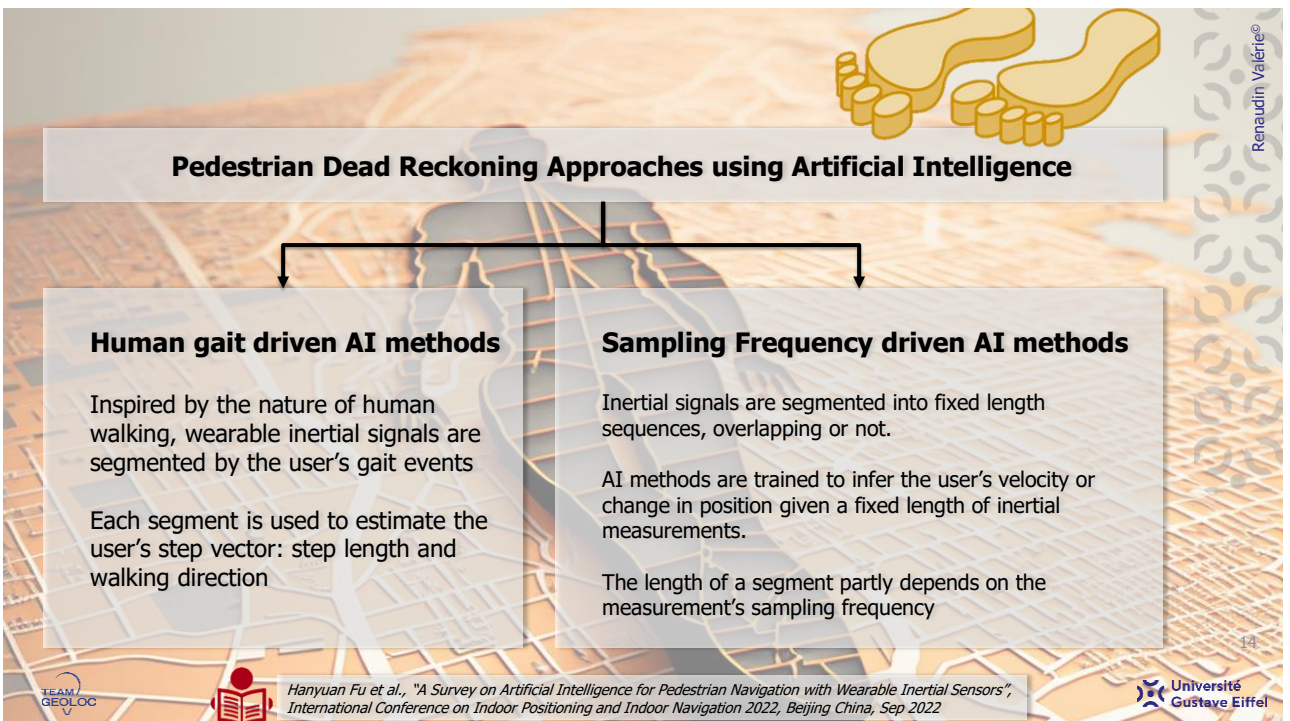
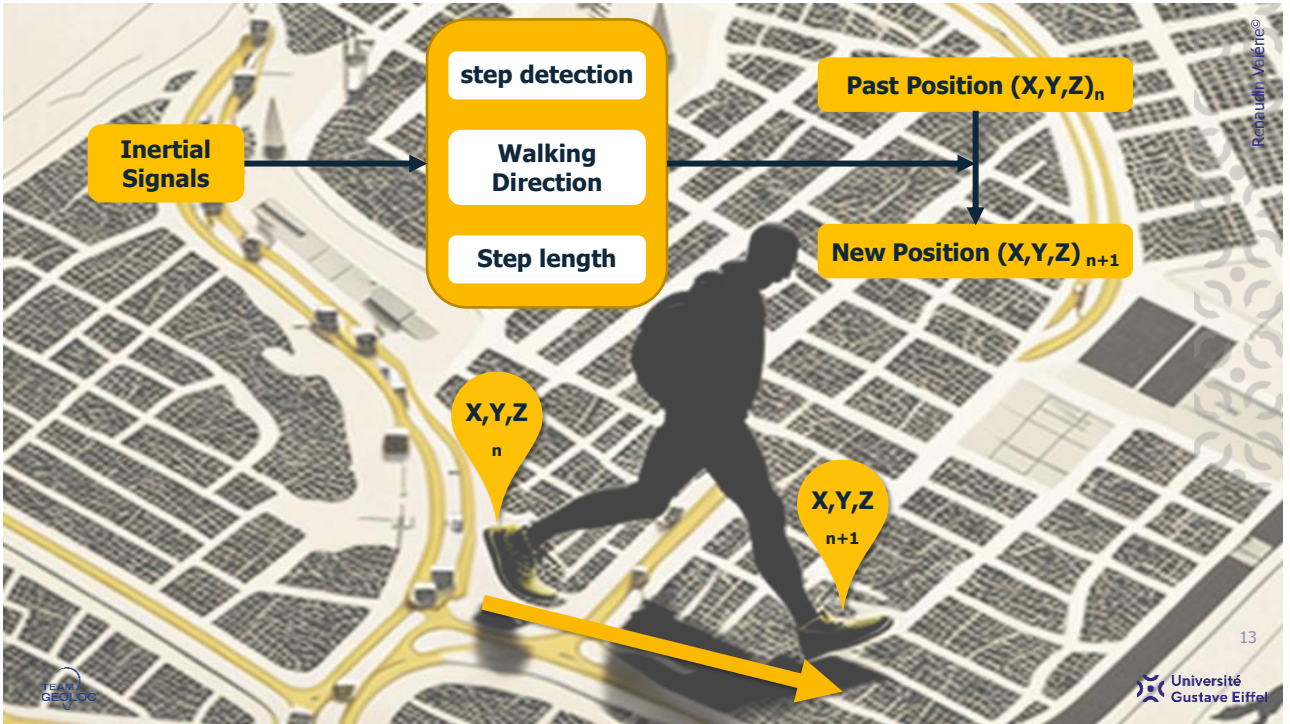



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Estimating Step Length and Heading with Wearable?

- What is the best wearable location on the human body to track a person on the map?
- What is the impact of the wearable location on the human body on the signal processing methods and performances?
- Does the use of navigation aids modify the walking gait?
- How to train any artificial intelligent model to recognize or estimate gait parameters?
- What is the best strategy to label time series of inertial data for learning human gait features with artificial intelligence: physics or human interpretation?

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EFFICIENT NAVIGATION AIDS: THE NEED FOR INDIVIDUALIZED APPROACHES



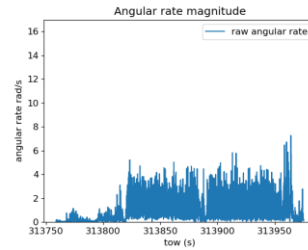
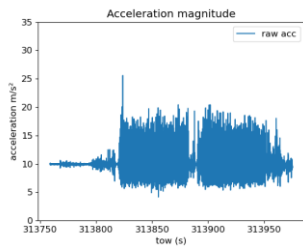
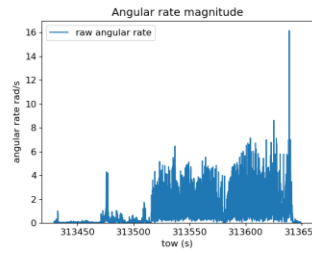
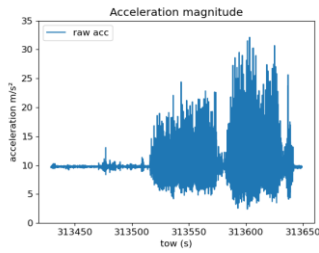
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INFLUENCE OF THE NAVIGATION TOOL ON THE GAIT OF A VISUALLY IMPAIRED PERSON




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INFLUENCE OF THE NAVIGATION TOOL ON THE GAIT OF A VISUALLY IMPAIRED PERSON



 More irregularities in the signal amplitudes and greater amplitude range in the first case (dog)

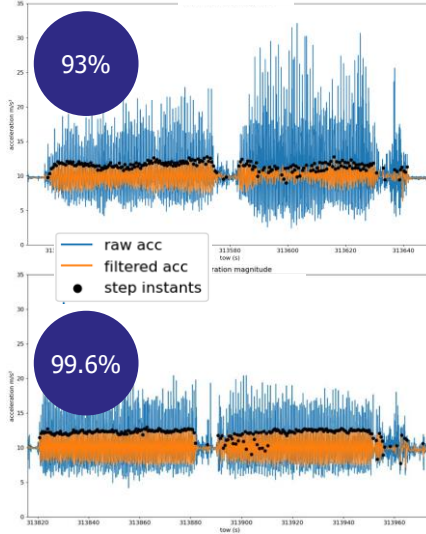
The dog walked slower during the 1st half of the trail. During the 2nd half, it knew better where to go and went faster and so did his owner

 Steady speed with white cane



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INFLUENCE OF THE NAVIGATION TOOL ON STEP DETECTION OF A VISUALLY IMPAIRED PERSON



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Step detection algorithm preprocesses inertial signals with a low pass filter

Steps are mostly detected from acceleration signal

Due to the volatile dynamic (strong high frequency component), the filter deforms the signal, especially in the second half, which can impact the step detection

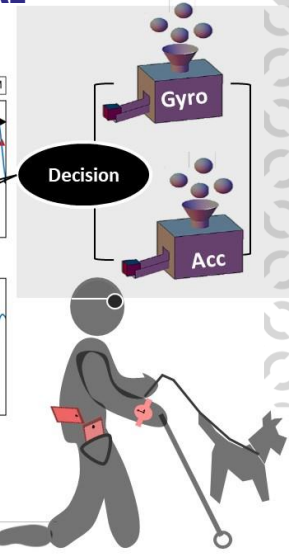
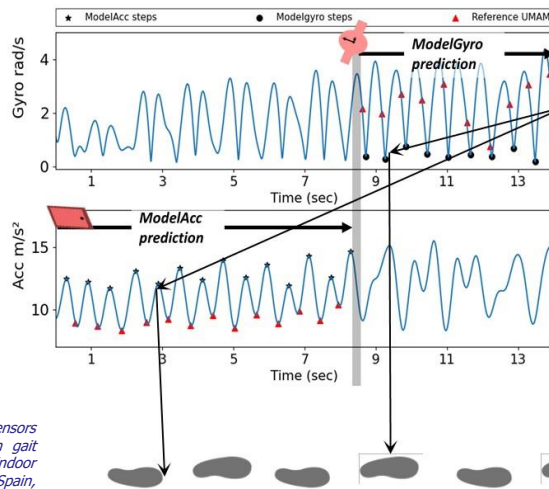
The filtered signal is less deformed

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FOCUS ON STEP DETECTION WITH WEARABLE AND AI

	Straight line	Complex in/out
phone	-2%	+34%
wristband	-3%	+19%
smartstep	-1%	+4%

SMARTSTEP algorithm
Machine learning applied to inertial signals from wearable devices

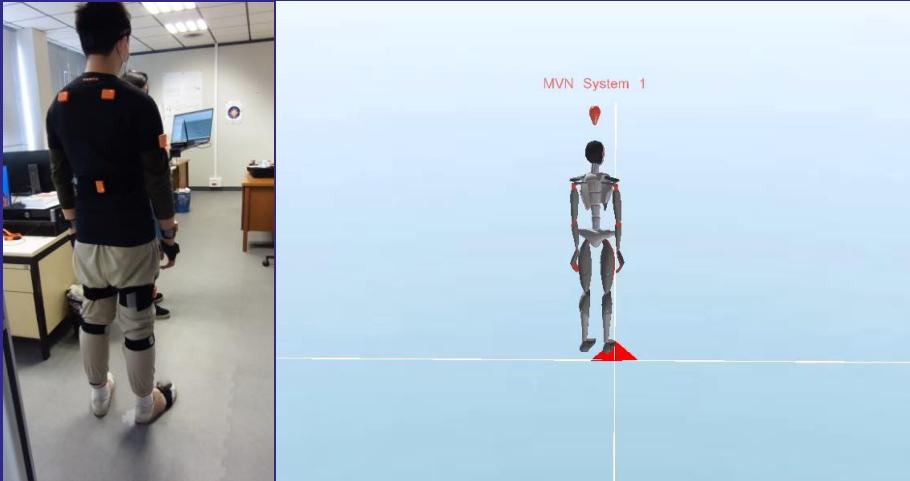


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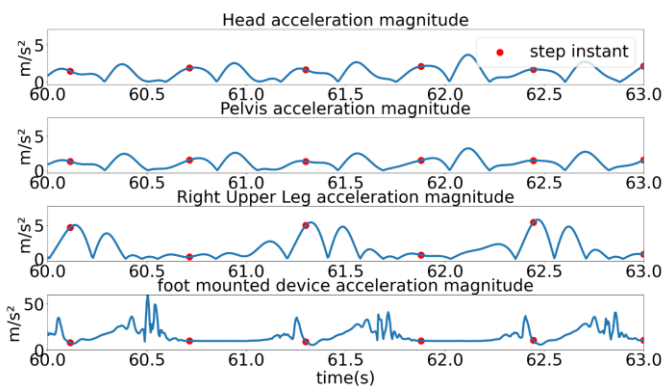
Al Abiad N, et al., "SMARTphone inertial sensors based STEP detection driven by human gait learning", International Conference on Indoor Positioning and Indoor Navigation (IPIN), Spain, November 2021.

UPPER/LOWER LIMBS CORRELATION

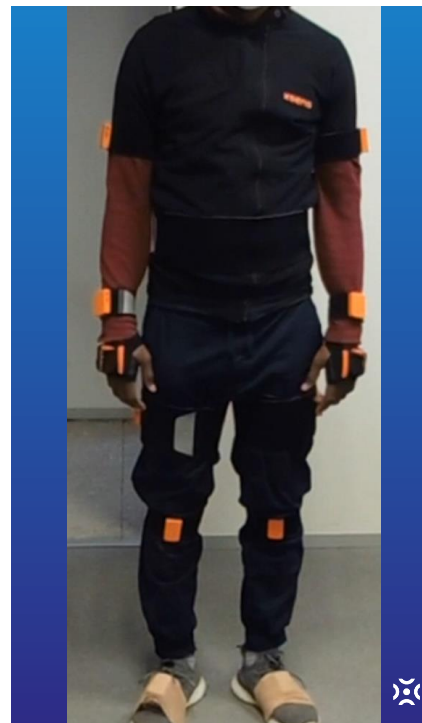
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POINTS OF INTEREST ARE NOT SYNCHRONIZED BETWEEN THE DIFFERENT BODY PARTS



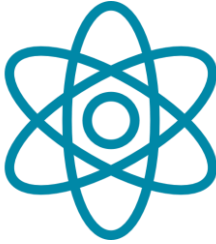
Ground truth step instants (flat foot period) projected on the acceleration norms of different body parts



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PHYSIC" VS "BRAIN": TWO LABELING STRATEGIES



Training dataset

10 subjects (6 Men and 4 Women) of various heights. Among the men, 2 are blind people. The full dataset has 753'121 observations, 1% being step instants.

Equipment

2 ULISS hardware: one fixed on the foot (reference) and one in hand

Physics Labeling



Koné Y, et al. (2021), "Zero Velocity Detection without Motion Pre-classification: Uniform AI Model for All pedestrian Motions (UMAM)", IEEE Sensors Journal



Brain Labeling



Al-Abiad N, et al., "Smartstep: a robust STEP detection method based on SMARTphone inertial signals driven by gait learning", IEEE Sensors Journal, 2022



3 SCENARIOS FOR THE EXPERIMENTAL ASSESSMENT OF STEP DETECTION



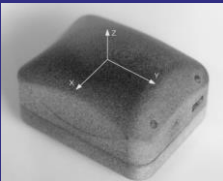
sighted/in hand/150m



sighted/in pocket/150m



blind/out jacket/80m



A sighted person walked into an office building. The trajectory included stairs. The person walked in "texting" mode during the first 1/2 the recording, and "swinging" for the rest

Same sighted subject and environment as Test 1 but the IMU sensor was in the subject's front trouser pocket (thigh)

A blind subject walked in a straight line and turned around in an outdoor park. The trajectory length is about 80m. The IMU was located in the jacket pocket (waist)



STEP DETECTION RESULTS FOR PHYSICS AND BRAIN LABELING STRATEGIES

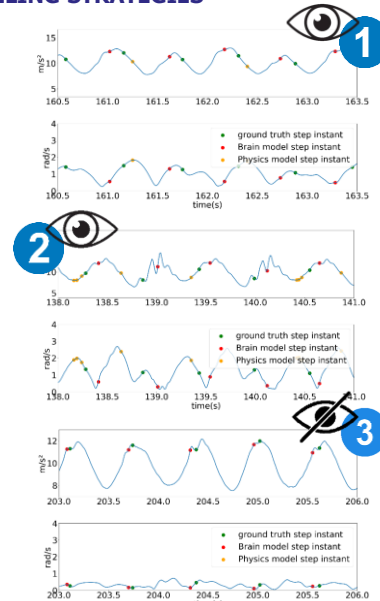
The "Brain" model detects over 85% of steps on all 3 tests and rarely over-detects

The "Physics" model gives almost random inferences on the first 2 tests and fails badly the third one with the IMU in the vest pocket

Test	N_{ref}	N_{pred}	Physics		Brain		
			TPR	ODR	N_{pred}	TPR	ODR
1	256	221	54.7	36.7	256	97.7	0
2	245	204	52.7	36.8	215	86.9	0.9
3	142	5	3.5	0	123	85.9	0.8



Renaudin V., et al (2022) "Physics" vs "Brain": Challenge of labeling wearable inertial data for step detection for Artificial Intelligence, the 9th IEEE International Symposium on Inertial Sensors & Systems, May 8-11, Avignon, France



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WHAT IS THE IMPACT OF HUMAN BODY ON GNSS SIGNALS TRACKING?



Global Navigation Satellite Systems (GNSS) positioning



A geometry problem in space

Geometric range between the satellite and the receiver antenna phase center coordinates

$$\rho_{user}^{sat} = \|\mathbf{r}^{sat} - \mathbf{r}_{user}\|$$

$$= \sqrt{(x^{sat} - x_u)^2 + (y^{sat} - y_u)^2 + (z^{sat} - z_u)^2}$$

Deriving the distance from the time of flight

$$\rho_{user}^{sat} = c\Delta t = c(t_u[reception] - t^{sat}[emission])$$

The satellites' clock is synchronized, but not with the user's receiver

There are therefore 4 unknowns:

3D coordinates and synchronization failure
→ 4 satellites!

Many other errors slow down the signal propagation: atmosphere, relativity, calculation errors, etc



Challenges of GNSS positioning in urban spaces



The urban environment reduces the accuracy

The surrounding environments contain obstacles disturbing/blocking the signal propagation

Two types of signals:

Line-of-sight (LOS)

Non-line-of-sight (NLOS)

The geometry of the tracked satellites in space impacts the quality of the intersection of the lines between the user and the satellites

Observing many satellites is an important key to accuracy



Challenges of GNSS positioning in urban spaces



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Adopt the receiver's point of view with a camera located on the foot and one in the hand to analyse the visible satellites

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Experimental setup

The same system in hand and on the foot

- GoPro Max 360 camera mounted on
- Ubiquitous Localization with Inertial Sensors and Satellites (ULISS)
 - Xsens MTI-7 9D Inertial Measurement Unit (IMU): 3D accelerometer, 3D gyroscope and 3D magnetometer at 200 Hz
 - Bosch BMP 280 pressure sensor at 50 Hz
 - Ublox ZED-F9P dual frequency GNSS receiver at 5Hz

All data (ULISS signals and images) are timestamped with GNSS data

EXPERIMENTAL IMAGES/GNSS DATA PROCESSING

Extraction of the images (GoPro Player application)

Extraction of equirectangular images
 Formatting in fisheye format on Python
 Extraction of corresponding metadata for synchronization with GNSS timestamps

Camera calibration

Relate the real coordinates of an object and its coordinates on the image
 If we consider an object seen by the camera with a elevation angle θ and azimuth φ :

$$\theta_d = \theta(1 + k_1\theta^2 + k_2\theta^4 + k_3\theta^6 + k_4\theta^8)$$

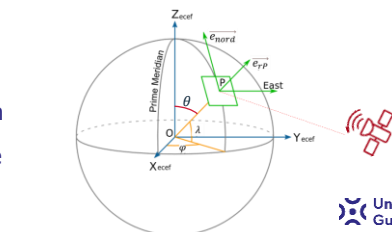
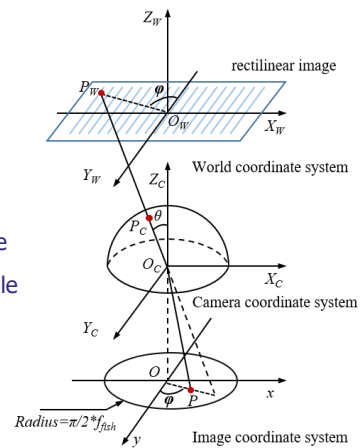
The representation of the object in the image is given in polar coordinates $(f_{\text{fish}}\theta_d, \varphi)$

GNSS and images in the same reference frame

Use of the Kalibr toolbox to estimate the transformation between the GNSS and camera frames
 Include the rotation matrix estimated for ULISS to point at the zenith

Project the GNSS satellites into the Images

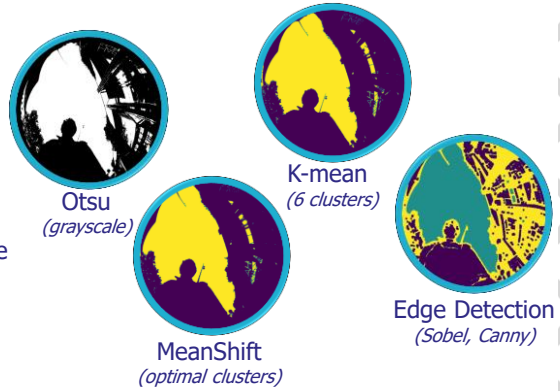
Estimation of the ULISS satellites' elevation and azimuth angles in the local frame located at the camera's position (point P)
 Use of spherical coordinates to plot the satellites' positions on the skyview



EXTRACTION SKY AREAS

With different segmentation methods

- "Holes" in the delimitation of the edges
- Assimilation of clouds to non-sky areas
- The windows or other reflective surfaces are assimilated to areas of non-sky



With Neural networks

- Fully Convolutional Network (FCN)
- High-Resolution Network (HRNet)
- Pyramid Scene Parsing Network (PSPnet)
- Masked-attention Mask Transformer for Universal Image Segmentation (Mask2Former)*

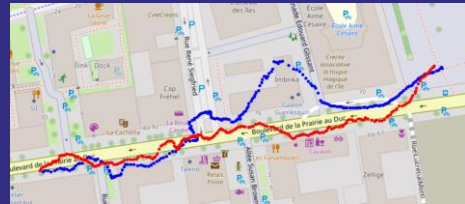
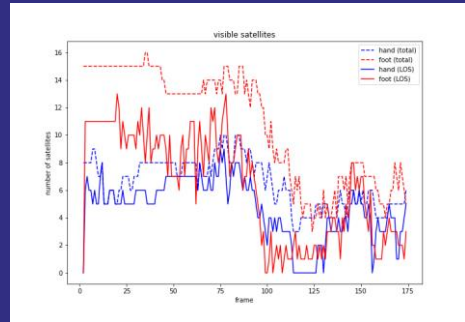
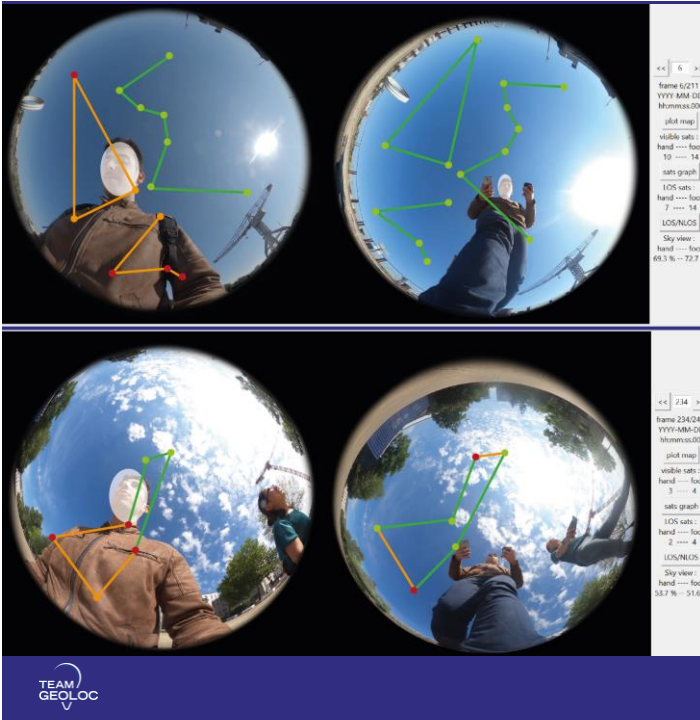


*Bowen Cheng et al, "Masked-attention Mask Transformer for Universal Image Segmentation", CVPR, 2022

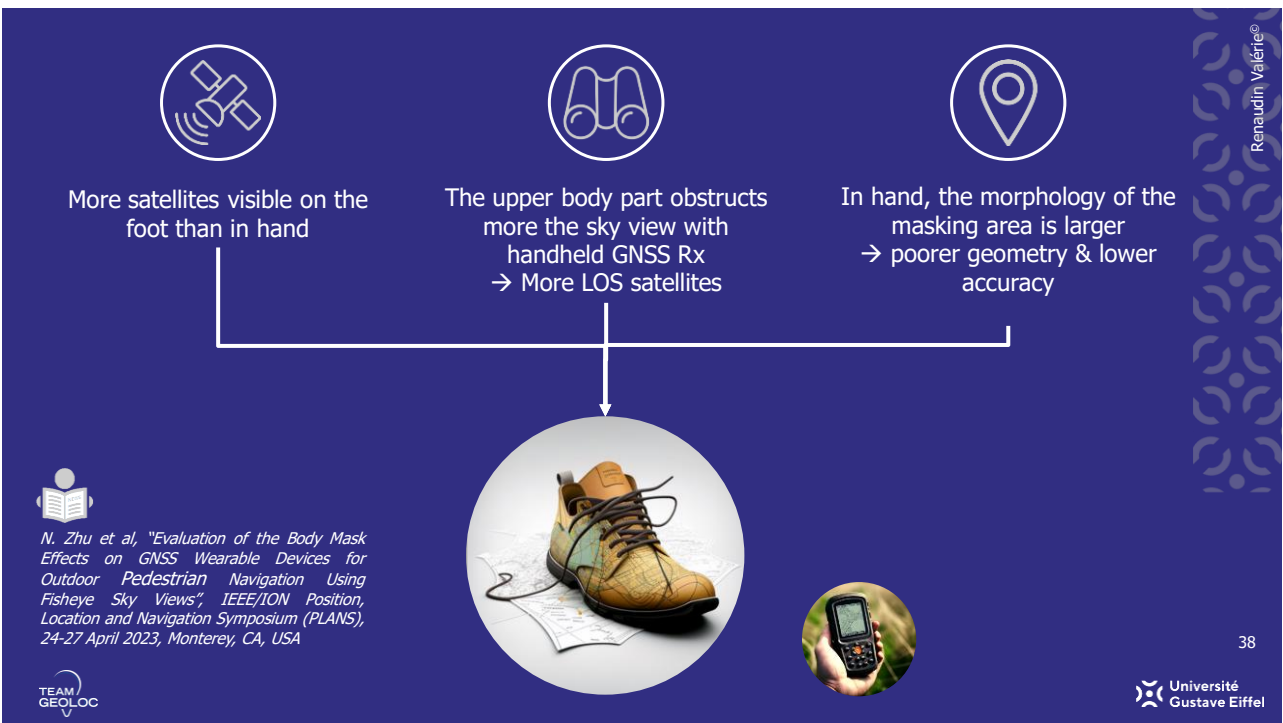


Green: visible satellite LOS
Orange: NLOS visible satellite
Red: Satellite not visible on this receiver, but visible on the other receiver





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Human morphology, gait and wearable sensors' placement change the data

Analyzing the impact of the human on the data quality questions the need for individualized data processing

But where does this end?
Can artificial intelligence based approaches mitigate personal and environmental variations?

Will you test your influence on your wearable sensors?

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Université Gustave Eiffel

Valérie RENAUDIN
valerie.renaudin@univ-eiffel.fr
06 19 71 22 12
<https://geoloc.univ-gustave-eiffel.fr/>