Adaptive robust navigation for safety-critical railway applications

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***Abstract*—GNSS is recognized as a game changer for the next railway signaling solutions since July 2021 by the EU Parliament. However, the satellite-based technology still faces major issues before full introduction. For safety critical functions, the positioning on-board unit needs to show its compliance with very stringent requirements. To ensure position availability and accuracy, solutions will result from a multisensor fusion (GNSS, IMU, odometer) supported by the use of digital maps and some barriers for error mitigation such as Fault Detection and Exclusion techniques. Main constraints for GNSS performance is caused by track surroundings (building, vegetation, bridges or tunnels) but interference also needs to be detected and managed as the train has to travel in public areas, close to highways or other infrastructure where jamming events in particular are now frequently observed. In this paper, based on recent development for railway applications, we outline a concept for a smart adaptation and mitigation of these effects, merging work performed for context detection, interference detection and classification and different weighted least squares. The different contributions will be described as well as the concept proposed.**

***Index Terms*—GNSS, land transport, satellite signal propagation, WLS, context detection, interferences.**

I. Introduction

The integration of GNSS-based solutions in safety-critical land transport applications has been studied for 25 years. However, GNSS penetration in some transport domains, such as railways, remains difficult due to GNSS receiver weakness in areas of dense traffic, where they are affected by masking obstacles and propagation difficulties caused by the built environment, trees and trenches. There is also interference and a high level of required performance. Safety-critical applications such as signalling require a high level of confidence in the information provided and the ability to demonstrate safety. Solutions under development rely on combinations of sensors and barriers to detect and mitigate threats. In rail, the roadmap to GNSS integration also comprises complementary solutions dedicated to mapping threat events [1], which are particularly useful in guided transport, but feature map solutions are also being investigated for urban applications [2]. Through its involvement in numerous projects, the University Gustave Eiffel has developed several threat detection and mitigation techniques. When combined, these techniques can form an adaptive, robust navigation chain for such applications. These techniques will also be of primary interest in new application contexts, such as those developed in the Pods4Rail project, which aims to develop an innovative rail-based door-to-door transport concept. The autonomous vehicle (pod) consists of a propulsion unit (carrier) and transport containers (transport unit). As the pod changes from one mode of transport to another, it will face different constraints and requirements. When stationary, the pod requires a moderate level of accuracy in its information. When on rails, however, its position can be used for signalling or traffic management, in which case it will need to reach a high integrity level. The possibility of an adaptive solution is therefore of great interest. In this paper, these different blocks and how they can be combined to provide this concept are briefly summarized. The first section of the paper will describe the main threats encountered by a train in its operational environment. The second, will summarize the different blocks that compose the chain. The last one will illustrate some capacities of these blocks on accuracy improvement before discussing the concept and opening perspectives.

II. The role of the environment on GNSS-based localization performance

The requirements for land transport differ from those seen in aeronautics due to different operational constraints, as well as the surrounding environment and additional environmental factors that considerably degrade user performance. Indeed, as is well documented in the literature, vehicles circulate in harsh environments such as urban areas, trenches and areas with trees alongside the track, not to mention going through tunnels.

A. Local masking effects

As GNSS-based positioning relies on measuring the time it takes for a signal to propagate, the pseudorange distance is optimally estimated when the signal is received in a LOS (Line of Sight) state. However, obstacles around the antenna can lead to a Non-LOS state if the direct path is blocked or cause multipath effects whereby signal echoes degrade the correlation peak used for ranging estimation [3]. Multipath and NLOS states have been extensively investigated in the literature because they are one of the main sources of positioning errors in such environments. This affects different blocks of the receiver chain, from the antenna to the estimation block, including receiver signal processing. The recent extension of use of machine learning has led to a number of papers analyzed in [4]. However, the impact of trees on signal reception has received comparatively little attention to date, despite being an important topic. [5] presented a first comparison of errors across different environments open sky, urban and vegetated conditions. The study revealed that pseudorange errors are more widely distributed in vegetation than in the open sky, but have a zero mean. In contrast, urban environments show pseudorange errors and the error distribution is slightly larger in vegetated environments than in open sky. More recent studies [6] and [7] analysed kinematic data and video-based classification of satellite states in order to describe signal reception through trees.

B. Interferences

GNSS interference has been extensively studied and documented in the aeronautical domain. Various reports and research articles have highlighted the risks associated with GNSS interference in aviation, particularly regarding its impact on navigation, landing procedures, and surveillance systems.

- ***Jamming*** refers to an intentional form of interference that induces disturbances in the GNSS band, causing performance degradation or can even entirely block the receiver from acquiring satellite signal.
- ***Spoofing*** involves the broadcast of counterfeit satellite signals to trick the GNSS receiver, leading to inaccurate estimation of position, navigation and timing information.

The concerns of GNSS interference have expanded beyond aviation, gaining attention in other transportation sectors. In the automotive industry, particularly within Intelligent Transport Systems (ITS), several studies are presented to explore the impact of interference [8] [9]. This is also discussed in rail [10] [11]. As GNSS applications expand into safety-critical domains, addressing interference has become an essential topic for ensuring reliable and safe operations.

III. Local effects detection schemes

Now that the different main threats to GNSS-based fail safe train positioning have been introduced, this section will provide an overview of the blocks available in our team that comprise a non-exhaustive but extendable cascading scheme for detection and mitigation, as shown in Fig. 1. The following mechanisms will be introduced: Interference detection and classification at signal level; CMC-based detections on observables (CMC is classically used to characterise multipath); or C/N0-based detections on observables (C/N0 characterises the power of the received signal); camera-based satellite state of reception classification; GNSS-based context detection; FDE and Weighting Least Squares.

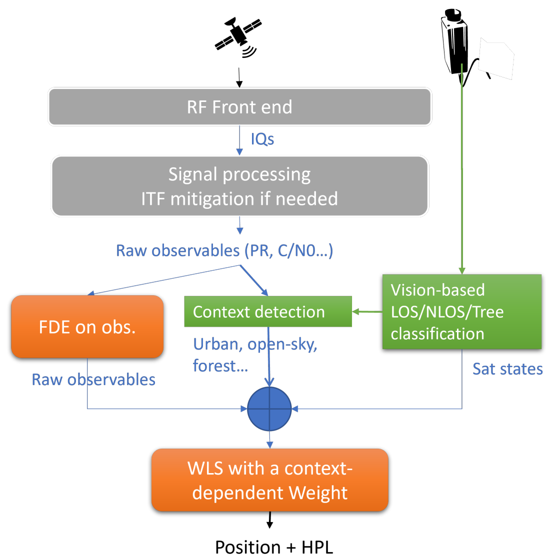

Fig. 1. Scheme of the cascading concept.

A. Context-detection

As presented in section II, the environment of reception plays a major role in land transport application and GNSS performance. This is the reason why context-aware GNSS-based navigation has been widely studied in particular using different machine learning techniques, each leveraging specific features to improve classification accuracy. Traditional machine learning models, such as Support Vector Machines (SVM) and Multi-Layer Perceptrons (MLP), primarily focus on statistical GNSS features (number of visible satellites (NVS), carrier-to-noise ratio (C/N0), azimuth and elevation angles, dilution of precision (DOP), and multipath indicators), making them effective for basic environmental classification [12], [13]. On the other hand, Convolutional Neural Networks (CNNs) specialize in spatial feature extraction, using time-series GNSS signals, C/N0 variations, satellite positioning data, and GNSS signal attenuation characteristics to enhance recognition in complex environments [14], [15], [16]. Meanwhile, Recurrent Neural Networks (RNNs), including LSTM (Long Short Term Memory) and GRU (Gated Recurrent Unit), are designed to capture temporal dependencies, analyzing C/N0 changes over time, satellite visibility history, and positioning error trends, making them well-suited for dynamic navigation scenarios [17], [18]. In addition to these methods, environmental context detection has been further refined by integrating vision-based enhancements. For instance, in [19], a GNSS-based method incorporating fisheye camera images was proposed to classify environments using satellite LOS (Line-of-Sight) and NLOS (Non-Line-of-Sight) using SVM model.

Our proposed solution extends the work of [19] by introducing an additional category, VEGE (Vegetation), and modifying the model to LSTM to better capture temporal dependencies, refining the feature vector to :

$$v(t) = \left[\mathrm{NSV}_k, \mu_{CN0,k}, \overline{\mathrm{elev}}_k, \overline{\mathrm{res}}_k\right] \quad (1)$$

with $k \in \{\mathrm{LOS}, \mathrm{NLOS}, \mathrm{VEGE}\}$, $S_{\mathrm{LOS}}, NSV_{\mathrm{k}}$, is the number of visible satellites in each state; The variable μ_{CN0} signifies the mean C/N0. The $\overline{\mathrm{elev}}_k$ denotes the average elevation angle, and the $\overline{\mathrm{res}}_k$ represents the average residual error.

B. Vision-based satellite state classification

Since [20], we develop some image segmentation algorithms for satellite state of reception classification. Our most recent developments rely on fish-eye images and neural networks allowing a 3 class prediction: LOS/NLOS and satellite received through vegetation [7]. We also investigate the interest of considering an ”uncertain class” in order to represent uncertain predictions and limit classification mistakes [21].

C. Observable-based detections

In the framework of the ERSAT-GGC project, we have developed a methodology for event detections based on the modeling of C/N0 nominal behavior and the definition of a threshold [22]. The model developed relied on the differenced C/N0 between frequencies [23] and was elevation dependent, relying on the principle that, in presence of significant multipath, the C/N0 behaviors not only deviate from the nominal values, but also differ in frequencies. The limits of the method are that, first, a calibration has to be performed depending on the equipment and its installation, and then, that dual frequency reception is required. Another indicator based on observables and published by DLR [24] is the CMC (Code Minus Carrier). CMC allows to isolate multipath error thanks to a combination of code and carrier phase measurements that removes all common error terms in code and carrier phase measurements after corrections of ionospheric and tropospheric delays.

D. Interference detection and classification at signal level

With the spreading of interference events, it becomes crucial to determine whether the receiver is operating under interference-free conditions or not. Several detection methods have been presented in the literature that rely on different observables and metrics throughout the receiver processing chain. These methods include Automatic Gain Control (AGC) monitoring, statistical analysis of digital IQs, spectral monitoring or C/NO-based detector. Recently, machine learning-based approaches have gained significant attention for interference detection and recognition [26] [27] [28].
Our work [29] has expanded the previous work in detection and classification with deep learning techniques. We explored ResNet and VGGNet architectures to tackle this challenge. Unlike many earlier studies that focused on interference cases with relatively distinguishable statistical characteristics, our work concentrated on different forms of frequency-modulated chirp-like signals with diverse patterns representing frequency evolution over time. We developed a dataset comprising 11 distinct jamming classes including Linear, Quadratic, Sawtooth, Triangular, S-curve, and Sigmoid among others. To introduce diversity within each class, we changed the signal parameters such as the start frequency, end frequency, sweep rate and relative jamming power. Some signals also incorporated additional parameters to modify the shape of the curves. Our approach utilized spectrograms images providing time-frequency representation as input to the network. The database consisted of a substantial collection of 148,500 sample images that participated in the testing, training and validation phases. Both ResNet and VGGNet models showed much similar performance, achieving an average accuracy of around 98%, with individual accuracy reaching as high as 100% in some cases.

IV. Results

This section illustrates some of the blocks using the dataset provided by [30]. This paper analyses the results in terms of accuracy performance. However, further work will be needed to assess their impact on integrity performance to achieve safety-related performance.

A. Dataset

The dataset was collected in February 4, 2022 by ISAE-Supaero in the surrounding of Toulouse, France [30]. 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. In this paper, we use GPS satellites only. As the dataset does not contain IQs or interference identified effect, this section will concentrate on detections of context, CMC and the effect of WLS on accuracy.

B. Observable-based detections

The database only contain mono frequency measurements. Thus the C/NO-based detection presented above is not applicable and we consider here the CMC-based multipath estimation. Fig. 2 shows CMC variations vs elevation for two different satellites (Sat 15 in green, 5 in blue) and highlights that low elevated satellites face more multipath than highly elevated ones. For a CMC-based preliminary fault detection and exclusion, a threshold above which measures will be excluded shall be defined considering an exhaustive calibration dataset recorded in an open sky area for nominal CMC description [24]. As the dataset we used covers the full range of satellite elevations but in every mixed environment and thus does not allow open sky calibration, for fig. 2, the 3σ threshold is computed based on the computation of elevation-based sigmas on the whole dataset and as a mean constant value for all elevation angles for concept illustration. With this detection, larger multipath errors are excluded from the computation but one shall consider that satellite state effects on remaining satellite still remain.

C. Weighted Least Squares

In the literature, the implementation of Weighted Least Squares (WLS) has been investigated to mitigate local errors

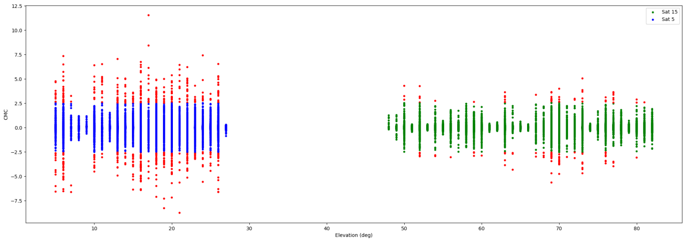

Fig. 2. CMC variations vs elevation for two different satellites. Red dots are CMC detected over an averaged 3σ threshold.

and enhance reliability of GNSS-based solutions. In [31], we have combined both the satellite state of reception and observable criteria and in [7] we compared the performance with different weighting schemes and depending on the reception context. WLS can be a way to strongly deweight multipath or NLOS signals as do the Additive weight [32] or the CAPLOC2013 one. Preliminary analyses show that we have not yet defined a single weighting scheme capable of achieving optimal accuracy everywhere, but show the interest of adapting schemes to the environment. In our data, a LOS/NLOS-based WLS allows us to reduce the median accuracy from 7.18 m (C/N0-based model) to 5.95 m for example. However, the same model underperforms in a vegetation area. Bearing in mind that the models can be refined, this still suggests that the different levels of detection and models are complementary rather than redundant.

D. Context detection

The LSTM model introduced in section III.A is trained on a dataset with four identified classes: urban, open sky, urban canyon, and vegetation, manually labelled and where urban canyon is mainly composed of building when urban can be a mix of building and some trees. The model is applied to the complete trajectory. Fig. 3 shows the resulting map. The model achieved an overall accuracy of 92% with optimized hyperparameters, demonstrating its effectiveness in context detection. While the performance is strong, some misclassifications are observed in particular between trees and urban that face the highest misclassifications (5 to 9%) probably because of similarities in their descriptions. This indicates room for improvement in refining class definitions to limit overlapping, trajectory analysis and increasing the model's adaptability to different environments.

This context detection allows us to refine previous analysis and weighting models relying on the satellite state of reception only [7]. Indeed, fig. 4 distinguishes the CMC values for open-sky LOS and LOS in an urban canyon area and clearly illustrates that the satellite state shall be considered with its context environment. In [33], context-aware stochastic functions are defined from function fitting between C/N0 and median code residuals. With our different tools, our proposal is to extend it and consider both context and satellite state for the definition of adaptive weights. Weight will then be expressed as $\frac{1}{\sigma^2}$ with

$$\sigma(i,k) = f(\text{SatState}(i,k), \text{Env}(k)) \quad (2)$$

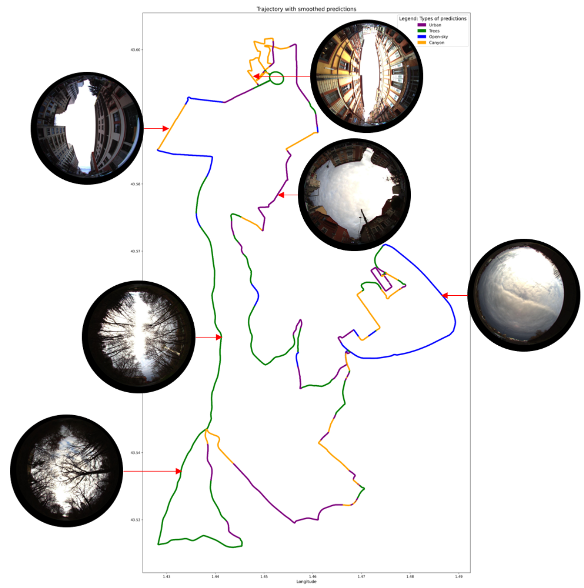

Fig. 3. Context map.

$$\text{SatState} = \{\text{LOS, NLOS, VEGE}\} \quad (3)$$

$$\text{Env} = \{\text{urban, open sky, trees...}\} \quad (4)$$

where i is the satellite number, k the epoch.

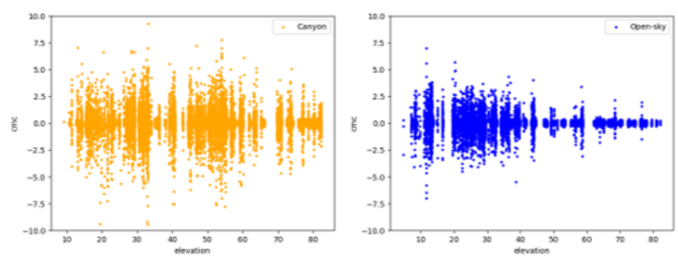

Fig. 4. CMC variations of LOS satellites in an urban canyon and in an open sky area.

In its complete version, as refered to fig. 1, the positioning estimator will rely on this context detection block to select the optimal weighting schemes (cf section C) and thus provide a context-dependent optimal position estimation.

V. Conclusions and Perspectives

This paper summarises the robust GNSS-based positioning solutions developed or implemented by our team for use in varying transport environments. The different layers applied aim to increase robustness to interference, local effects such as multipath or NLOS reception and take benefit of the recent progresses on context awareness to enhance position accuracy. The concept comprises a first layer dedicated to signal interference detection and, if necessary, mitigation. The cleaned signals are then processed by the receiver, and a fault detection and exclusion scheme is applied to the observables. The objective is to eliminate outlier measurements. In parallel, combining these observables with vision will enable us to classify the signal reception context. The final step uses both contextual knowledge and each satellite reception state to optimise the use of the received signals using a weighted least squares approach. The first studies demonstrate the potential accuracy of the concept, but the full concept has yet to be evaluated. It will also require the integration of fault detection mechanisms and integrity monitoring [25]. More studies will evaluate the complementarity and/or redundancy if there is, of the proposed layers. Finally, the scenario to be developed will depict the pod travelling successively by road or rail with either informative or critical safety requirements throughout the journey and will have to evaluate how such a scheme can also enhance integrity.

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