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On the use of Vision for the Weighting of GNSS observation: comparisons

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Abstract—Positioning is a critical function in every intelligent vehicle application. Most applied system is a GNSS (Global Navigation Satellite System)-based receiver, cheap and offering a continuous meter-level accuracy. However accuracy strongly depends on the satellite signal reception state: LOS (Line of sight), that is direct, optimal signal or NLOS (Non LOS), i.e received without direct visibility and after one or more reflections of the signal. Based on previous work, this paper summarizes different weighting schemes applied to mitigate these local effects on GNSS signals and enhance position accuracy in land transport environment. A database collected by ISAE is used for application and comparison of the different schemes. One of them not only relies on GNSS signals but also on satellite state identification thanks to the use of a fisheye camera. This state allows us to deweight degraded measurements without excluding them, in order to keep availability. The paper shows that considering this additional information allows the WLS (Weighting Least Square) to significantly increase accuracy in every types of environments. If state of the art weighting schemes already improve accuracy by 65 and 77% over ordinary least squares in the 2D plan, our weight further improves accuracy by 40% compared to the classical elevation-based weight.

Index Terms—GNSS, Localisation, Weighting schemes, Vision

I. INTRODUCTION

GNSS-based localisation systems are nowadays part of our everyday lives. Embedded in smartphones, they inform us about our own positions and are the core of a number of applications: from navigation of course, to sport, social networks, weather forecast, delivery services etc. In land transport applications, they allow for guidance, traffic management, toll, emergency services... with different levels of requirements. The generalization of such tools increased performance requirements with new services. However, GNSS receivers suffer from degraded performance in many land transportation environment such as urban areas. Indeed, optimal performance require a number a satellite signal to be received in a Line of Sight (LOS) condition, meaning that any obstacle can disturb signal propagation and time of arrival estimation, basis for position computation.

Main disturbance in land transport area is multipath and NLOS (Non Line of Sight). Multipath is usually characterised by the reception of both a direct signal and one or more echoes of the same signal. NLOS is a particular case where echoes are received in absence of the direct ray. If some other error sources can be corrected by models, as atmospheric delays, these effects are by definition very local, that make them difficult to model. Literature is abundant on multipath mitigation, especially in urban areas. Considering GNSS as a standalone solution, mitigation techniques address antenna technology, receiver signal processing or estimation block. But some more solutions also include the use of complementary heterogeneous sensors to compensate some of the GNSS drawbacks. Following previous work [1], this paper intends to compare different mitigation techniques based on weighted least squares from state of the art literature on a real data set. Most of the weighting schemes applied here rely on GNSS alone, but one will benefit from satellite state of reception knowledge given by a fisheye image processing algorithm developed in detail in [2]. Our study is performed in the framework of the French Ferromobile project, that deals with the development of a multimodal, flexible and electric vehicle capable of travelling both on roads and rails. The vehicle will be equipped of an on-board positioning system, which requires to be accurate and robust whatever its surroundings.

II. MAIN WLS

One of the techniques to achieve precise positioning within the Global Navigation Satellite System (GNSS) is the implementation of sophisticated weighting schemes for satellite signals to mitigate local errors and enhance reliability. Over the years, numerous weighting methodologies have been proposed and refined, each endeavoring to optimize positioning accuracy by considering factors such as signal quality, satellite geometry, and environmental conditions.

In GNSS applications, the signal propagation time between the receiver and the satellite is typically represented using pseudo-range measurements ρ . These ranges account for mea-

surement errors such as ionospheric and tropospheric delays, local effects and other noises.

The pseudo-range residual measurements [3] as follows :

$$\Delta\rho = H\Delta x + \varepsilon \quad (1)$$

where H is the design matrix ($n \times 4$). The vector ε comprises pseudo-range measurement errors, which are presumed to follow a normal distribution, denoted as $\varepsilon \sim N(0, \Sigma)$.

H is designed as:

$$H = \begin{bmatrix} a_{x1} & a_{y1} & a_{z1} & 1 \\ a_{x2} & a_{y2} & a_{z2} & 1 \\ \vdots & \vdots & \vdots & \vdots \\ a_{xn} & a_{yn} & a_{zn} & 1 \end{bmatrix} \quad (2)$$

where $\mathbf{a}_i = (a_{xi}, a_{yi}, a_{zi})$ are unit vectors that indicate the direction from the linearization point to the i -th satellite.

In case 1, where $n = 4$ and the linearization point is very close to the user's true position, Δx is a vector representing the variations in position and time offsets.

In another case $n > 4$, the ordinary least squares (OLS) method can be employed to estimate Δx :

$$\Delta x = (H^T H)^{-1} H^T \Delta\rho \quad (3)$$

Performing weighting enhances reliability. Therefore, to achieve a more accurate localization estimate, Δx should be defined using the estimation technique of Weighted Least Squares (WLS) :

$$\Delta x = (H^T W H)^{-1} H^T W \Delta\rho \quad (4)$$

Where W denotes the measurement weighting matrix, typically defined as Σ^{-1} , i.e., the inverse of the covariance matrix of observation error.

Therefore, the estimated coordinates \hat{x} are obtained by combining the linearization point with the variation vector Δx .

$$\hat{x} = \Delta x + x \quad (5)$$

In this paper, we evaluate various weighting schemes, such as Elevation-based WLS(Groves) [4], Sigma- ϵ [5], and CAPLOC-WLS [1]. These schemes correspond to the carrier-to-noise ratio (C/N_o), satellite elevation, and line-of-sight (LOS) versus non-line-of-sight (NLOS) satellite classifications, among other factors.

A. Elevation-based WLS(Groves)

A weighting model utilizing elevation as a criterion exists in the literature [4]. This model, referred to as Elevation-based WLS(Groves) by us, is based on an exponential elevation-based weighting scheme. This scheme only relies on the satellite elevation, without any knowledge on its satellite state of reception (LOS) or not), even in, in practice, higher satellites are more likely (LOS) than lower elevated ones.

$$\sigma = a + b \cdot \exp(-\theta_i/\theta_0) \quad (6)$$

Where θ_i is the elevation angle of the i satellite. And the constants are $a = 0.13$ m, $b = 0.56$ m and $\theta_0 = 0.1745$ rad [6].

B. Sigma- ϵ

Geodetic antennas designed for high-precision measurement and positioning applications exhibit variations in carrier-to-noise ratio (C/N_o) with respect to antenna gain. Langley [7] derived a formula to express the functional relationship between phase variance and C/N_o values.

The Sigma- ϵ weighted model was initially proposed by Hartinger [8]. Subsequently, Wieser [5] discovered that certain antenna receivers required an additional term, V_i . Consequently, the Sigma-weighted model is now expressed as:

$$\sigma^2 = V_i + C_i \cdot 10^{-\frac{C/N_o}{10}} \quad (7)$$

Where C/N_o is measured carrier-to-noise power-density ratio [dB - Hz], and $V_i [m^2]$ and $C_i [m^2 Hz]$ are the model parameters. The subscript i indicates the L_i signal, such as $L1$ and $L2$ for GPS. Empirical values were chosen as follows : $V_i = 0$, $C_1 = 1.1 \cdot 10^4 m^2 Hz$.

As C/N_o varies with satellite elevation, but is also impacted by propagation conditions, we could expect that this model may better consider available satellites than the first presented one.

C. CAPLOC-WLS

The aforementioned weighting schemes exhibit limited accuracy in the presence of strong urban multipath conditions [1]. For instance, satellites with low elevation angles θ_i can still exhibit high C/N_o values.

Consequently, Tay et.al proposed an enhanced weighting scheme that integrates both C/N_o and θ_i the elevation angle of the satellites, as well as an indicator for line-of-sight (LOS) and non-line-of-sight (NLOS) satellites [1].

CAPLOC-WLS is a solution that uses a combination of images and estimation technique to weight different satellites according to their reception state.

The images are acquired using fisheye cameras to characterize the surrounding environment all along the run. The acquired image pixels are classified into two principal regions: sky and non-sky [2] (see Fig. 1.).

A classification method [9] based on deep learning identifies occlusions and obstructions caused by buildings, vegetation, and other elements to ascertain the satellite position within the sky image (see Fig. 2.).

The line-of-sight (LOS) received signal is represented in the sky region, while the non-line-of-sight (NLOS) received signal is characterized in the non-sky region.

The variance of CAPLOC-WLS can be written as :

$$\sigma^2 = k \times \frac{10^{-\frac{C/N_o}{10}}}{\sin^2 \theta_i} \quad (8)$$

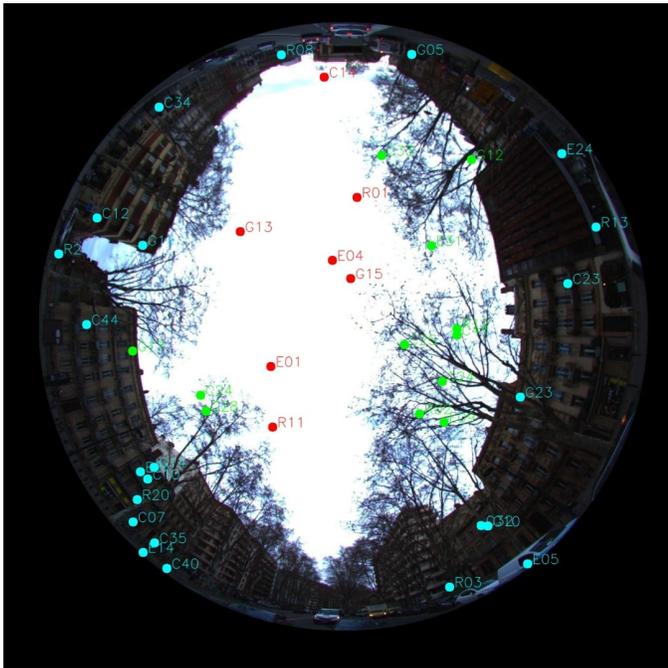


Fig. 1. Fisheye lens image of an urban environment, where red points represent LOS signals, blue points represent NLOS signals, and green points represent mixed regions between NLOS and LOS

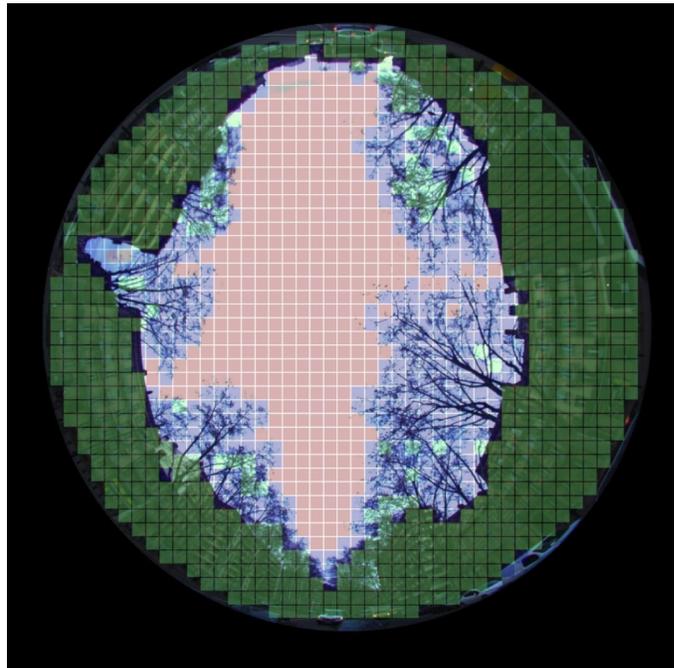


Fig. 2. Classified fisheye lens image of an urban environment into several classes, where red pixels represent sky, and blue and green obstacles

With k empirically fixed:

$$k = \begin{cases} 1 & \text{if LOS} \\ 2 & \text{if NLOS} \end{cases}$$

When the received signal is line-of-sight (*LOS*), k is set to 1. However, when the signal is non-line-of-sight (*NLOS*), k assumes a different value.

III. OUR DATABASE

The proposed algorithms were tested and validated, with results compared using the dataset from Toulouse, France, collected in February 4, 2022 by ISAE-Supaero [10].

During the measurements, a Ublox EVK-M8T receiver and a NovAtel VEXXIS GNSS-804 antenna were utilized. Data were collected at a rate of 5 Hz using the ROS platform. Higher frequencies are capable of handling higher speeds, while a frequency of 1 Hz is suitable for static or low-speed scenarios.

In this paper, we used GPS satellites only

Fig. 3. illustrates the acquisition trajectory as viewed in Google Earth, encompassing terrain characterized by deep urban canyons and forested regions.

IV. PERFORMANCE ANALYSIS

A. KPIs (Key Performance Indicators)

To evaluate the performance of various weighting schemes, we will analyze several factors, including root mean square error (RMSE) in 3D, root mean square error (RMSE) in 2D and horizontal position error (HPE).

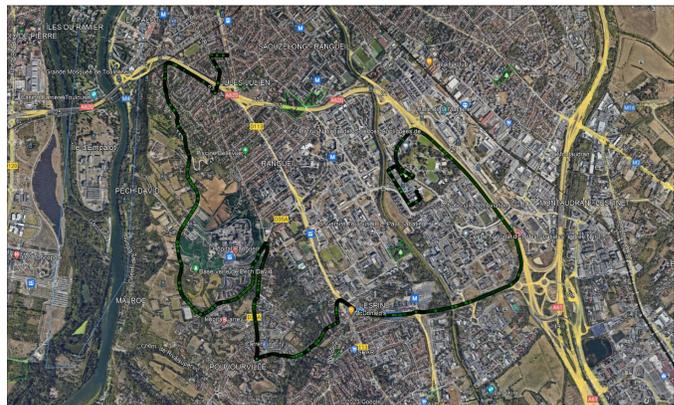


Fig. 3. Reference Trajectory in Toulouse, France

B. Comparisons

Table I presents a detailed comparison of the 3D root mean square error (RMSE) across various weighting schemes, including CAPLOC-WLS, Elevation-based WLS (Groves), Sigma- ϵ , and OLS. The results clearly highlight the superior performance of CAPLOC-WLS, which achieves an RMSE of 5.17 meters. This value is notably lower than that of some other schemes, reflecting its exceptional accuracy in 3D positioning.

The Elevation-based WLS (Groves) method, with an RMSE of 8.65 meters, demonstrates a significant improvement of 61.38% over the traditional OLS method, which has an RMSE of 22.40 meters. This substantial enhancement underscores the effectiveness of incorporating elevation-based weighting in improving positioning accuracy.

TABLE I
3D PERFORMANCE COMPARISON OF WEIGHTING SCHEMES: OLS, ELEVATION-WLS(GROVES), SIGMA- ϵ , AND CAPLOC-WLS FOR $k = 2$

OLS	Elev. WLS(Groves)		Sigma- ϵ		CAPLOC-WLS	
RMS(m)	RMS(m)	Imp.(%)	RMS(m)	Imp.(%)	RMS(m)	Imp.(%)
22.40	8.65	61.38	4.83	78.44	5.17	76.92

TABLE II
2D PERFORMANCE COMPARISON OF WEIGHTING SCHEMES: OLS, ELEVATION-WLS(GROVES), SIGMA- ϵ , AND CAPLOC-WLS FOR $k = 2$

OLS	Elev. WLS(Groves)		Sigma- ϵ		CAPLOC-WLS	
RMS(m)	RMS(m)	Imp.(%)	RMS(m)	Imp.(%)	RMS(m)	Imp.(%)
16.75	5.84	65.13	3.70	77.91	3.41	79.64

The Sigma- ϵ method demonstrates a substantial improvement with an RMSE of 4.83 meters, reflecting a 78.44% enhancement over OLS. This indicates a marked advancement in accuracy and a notable performance advantage over the Elevation-based WLS (Groves).

CAPLOC-WLS, however, stands out with a remarkable 76.92% improvement over OLS, showcasing its superior capability in reducing positioning errors. While Sigma- ϵ also shows significant performance with a 78.44% improvement over OLS, CAPLOC-WLS surpasses it in terms of 2D positioning accuracy, demonstrating its exceptional positioning capabilities.

In contrast, Tables II and III provide a comprehensive evaluation of positioning accuracy across various weighting schemes, focusing on the 2D root mean square error (RMSE) and horizontal position error (HPE), respectively.

Table II compares the 2D RMSE for OLS, Elevation-based WLS (Groves), Sigma- ϵ , and CAPLOC-WLS. CAPLOC-WLS demonstrates outstanding performance with an RMSE of 3.41 meters, reflecting a remarkable 79.64% improvement over the OLS method, which has an RMSE of 16.75 meters. Sigma- ϵ follows with an RMSE of 3.70 meters, representing a 77.91% improvement over OLS. Elevation-based WLS (Groves) shows an RMSE of 5.84 meters, indicating an 65.13% improvement

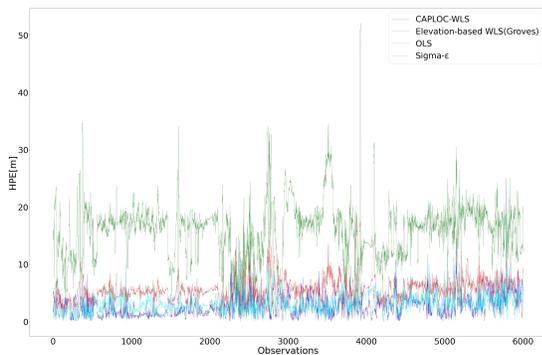


Fig. 4. 2D Positioning Errors for Different GNSS Weighting Strategies in Toulouse, France

TABLE III
HORIZONTAL POSITION ERRORS (HPE) IN GNSS LOCALIZATION ACROSS DIFFERENT WEIGHTING SCHEMES

	Mean(m)	Median(m)	95%
OLS	16.04	16.77	23.22
Elev. WLS(Groves)	5.52	5.43	8.59
Sigma- ϵ	3.30	3.01	6.28
CAPLOC-WLS	2.87	2.58	6.16

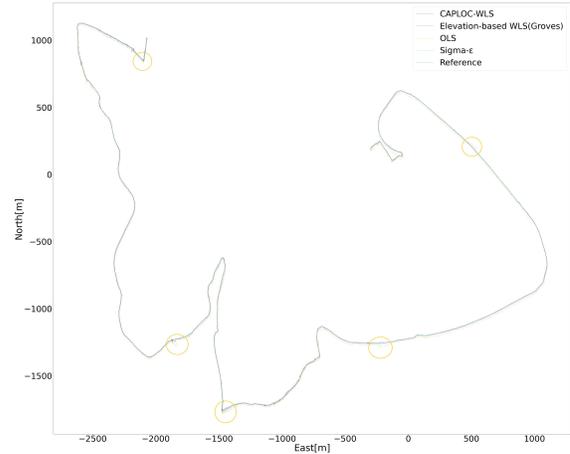


Fig. 5. 2D Positioning Trajectories for Different GNSS Weighting Strategies in Toulouse, France

over OLS, though it still lags behind CAPLOC-WLS and Sigma- ϵ in terms of accuracy. Table III, on the other hand, provides a detailed analysis of horizontal position errors, emphasizing the mean, median, and 95th percentile errors. CAPLOC-WLS excels with a mean HPE of 2.87 meters, a median of 2.58 meters, and a 95th percentile error of 6.16 meters, clearly outperforming other methods. Elevation-based WLS (Groves) shows a mean HPE of 5.52 meters, a median of 5.43 meters, and a 95th percentile error of 8.59 meters. In comparison, Sigma- ϵ demonstrates a mean HPE of 3.30 meters, a median of 3.01 meters, and a 95th percentile error of 6.28 meters. OLS present larger errors, with OLS having a mean HPE of 16.04 meters, highlighting its less favorable performance.

Fig. 4. and Fig. 5. delve into a more granular error analysis. Fig. 5. compares the trajectories obtained using different weighting schemes. It is evident that CAPLOC-WLS (depicted in blue) aligns more closely with the reference trajectory (in green), whereas the trajectories from other schemes exhibit greater deviations, particularly in complex paths and sharp turns.

Fig. 4. further analyzes horizontal errors. CAPLOC-WLS(blue) demonstrates the smallest error margin, followed by Sigma- ϵ (cyan), while Elevation-based WLS(Groves)(red) and OLS(orange) display the highest errors.

Furthermore, CAPLOC-WLS also demonstrates superior

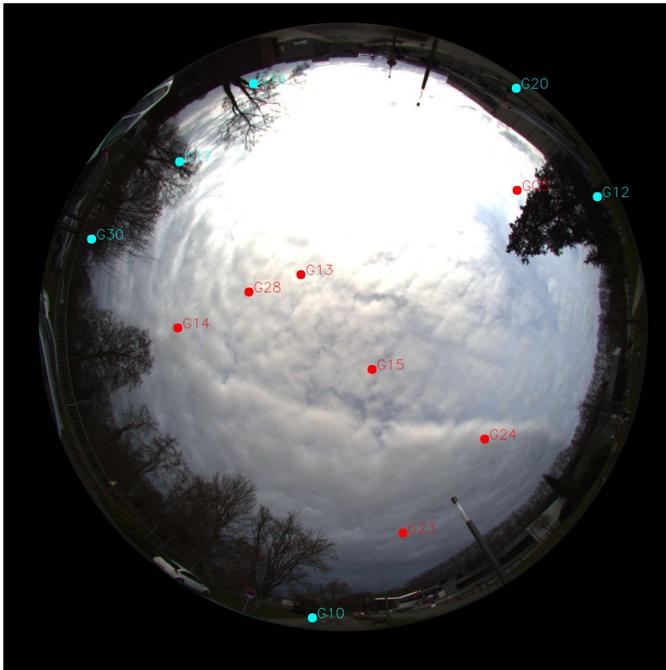


Fig. 6. Fisheye lens image of Fig. 8., where red points represent LOS signals, blue points represent NLOS signals

performance in the vertical component, reinforcing its overall performance and robustness in 3D GNSS positioning. These results collectively affirm that CAPLOC-WLS not only excels in 2D accuracy and horizontal positioning but also in vertical accuracy, underscoring its comprehensive performance and robustness in GNSS localization across all dimensions.

Fig. 6. and Fig. 7. clearly demonstrate the precise marking of Non-Line-of-Sight (*NLOS*) signals (blue) achieved by our detection methodology [2] [9].

Fig. 8. illustrates the GNSS positioning results on a multi-lane highway. The background satellite image shows the highway and its surrounding environment. The different colored dots represent the GNSS positioning results using various weighting schemes: CAPLOC-WLS (blue), Elevation-based WLS (Groves) (red), OLS (orange), and Sigma- ϵ (cyan). The reference trajectory is shown in green (Fig. 9. employ the same representation method).

The distribution of the dots indicates that the blue and cyan points are mainly concentrated on one side of the highway, while the orange and red points are more widely spread. This suggests that different weighting schemes produce varying positioning results in the same environment. The Elevation-based WLS (Groves) (red) positioning results are close to the reference trajectory. The CAPLOC-WLS (blue) positioning results and the Sigma- ϵ (cyan) results are closer to the reference trajectory, indicating higher positioning accuracy in this environment.

The multi-lane highway has fewer buildings and other obstacles, allowing various weighting schemes to provide relatively good positioning results. However, CAPLOC-WLS

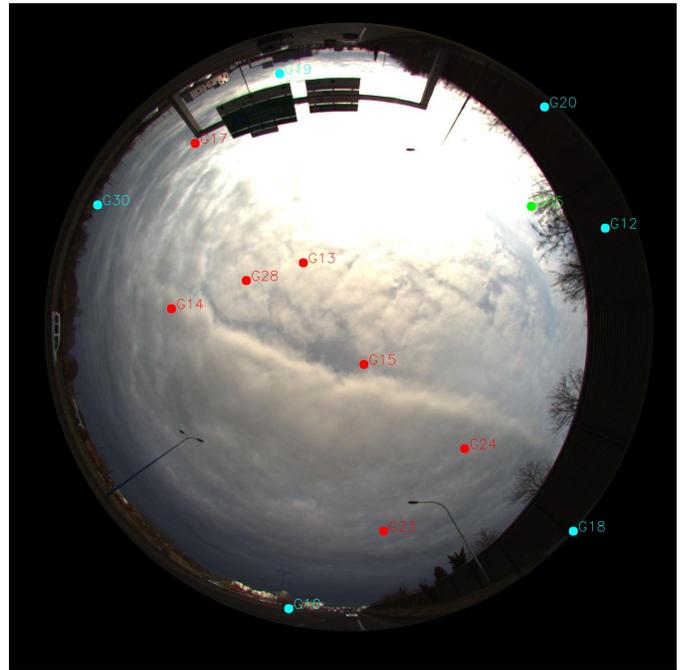


Fig. 7. Fisheye lens image of Fig. 9., where red points represent LOS signals, blue points represent NLOS signals, and green points represent mixed regions between NLOS and LOS

and Sigma- ϵ demonstrate higher consistency and accuracy compared to OLS and Elevation-based WLS (Groves), which show more variation and spread.

In contrast, in an urban environment characterized by high-rise buildings, as depicted in Fig. 9., the positioning results exhibit more significant deviations from the reference trajectory compared to the highway environment (see Fig. 8.). The presence of high-rise buildings creates multipath effects and signal blockages, leading to larger positioning errors. The blue points (CAPLOC-WLS) still show relatively better performance, staying closer to the reference trajectory, whereas the orange, cyan, and red points (OLS, Sigma- ϵ , and Elevation-based WLS (Groves)) exhibit more significant deviations.

This urban environment demonstrates the challenges posed by strong urban canyons, where GNSS signals are reflected and blocked by tall buildings, significantly impacting positioning accuracy. Despite these challenges, CAPLOC-WLS shows more robustness in maintaining closer alignment with the reference trajectory.

V. CONCLUSIONS AND PERSPECTIVES

Positioning performance and robustness are critical metrics for evaluating GNSS applications in land-based transportation, such as rail and road. In urban environments, the multipath effects are a significant source of large positioning errors that require to be mitigated to reach acceptable performance.

This paper introduces and compares several distinct weighting schemes, namely CAPLOC-WLS, Elevation-based WLS (Groves), OLS, and Sigma- ϵ . Our primary focus is on CAPLOC-WLS.



Fig. 8. Geospatial Trajectory Analysis of GNSS Weighting Schemes on Urban Motorways



Fig. 9. High-Precision GNSS Path Tracking in Urban Environments: A Comparative Study

CAPLOC-WLS for GNSS Positioning with Fisheye Camera: The fisheye camera captures images of the sky, which are then processed by a deep learning algorithm to determine whether the received signal is line-of-sight (*LOS*) or non-line-of-sight (*NLOS*). A scalar k is subsequently assigned to the signal based on its state.

The performance analysis in Section 5, which includes comparisons of error values, ENU trajectories, and satellite map trajectories, demonstrates that CAPLOC-WLS is a robust weighting scheme with superior positioning accuracy across diverse environments, including urban, suburban, and highway settings. CAPLOC-WLS consistently corrects the positioning errors that other weighting schemes fail to address, reaching a mean horizontal error equal to 2.9m compared to the 5.5 and 3.3m obtained with state of the art WLS algorithms.

Robust and accurate positioning in every environment will enhance GNSS-based solution deployment in various applications such as autonomous cars, train localisation, robotics that can frequently occur in constrained environments. The use of a camera however reveals some issues. For some applications, as in rail, the need of an external camera still remains a difficult constraint for maintenance in particular, but evolution of equipment size may reduce this issue in the future.

Moreover, the use of an optical sensor is dependent on external factors such as light, meteorological conditions, cleaning, need for camera calibration... Some of the degradations will be mitigated by specific algorithms under development. Some other conditions, as for example, too low lightning conditions could benefit from the use of other sensors. As a next step, we plan to investigate the integration of GNSS and Inertial Navigation Systems (INS) to further optimize GNSS positioning in conjunction with the CAPLOC-WLS weighting scheme.

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