2025-04-03

Webinaire 3D MAGIS

Caractérisation de la vue des satellites par modèle 3D ou image Street View pour améliorer le positionnement en mobilité douce

Projet ANR-23-CE22-0004 ReSilientGAIA

Benjamin BEAUCAMP, Post-doctorant, GEOLOC (Université Gustave Eiffel)
benjamin.beaucamp@univ-eiffel.fr

Université Gustave Eiffel

Co-auteurs:
Thomas LEDUC, AAU-CRENAU (CNRS)
Myriam SERVIERES, AAU-CRENAU (École Centrale de Nantes)
Ni ZHU, GEOLOC (Université Gustave Eiffel)

Projet ANR ReSilientGAIA

RÉPUBLIQUE FRANÇAISE
Liberté
Égalité
Fraternité

ReSilientGAIA

anr agence nationale de la recherche
AU SERVICE DE LA SCIENCE

ReSilientGAIA - Reliable Positioning System for Soft Mobility Safety Enhancement with a Green AI Approach

Système de Positionnement Fiable pour Améliorer la Sécurité de la Mobilité Douce avec une Approche d'IA Verte

Project Investigator: Ni ZHU, Chargée de Recherche
Postdoc researcher: Benjamin Beaucamp
Laboratoire GEOLOC de l’Université Gustave Eiffel (campus Nantes)

Context

A transition towards **sustainable mobility**:

- The mobility transition strategy in Europe has shifted the way that people move in their daily life towards low-carbon emission solutions;
- A growing number of soft mobility modes are emerging in urban environments, reducing traffic jams, carbon emissions and urban noise.
- But soft mobility users are more vulnerable than other road users;
- Soft mobility with degraded perceptions: visually impaired people, autonomous bicycle sharing, etc.

It is necessary to develop a location system dedicated to soft mobility, with enhanced security and integrity.

Objectives (1/2)

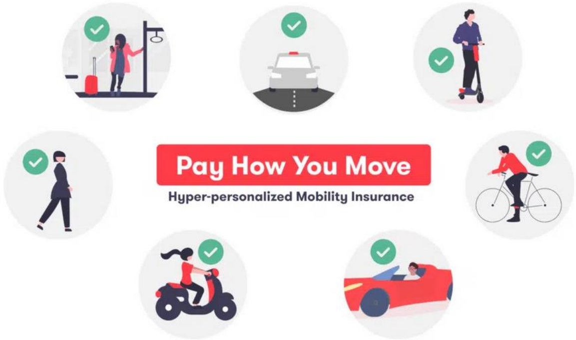
Add safety control in a new reliable positioning algorithm based on multisensory fusion for soft mobility users. Two new safety functionalities will be added to the location-based applications:

- Automatically detect, exclude or repair the faulty measurements from multi-sensors;
- Estimate an uncertainty indicator to bound the positioning errors. In case that the estimated positioning error bound is bigger than the minimum tolerable positioning errors, a timely warning alarm will be sent to the users.

Boost the potential of AI together with the traditional positioning integrity monitoring method.

Objectives (2/2)

- Improve the safety of vulnerable road users with a reliable positioning system
- Meet the requirements of the safety and reliability-critical location-based applications
- Enable the autonomous soft-mobility sharing system for the human-scale cities*



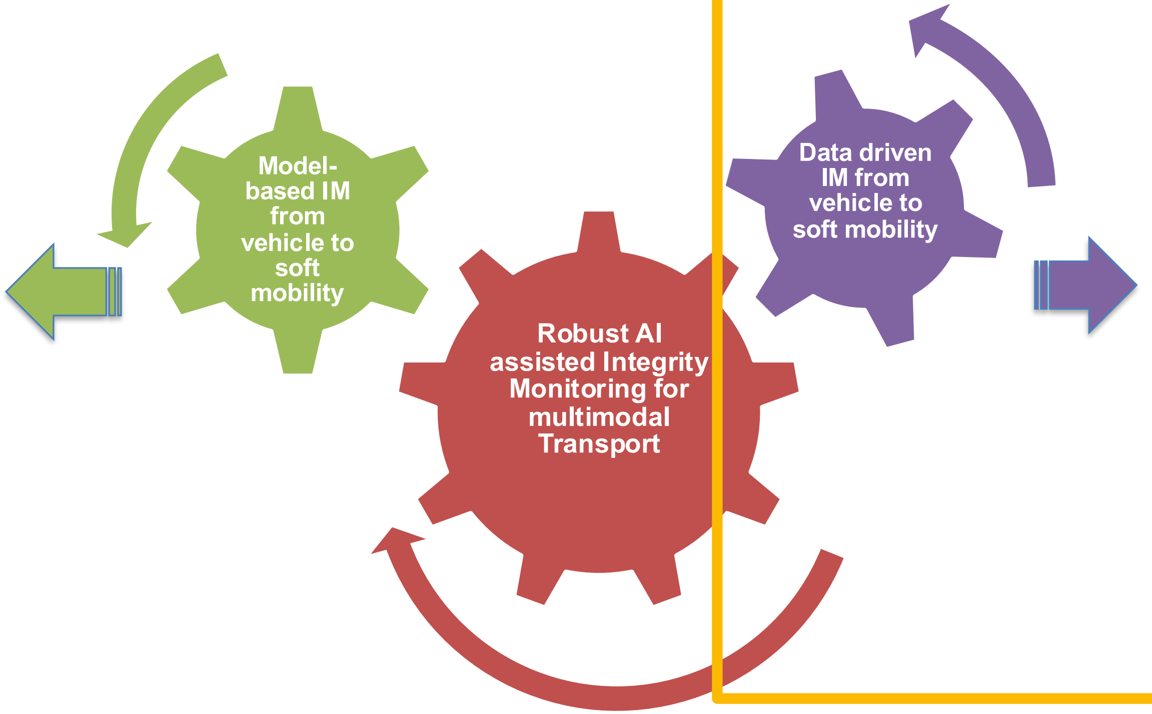
* Sanchez, N. C., Martinez, I., Pastor, L. A., & Larson, K. (2022). On the performance of shared autonomous bicycles: A simulation study. *Communications in Transportation Research*, *2*, 100066.

Université Gustave Eiffel

Methodologies (1/2)

Design an **AI-assisted** positioning **Integrity Monitoring (IM)** algorithm to enhance the accuracy and reliability of the multisensory positioning systems dedicated to soft mobility.

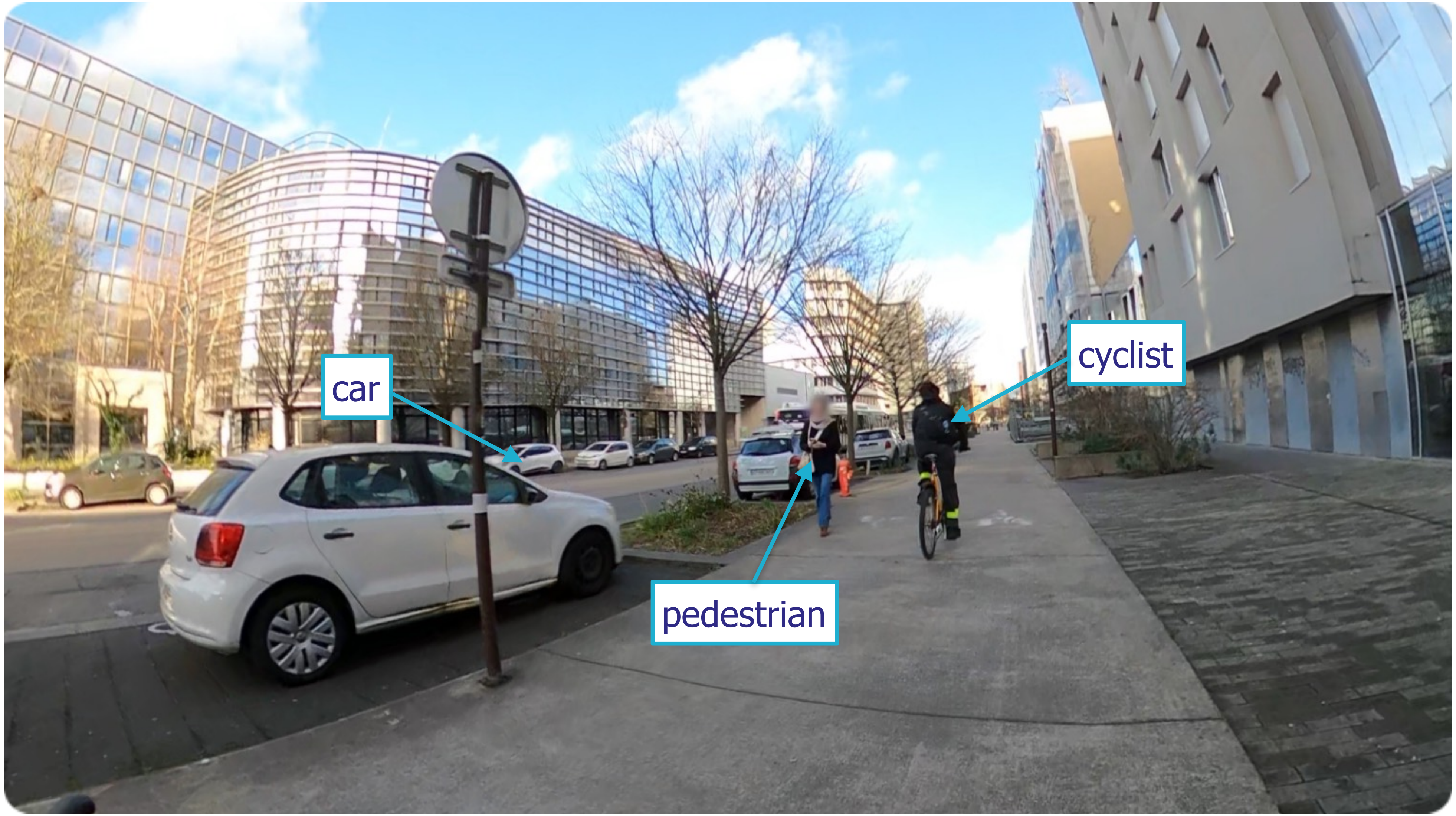
- Consistency check using redundancy of multisensor
- Measurement weighting in navigation filter
- Adaptive navigation filter



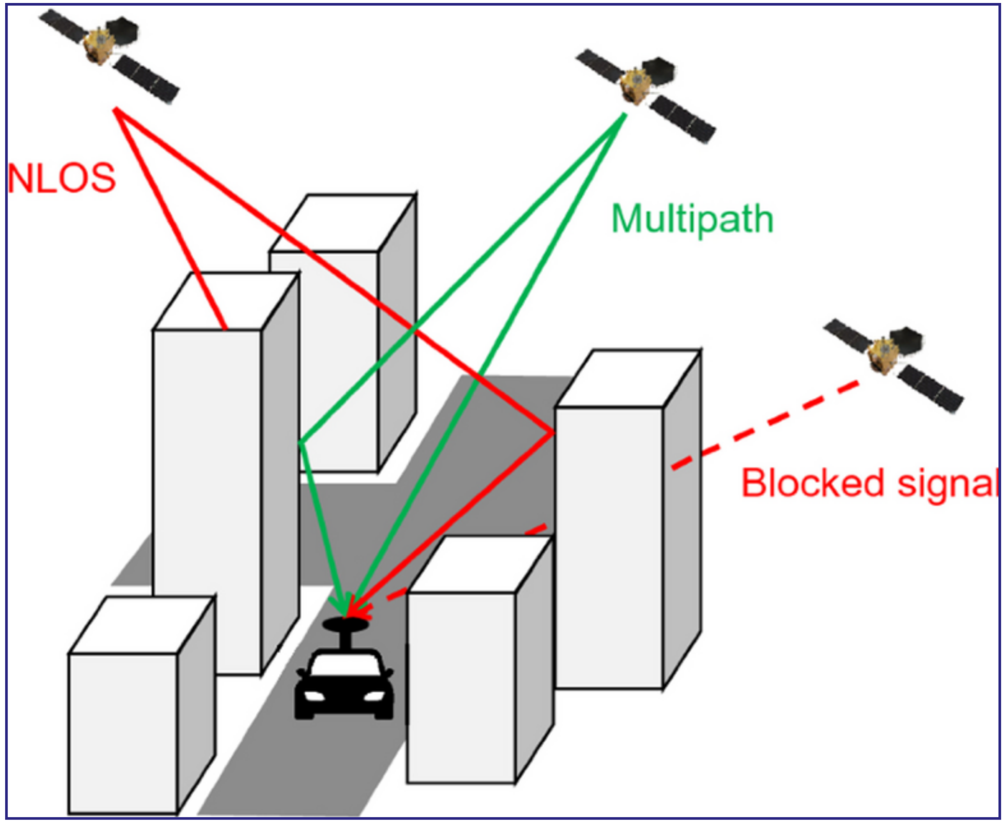
- Sensor measurement quality distinction: GNSS LOS / NLOS / Multipath, IMU noises / drift
- Environmental information aggregation to enhance AI model
- Cross-domain transfer learning

Satellite Positioning in Urban Environments

Satellite Positioning in Urban Environments



Satellite Visibility in Challenging Environments



Mohanty, A., Gao, G. A survey of machine learning techniques for improving Global Navigation Satellite Systems. EURASIP J. Adv. Signal Process. 2024, 73 (2024)

Satellite visibility identification:

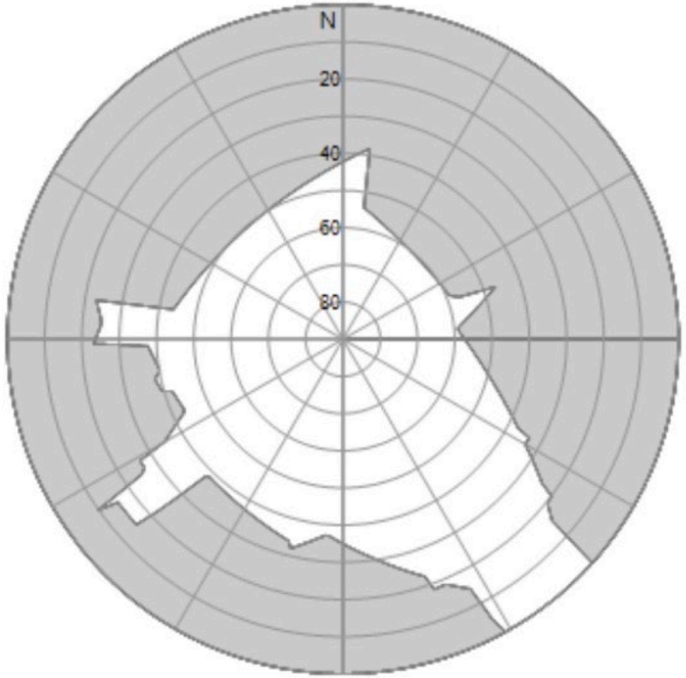
- Enhances Fault Detection and Exclusion (FDE)
- Enables pseudorange correction for the reflected signals [1]
- Enables position error estimation with Neural Networks [2]

→ High quality annotations are needed, to train ML models that can detect NLOS signals

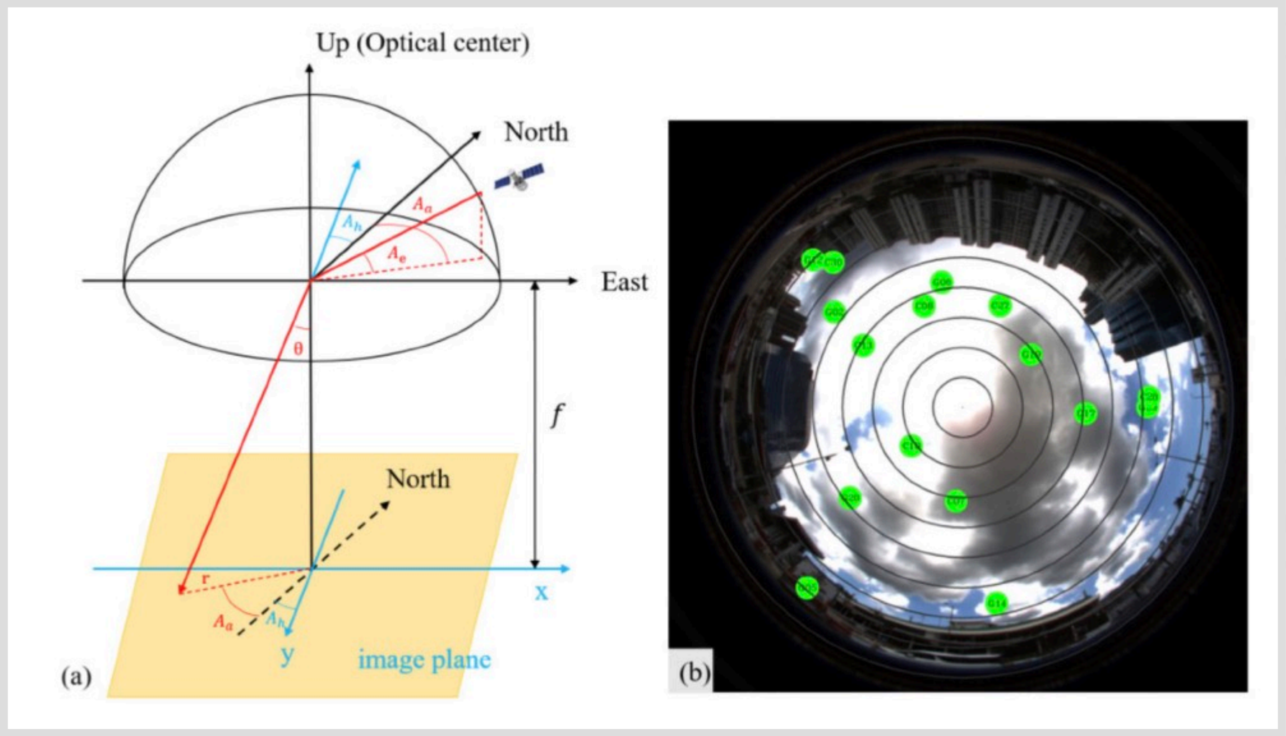
[1] R. Hu, W. Wen, and L. Hsu, "Fisheye Camera Aided GNSS NLOS Detection and Learning-Based Pseudorange Bias Correction for Intelligent Vehicles in Urban Canyons," in 2023 IEEE 26th International Conference on Intelligent Transportation Systems (ITSC), Sep. 2023, pp. 6088–6095. doi: 10.1109/ITSC57777.2023.10422540.
[2] G. Zhang, P. Xu, H. Xu, and L.-T. Hsu, "Prediction on the Urban GNSS Measurement Uncertainty Based on Deep Learning Networks With Long Short-Term Memory," IEEE Sensors J., vol. 21, no. 18, pp. 20563–20577, Sep. 2021, doi: 10.1109/JSEN.2021.3098006.

LOS/NLOS Annotation

3D model [3]



Sky View Image [4,1]



[3] H. F. Ng, G. Zhang, and L.-T. Hsu, “Range-based 3d mapping aided gnss with nlos correction based on skyplot with building boundaries,” in Proceedings of the ION 2019 Pacific PNT Meeting, 2019, pp. 737–751.

[4] Juliette Marais, Sébastien Ambellouis, Cyril Meurie, Julien Moreau, Amaury Flancquart, et al.. Image processing for a more accurate GNSS-based positioning in urban environment. 22nd ITS World Congress, Oct 2015, Bordeaux, France. 12p. ⟨hal-01471581⟩

Goals of Our Study

Objectives:

- How can we accurately label the visibility of satellites?
- Is the visibility of satellites comparable between cars and soft mobility users?

Approach:

Data collection → LOS / NLOS annotation → Evaluation

Data collection:
- 3 environments
- 3 mobilities

LOS / NLOS annotation:
- Image-based
- 3D model-based

Data Collection

Data Collection

Acquisition sites in Nantes, France

Semi-open

Urban (1)

Urban (2)

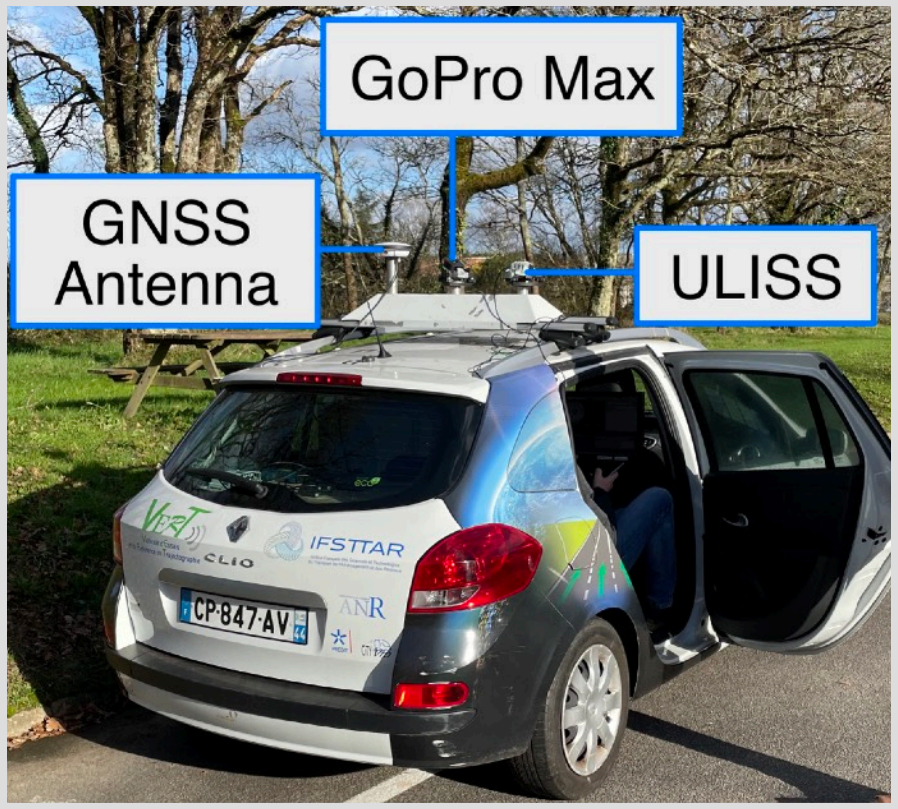
Université Gustave Eiffel

Data Collection

Sensors

Pedestrian

E-scooter

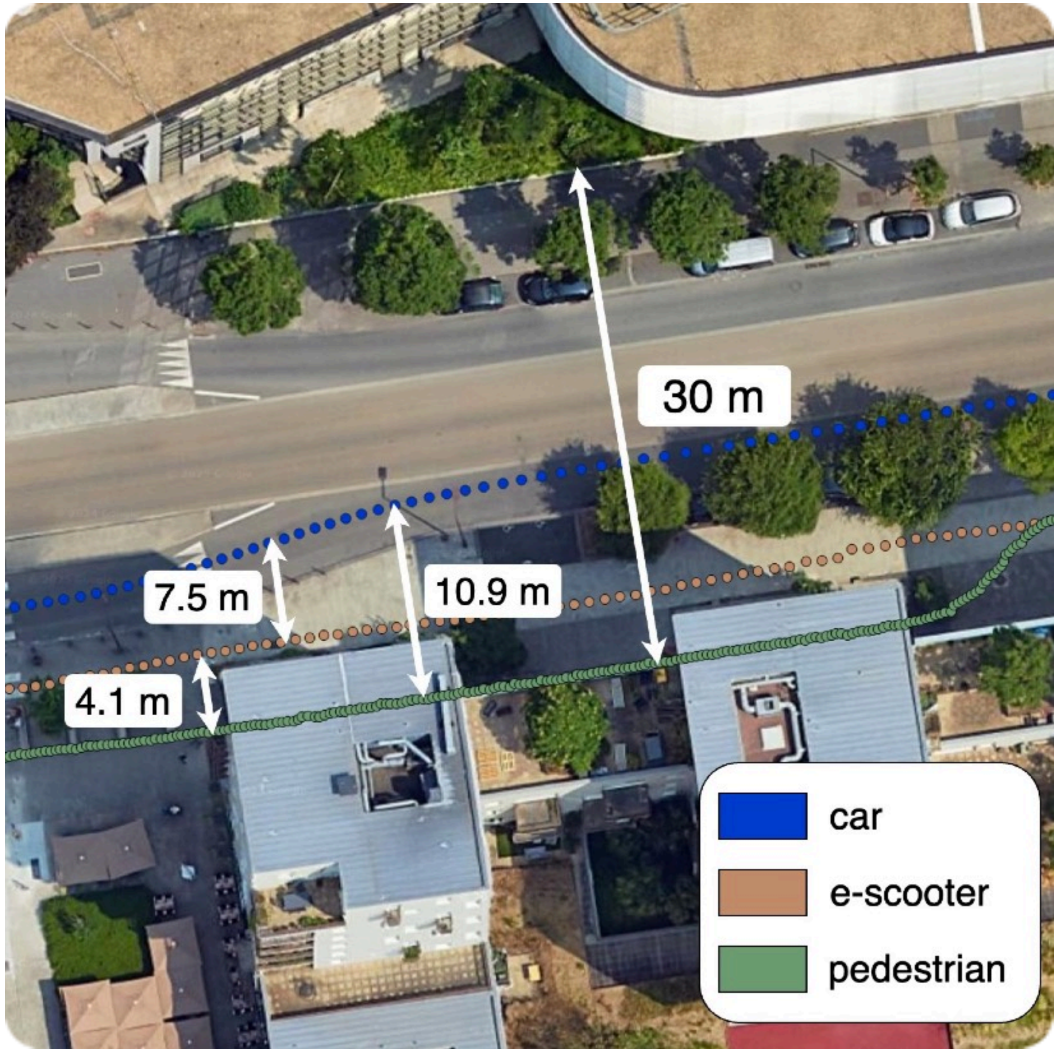


Instrumented vehicle

Université Gustave Eiffel

Data Collection

Multi-modal acquisitions



Acquisition Site	Transport mode	Length (m)	Epochs
Semi-open	Car	408	523
	Pedestrian	413	1212
Urban (1)	Car	1151	1158
	E-scooter	1107	1482
	Pedestrian	1147	3630
Urban (2)	Car	722	653
	E-scooter	727	1095
	Pedestrian	740	2206

Constellations: GPS, GALILEO, GLONASS

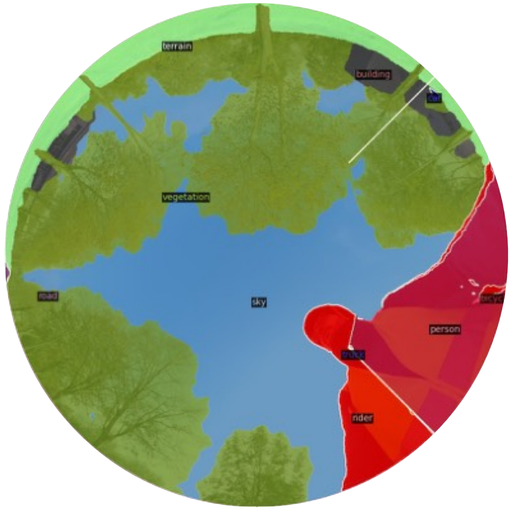
Satellite Visibility Annotation

Obtaining the Skymask

SVI

Equirectangular image

Segmentation +
projection

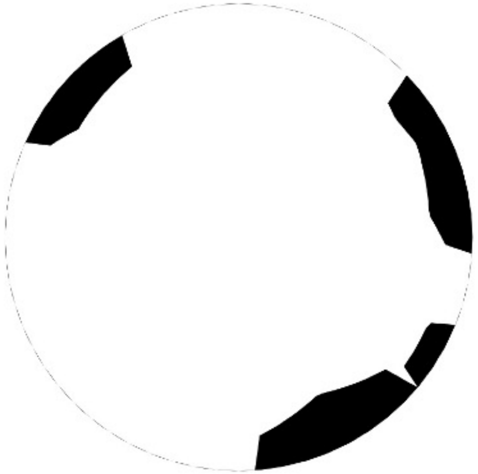


Segmented skymask

3D city
model

BD TOPO ®

Ray-tracing +
projection



Building skymask

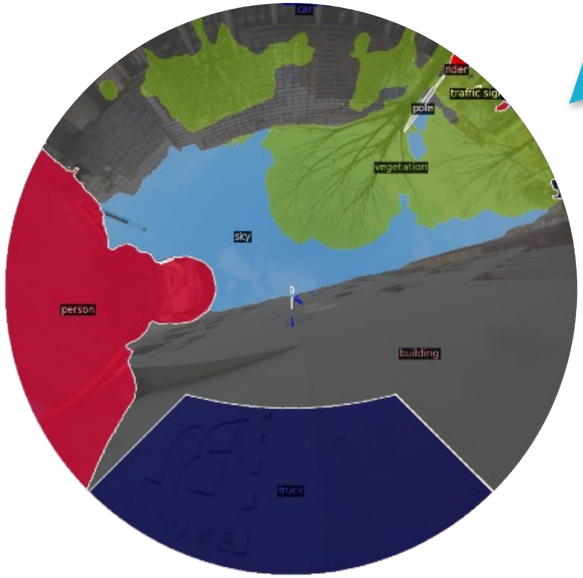
Details about the SVI process

Equirectangular image

1

Segmented skymask (equirectangular)

2



3

Segmented skymask (fisheye)

Satellite visibility labels

Université Gustave Eiffel

Comparison of two techniques

Overview

3D City Model

Uses building footprints and heights.
Database used: IGN BD TOPO® [5]

Nationwide coverage, widely available

No vegetation, outdated/missing structures

Sky View Image (SVI)

Uses fisheye images and Semantic Segmentation with Mask2Former [6] trained on Cityscapes [7]

Captures real-world obstructions (trees, street furniture, human body)

Requires accurate camera pose & image processing

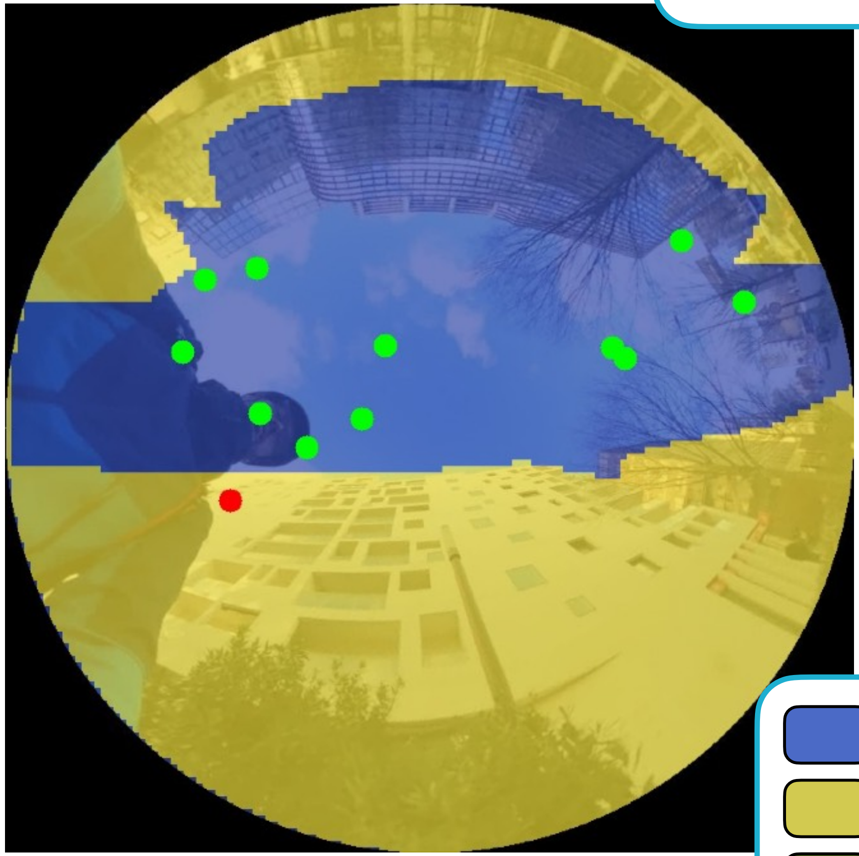
[5] https://geoservices.ign.fr/documentation/donnees/vecteur/bdtopo
[6] B. Cheng, I. Misra, A. G. Schwing, A. Kirillov, and R. Girdhar, "Masked-attention Mask Transformer for Universal Image Segmentation," in Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition, 2022, pp. 1290–1299. doi: 10.48550/arXiv.2112.01527.
[7] M. Cordts et al., "The Cityscapes Dataset for Semantic Urban Scene Understanding," in Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition (CVPR), 2016, pp. 3213–3223.

Comparison of Visibility Annotation Techniques

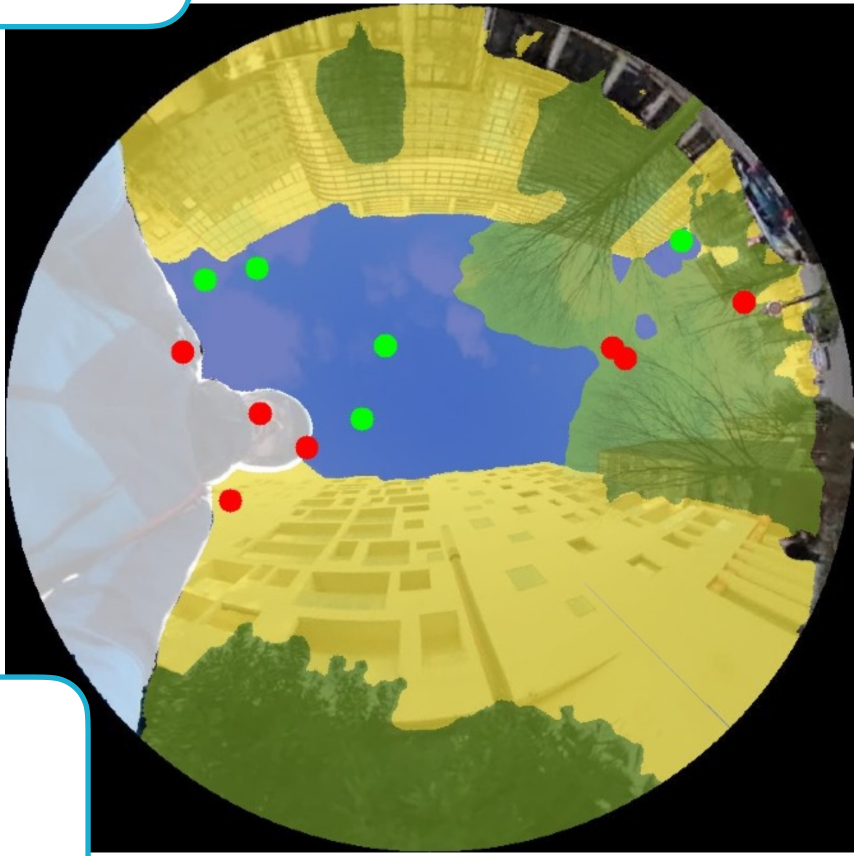
Satellite Visibility Annotation

Comparison of the masks at the same location

LOS NLOS



3D city model-based technique

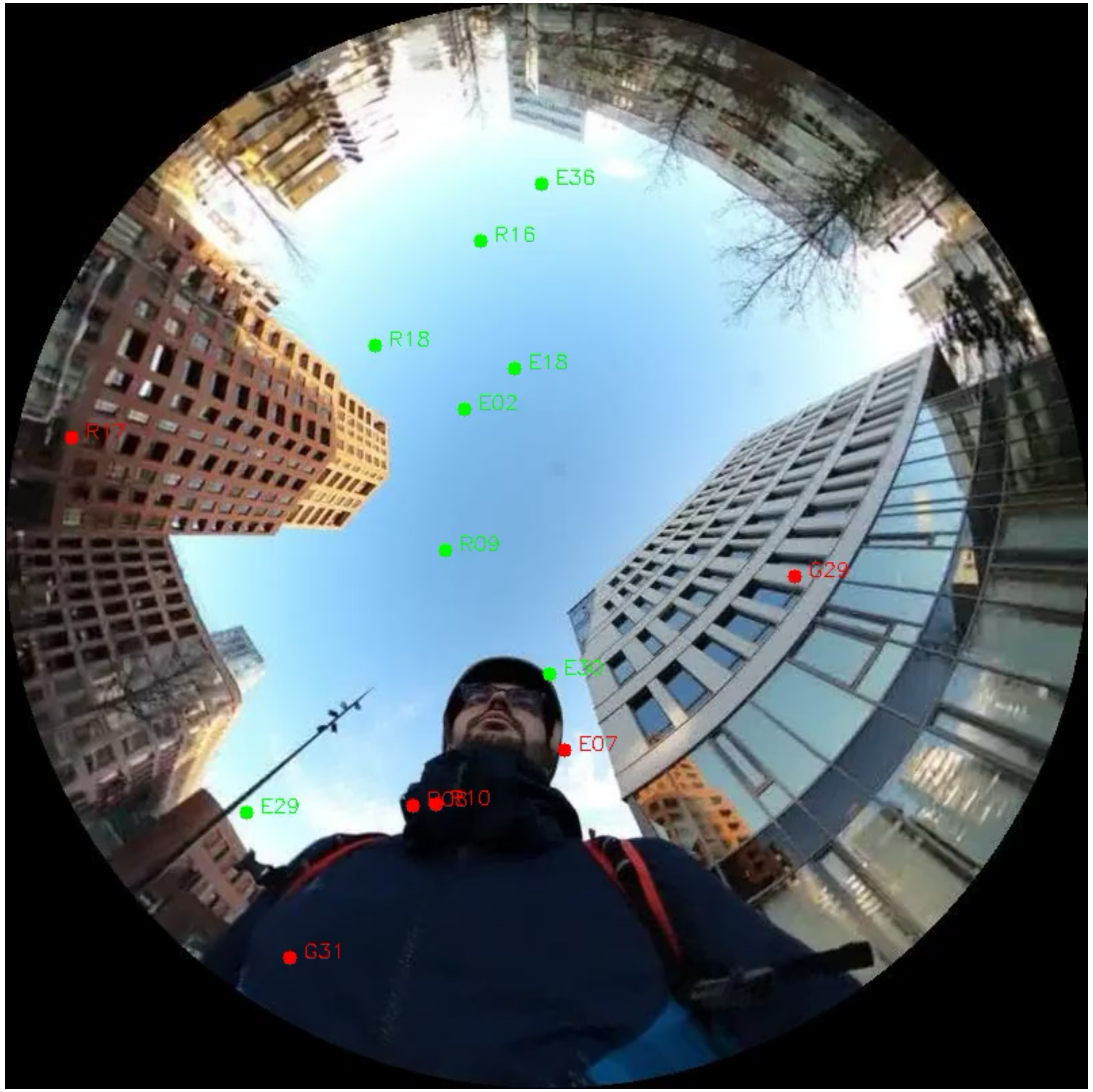


SVI-based technique

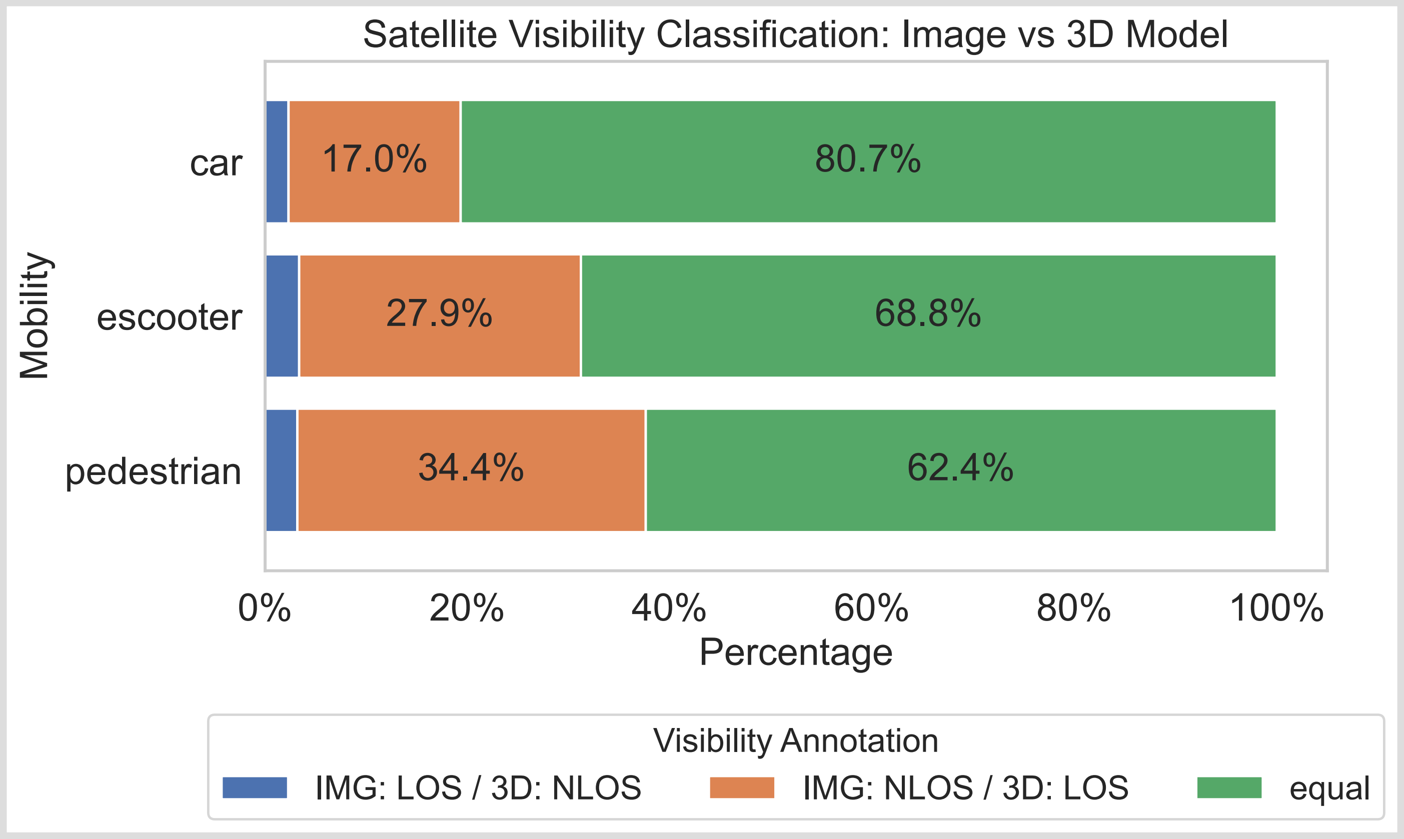
Sky
Building
Vegetation
Bodymask

Pedestrian Footage

Annotation with the SVI-based technique (speed x4)



Agreement Between Both Methods



- High agreement between both methods in the car scenario
- The 3D model-based approach over estimates the number of LOS satellites

Université Gustave Eiffel

Sources of error

3D City Model

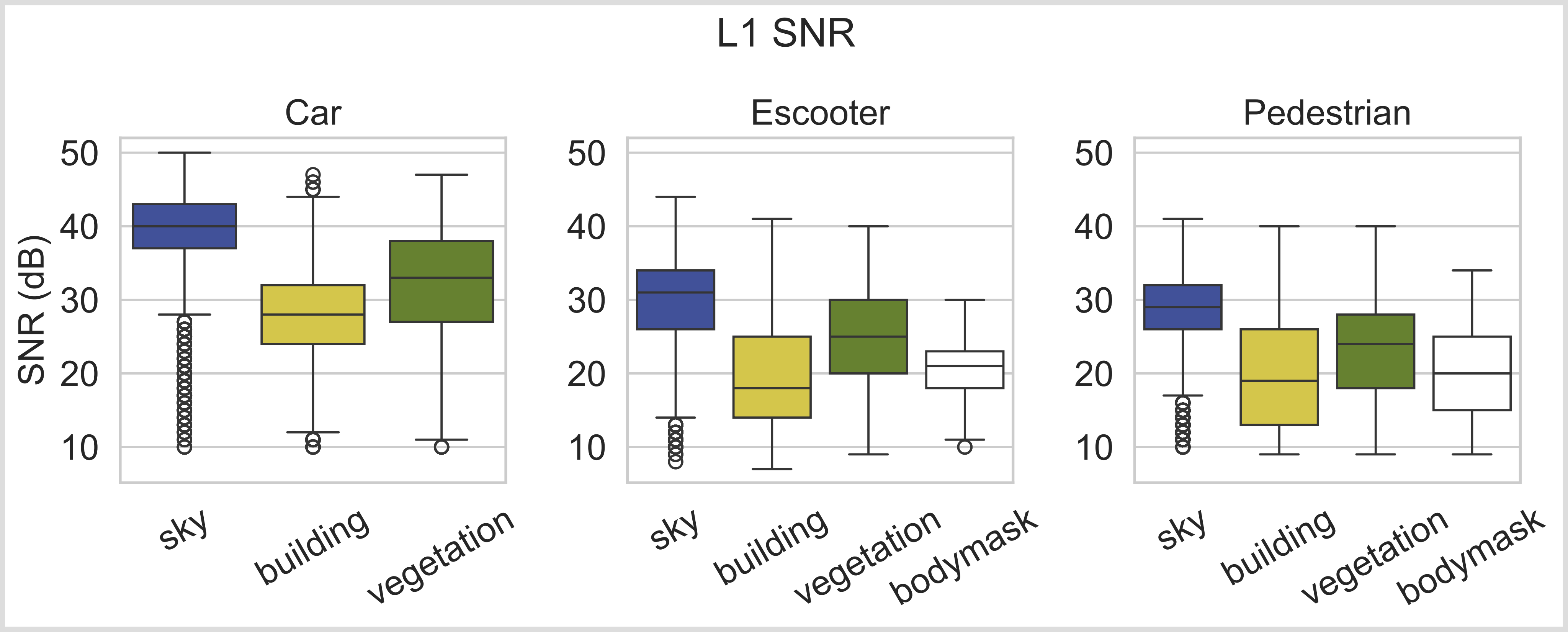
- Lack of vegetation and human body mask
- Architecural inaccuracies
  - Errors in building height
  - Simplified architectural representation
  - Missing buildings
- Errors in the reference track

Sky View Image (SVI)

- Major: Errors in camera pose estimation
- Minor: errors in semantic segmentation, in particular at the edge of vegetation and complex buildings
- Errors in the reference track

Validation of the Visibility Annotation

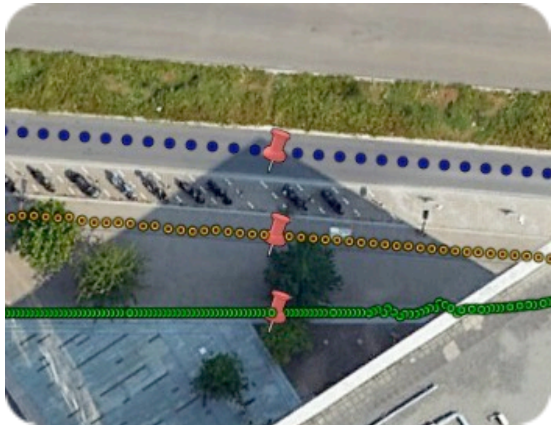
Effect of different obstacles

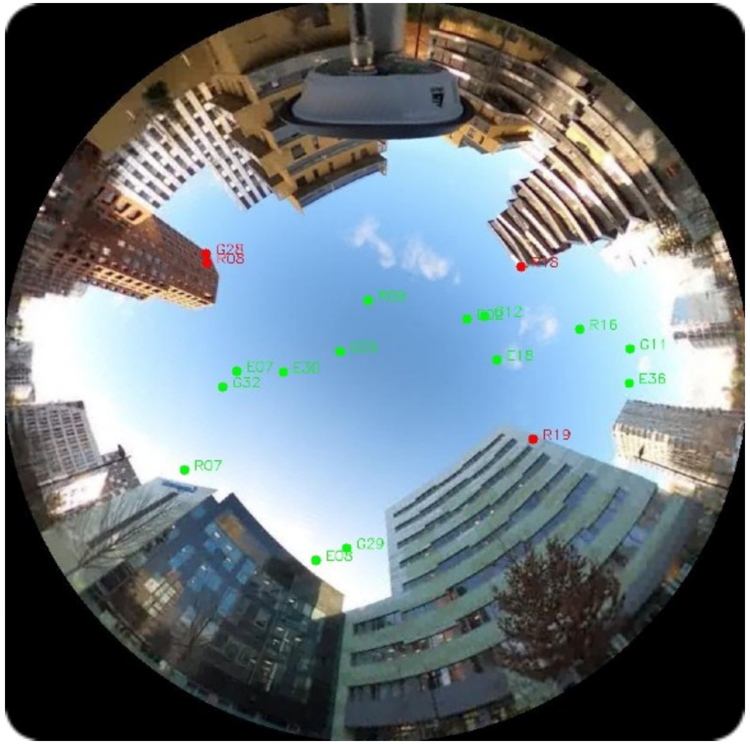


Université Gustave Eiffel

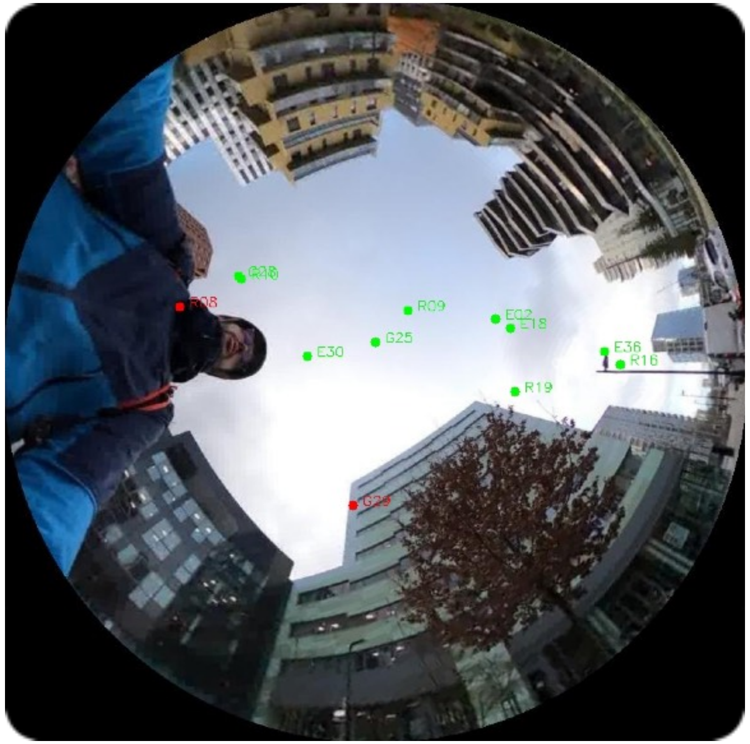
Comparison of Mobilities

Same Street, Different Perspective

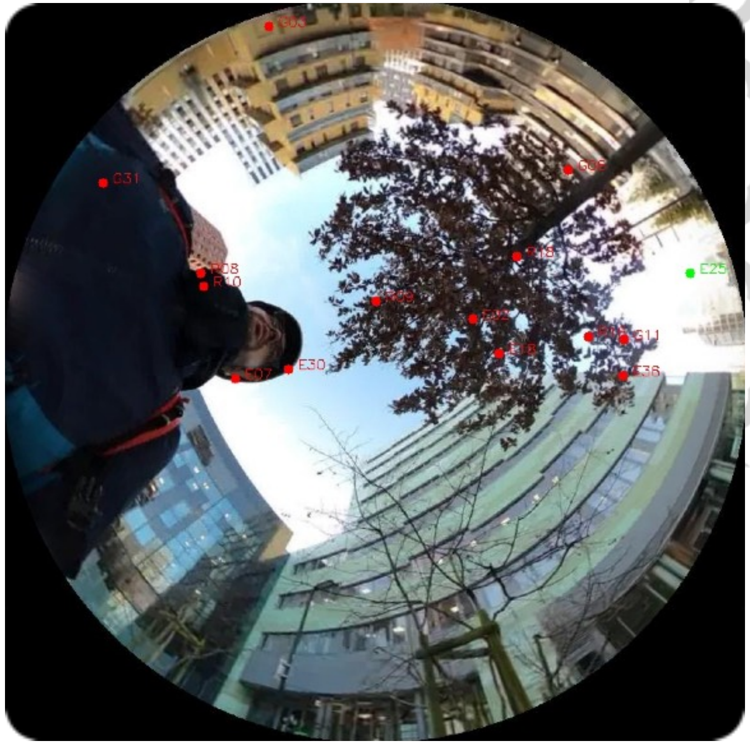




Car



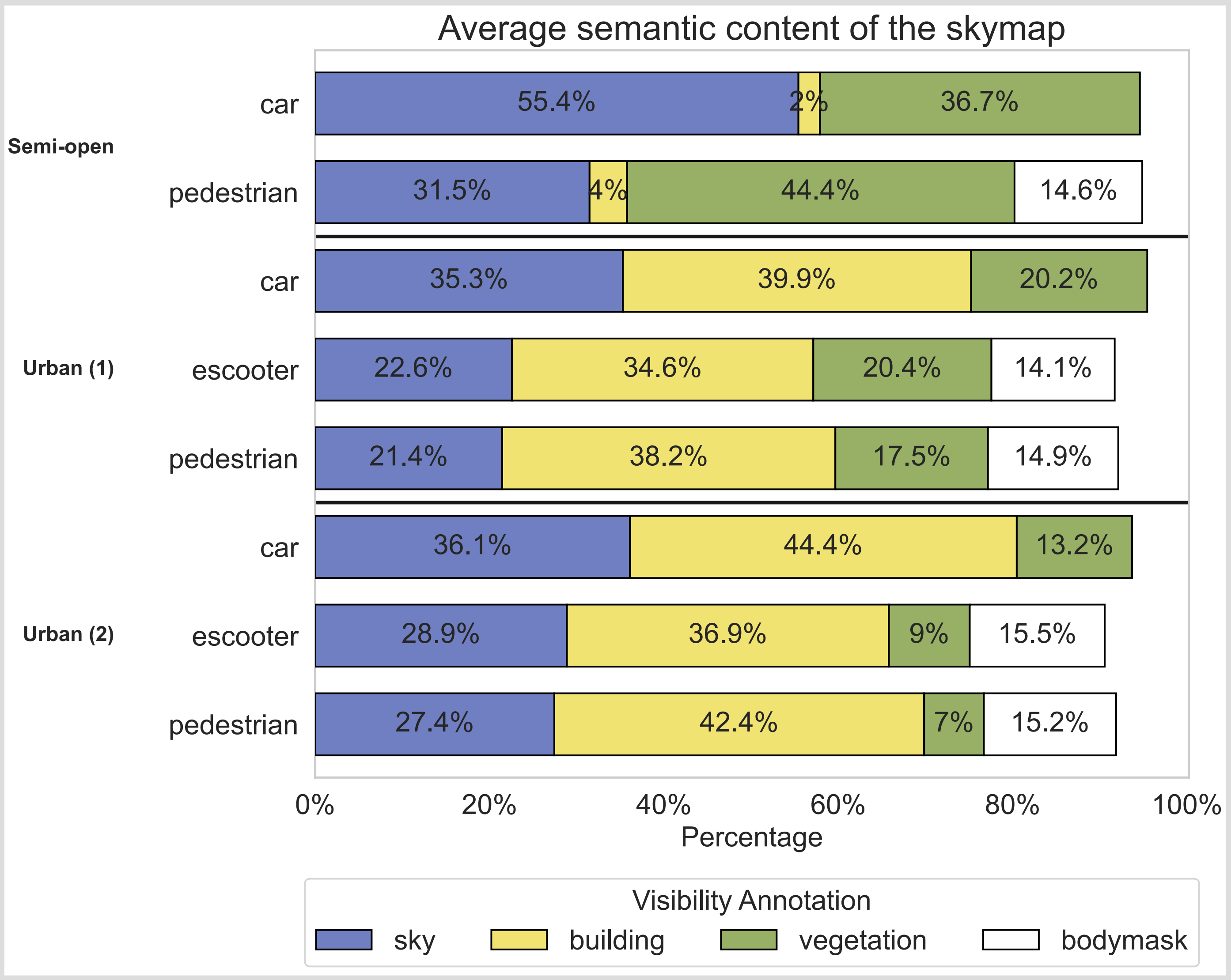
E-scooter



Pedestrian

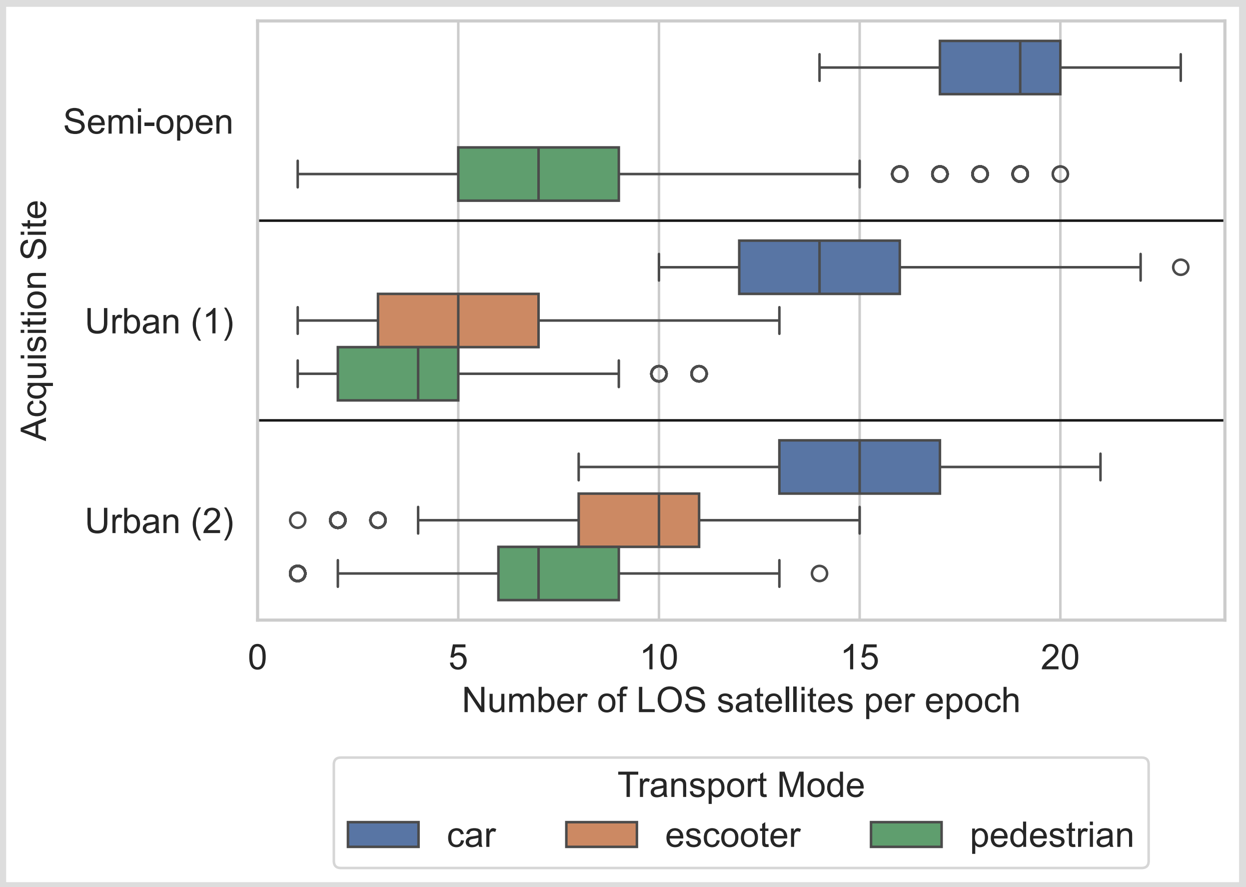
Université Gustave Eiffel

Semantic Content Analysis of the SVIs



- Soft mobility users see systematically less sky
- The human body mask accounts for 15% of the image content

Number of LOS Satellites



- Soft mobility users consistently see less LOS satellites
- The median number of LOS satellites is as low as 4 for the pedestrian scenario in Urban (1)
- Large variation in number of LOS satellites for pedestrians in the semi-open environment

Conclusion

Summary of the Research

Takeaways:

- Sky View Images have the advantage of representing the actual environment that the receiver was in at the time of data collection
- 3D city models are suitable for vehicle datasets, less so for soft mobility
- Soft mobility users are more impacted by the surrounding environment than vehicles

Main challenge:

- Obtaining reference positions in soft mobility scenarios is a difficult task

Final thoughts

- The visibility labels obtained with the SVI-based method can help develop ML models to distinguish line-of-sight and non-line-of-sight signals for both cars and soft mobility users.
- Future work: extending this study needed to canyon streets

- This study is a first step toward understanding GNSS challenges for different urban mobility types
- More research is needed to achieve a deeper understanding of the differences between vehicle and soft mobility users in the urban space. This is useful to help inform the design of ML models adapted to different types of users.

Benjamin BEAUCAMP

benjamin.beaucamp@univ-eiffel.fr

Université Gustave Eiffel

References

[1] R. Hu, W. Wen, and L. Hsu, “Fisheye Camera Aided GNSS NLOS Detection and Learning-Based Pseudorange Bias Correction for Intelligent Vehicles in Urban Canyons,” in 2023 IEEE 26th International Conference on Intelligent Transportation Systems (ITSC), Sep. 2023, pp. 6088–6095. doi: 10.1109/ITSC57777.2023.10422540.

[2] G. Zhang, P. Xu, H. Xu, and L.-T. Hsu, “Prediction on the Urban GNSS Measurement Uncertainty Based on Deep Learning Networks With Long Short-Term Memory,” IEEE Sensors J., vol. 21, no. 18, pp. 20563–20577, Sep. 2021, doi: 10.1109/JSEN.2021.3098006.

[3] H. F. Ng, G. Zhang, and L.-T. Hsu, “Range-based 3d mapping aided gnss with nlos correction based on skyplot with building boundaries,” in Proceedings of the ION 2019 Pacific PNT Meeting, 2019, pp. 737–751.

[4] Juliette Marais, Sébastien Ambellouis, Cyril Meurie, Julien Moreau, Amaury Flancquart, et al.. Image processing for a more accurate GNSS-based positioning in urban environment. 22nd ITS World Congress, Oct 2015, Bordeaux, France. 12p. ⟨hal-01471581⟩

[5] https://geoservices.ign.fr/documentation/donnees/vecteur/bdtopo

[6] B. Cheng, I. Misra, A. G. Schwing, A. Kirillov, and R. Girdhar, “Masked-attention Mask Transformer for Universal Image Segmentation,” in Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition, 2022, pp. 1290–1299. doi: 10.48550/arXiv.2112.01527.

[7] M. Cordts et al., “The Cityscapes Dataset for Semantic Urban Scene Understanding,” in Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition (CVPR), 2016, pp. 3213–3223.