

2 February 2021

RENAUDIN Valérie

Indoor positioning technologies
*limitless creativity to model the complexity
of cities and human gaits*



**Université
Gustave Eiffel**

A unique, atypical and pioneering University created in 2020 grouping

- 1 research institute
- 1 university
- 1 school of architecture
- 3 engineering schools



École d'architecture
de la ville & des territoires
Paris-Est



ENSG
Géomatique

ESIEE
PARIS

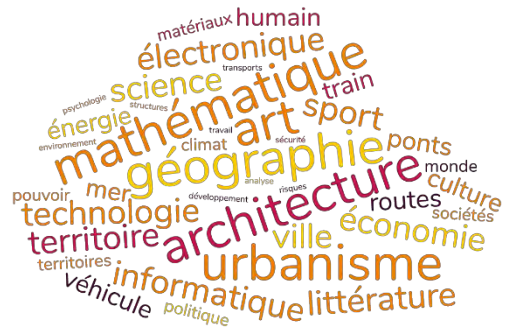


UP
EM
UNIVERSITÉ
PARIS-EST
MARNE-LA-VALLÉE

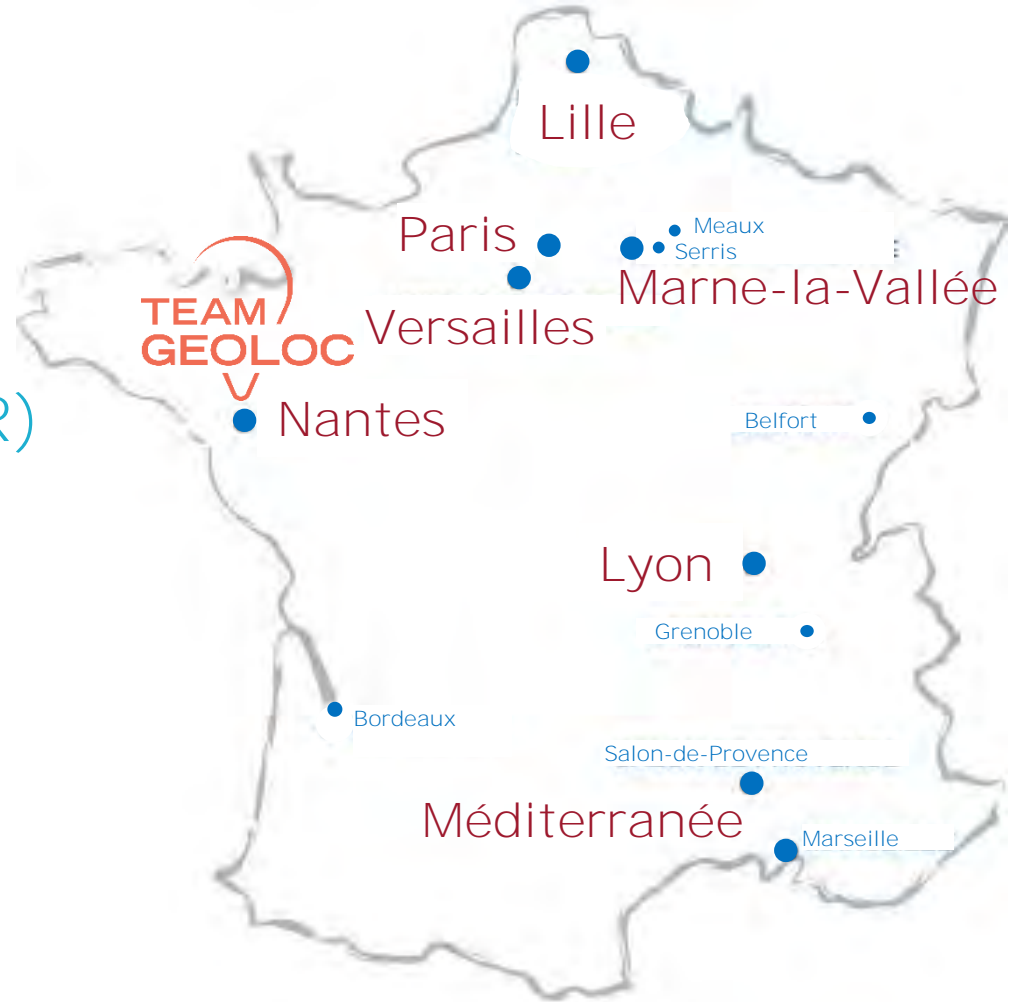


Université
Gustave Eiffel

A National Multidisciplinary University...



- 2 associated institutes
- 2 associated schools
- 6 units of training and research (UFR)
- 6 institutes
- 23 research units: laboratories, teams, departments, institutes
- 7 Main campuses in France



Positioning and navigation: a catalyst for new forms of mobility



TEAM
GEOLOC

GEOLOC Research Activities

Geolocation at the service of the evolution of mobility



Ubiquitous positioning
and navigation methods
and systems



Evaluation and definition
of positioning
performance



NUMEROUS TECHNOLOGIES ARE PROPOSED TO MEET THE
INDOOR CHALLENGES

SOME POPULAR INDOOR TECHNOLOGIES ON THE MARKET



Light Fidelity



Motion Detection



Facial Recognition



Smartphone

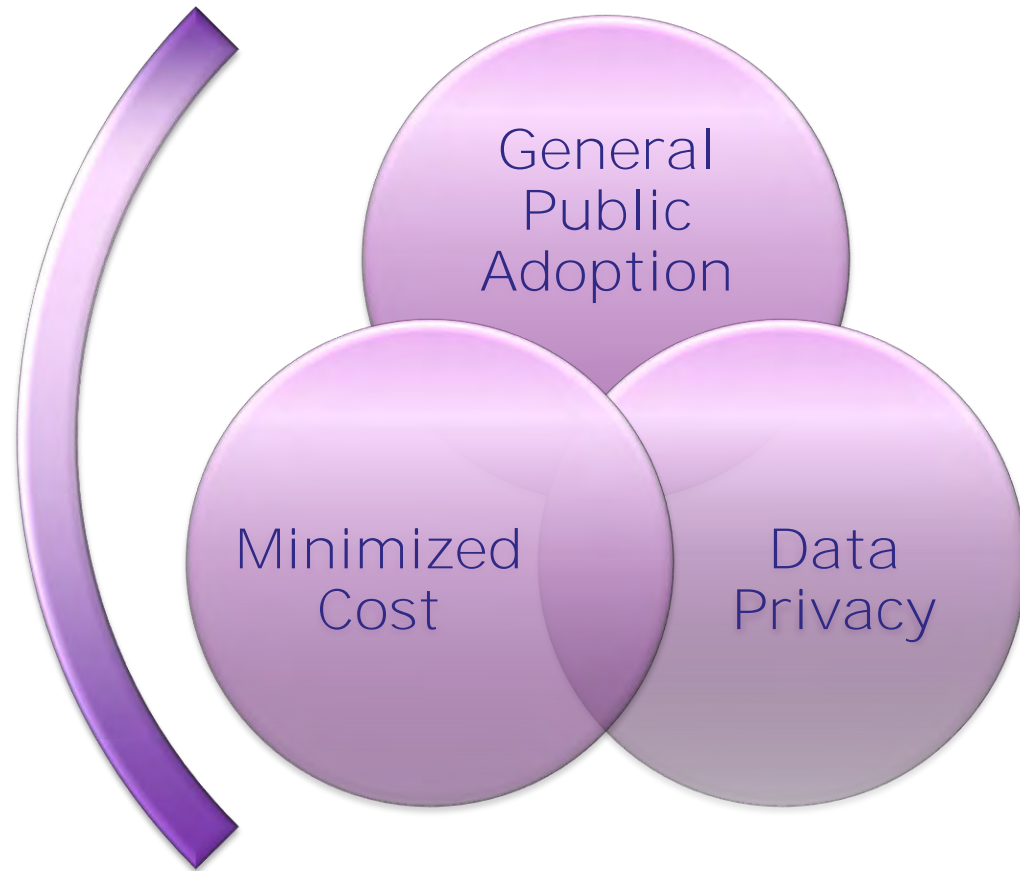


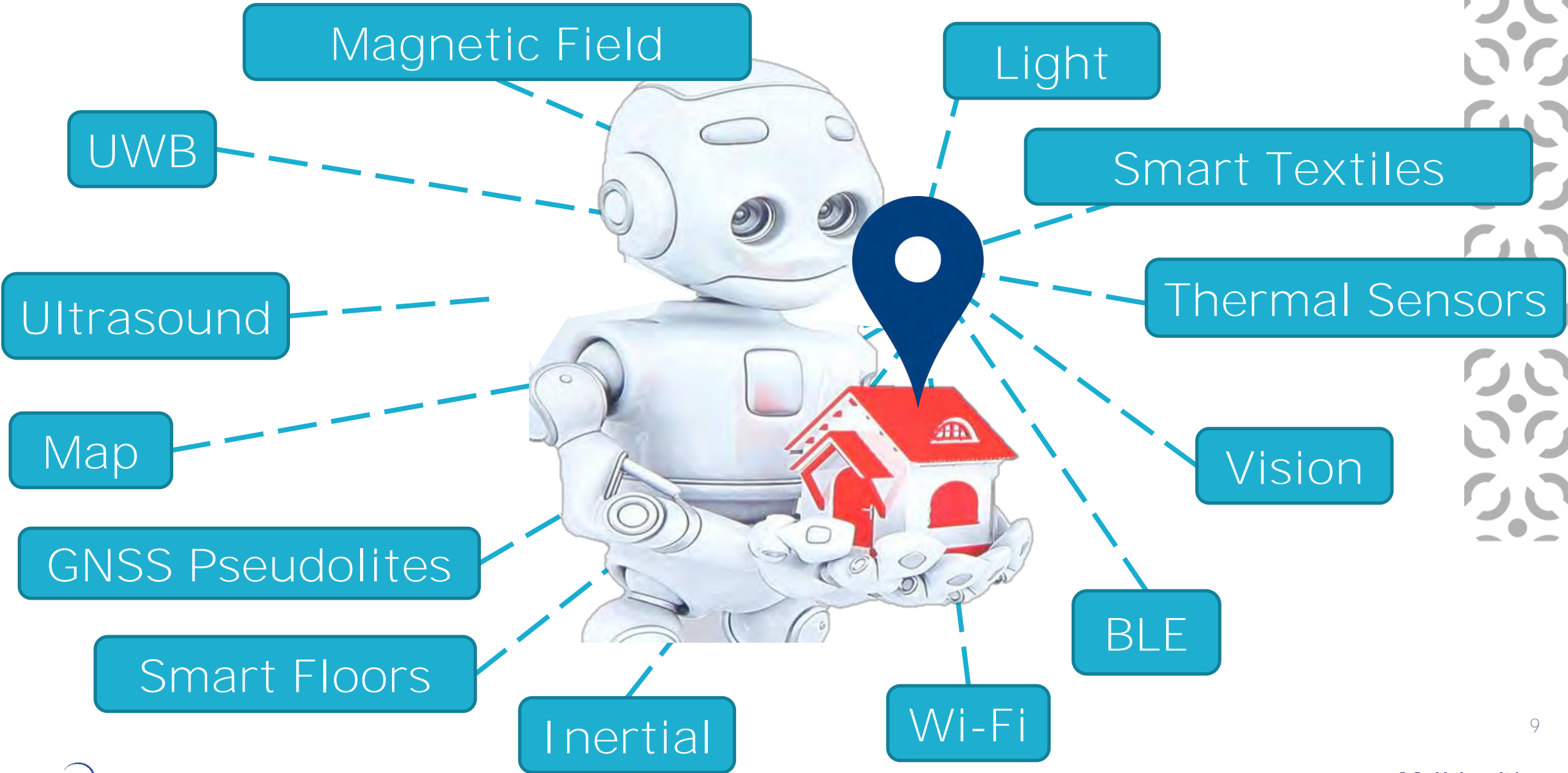
Vocal Assistant

Application Fields



Social Context







self-contained technique

indoor infrastructure equipment

Indoor infrastructure equipment

Radio-propagation
(WiFi, UWB, BLE, RFID)

Magnetic prints

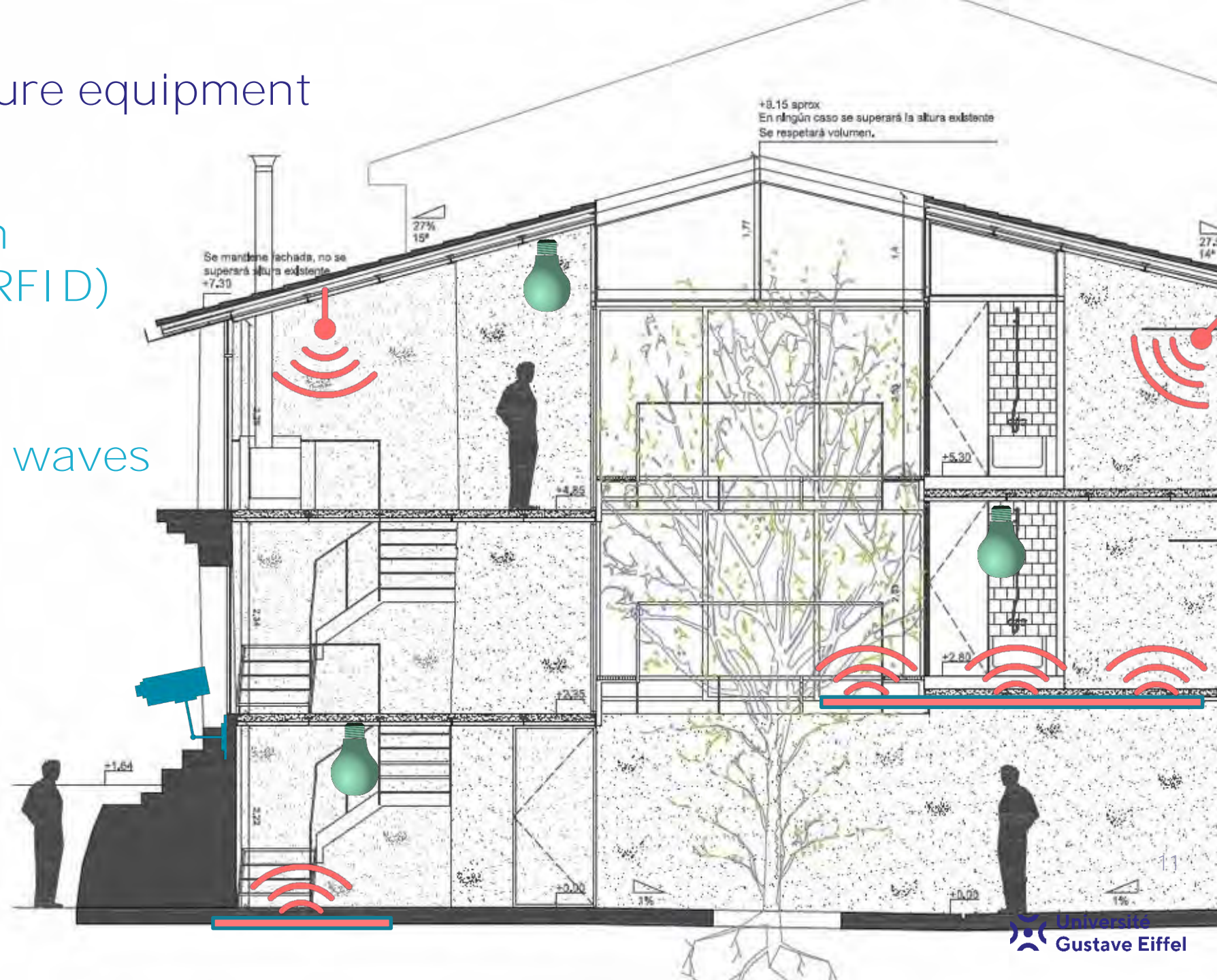
Ultrasound, sound waves

Vision, camera

Light

Thermal sensors

Smart floors



Self-contained technique

Vision (VO, AR)

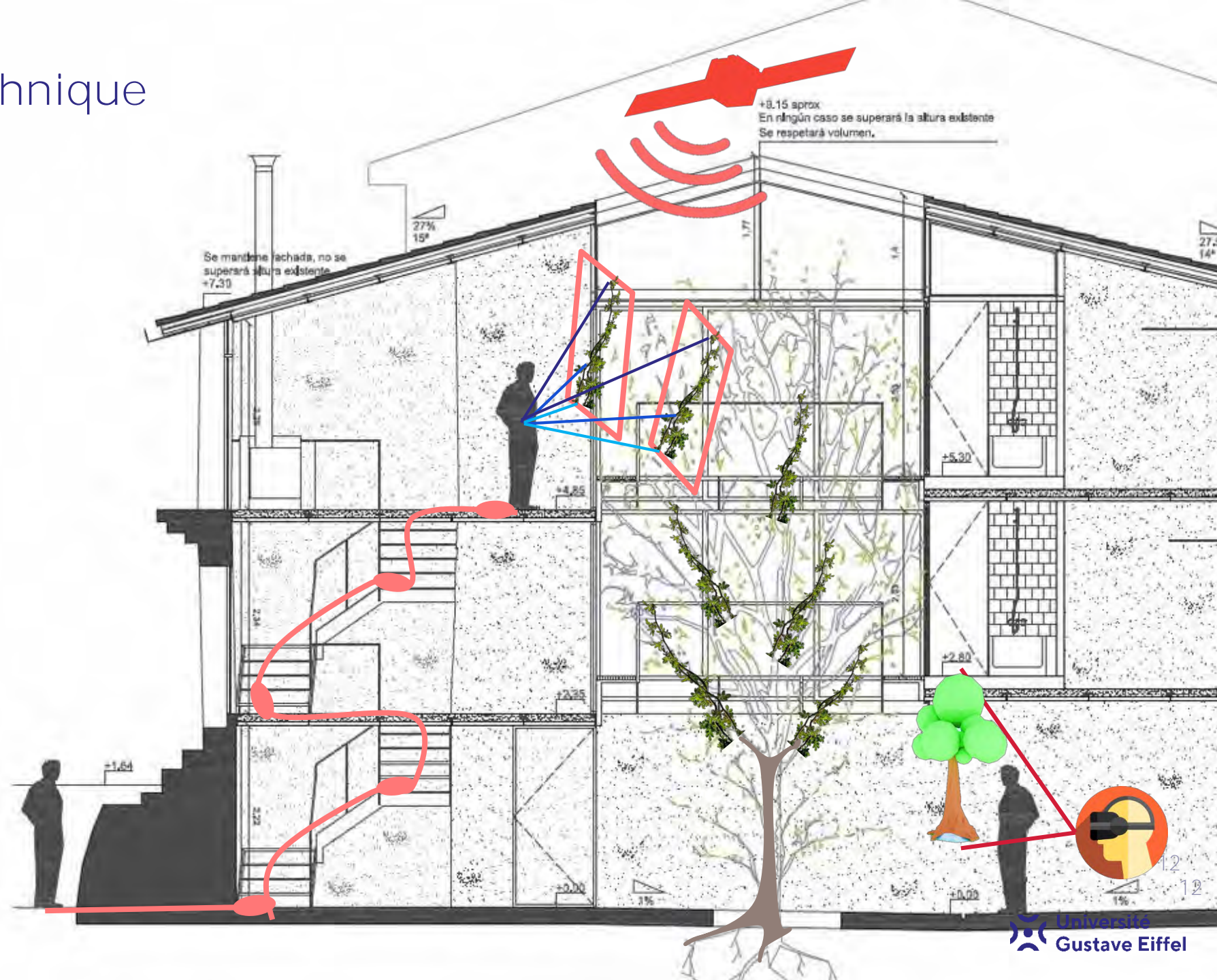
Inertial sensors

Magnetic field

GNSS

Smart textiles

NB IOT - 5G





POSITIONING ALGORITHMS: MULTIPLE STRATEGIES

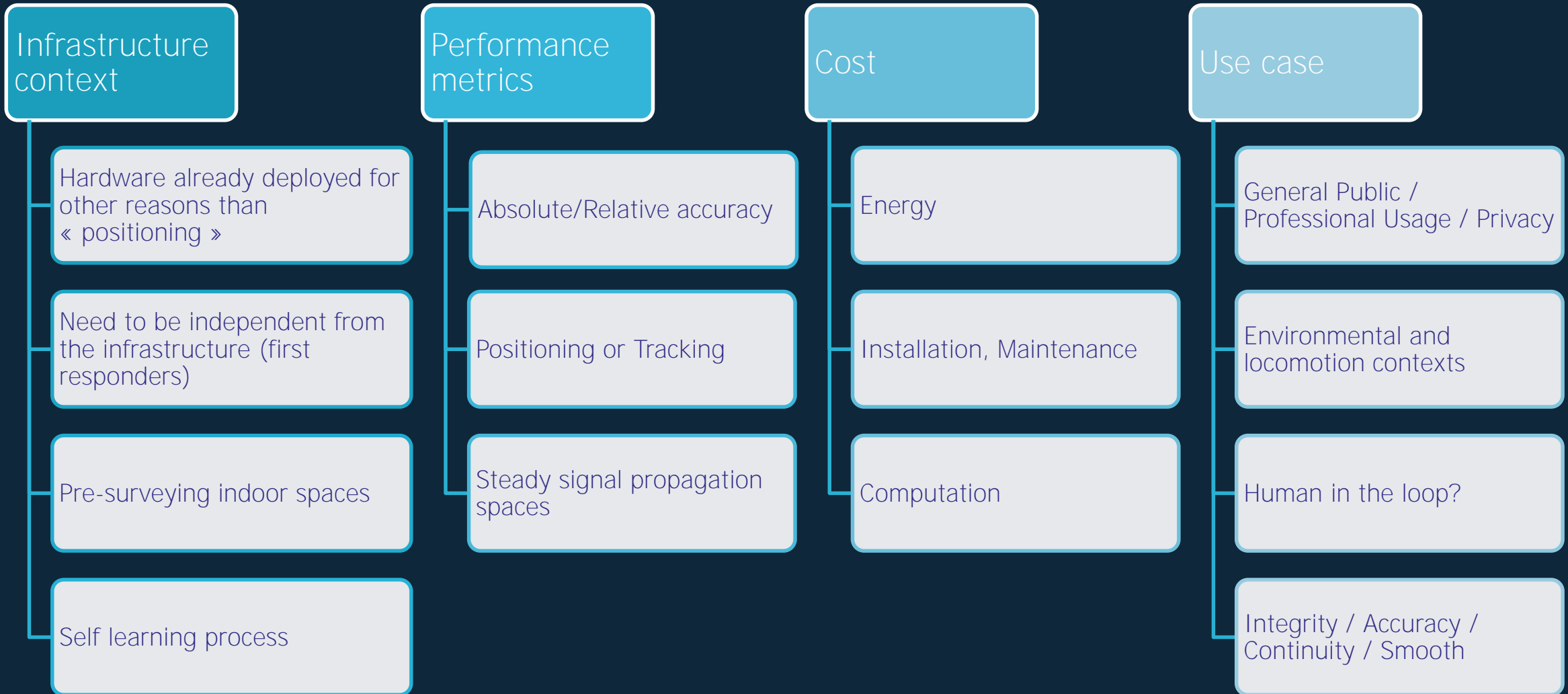
Despite decades of research, no universal solution has been adopted indoors

Seamless, ubiquitous and accurate positioning means sensor fusion

Difficulties to integrate all technologies. How to choose?

Sensor fusion is the key!

A question of criteria?



Main sensor fusion strategies

Linear Quadratic Estimation

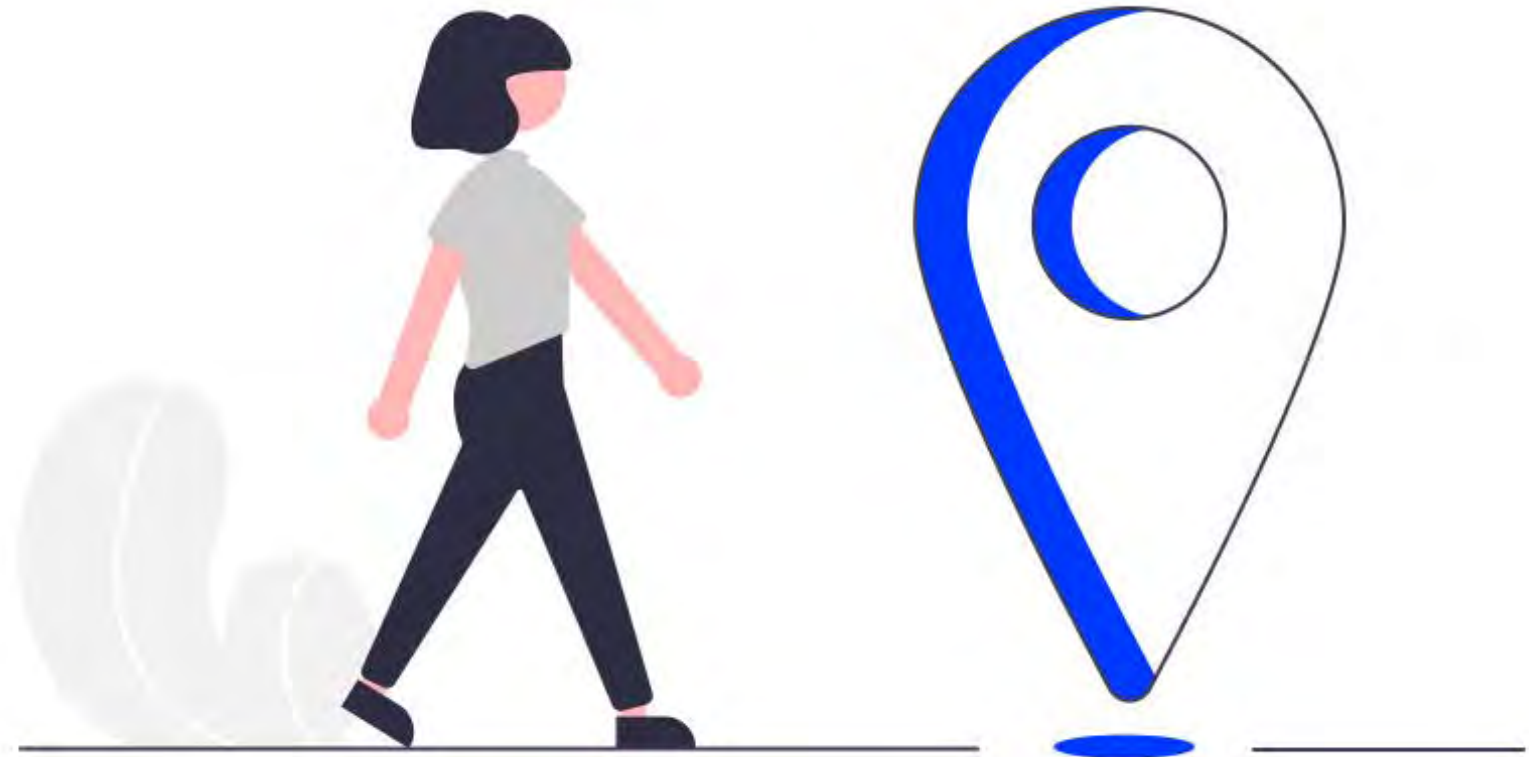
- Kalman **Filters**, ...
- Minimization of the quadratic error
- Suitable for real time processing approach
- Mature and easy to implement
- Not suitable for integrating spatial constraints

Sequential Monte Carlo

- Particle Filter, ...
- Non-linear state-space modelling by particles clouds corresponding to distribution
- Easy integration of spatial and movement constraints
- Significant computation costs

Learning Methods

- Neural network, Decision tree, Clustering, Dimension **reduction**, **LSTM**, ...
- Native approaches to classify / recognize context
- Require large amounts of data
- How to control data quality? Supervised/Unsupervised?



TESTING IN REAL LIFE CONDITIONS: A NECESSITY!

Renaudin V, Ortiz M, Perul J and al (2019), *"Evaluating Indoor Positioning Systems in a Shopping Mall: The Lessons Learned From the IPIN 2018 Competition"*, IEEE ACCESS, pp.148594-148628. Institute of Electrical and Electronics Engineers -- IEEE.

Potorti F, Park S, Crivello A, Palumbo F, Girolami M, Barsocchi P, Lee S, Torres-Sospedra J, Jimenez AR, Perez-Navarro A, Mendoza-Silva GM, Seco F, Ortiz M, Perul J, Renaudin V, and al., *"The IPIN 2019 Indoor Localisation Competition -Description and Results"*, IEEE Access, November, 2020, 47p. Institute of Electrical and Electronics Engineers (IEEE).

Indoor Positioning Challenge organized by the ANR and DGA in France

DGA and ANR launched the challenge MAîtrise de la Localisation Indoor (MALIN)



indoor positioning in non collaborative environment

Objectives

- compare different architectures enabling the positioning of persons in complex environments such as buildings or undergrounds in the absence or partial availability of GNSS signals
- support innovation in the domain of autonomous positioning of soldiers and emergency response officers
- address the issue of Indoor-Outdoor transitions



CHALLENGE

MALIN



2

Funding Bodies
(ANR, DGA)



6

Teams

3

Competitions

2

Scenarios
(Reference,
Evaluation)

CYBORGLOC



LOCA 3D



SMART-ILOC



RIVOLI



POUCET



TMI-REDY

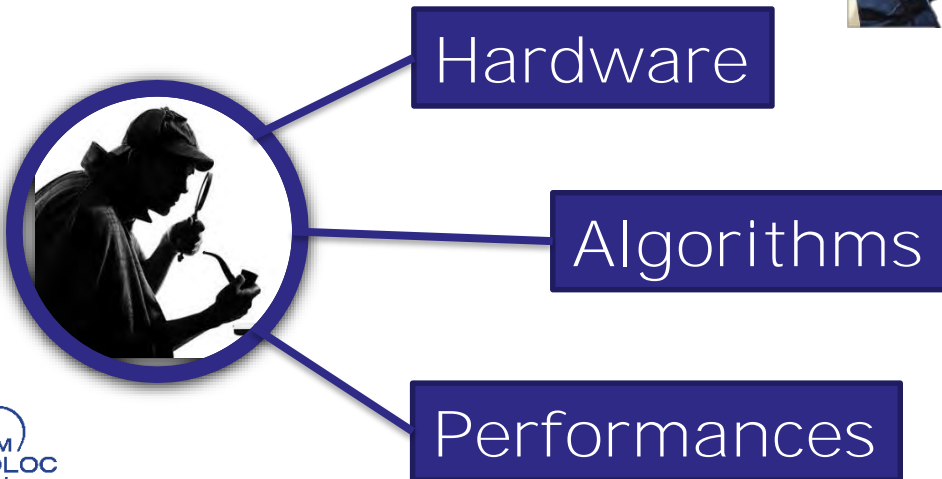
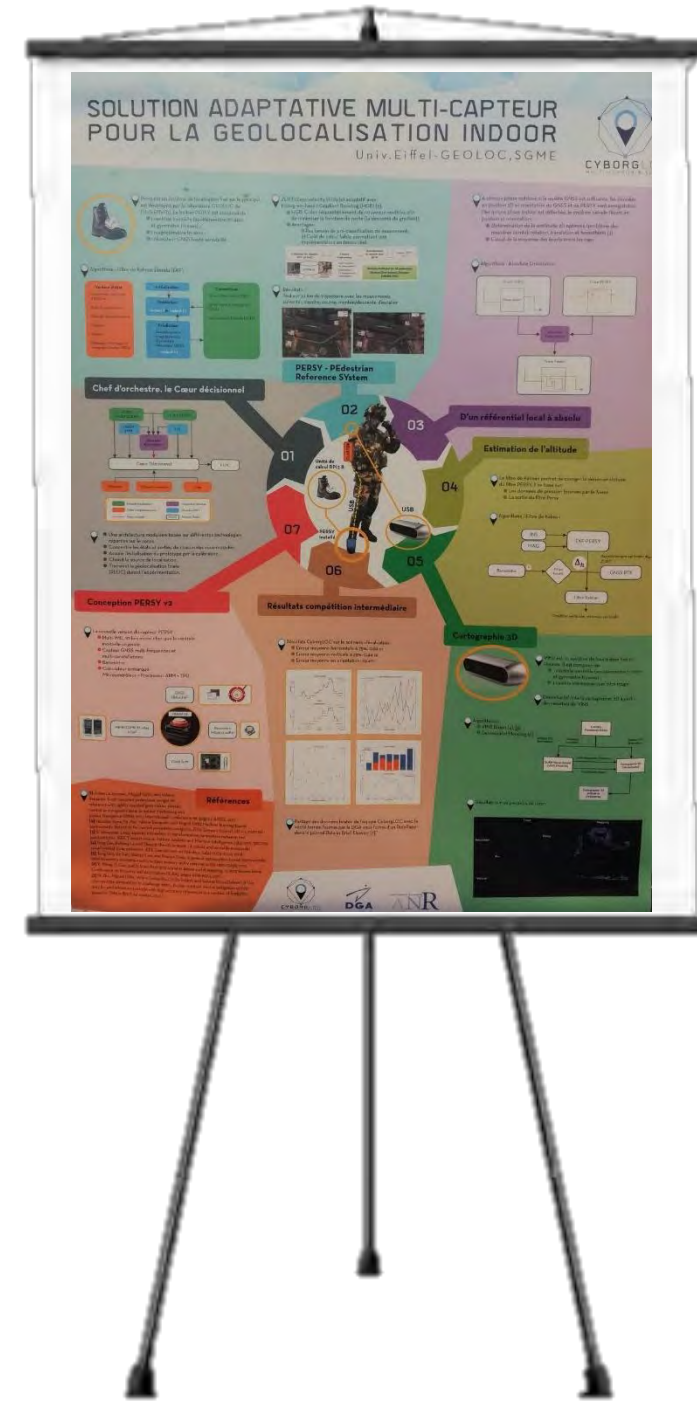


TEAM CYBORGLOC



Technologies

- For the positioning
 - Foot mounted inertial, magnetic field sensors
 - Barometer and GNSS on the torso
- For mapping
 - Camera on the shoulder



CYBORGLOC: Hardware

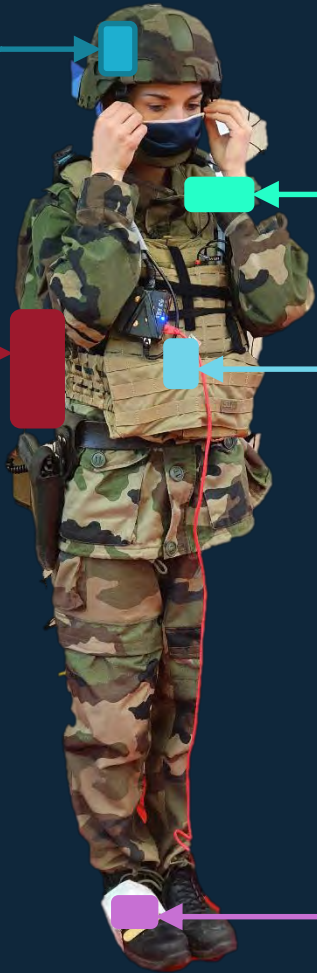
GNSS M8N

Computing cluster

Stereo camera/
inertial
Realsense
D435i

Barometer

PERSY



Components and characteristics	
Weight	< 300 g
Gyroscope drift	0,5 %/h
Accuracy of the estimated trajectory (% of the distance travelled)	0,3 %
STIM300 (Sensoror)	
Sampling Frequency	160 Hz
Triaxial accelerometer	
Triaxial gyroscope	
HMC5983 (Honeywell)	
Sampling Frequency	160 Hz
Triaxial magnetometer	
NEO-M8T (Ublox)	
Single-frequency, dual-constellation GNSS receiver	5 Hz
SD card	
Battery	
Battery life	4 hours

Positioning algorithms: a classical strapdown inertial navigation approach

Evolution of the velocity ($\dot{\mathbf{x}}$) of the mobile in time

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

Evolution of the position (\mathbf{x}) of the mobile in time

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

With only an accelerometer bias error modeling

$$\ddot{\mathbf{x}} = \mathbf{f} - \mathbf{g} - \mathbf{b}_f + \mathbf{w}_f$$

\mathbf{g} is known in the local geographical frame and \mathbf{f} is measured in the inertial sensors frame → How to estimate the orientation ?

Positioning algorithms: estimating the orientation with quaternions

Acceleration in the local frame

$$(0, \ddot{\mathbf{x}}^n) = \mathbf{q}_b^n \circ (0, \ddot{\mathbf{x}}^b) \circ \bar{\mathbf{q}}_b^n - (0, \mathbf{g}^n)$$

Evolution of the attitude angles quaternion

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

Relation between quaternion and angular rates

$$\mathbf{q}_\omega^b(t) = \begin{pmatrix} \cos\left(\frac{\|\boldsymbol{\omega}_{nb}^b\| \Delta t}{2}\right) \\ \sin\left(\frac{\|\boldsymbol{\omega}_{nb}^b\| \Delta t}{2}\right) \frac{\boldsymbol{\omega}_{nb}^b \Delta t}{\|\boldsymbol{\omega}_{nb}^b \Delta t\|} \end{pmatrix} + \mathbf{w}_{q_\omega}^b$$

With only a gyroscope bias error modeling

$$\boldsymbol{\omega} = \boldsymbol{\omega} + \mathbf{b}_\omega + \mathbf{w}_\omega$$

Positioning algorithms: mitigating **gyroscopes'** error with magnetometer

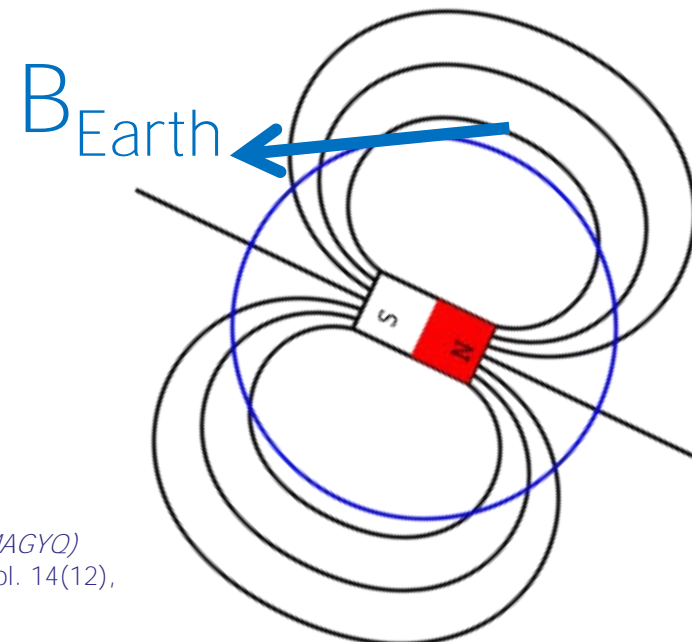
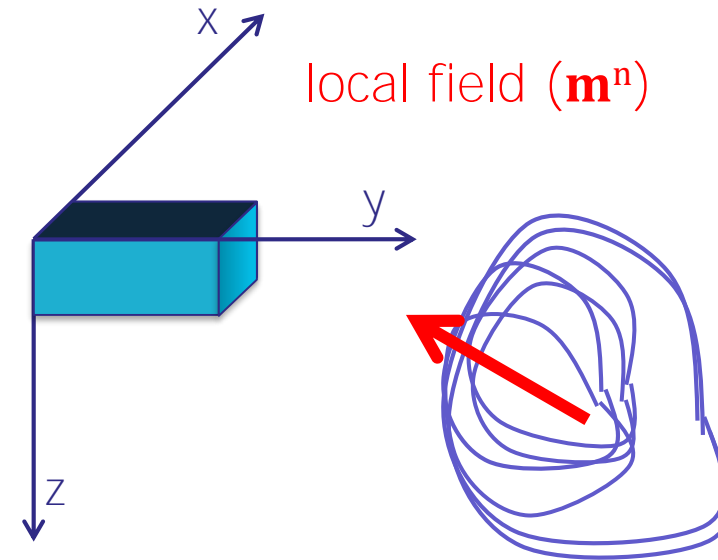
When the local magnetic field is static, even indoors, 2 corrections are possible

Quasi Static Field Update

All measured magnetic field in the local map frame are the same

Magnetic Angular Rate Update

Quaternions derived from the magnetic and gyroscope angular rates over a same period are the same



Positioning algorithms: mitigating the propagation of accelerometer errors

Biomechanics features in walking gait captured by foot mounted

Main principle: during the stance phase, the foot velocity equals zero

$$\dot{\mathbf{x}}^n = \mathbf{0}$$



Zero Velocity Update

Observation Equations: δ is the perturbation of the state

$$\begin{bmatrix} 0 \\ \delta \dot{\mathbf{x}}^n \end{bmatrix} = \mathbf{q}_b^n \circ [0 \quad (\mathbf{f}^n - \mathbf{b}_f^n)^T]^T \circ (\mathbf{q}_b^n)^{-1} \delta t + \begin{bmatrix} 0 \\ \mathbf{g}^n \end{bmatrix} \delta t$$

$$\begin{bmatrix} 0 \\ \delta \mathbf{x}^n \end{bmatrix} = \dot{\mathbf{x}}^n \delta t + \frac{\mathbf{q}_b^n}{2} \circ [0 \quad (\mathbf{f}^n - \mathbf{b}_f^n)^T]^T \circ (\mathbf{q}_b^n)^{-1} \delta t^2 + \begin{bmatrix} 0 \\ \mathbf{g}^n \end{bmatrix} \delta t^2$$

Positioning algorithms: correctly detecting zero velocity instants

Main principals of zero velocity detectors

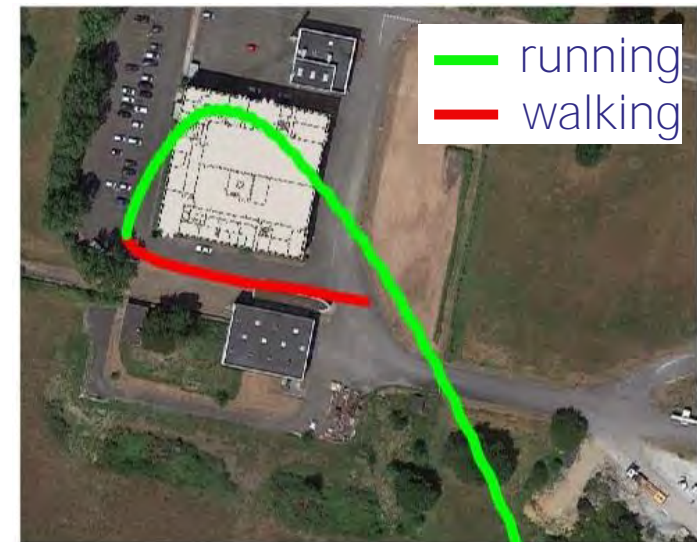
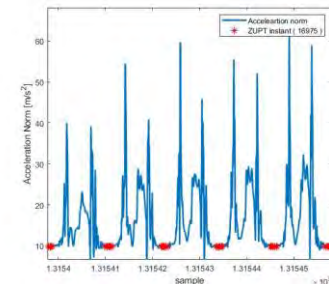
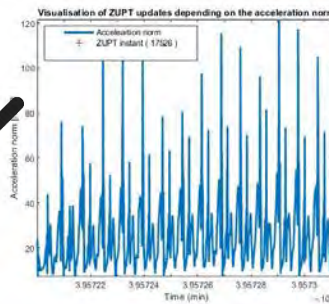
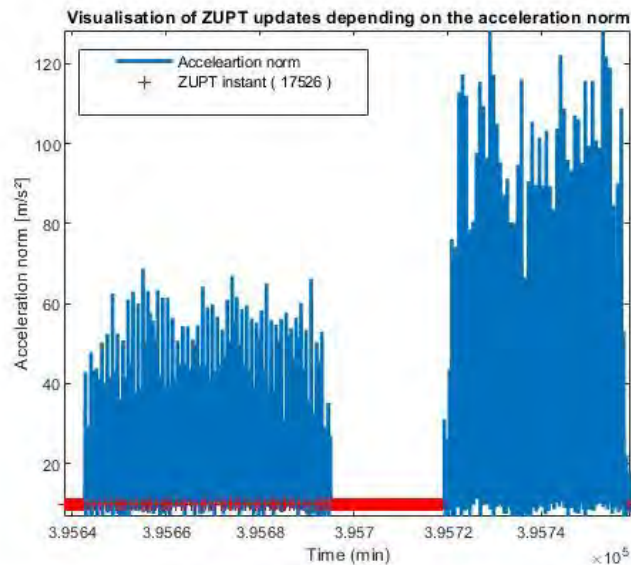
Use of activity thresholds

Adopt time windows based analysis for real time application

Process signals statistics: variance, norm, frequency components, etc.

Problems

How to fix all thresholds? How to adapt to different motions/humans? Which window sizes?

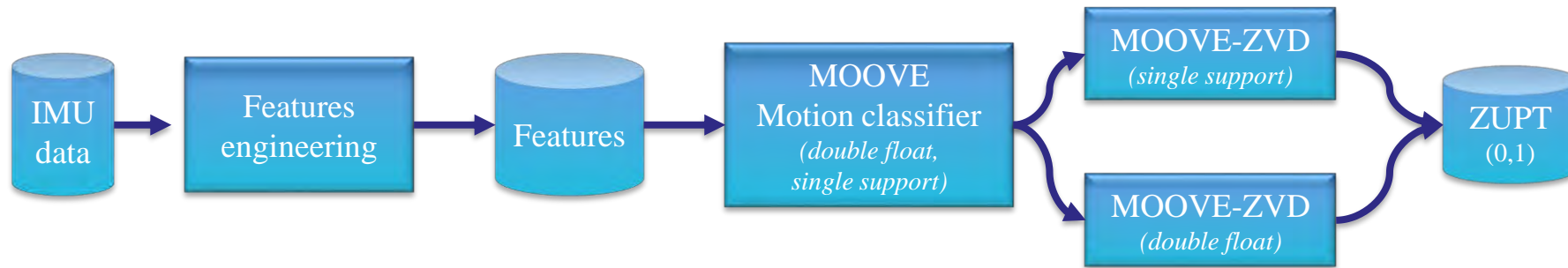


Positioning algorithms: correctly detecting zero velocity instants

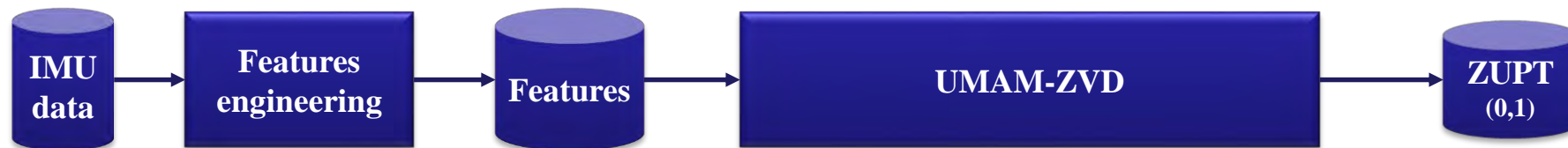
Adopting machine learning to detect a large variety of human dynamics

Creation of 2 models using hist gradient boosting approach

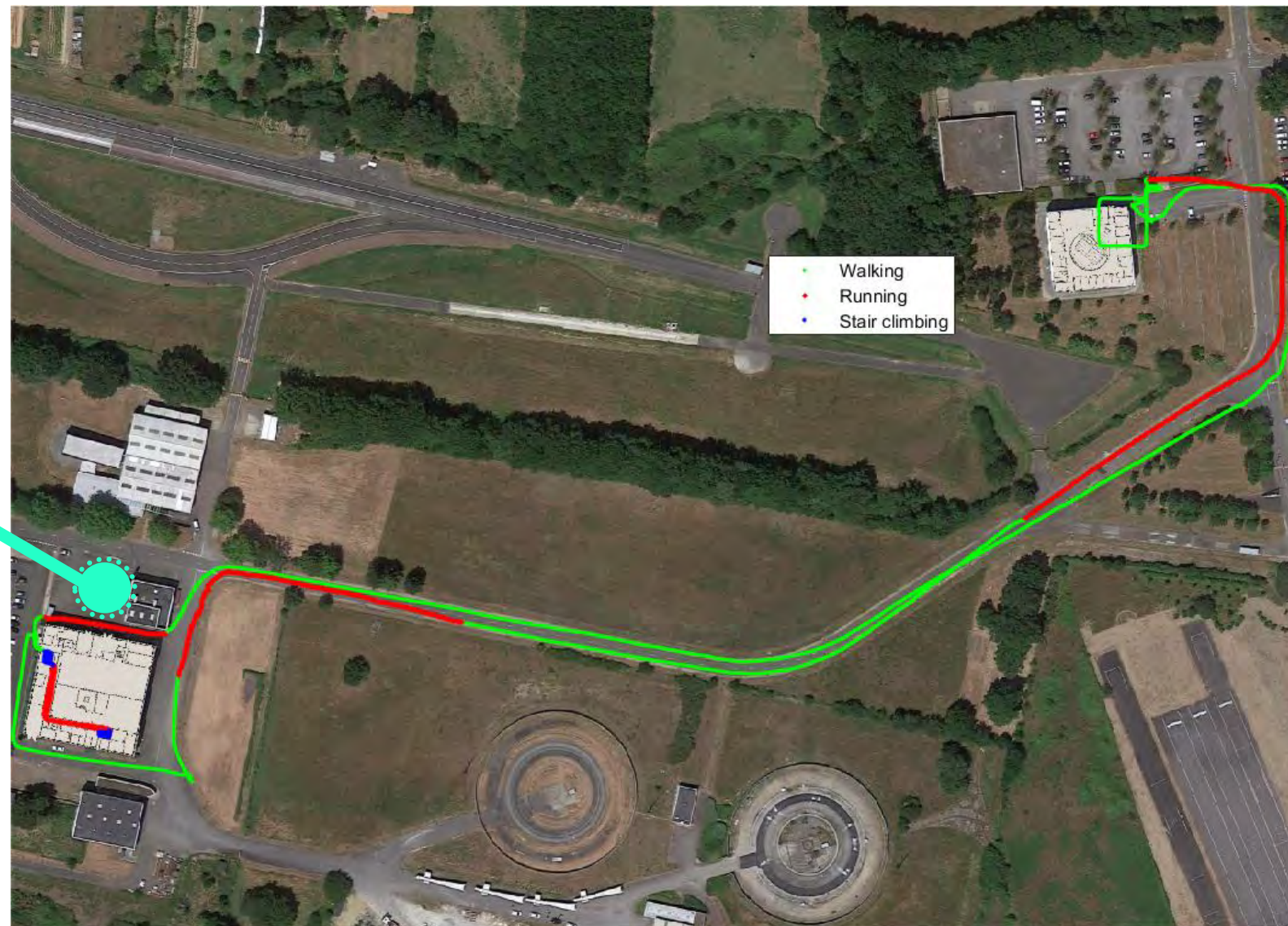
Mixed AI models with movement pre-classification (MOOVE)



Uniform AI Model for All pedestrian Motions (UMAM)



Positioning algorithms: correctly detecting zero velocity instants



Positioning algorithms: 2 complementary filters

Altitude filter

- Use of barometer data to correct the estimated altitude:

T_{ref} , P_{ref} temperature and pression of reference, h_t is the altitude at time t

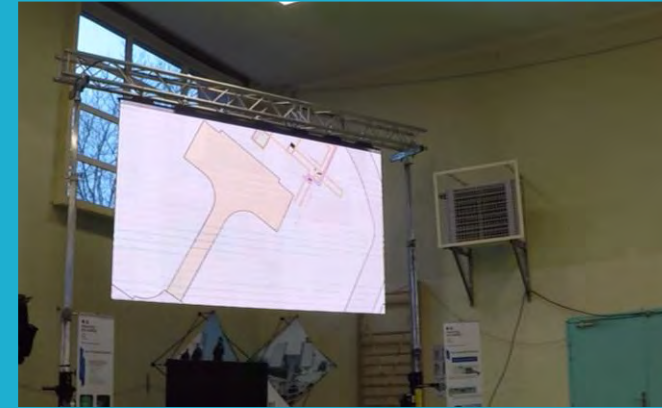
L, R and g_0 are fixed variables

$$\delta h_t^n = -\frac{T_{ref}}{L} \left(1 - \left(\frac{P}{P_{ref}} \right)^{\frac{-LR}{g_0}} \right) - h_{t_0 t}^n$$

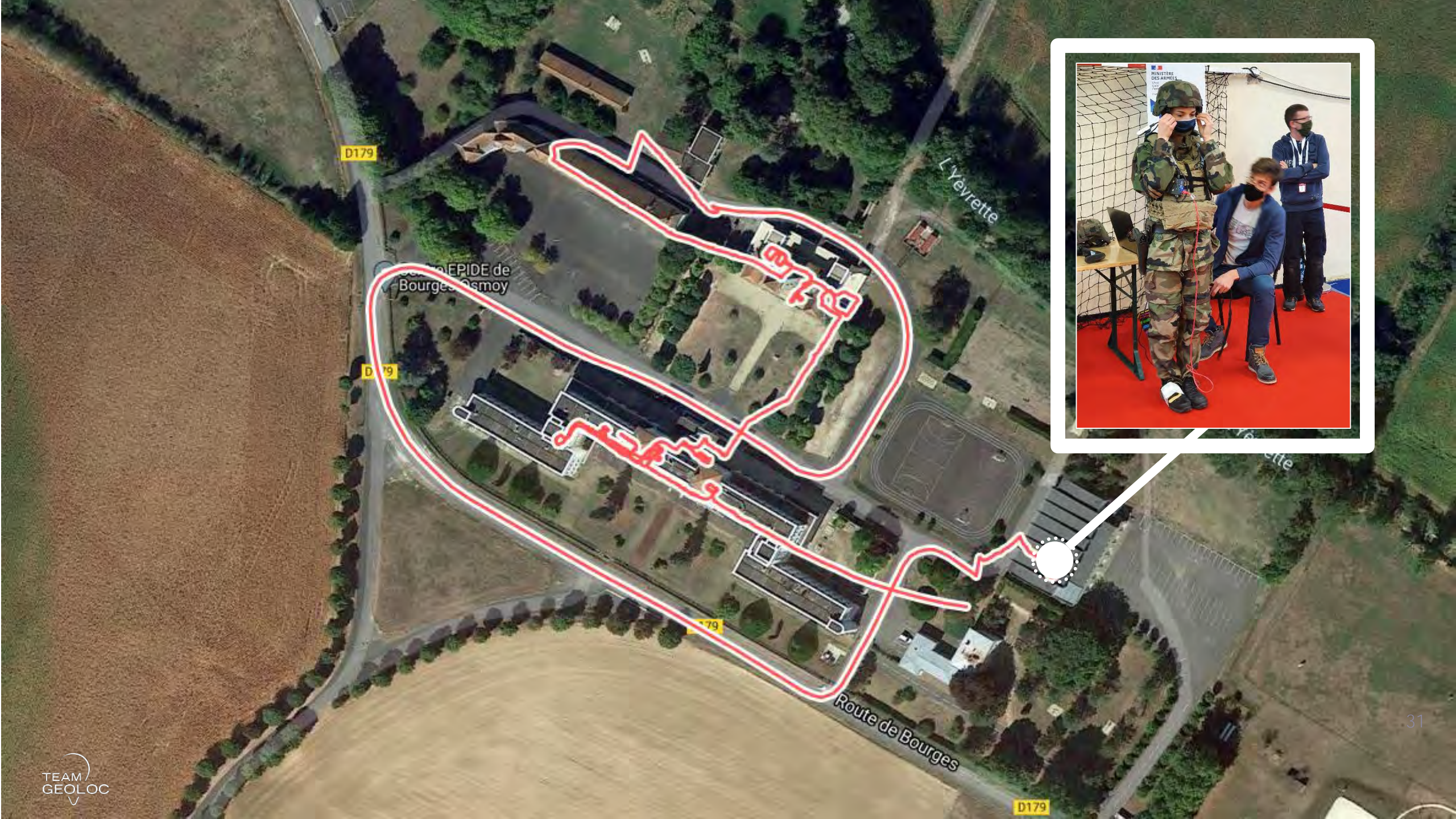
Rotation/Translation filter

- To mitigate misalignment issues between the inertial unit mounted on the foot and the walking direction (Rotation, Translation)
- Estimation of optimal 2D similarity between a track estimated by GPS signals and the track estimated by inertial and magnetic field signals
- Loose coupling introduces potential issues related to Non Line of Sight signals → Tight coupling

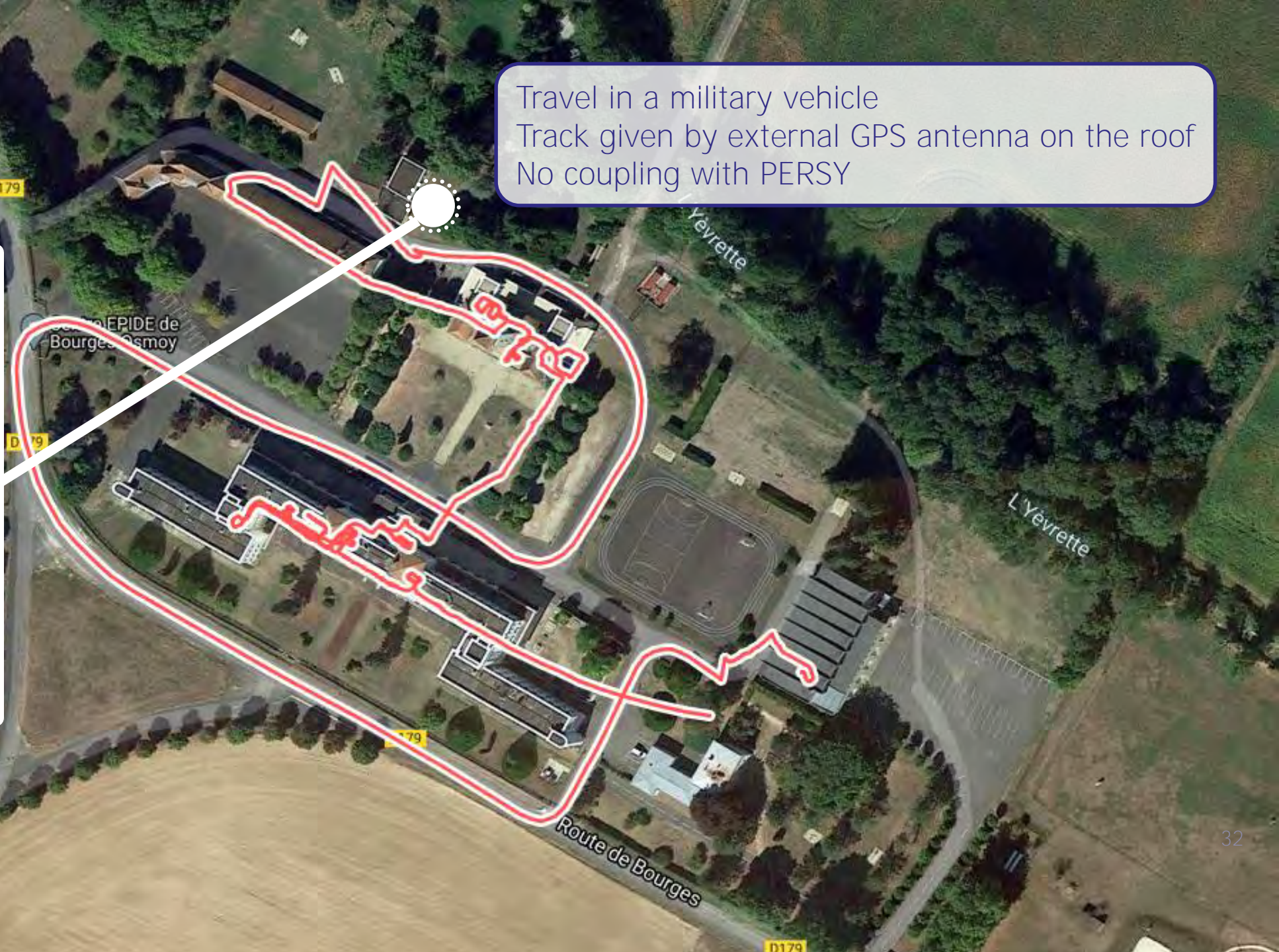




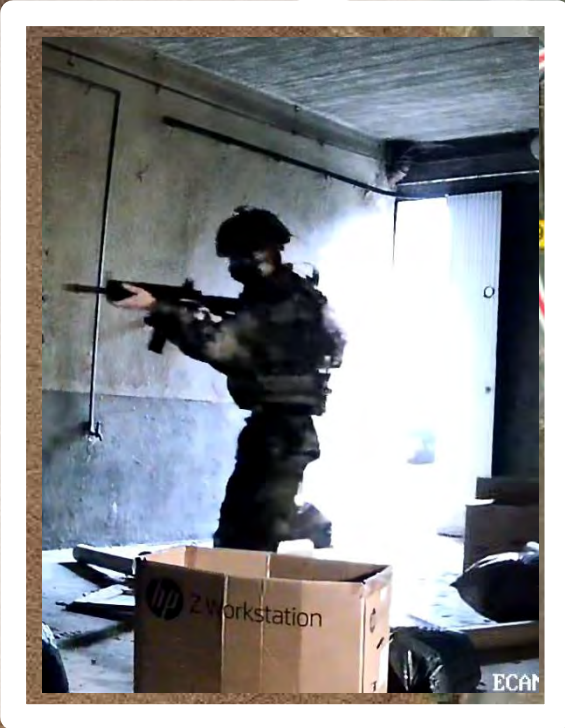
THURSDAY 27: EVALUATION SCENARIO
WITH REAL TIME DISPLAY OF THE TRACK ON A LARGE SCREEN

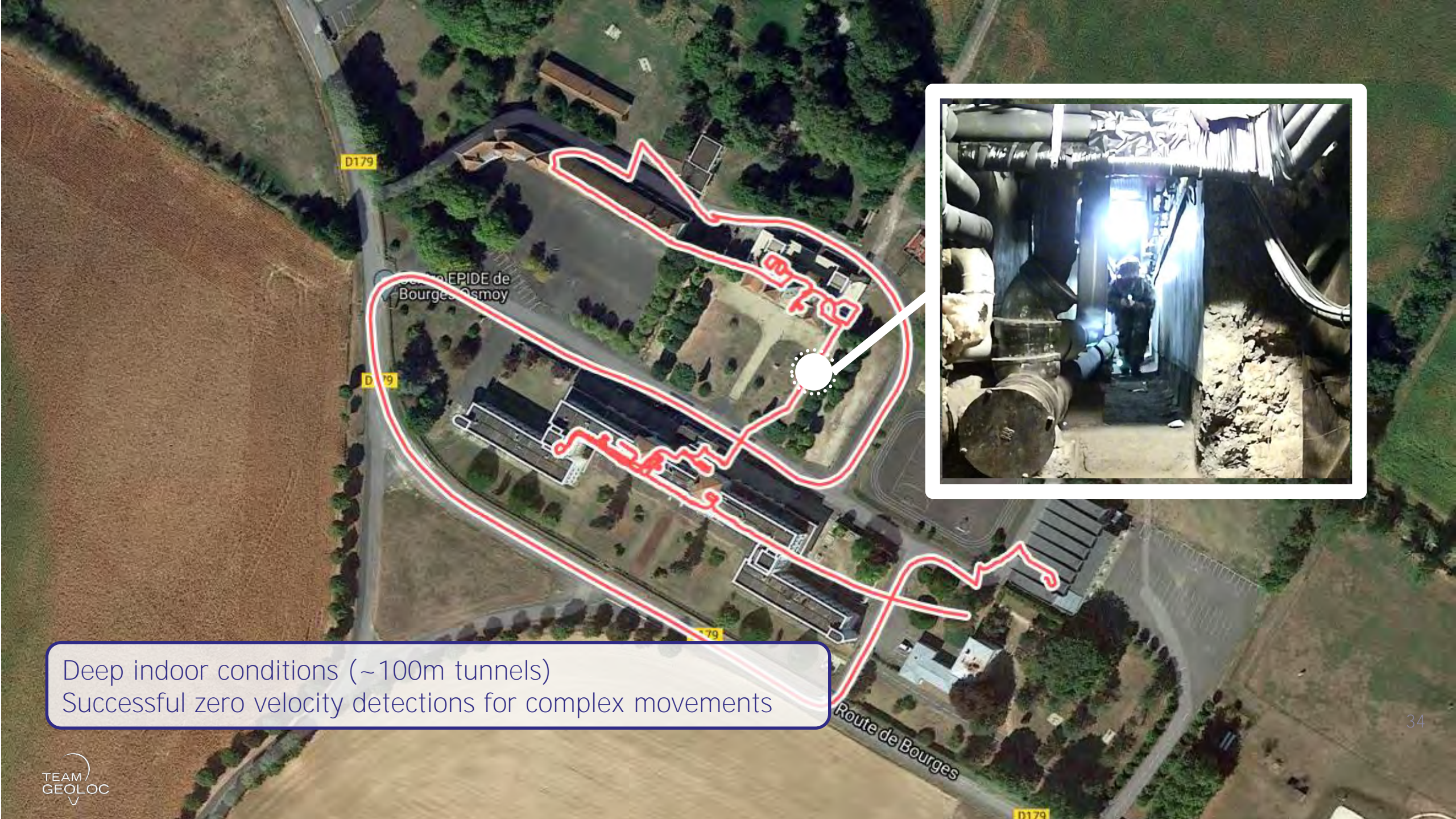


Travel in a military vehicle
Track given by external GPS antenna on the roof
No coupling with PERSY

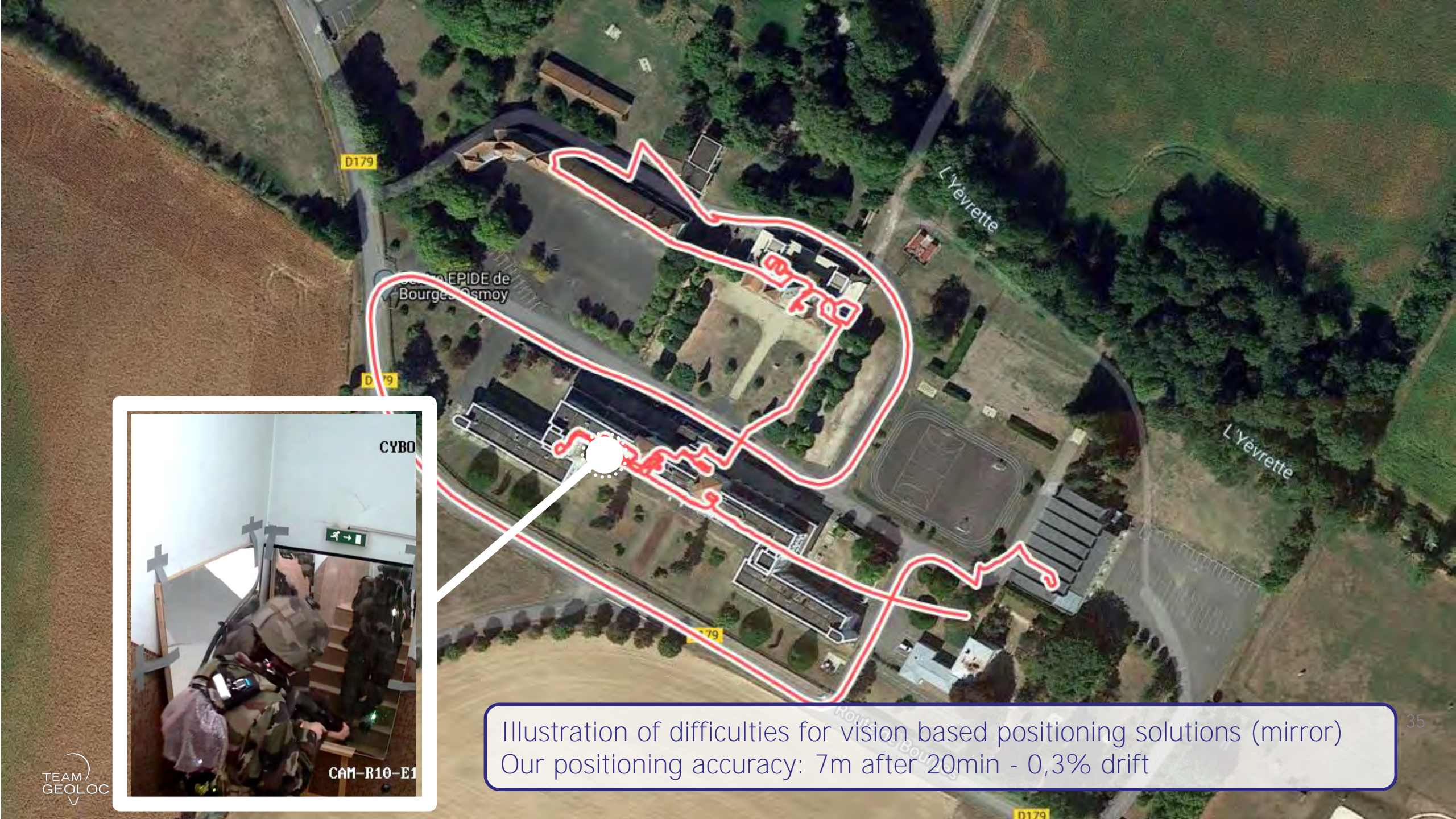


Entering into the building
Rotation/Translation correction with GPS outdoor
3m positioning error





Deep indoor conditions (~100m tunnels)
Successful zero velocity detections for complex movements



D179

EPIDE de
Bourges Osmoy

L'Yevrette

L'Yevrette

D179

D179



CYBO

CAM-R10-E1

Illustration of difficulties for vision based positioning solutions (mirror)
Our positioning accuracy: 7m after 20min - 0,3% drift

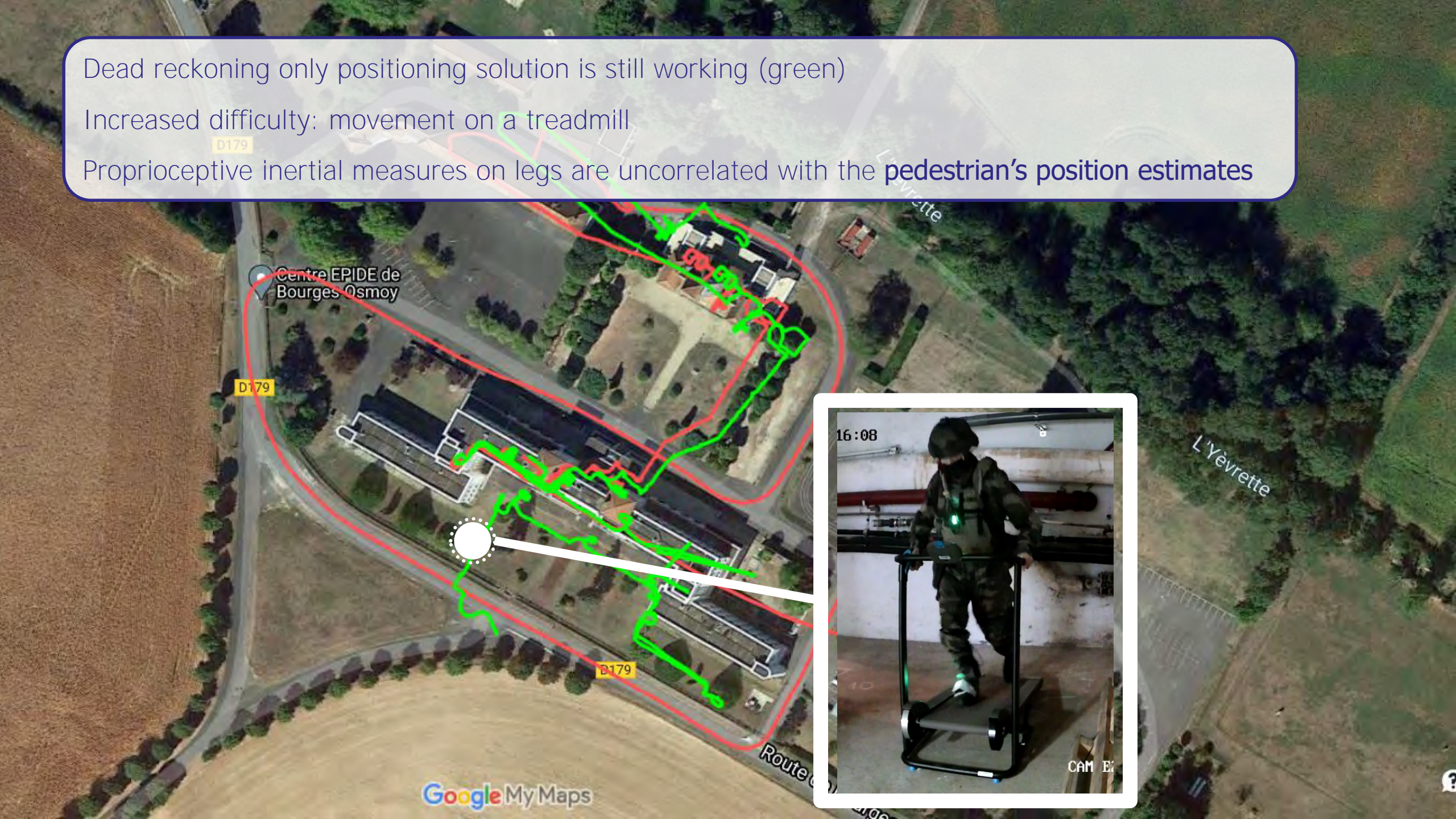
No zero velocity period detected during crawling
Motion not learned in the machine learning models
Coordinates estimation stopped intentionally (outliers)!



Dead reckoning only positioning solution is still working (green)

Increased difficulty: movement on a treadmill

Proprioceptive inertial measures on legs are uncorrelated with the pedestrian's position estimates



TO CONCLUDE: SOME KEY FIGURES OF OUR ACHIEVEMENT IN SHORT

2.5
km

Total traveled distance
(without the vehicle part)

45
min

Duration

4
levels

3 floors &
1 underground

9
mvt

waling, running, stairs
climbing/backward descending,
crawling, ladder, side stepping,
treadmill, tour on itself

0.3 % positioning error over the total traveled distance >> Well above state of the art performances, especially in harsh conditions

Classical indoor positioning performance of dead reckoning 1 - 0.5%, evaluated on short distances (~100 m), simple movements

Inertial, magnetometers and barometers positioning solutions are found to be more robust than vision based solutions

Artificial intelligence implemented in real-time has successfully enabled the integration of a wide variety of human gait movements → Understanding the physics is key!

Our solution was in the top 2 of the final competition (the most challenging one)!

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