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GNSS, IMU, Camera and LIDAR Technology Characterization for Railway Ground Truth and Digital Map Generation

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Abstract

Satellite navigation in combination with affordable onboard sensors are key enabling technologies to support the digitalisation in railway transport. However, the adoption of these technologies still requires common methodologies to evaluate anywhere the positioning performance. For this, the comparison with a reference ground truth as well as the availability of digital railway maps is necessary. However, the development of a reliable Ground Truth and Digital Map solutions based on affordable onboard sensors requires on its side first a rigorous characterization of each sensor technology. This paper provides with the most important aspects for the characterization of GNSS, IMU, Camera and LIDAR technologies for its use in railway environment within the context of the European RAILGAP project.

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Keywords: EGNSS; railway localization; error and threat modelling; sensor fusion; artificial intelligence

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1. Introduction

Future railway signaling and control systems are expected to rely primarily on onboard sensors in order to reduce trackside costs and increase traffic capacity. For the localization function, the use of Global Navigation Satellite Systems (GNSS) is a key element to achieve the required safety levels by profiting from available infrastructures developed at European level (EGNSS), with the use of additional sensors like Inertial Measurement Units (IMU), Cameras and Laser Imaging Detection and Ranging (LIDAR) in combination with EGNSS can offer an affordable localization solution to achieve global availability and continuity.

Beyond signaling and control, the use of affordable onboard localization solutions is also a promising option for other railway applications. In order to evaluate the performance of these new solution, the European project RAILGAP (RAILway Ground truth and digital mAP) investigates the generation of high precision, accuracy and reliable railway Ground Truth (GT) and Digital Map without dependence or modification of trackside equipment.

Irrespective of the railway use case, the operation of GNSS, IMU, Camera, LIDAR sensors to provide accurate and reliable information is a complex task. On one side, each of the technologies or systems must be properly characterized. Individual and common errors and fault modes must be identified, modelled and monitored. Then, the combination of the sensor's measurements requires the design of advanced signal processing algorithms to provide not only a final localization or positioning information but also associated confidence metrics. All this can only be achieved by a combination of analytical as well as real data analysis methods (GPS.gov 2021).

One of the first goals of RAILGAP is therefore the derivation and validation of the necessary error models, fault detection methods and sensor fusion solutions based on multiple technologies, for accurate-precise and robust/trustable railway positioning, trajectory determination and environmental Digital Map construction. This is supported by the analysis of large dataset collected in railway environments by commercial trains.

This paper first provides the rationale for the need of onboard sensor solutions for signaling, control and ground truth, digital maps generation. Then, the key elements and methodology for the characterization of specific sensor technologies to be used in the railway environment is provided.

2. Railway Ground Truth and Digital Map

The RAILGAP project focuses on developing innovative High Accuracy, High Integrity Ground Truth and Digital Maps, which are essential elements of a Validation & Verification (V&V) environment for an EGNSS-based train positioning system. Both ground truth and trackside digital map will make use of specific algorithms and a careful analysis and characterization in the rail environment of different sensor technologies in combination with EGNSS, with the aim of removing any need for trackside infrastructure. With this approach, RAILGAP will contribute to the roadmap towards the adoption of EGNSS for not-safe and safe applications (e.g. satellite positioning in the railways European Railway Traffic Management System (ERTMS) ecosystem).

The RAILGAP developments follows the approach described below:

- Acquisition of measurements from EGNSS receivers and sensors such as IMUs, LIDARs, and Cameras, and characterization of these technologies to quantitatively evaluate their performances in railways environments. In particular, the following activities will be performed:
  - ✓ Provision of error models and definition of Normal and Degraded scenarios for every sensor;
  - ✓ Model generation of synthetic data (i.e. artificially generated in laboratory), corresponding to degraded working conditions;
  - ✓ Definition, selection and validation of Fault Detection and Exclusion (FDE) algorithms for computing high accuracy, high precision, high integrity 1D and 3D Absolute and Relative Positions, and odometry information.
- Definition of a methodology and the related tools for building a novel High Precision and Accurate, Reliable Ground Truth, i.e. 'reference data sets', based on EGNSS as primary source by using Trains in Commercial Service. The Ground Truth is expected to be used for performing off-line detailed error and performance analysis on the key performance indexes of new or enhanced on-board equipment or solutions. The error analysis is expected to address the assessment of both systematic and random errors. Noteworthy, the building process of the Ground Truth does not require the installation of equipment on the signaling trackside

or any modification of the exiting signal trackside, and it is robust with respect to the effects caused by disturbance and error sources like phenomena affecting radiofrequency propagation (e.g. multipath, shadowing, and masking), vibrations, climatic events, etc.

- Building of the Trackside Digital Map by using the acquired measured information through commercial trains, that is, not dedicated diagnostic trains or not railway carriages. This Map also includes information suggested by the error modelling and FDE Algorithms, if any; this additional information might be required for meeting the estimation integrity requirements associated with the Ground Truth and the Digital Map. The methodology for building the Digital Map also includes techniques for performing the continuous monitoring and control of the Trackside Digital Map in order to detect critical deviations with respect to the version assumed to be the reference Map. The use of Digital Maps in On-Board Signaling Subsystems, like innovative Automatic Train Protections (ATP) that use new technologies such as GNSS, IMU, LIDAR for train positioning or Automatic Train Operations (ATO), has been recognized as a key requirement. However, specific relevant challenges in the adoption of Digital Maps will be represented by the cost of building and maintenance of the Maps

According to the approach above, the building processes for Ground Truth and Digital Map are based on the post-processing of measurement data recorded, by using not only specific diagnostic/test trains but also commercial trains, provided that they are equipped with the RAILGAP measurement system. The train will act as a ‘measurement train’ and the use of the Artificial Intelligence (AI) techniques to off-line process the big amount of data collected during the commercial service will allow the extraction of the required information. The RAILGAP measurement system will be made up of COTS (i.e. Commercial Off The Shelf), that is, sensors like GNSS receivers (and related Antennas), cameras, IMUs, and LIDARs.

3. Onboard Sensors Characterization Methodology Overview

The railway environment presents many hazards for the EGNSS technology and EGNSS performance is strongly dependent on the number of visible satellites that can be reduced in urban or forest canyons, or even none in tunnels. The railway specific scenarios complicate the chances of a unique EGNSS solution to fulfil the stringent railway requirements. In order to guarantee the required reliability, safety and availability, any railway localization or trajectory determination function must consider the use of different sensor data in addition to the odometric system already existing on board the train. Furthermore, the construction of enhanced digital maps that not only provide topographic information of the railway tracks but also key elements of the surrounding essential for signalling purposes require the use of camera or LIDAR sensors.
However, the inclusion of new technologies requires the proper assessment of their specific behaviour in the railway environment and it also augments the number of possible faults to the system.
The statistical assessment of the sensor and algorithms performance in RAILGAP will be performed at different levels of the sensor processing chain. They constitute possible layers of protection for any resilient multisensor estimation process that allow to assess the reliability of the position and other magnitudes solution and to provide conservative and realistic confidence intervals. A general structure of the foreseen multisensor estimation process characterization and assessment is proposed in Figure 1.

The project will provide design and statistical assessment for each layer of the algorithm:

1. At the sensor level: The nominal performance of the different sensor measurements errors will be assessed here as well as the identification of the sensor fault modes or threats. Some of the sensor faults that have been identified can be handled before the combination with other technologies. Furthermore, some dependency of error/threat models can be identified or tailored to certain track locations.

2. At the fusion level: In general, the core of any sensor fusion algorithm is based on some type of filtering or smoothing, like the Extended Kalman Filter. The optimal estimator will be defined and evaluated associated to a layer of fault detection and exclusion to ensure a high level of integrity.

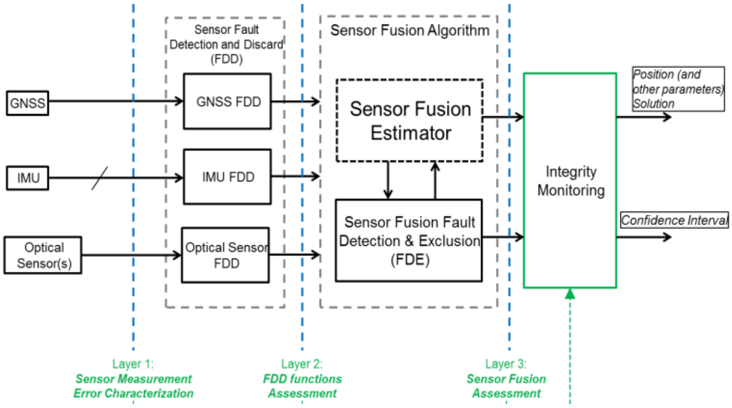

Figure 1. General sensor fusion architecture and necessary statistical performance layers

In the next sections, the key important elements for the independent characterization of each of the sensor technologies considered in RAILGAP are further detailed.

4. Global Navigation Satellite System

Satellite-based navigation solution are now widely spread in every day's life as they offer an absolute continuous position everywhere and anytime. GNSS solutions are based on time of propagation measurement that characterize the distance between satellites and the receiver. Mass market receivers rely on code measurement and provides accuracy of couple of meters. For RAILGAP needs of generating GT and creating Digital maps, a more accurate solution is required. For that reason, carrier-phase measurement will also be exploited, that can improve accuracy up to an order of less than a meter.

However, both pseudoranges and carrier-phase measurements are affected by a number of systematic errors or biases and random noises. Those error sources, by the point of origin, are divided into: satellite related errors (clock bias, orbit errors…), propagation medium related errors (ionospheric and tropospheric delays) and receiver related errors (hardware noise, clock bias and multipath). Most of the errors can be minimized by implementing mathematical models (for example, tropospheric delay), augmented solutions (SBAS for ionospheric delays), using two frequency measurements (for the removal of the ionospheric delay) or with post processed data (precise orbit determination). All of these technics and tools are investigated for use in the final RAILGAP solution. However, this is not the case with multipath, which are strongly dependent on the surroundings of the receiver's antenna (both the antenna installation and a wider surrounding such as trees, train stops etc.) and on the positions of the observed satellites. Moreover, since the environment is not-controlled in terms of electromagnetic propagation, signal reception can also suffer from (intentional or not) interference.

In order to ensure that GNSS can contribute to the RAILGAP solution for GT and Digital map building in an accurate and safe way, it is of upmost importance to detect signal propagation and thus, measurement, degradation. Which is the role of the fault detection layers presented in Figure 1.

Fault detection requires a precise knowledge of nominal modes in order to bound the estimated error and detect if and when a measurement is exceeding a certain threshold. In RAILGAP, the first task is dedicated to the characterization of the GNSS nominal errors. This characterization consists in the computation of residual pseudo-range errors after the correction of every possible know errors mentioned before. In nominal conditions, i.e. when the antenna is in an open sky conditions, the remaining errors should be the installation-caused errors (primarily multipath), receiver noise and residual noise due to the imperfection of the applied corrections. In other conditions of reception, local effects will be added.

First results show the impact of the hardware installation on the error characterization. The data used for the following analysis was collected during the ERSAT GGC project. This dataset was used because the antenna installation in the RAILGAP project is going to be the same as the one used in the Sardinia Trial Site of the ERSAT GGC project in Italy.
The accuracy of characterization of the nominal case, directly affects the accuracy of fault detection and the contribution of the GNSS receiver in the multi-sensor final solution. Additionally, time-correlated error models are also going to be considered for the implementation of sequential-estimators-based GNSS/INS integration algorithms in order to achieve the level of accuracy RAILGAP requires.

a b

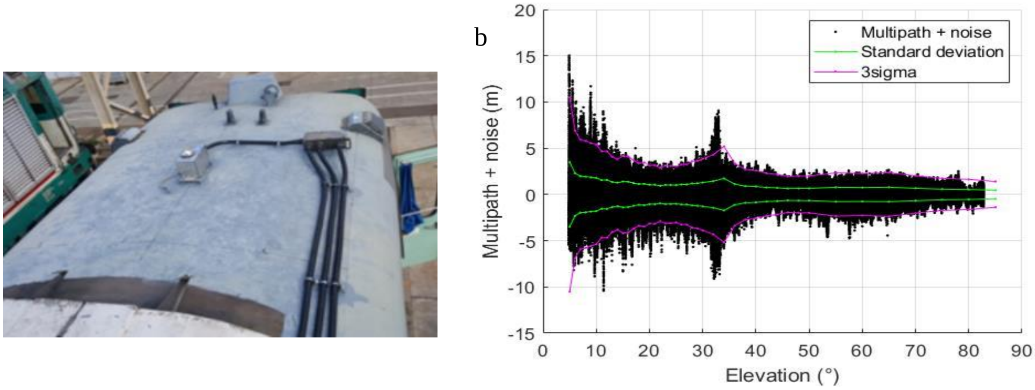

Figure 2 (a) Antenna installation; (b) MP, noise and standard deviation, GPS L1, ERSAT GGC, Italy.

5. Inertial Measurement Unit

An Inertial Measurement Unit (IMU) is usually composed of a triad of accelerometers and a triad of gyroscopes measuring, respectively, specific forces and angular velocities on three perpendicular axes. Besides, an IMU also contains a clock (usually quartz) and in many occasions a temperature sensor. The IMU sensor is therefore able to provide periodic measurements related to the dynamics of a vehicle at a given frequency, usually between 100-1000 Hz depending on the grade (i.e., quality) and specific technology of the accelerometer and gyroscope sensor. Nowadays, for most navigation applications, the accelerometers are fixed to the vehicles body frame and in a similar sensor frame as the gyroscopes. This is commonly known as strapdown technology. In this case, the gyroscopes' angular velocities are integrated over time to maintain an estimation of the attitude of the vehicle from an initial attitude. The knowledge of the attitude can then be used to rotate the accelerometers' specific forces into the desired navigation frame and then, integrated once over time to obtained velocity and twice to obtain position from a starting reference velocity and position. The IMU sensor plus the described computations to obtained attitude, velocity and position is known as Inertial Navigation System (INS).

Due to different error sources in the specific forces and angular velocities measurements that are integrated, the INS solution accumulates increasing error over time (known as drift). In order to reduce the magnitude of the drift over time, 1. the IMU measurement deterministic errors must be properly determined and modelled, 2. The stochastic IMU errors must be properly characterized so that the INS can be rigorously combined with other sensors like GNSS to provide a stable solution over time with guaranteed error estimation. The combination of INS with GNSS is out of the scope of this paper and it will be addressed in the next steps of RAILGAP project. As anticipated, the IMU measurement errors can be divided into deterministic and stochastic. A general model for an accelerometer or gyroscope measurement vector $\boldsymbol{x}$ is:

$$\boldsymbol{x} = (\boldsymbol{I} + \boldsymbol{S} + \boldsymbol{M})\bar{\boldsymbol{x}} + \boldsymbol{b} + \boldsymbol{b_0} + \boldsymbol{\eta}, \tag{1}$$

where $\bar{\boldsymbol{x}}$ represents the true specific force or angular velocity, $\boldsymbol{I}$ is an identity matrix, $\boldsymbol{S}$ is a diagonal matrix containing scale factors, $\boldsymbol{M}$ is a matrix representing the non-orthogonal misalignments between sensor axis, $\boldsymbol{b}$ is a constant bias, $\boldsymbol{b_0}$ a random bias and $\boldsymbol{\eta}$ represents a stochastic noise component. The scale factors, constant bias and their dependency with temperature as well as the misalignments can be estimated by manufacturers by precise calibration procedures and the measurement output of IMU sensors can be compensated for those errors except for low-cost sensors where its deviation from manufacturer values may change rapidly over time. The random bias, also known as turn-on bias, changes every time the sensor is switched on. This bias is small in high quality sensors and significant in lower-cost IMUs. It can be partially estimated by an initial alignment procedure or must be estimated when the INS is coupled with other sensors like GNSS. The noise error cannot be known a priori and it evolves over time with certain stochastic behavior. Its characterization is the main focus in RAILGAP so that the derived models can be used for the design of rigorous GNSS/INS estimators. The first step consists on the identification of the types of noises. This is done traditionally by analyzing static IMU time-series data and the use of Allan Deviation (AD) estimators, that provide information of the dominant noises at different time intervals. Different types of noises are depicted in the AD domain in Figure 3. Then, it is possible to choose simple models to characterize the AD curve. The most common ones for inertial sensors are white noise and Gauss-Markov. Parameters of the chosen models can be estimated to fit the AD curve as shown exemplary in Figure 4. Finally, and since the AD presents spectral ambiguity, the models are validated with the time-series data in the Power Spectral Density (PSD) domain and eventually adjusted so that the model PSD overbounds the empirical PSD since this has been demonstrated to guarantee conservative error estimation for any estimator using and modeling the IMU measurements (Langel, Garcia Crespillo and Joerger 2020).

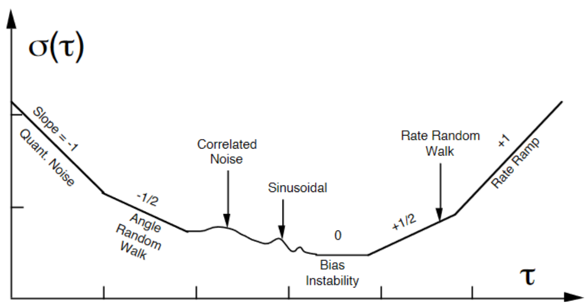

Figure 3 Allan deviation and random processes (IEEE FOG standard 1998).

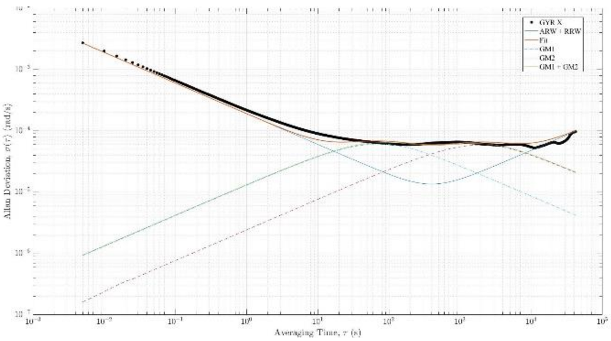

Figure 4 Allan deviation model fit example.

6. Camera

The recognition of railway signs and elements along the routes is one of the objectives of RAILGAP. In particular, the system must recognize the different elements located on the railway from the images obtained during the trip by a camera installed on their front. This object detection will be combined with information from other sensors to determine its absolute position to create the digital map. To determine the position of objects, two different techniques have been selected:

Using a stereo camera, it is possible to calculate the distance to the object by the disparity between the images taken by two cameras. On the other hand, those images are processed by a neural network that detects the objects. By combining both types of information, distance and object identification, it is possible to determine the relative position of objects. Using this solution, it would not be necessary to combine the information from the stereo camera with other sensors, however, since the distance to the target varies inversely with the disparity, the error of this type of technique depends on the optics of the lens, the resolution of the images, and the separation between the optical axes of both cameras. The following formula sets the disparity (x-x') as a function of the baseline (B), the cameras focal length (f), and the depth of the object (Z):

$$\boldsymbol{disparity = (x - x') = Bf/Z} \quad (2)$$

Combining the camera information and the LiDAR information: Using the images captured by the camera and AI techniques, it is possible to detect the objects on the railway; this information could be used to select the points provided by the LiDAR to obtain the distance to this object. With this solution, it is necessary to calibrate the LiDAR with the camera to be able to combine the information consistently.

From the aforementioned techniques, it is obtained a *Depth Map* of the observed scenario, which represents the distance from the camera and each pixel of the observed scene. This depth map is processed to calculate the displacement between subsequent image acquisitions due to the movement of the train.

In order to evaluate the performances of the stereo camera sensor, 100 intensity images of a target and the corresponding disparity maps were acquired outdoor, slightly before noon, at different distances. Multiple acquisitions were performed for several distances from 0 to 25m, and the mean and standard deviation statistics were computed to evaluate the sensor performance at estimating distance. The sensor used for all the acquisition was the Nerian's Karmin3 stereo camera with Scenescan Pro for the disparity computation.

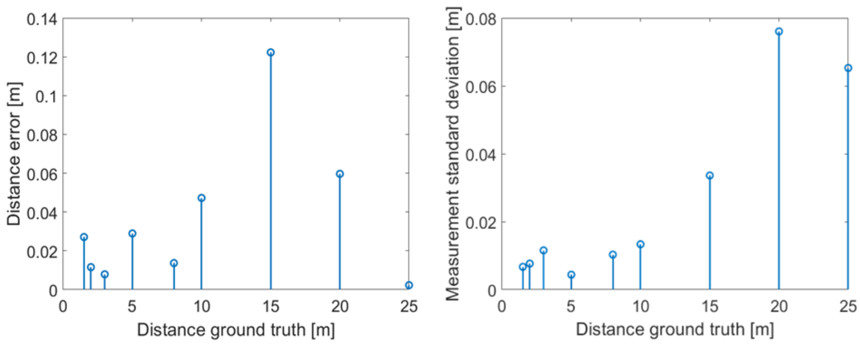

Figure 5. Overall mean and standard deviation for different target distances.

7. LIDAR

LIDARs (Light Detection and Ranging or Laser Imaging Detection and Ranging) devices, differently from stereo cameras and other 3D imaging devices, estimate the distance through the measure of the round-trip delay of a laser pulse to the object. The shorter wavelengths of the optical waves, compared for instance to the radio frequency waves used by radars, translates into better resolution, and a more favorable choice for 3D imaging. However, the advantage of the LIDAR is its integration capability on electronic and photonic chips that can lower its cost, size, and power consumption, making it accessible for many applications (Behroozpour, Sandborn and Wu 2017), such as autonomous vehicles guidance, monitoring man-made structures, developing objects modeling and so on. During each scan, LIDARs collect a point cloud with x, y and z coordinate values (and additional information like reflectance or color, if supported by the device).

A LIDAR has the capability to detect all the 360-degrees surrounding objects with high accuracy. During each scan, the LIDAR sensor collects a cloud of points with x, y and z coordinate values of surrounding objects. Since the LIDAR is an active sensor, it can work both in days and nights, but, in general, with a non-negligible influence of weather condition on its performance. The LIDAR is also characterized by high accuracy and reliability, which is the major reason that these sensors have been used as a critical component of self-driving vehicle sensor systems (Wu, Xu and Zhao 2020)0.

For the application of LIDAR technology in railway environment, several sources of error should be considered, and they can be mainly classified in two categories, namely: environmental conditions and sensor's faults.

Concerning the former, the following influencing factors can be identified:

- Lighting conditions: other light sources with wavelength similar to the one employed by the LIDAR may alter the acquired point cloud by introducing artifacts.

- Weather conditions: weather phenomena may degrade the point cloud acquired by the LIDAR. More specifically, fog, rain, or snow may alter the measured range by attenuating the LIDAR pulses.
- Occlusions: occlusions may prevent the LIDAR from acquiring information concerning a portion of the surrounding scene. Examples of causes of occlusions are the presence of dirt on the sensors, or physical obstacles in the surrounding environment.
- Ambient conditions: temperature affects optical, electronic and mechanical components of the acquisition devices.

Taking all this into account, it is possible to model LIDAR measurements in the range domain as a mixture of four conditional probability distributions of the kind $p(z_t^k|x_t, m)$, where z_t^k is the measurement for the k-th point at time t, x_t is the position of the sensor and m represents the position of the object whose distance the LIDAR is actually measuring.

The identified error sources may cause two effects on the output provided by the LIDAR: 1. the point cloud is composed of a reduced number of points; 2. errors in the distance computation procedure occur.

For this reason, it is not possible to isolate the error sources by processing the LIDAR output. However, the sensor itself may provide an internal monitoring thus activating alarms when anomalous situations occur. For instance, the Livox Horizon provides the following system status:

- Temperature status: indicates if there is any temperature abnormality. Temperature status includes normal, warning, and error.
- Voltage status: indicates if there is any internal voltage abnormality. Voltage status includes normal, warning, and error.
- Motor status: Indicates if there is any internal motor abnormality. Motor status includes normal, warning, and error.
- Dust warning: indicates if a significant amount of dust is detected on the optical window, if the optical window is covered by objects, or if there is an object less than 0.3 meters away from the LIDAR sensor.
- Service life warning: indicates if the LIDAR sensor is nearing the end of its service life. The LIDAR sensor can still work for a short period once this warning appears.

8. Conclusions

The paper provided an overview of the main goals of the EU project RAILGAP and how a proper characterization of different sensors will enable building robust and accurate ground truth and digital map, filling an important gap for the development and assessment of new solutions in railway applications. During the RAILGAP project, the collection of a large measurement dataset in diverse railway scenarios will be carried out with trains under commercial operation that will allow, for the first time, to perform a rigorous error modelling and statistical assessment of the different technologies under railway environment. Next contributions of the project will be the development of the Ground Truth and Digital map relying on these characterizations.

Acknowledgements

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References

"GPS.gov," 17 November 2021. [Online]. Available: https://www.gps.gov/applications/rail/. [Accessed 3 March 2022].

Langel, S., Garcia Crespillo, O., Joerger, M., 2020. A New Approach for Modeling Correlated Gaussian Errors using Frequency Domain Overbounding. In: 2020 IEEE/ION Position, Location and Navigation Symposium, (PLANS), Portland, OR, USA

IEEE standard specification format guide and test procedure for single-axis interferometric fiber optic gyros, pp. 952-1997, 1998.

B. Behroozpour, P. A. Sandborn and M. C. Wu, "Lidar System Architectures and Circuits," IEEE Communications Magazine, vol. 55, no. 10, pp. 135-142, 2017.

J. Wu, H. Xu and J. Zhao, "Automatic Lane Identification using the Roadside Lidar Sensors," IEEE Intelligent Transportation Systems Magazine, vol. 12, no. 1, 2020.