ENHANCE RAILWAY DIGITAL MAP FOR SLAM: FEASIBILITY STUDY

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ABSTRACT

Safe train positioning is a challenging task that boosts the traffic capabilities and the quality of train localization and integrity information, but above all enables cost reductions in infrastructure train detection systems such as balises and track circuits. Prominent technologies, namely, global navigation satellite system and inertial measurement unit sensors are arising to incorporate in train positioning. Typically, trains run on harsh railway environments including interference, insufficient satellite availability and signal blockages in specific areas like tunnels and urban canyons or due to meteorological conditions changes. Currently, these problems are solved with the use of balises for full supervision modes and drivers for staff responsible/shunting modes. However, autonomous trains with fully automatic driving and without drivers will need to deal these issues. Simultaneously localization and mapping algorithms based on radar and/or lidar sensors have shown great potential of being candidate positioning solutions for future train transportation. This paper presents a state of the art on these techniques and a testing architecture as part of a study on the feasibility of candidate sensors for safe autonomous train positioning in order to assess the viability of absolute positioning without need on infrastructure devices.

Keywords: SLAM, mapping, autonomous driving, railway, sensors.

1 INTRODUCTION

Autonomous driving systems navigation requires a precise mapping and localization solution. In this context, simultaneous localization and mapping (SLAM) is a suited and popular solution [1]. For solving the navigation problem, there are two major questions to be answered. First the environment on which the system is located needs to be identified and secondly the system must be localised within this environment. There are therefore two problems to address; localization means estimating the pose; and mapping which is building a map. It is challenging because there is a dependency between the two tasks: a map is needed for localization and a location estimate is needed for mapping. SLAM is addressing these two problems jointly. It computes the positions and at the same point in time while estimating these poses, a map of the environment is built. A map is a model of what the environment looks like. It can be a dense 3D model or specific positions of landmarks (distinct points or features) in the environment extracted from the sensor data.

The objective of this paper is twofold: firstly, to summarise the state of the art of the SLAM algorithms and their digital map usage, and secondly to describe a testing architecture that allows recording all required sensor's information with high precision and low delay under the railway domain. The recorded data will be part of the feasibility study of a positioning system based on extended maps focused on the proposed sensors.

This document is structured as follows: first, a background on railway maps modelling, sensors and positioning algorithms is presented. Then, relevant SLAM techniques are detailed. In the next section, the identified testing architecture is presented. Finally, the document concludes with discussion and conclusion sections.

WIT Transactions on The Built Environment, Vol 213, © 2022 WIT Press
www.witpress.com, ISSN 1743-3509 (on-line)
doi:10.2495/CR220211

2 BACKGROUND

2.1 Positioning algorithms

Localization represents an elemental requirement for autonomous systems navigation. It is the task of determining the system geo-position relatively to a reference frame in an environment. In this section, the most common localization approaches are presented.

2.1.1 GNSS

Global navigation satellite system (GNSS) represents a widely used pervasive technology in autonomous driving systems for navigation. It rose in the 1980s and is widely used up to now. It presents a solution for absolute positioning [2]. It determines the absolute position of a point using only the measurements made in the associated station based on simple data processing algorithms. No restrictions are sustained by the GNSS receiver antenna position. This solution remains insufficient by itself because of the availability issues, thus not enough accurate.

2.1.2 GNSS and IMU

For positioning autonomous systems, GNSS solutions cannot be used as a stand-alone system. In order to remedy dead reckoning errors in intervals with absolute position readings, GNSS-IMU fusion systems are proposed [3]. IMU captures and measures the changes in position and orientation. This information is processed when localizing the system with dead reckoning. The GPS readings are used in addition to the map information for correction of accumulated errors. The accuracy required for autonomous driving systems represents a major challenge for this solution.

2.1.3 GNSS with IMU and odometry

For bridging the GNSS outages, IMU solutions are coupled with odometry [4]. In addition to fusing GNSS with IMU, wheel speed sensors are used as a backup or alternative to GNSS-based positioning. Unlike GNSS, odometry measurements are available and generally don’t suffer from environmental influences, except wheel pulse generators and radars output errors which depend on environmental conditions like wet leaves and snow.

Reuper et al. [5] concluded that thanks to the integration of odometry model, more accurate measurements are obtained into the localization algorithm comparing to GNSS-IMU based results.

2.1.4 Simultaneous localization and mapping

Autonomous trains are safety critical systems. Their localization is a challenging task. An appropriate approach should be able to determine the absolute position measured with on-board sensors and the relative topological position. The mapping approach aim then to generate an automated map and maintain it based on measurements of sensors. Another challenge for railway applications, is that the near field environment is very similar (same objects such as trach rails, catenary, and signs for many kilometres). So, the opportunity to discriminate the position is harder than other environments such as roads for cars. Among the possible solutions that can face these challenges, we distinguish the SLAM approaches which attracted more and more research and industrial attention in recent years.

SLAM is a problem initiated in 1986 by Smith and Cheeseman, and get more popular during the 1990s [1]. Solving a SLAM problem amounts to estimating a system’s position in the environment and constructing a map of the surroundings simultaneously. The research in this field involves many topics such as data analysis, sensor data extraction and primitive search and map storage. The availability of new and different sensors have created new data representations and consequently new mapping systems. Nowadays, SLAM is used for various applications ranging from autonomous driving to spatial exploration. SLAM is an estimation problem of both the trajectory or pose of the system and the position of landmarks in the environment [6]. The estimation techniques can be categorized into two main classes: filter-based and optimization-based approaches; which will be detailed in the next section.

2.2 Sensors and hardware

Sensor technologies have experienced remarkable progress in recent years. They now play a crucial role in the development of autonomous driving systems. Various sensors are widely used in different applications such as environment perception, geo-data analysis, mapping and localization [7]. In the following, we present three main types of exteroceptive sensors, which are cameras, radars and lidars.

Cameras are passive sensors because they do not emit any signals. They can sense colour and provide rich information of the environment. However, their performance is affected by illumination and weather conditions. Also, from a single camera, it is difficult to obtain depth information. 360° 2D vision can be assured by omnidirectional cameras. In fact, panoramic views can be exploited for navigation, localization, and mapping.

Radars can cover the cameras' drawbacks since they provide depth information. That is distance to objects can be measured effectively. Contrary to cameras, they are active sensors. They emit radio waves that can interfere with other systems. Similarly to radars, and instead of radio waves, lidars emit infrared light waves. These electromagnetic waves are used to detect objects in the near field environment by a light beam and measure the distance and angle of the reflecting objects. They allow then to measure the distance between the object and the sensor in addition to other physical properties. 3D points highly accurate represent the result of the measurement. The coordinates of these points are provided in local coordinate systems according to the lidar system type and usage area. Coordinates in global positioning systems can be obtained if we dispose of stationary use with known position. Otherwise, further sensors are needed.

Table 1 summarizes the advantages and disadvantages of each of these sensors.

Table 1: Sensor's comparison.

	Advantages	Drawbacks
Lidar	Rotativity 360 degrees Mature technology (used since the late 1980s) High accuracy	Medium range (<200m) Affected by weather (such as fog or snow having a negative impact on their performance) Large size High cost
Radar	High range Small size Medium cost	Interference with other systems (it is an active sensor which emits radio waves) Affected by weather (such as rain or clouds)
Camera	Passive sensor (does not interfere with other systems) Colour Low cost Small/medium size	Affected by illumination Affected by weather Low accuracy

3 RELEVANT SLAM TECHNIQUES

A SLAM system architecture comprises two main components: the front-end and the back-end. The first component performs sensor data abstraction into models. However, the second component deals with inference on the abstracted data produced from the front-end.

There are two formulations of the SLAM problem [1]. In the first one, known as full SLAM, the whole trajectory and the map are estimated based given all control inputs and measurements. The goal is to compute the map and the joint posterior over all poses based on the total sensor data. Given the system's controls $u_{i:t}$ and observations $z_{i:t}$, construct a map of the environment m and a path of the system $x_{0:t}$. Since the observations and motions are uncertain, probability theory is used to express uncertainty. Then full SLAM refers to the full trajectory of all locations $x_{0:t}$ and the map m:

$$p(x_{0:t}, m|z_{0:t}, u_{0:t}). \tag{1}$$

The complexity of the full SLAM grows with the considered variables number; thus it is difficult to compute. Therefore, the second formulation is about the online SLAM. Its goal is to estimate the current position based on the last sensor data. Then the online SLAM refers to the estimation of the current location state x_k and the map m:

$$p(z_k|x_k, m). \tag{2}$$

The goal of SLAM is to estimate the pose and model the environment simultaneously. However, the matching between the observations and the map is unknown because the path and the map are both unknown and the map and pose estimates are correlated. It is then a hard problem and is the typical case for lidar based sensors. However, radar based sensors, the digital map is computed in advance or in a recording process and then they do the matching.

3.1 Filter-based SLAM

Filter-based SLAM techniques derive from Bayesian filtering and are based on two steps that iterate and integrate sensor data to estimate the system pose on the map [1]. The first step predicts the map states using an evolution model and control inputs. In the second step, the observation coming from the sensor data is compared to the map to correct the predicted state. The model that matches the observation against the map is called an observation model. There exist four sub-categories of filter-based techniques, which are:

3.1.1 Extended Kalman filter

These methods are derived from the Kalman filter (KF). KFs handle linear systems and assume that data are affected by Gaussian noises [6]. They present high convergence properties but are rarely used for SLAM. However, the extended Kalman filtering is common in SLAM for non-linear filtering. Its principle is to add linearization step for non-linear models. The current position is performed using the linearization through a first order Taylor expansion. EKF is based on five steps, which are:

- Pose prediction: predict the state given the previous pose;
- Observation: take the real measurement;
- Measurement prediction: predict the expected measurement given the belief state;
- Matching or data association: associate the obtained measurement of the landmarks (based on the map) with the predicted observation;

- Estimation: compute the difference between the obtained measurement and the predicted measurement and update the state (mean and covariance matrix) via the Kalman gain.

The disadvantage of KF based SLAM algorithms is that the computational complexity increases with the environment landmarks added to the state vector [14]. Moreover, matching the observations and landmarks in the state vector may cause filter to diverge when data association is wrong. Some works proposed to improve EKF by reducing complexity and memory usage. Alternatives such as CEKF were proposed [8]. They consider local areas of the stochastic map. CEKF, in contrast with EKF, don't perform full SLAM update since it is working in a local area; however this reduces the computation complexity.

3.1.2 Unscented Kalman filter

Initiated by Julier et al., UKF method got popular during the 2000s. It tried to address the problem of EKF with highly non-linear systems by avoiding the computation of Jacobian matrices. They introduced the concept of sigma points, which are sample particles weighted around the expected measurements thanks to likelihood functions. They are used as input to the non-linear function to update the estimate. UKF reduces estimation errors, but the main disadvantage of this method is its high computational complexity $O(k^3)$, where k is the number of landmarks.

3.1.3 Information filter

Information filter is a variant of Kalman filter. Its principle is to use the inverse of the covariance matrix as information matrix [1]. But converting every measure to its inverse form is costly. However, the main advantage of this method is a near constant-time update step by making the information matrix sparser. The update is then additive and no longer dependent of the observation's integration order.

3.1.4 Particle filter

Particle filter-based algorithms assume that a state is sampled with a set of particles depending on its probability density [1]. As Kalman filter, measurement prediction and update according to the observation are performed. However, the particles are updated by weighting them with reference to their likelihood regarding the measures. For each update step, particles are handled as follows: some are kept (the most likely), the others are eliminated, and new particles are generated. The main drawback of this method is the requirement of a set of particles per landmark. However, its advantage is that it can accommodate with any distribution and does not require an assumption of Gaussian noise.

3.2 Optimization-based SLAM

As in filter-based techniques, optimization-based SLAM approaches are composed of two steps. In the first step, the sensor data are leveraged to identify the constraints of the localization problem by matching the new observations against the map. In the second step, the system pose and the map are computed and refined. Two main sub-categories can be identified; bundle adjustment and graph SLAM.

3.2.1 Bundle adjustment

BA is a visual feature-based SLAM. Based on images and camera parameters, it refines the visual reconstruction of the map based on a number of 3D points [1]. The goal is to estimate the location of the camera and the 3D points locations jointly so that the error where the point is projected to is minimized.

3.2.2 Graph SLAM

3.2.2.1 Pose graph-based SLAM

The idea is to use a graph to represent the SLAM problem where a node corresponds to a pose during the mapping and an edge between two nodes correspond to a spatial constraint between them. A graph-based SLAM problem amounts to build a graph and find the nodes configuration that minimizes the error introduced by the constraints. The principle is to have an interplay between the front-end where the graph is constructed from raw data and back-end where the output graph is optimized; then the node configuration is updated. The configuration is such that the real and predicted observations are as similar as possible. The difference value between the predicted and actual measurements is the error. The goal is to find the state that minimizes the error given all measurements.

3.2.2.2 Graph with landmarks

Nodes can represent poses or landmark locations and edges can represent landmarks observations or odometry measurements [1]. The optimization goal corresponds to minimizing the landmark locations and system poses. The minimization is generally simplified by a local approximation using methods such as Gauss–Newton, Gauss–Seidel relaxation, Levenberg–Marquardt or gradient descent.

Autonomous driving systems designed to perform SLAM are using exteroceptive sensors. lidar can provide accurate 3D mapping of the environment comparing to radar. Applied to a SLAM technique, this sensor can achieve a low drift motion estimation for an acceptable computational complexity. The main solution is the scan-matching approach followed by a graph optimization. Scan-matching is a process used for creating 3D maps with lidar data, giving precise information on motion. Iterative closest point (ICP) is the most common technique for registering 3D point clouds. It is an iterative algorithm for local scan matching.

Table 2: Main algorithms complexity and scalability.

Criterion \ Algorithm	EKF	Information filter	Particle filter	Graph SLAM
Computational complexity	$O(n^2)$	Constant	M.log(n)	Edges
Large scale	–	+	+	+

n = number of landmarks; M = number of particles.

4 TESTING ARCHITECTURE

4.1 Candidate sensors

To assess SLAM algorithm on railway environment two main technologies are proposed, radar and lidar. Both sensors have been widely used in SLAM algorithms as it is described in Bresson et al. [1].

4.1.1 Radar

The proposed radar sensor is an automotive radar sensor, which is already in-service for automotive passenger and commercial vehicle applications especially for the functions adaptive cruise control (ACC) and emergency brake assist (EBA). In Fig. 1 it can be seen the field of view of the proposed sensor. It is based on a 77 GHz frequency with digital beam-forming scanning antenna, which offers two independent scans for far (FRS) and near range

(NRS), as described in Fig. 1. The sensor uses a pulse compression radar modulation to avoid the drawbacks of both the classical Pulse–Doppler and the frequency-modulated continuous wave radar (FMCW) approach. Since the radar sensor is a sensor that could potentially be used for object detection and collision avoidance purposes, it is foreseen to install three radars per cab. One radar per side and one at the centre of the cab facing forward. In this way, a coverage of all three radars would reach to 260°. Notice, that this angle would need to be verified with final train set up. Fig. 2 shows a view of the radars installed at the front of the train cab.

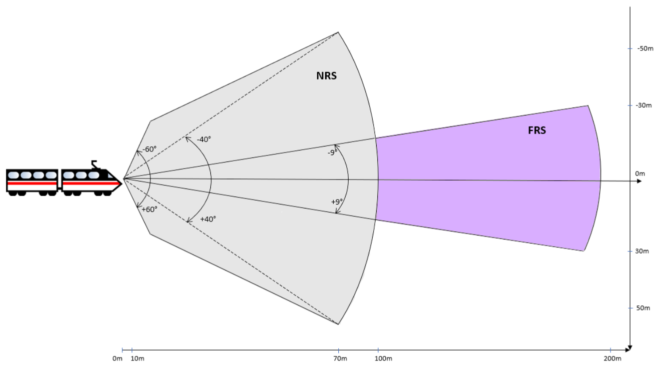

Figure 1: Radar horizontal field of detection.

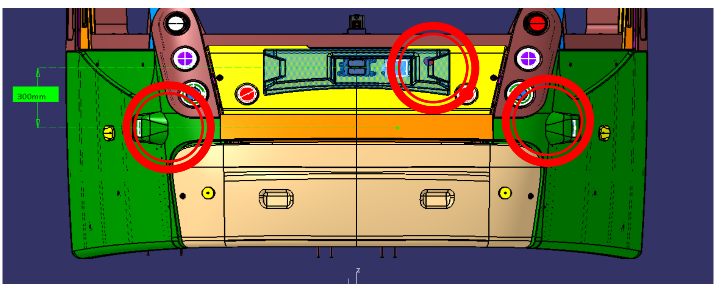

Figure 2: Radar location on train (surrounded objects).

4.1.2 Lidar

The proposed lidar sensor is an automotive sensor. In Fig. 3 the lidar location at the front of the train cab can be seen. The sensor is a time-of-flight sensor, operating at a near-infrared (IR), 1064 nm, wavelength that consists of a single laser illumination module and sensor receiver module (both build-in the HFL118 sensor head).

Laser illumination module, periodically (e.g. every 40 ms) emits a single, very short (~ 3 ns), laser pulse, that is spatially diffused (both horizontally and vertically), to provide the illumination in the full FOI (field of illumination) region (e.g. 120° (horizontal) × 30° (vertical)).

Sensor receiver module captures, and samples all return signals (reflections from targets) that were illuminated in FOI, returned within FOV (field of view), and received within the

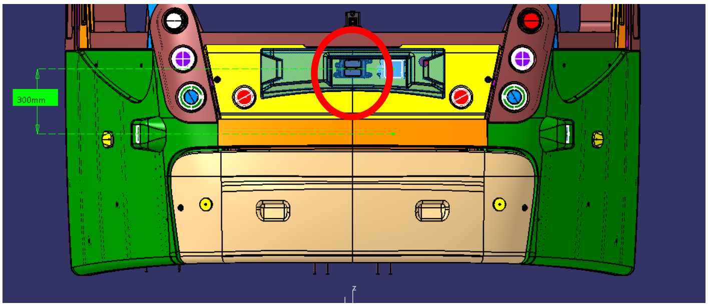

Figure 3: Lidar location on train (surrounded object).

shutter open-time period. Receiver module optics is specifically designed to match the FOV with FOI, exactly. And shutter open time (together with lidar link budget calculations) determines the maximum range of flash lidar. HFL118 shutter open time is set to ~400 ns. These extremely fast shutter speeds provide the instantaneous "Flash" mapping of the 3D environment. Fig. 3 shows the view of the lidar installed at the train cab.

4.1.3 Other sensors

It is worth to notice that the full system for positioning may not be able to perform without the inputs from other sensors than radar and lidar. For such, the idea is to complement the recording scheme by using the following additional sensors:

- GNSS receiver
  - Dual constellation dual frequency receiver and antenna are proposed.
- Inertial measurement unit (IMU)
  - Six degrees of freedom sensors are proposed with both accelerometers and gyroscopes.
- Speed sensor (tachometers)
  - Tachometers based on Hall effect are proposed as part of the speed measurement system.
- Camera
  - Fish-eye cameras are set as part of the validation of the sensor set-up and as visual inspection tool for the performance.

Since the additional sensors are not considered as the core of the SLAM problem, their detailed description is considered out of the scope.

4.2 Test recording architecture

The test recording architecture is the hardware/software set-up required to fit in the train for the purpose. Fig. 4 presents an illustration of the proposed architecture for the set-up. This architecture comprises on one side the three radars per cab, one lidar and one fisheye camera. The idea is that the three radars set-up allow to have a full field of view of the train environment increasing the likelihood for positioning algorithms. All these sensors provide their information to the railway certified recording platform, which is based on a UNIX operative system over an ARM architecture. In addition, GNSS receiver data, IMUs and Speed values are also provided to the recording platform so that all the components to measure the train position based on SLAM algorithms are ready to assess.

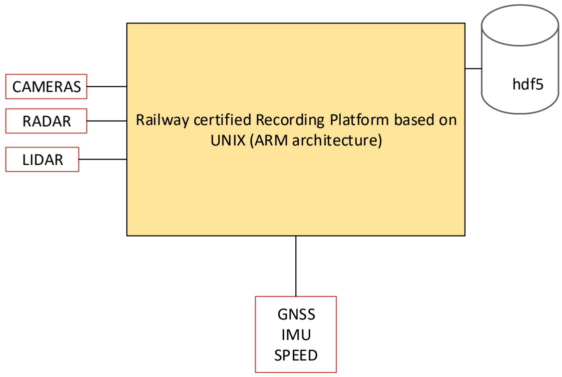

Figure 4: High level architecture set-up for testing.

Based on the testing architecture the appropriate recordings can be carried out and in post-processing mode the expected feasibility study of positioning algorithm can be analysed.

4.3 Test environment

The test recording scenario will be installed in the tram of Zaragoza. The Urbos 3 model, manufactured by CAF in their plant in Zaragoza, uses the very latest technology, aiming to offer a service which is effective, comfortable and environmentally friendly. The design comes from the Fabrizio Giugiario School, which is responsible for the different models of Ferrari and Maserati. From the outset, CAF worked with ONCE and the DFA Foundation to make the Tram fully accessible to all (https://www.tranviasdezaragoza.es/en/informacion/nuestro-tranvia). The tram consists of five modules with a total length of 32.314 m, 296 passenger capacity and a maximum speed of 70 km/h (https://www.caf.net/en/productos-servicios/proyectos/proyecto-detalle.php?p=61).

The tram circulates over the city of Zaragoza where there is mainly an urban environment but also there are shunting yard environments. Both are considered challenging environment for localization purposes and interesting for the TAURO project. The following figure is an illustration from Open Street Maps (https://www.openstreetmap.org) from the expected lines at which the tram is operating.

4.4 Test performance evaluation

In order to evaluate the feasibility study of the proposed SLAM algorithm a ground truth (GT) of the recorded data must be provided. A GT is the absolute true of the train's position used as a reference to validate the outcome of the positioning performance. In order to illustrate this process Fig. 5 depicts the performance evaluation methodology to be carried. On one hand, the SLAM algorithm is executed using an extended digital map based on radars and lidars plus the other sensors. On the other hand, the GT of the train is carried out by using balises, speed sensors, IMU sensor and a geographical digital map. The digital map is based on balise data information plus track segmentation with reference to absolute positions, so that the GT algorithm can always tell you in which track and which position within the track the train is located on. With both sides providing a positioning algorithm a comparison of both is the key for the feasibility study.

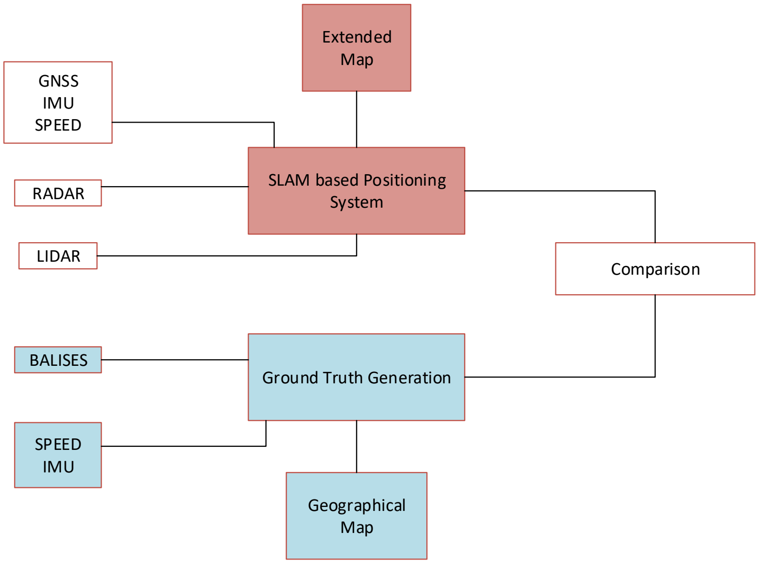

Figure 5: Test performance evaluation diagram block.

5 DISCUSSION

Recent works proposed new customised map formats in order to meet the need for autonomous driving. They aim to include geometric information to topological maps. Enhanced map (Emap) [10] is a customized map format designed for a lane-level localization. A series of straight lines, circles and clothoids represent the lanes. This representation is based on GNSS and dead reckoning measurements. The average lane accuracy was in order of 1m. Czerwionka et al [11] proposed a graph representation of the lanes and the relationships between them. RNDFGraph is based on the route network definition file format (RNDF). It is used to generate splines based on waypoints for ensuring a smooth trajectory. This representation was used in German highways for path planning and can be used for localization purposes. Graph SLAM in addition to line-segment features extracted from 3D lidar were combined with an OpenStreetMap map [12]. The Emap consists of a set of segments that describe the geometry in addition to the topological information of these segments (3D coordinates). The segments are linked to their neighbour's contrary to standard maps where the topology of the map is associated to the nodes. The lane estimation integrated to the map was performed using particle filter. An average accuracy of 5 cm was reached.

A huge amount of data is gathered thanks to sensors and several online resources (panoramas, geographic maps, etc.). Leveraging the available resources can be used to create knowledge supporting the autonomous driving functions' needs such as localization and mapping.

The safety of localization algorithms is a challenging issue. Failures and their impact on localization, must be considered for ensuring that an autonomous driving system operates safely.

6 CONCLUSION AND FUTURE WORK

A state of the art on SLAM methods for autonomous driving systems was presented in this document. In addition to the techniques of building maps, conceptual modelling and standards of railway maps were detailed. They include geometric and topological representation of infrastructure and environment features. These features are obtained thanks to the amount of available data extracted from the various sensors generally used for autonomous driving. A comparison of the main exteroceptive sensors was carried out in this document. Leveraging sensor data using the appropriate mapping algorithms can enhance the representation of the digital track maps.

This document describes the test architecture and the test environment set-up to test SLAM algorithms. The proposed system is based on multipurpose sensorisation and it aims to provide to bases for the further analysis to be carried out within Task 1.3 on the feasibility study of these sensor as part of the extended digital map. In addition, the performance evaluation methodology is also described in the document to allow the reader to understand how the process of feasibility study is going to be carried out.

ACKNOWLEDGEMENTS

This work was accomplished within the framework of the TAURO (Technologies for the Autonomous Rail Operation) project. This project has received funding from the Shift2Rail JU under the European Union's Horizon 2020 research and innovation programme. Grant agreement no. 101014984.

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