Graph-based Robot Localization in Tunnels using RF Fadings

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Abstract. Robot localization inside tunnels is a challenging task due to the hostile conditions of the environment. The GPS-denied nature of the scenario together with the low visibility, slippery surfaces, and the lack of distinguishable features, make traditional robotics methods based on cameras or laser unreliable. In this paper, we address the robot localization problem with an alternative graph-based localization approach, taking advantage of the periodic nature of the RF signal fadings that appears inside tunnels under certain transmitter-receiver settings. Experimental results in a real scenario demonstrate the validity of the proposed method for inspection applications.

Keywords: RF fadings, tunnel-like environments, graph localization

1 Introduction

Inspection tasks in tunnel-like environments are crucial in order to detect and identify critical characteristics during the construction of the tunnel, rescue missions or regular service routines. In recent years, robots seem to be the best candidates to perform these tasks mainly due to their flexibility and the harsh and even dangerous conditions of the environment that makes the human intervention risky.

However, accurate robot localization in tunnel-like scenarios represents a challenge due to the darkness and absence of distinguishable features in their longitudinal direction that makes traditional methods, based on cameras or laser sensors, inefficient. Moreover, GPS sensors cannot be used in underground environments. [1] presents an autonomous platform for exploration and navigation in mines where the localization is based on the detection and matching of natural landmarks over a 2D survey map using a laser sensor. In the case of tunnels, these natural features are almost non-existent.

Recent promising works explore the use of Radio Frequency (RF) signal for indoor localization. In [2] the authors propose the use of an Ultra Wide-Band (UWB) ranging sensor in combination with a LiDAR to obtain the localization in a tunnel fusing the information with a Gaussian Particle Filter (GPF). Nevertheless, the use of RF-based indoor localization implies a previous commissioning step to place at least three anchor nodes with high precision in the infrastructure to calculate the position by trilateration algorithms.

In [3, 4] the authors present several intensive studies about the RF signal propagation inside tunnels. Those works show that, on the one hand, tunnel-like environments behave as waveguides extending the communication range, but on the other hand, the signal suffers from strong attenuation (fadings). The authors also demonstrate that it is possible, under certain transmitter-receiver setups, to obtain predictable periodic fadings. The periodic nature of the RF signal is exploited in [5] to design a discrete robot localization system based on the identification of the RF signal minima and matching them with the known signal propagation model acting as an RF map.

Recent advances in the field of graph-SLAM result in new localization approaches that model the localization problem as a pose-graph optimization [6] with the advantage of easily incorporating measurements from different sources of information to the graph, not only local (wheel odometry) but also global measurements (GPS, IMU).

Taking into account the aforementioned works, in this paper we address the robot localization problem in tunnels as an online pose-graph localization problem, where we originally introduce the results of our RF signal minima detection method into the graph optimization taking advantage of the periodic nature of the RF signal inside tunnels.

Our approach consists of identifying the minima of the signal which are related to a global position provided by a previously obtained RF map (corresponding to the signal propagation model). The absolute position of each minimum is added as a constraint to the pose-graph that is being generated with the information provided by the odometry during the displacement of the robot. Each time new information is incorporated into the graph, it is optimized and the position of the robot is corrected allowing to locate the main characteristics to be inspected more accurately. The main advantages of approaching the robot localization problem using a graph-based representation are twofold: it allows to easily incorporate delayed measurements into the estimation process, and to recover (undo) from wrong decisions such as the inclusion of incorrect measurements.

The paper is structured as follows. The next section describes the related work about the fundamental aspects of the electromagnetic propagation in tunnel-like scenarios. The proposed method to identify the RF minima signal is presented in Section 3. The formulation of the graph-based localization problem together with a detailed description of the strategy followed to incorporate the minima to the graph is explained in Section 4. Section 5 presents the results obtained in the real scenario. Finally, the conclusions are set out in Section 6.

2 Related work: Fundamentals of electromagnetic propagation in tunnels

As stated before, previous works [3, 4, 7] demonstrate two different behaviors of the RF signal in tunnels: on the one hand, the tunnel acts as an oversized waveguide, extending the communication range if the wavelength of the signal is much smaller than the tunnel cross-section dimensions. On the other hand, strong fadings appear due to the interaction between the propagation modes present in the waveguide. It is important to highlight that we refer to fadings in a spatial domain, as a consequence of the constructive and destructive interference between propagating modes (using a modal theory approach) or propagating rays (using a raytracing approach), unlike the well-known small-scale fadings, which are understood as temporal variations of the channel.

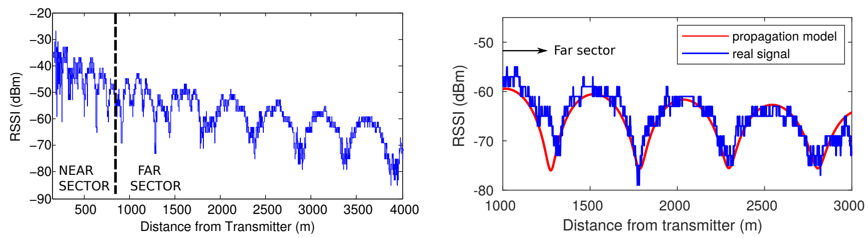
Depending on the distance from the transmitter, due to the different attenuation rate of the propagation modes, two regions can be distinguished in the signal. In the *near sector*, all the propagation nodes are present provoking fast fluctuation on the signal (*fast-fadings*). Once the higher order modes (which have higher attenuation rate) are mitigated with the distance the lower modes survive, giving rise to the *far sector*, where the *slow-fadings* dominate [8]. A specific periodic signal is obtained under the most adequate transmitter-receiver configuration (Fig. 1(a)). These studies also demonstrate that the period of the fadings depends on the operating frequency and the tunnel dimensions.

Lastly, the authors adopt the Modal Theory approach, modeling the tunnel as a rectangular dielectric waveguide. We encourage the reader to see [9] for a complete 3-D fadings structure analysis in tunnels. With this approximation, the obtained theoretical propagation model matches closely the experimental data. The similarity between both signals (Fig. 1(b)) are enough to make us consider them useful for localization purposes, using the propagation model as a position reference.

3 RF Signal minima detection

As stated before, the agreement between the signal propagation model and the real RF signal let us consider the first one as an RF map, which relates the RSSI values to the distance along the tunnel. Due to the noisy nature of the RF signal, the most distinguishable features of the RF waveform are the valleys (fadings). The goal of the presented method is to identify the minima of the real signal during the robot displacement and to extract the reference position associated to each valley from the RF Map. The information provided by the virtual minima detector will be added to the pose-graph as it will be explained in Section 4.

The first step of the proposed method consists of extracting a discrete model representing the theoretical minimum model from the RF Map. Using the propagation model described in Chapters 2.1 and 3.2 of [10], it is possible to know the position of each valley along the tunnel and then, the theoretical minimum



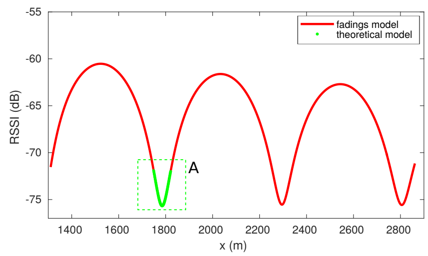
(a) Periodic Fadings (b) Propagation model vs real data

Fig. 1. Measured Received Power at 2.4 GHz inside the Somport tunnel, from [4]. The transmitter was kept fixed and the receiver was displaced along 4 km from the transmitter. The signals were sampled with a spatial period of 0.1 m. In (b), the red line represent the modal theory simulations, and the blue the experimental results for the far sector.

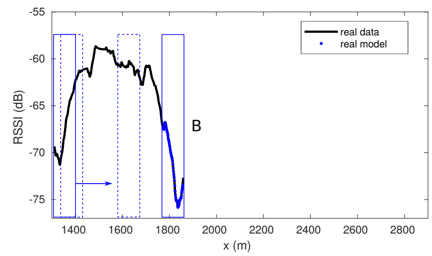
model can be obtained in advance. During the displacement of the vehicle, the algorithm tries to match the discrete real model, generated during the movement, with the theoretical model. When the two models match, a minimum is found and the information about the estimated position of the minimum together with its corresponding position in the map is available.

Fig. 2 shows the steps of the proposed strategy. The discrete theoretical model is extracted from the RF signal model in advance (Fig. 2(a)). The theoretical model consists of a set of points (x, y) where x is the position corresponding to each theoretical RSSI value y. Both values are provided by the RF map. The real model is obtained by accumulating points (x_t, y_t) during a certain period of time T corresponding to a fixed distance D (Fig. 2(b)). x_t is the position estimated by the odometry and y_t corresponds to the actual RSSI value provided by an RF sensor. Once the real model is available, the matching process starts using the previously recorded theoretical model. The points enclosed in the B blue area represent the real model used to describe the matching procedure that involves the following steps:

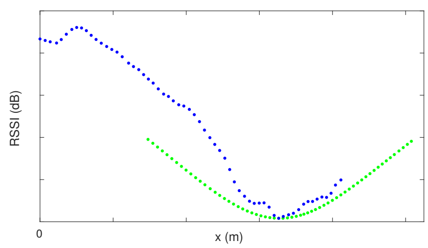
– Relate the theoretical model to the reference system of the real model (Fig. 2(c)). Both models have in common the minimum value.
– For each real point, calculate the Mahalanobis distance d_m between the real point and the closest neighbors from the theoretical model. Fig. 2(d).
– Classify each point as inlier or outlier based on the Mahalanobis distance.
– If the number of inliers is greater than a certain threshold and the ratio between left and right inliers is balanced, we can conclude that a minimum has been found. Fig. 2(e).
– The Mahalanobis distance is again calculated between the real minimum detected and the minimums of the theoretical model, selecting the theoretical one with the least distance. Fig. 2(f).



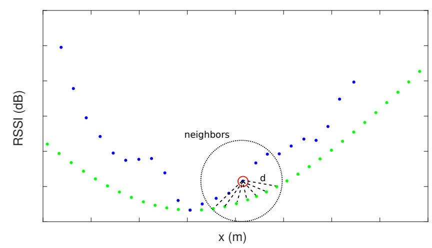
(a) Theoretical model extraction from RF signal model



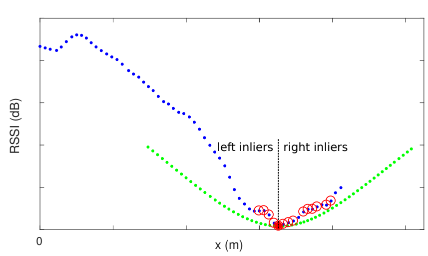
(b) Real model extraction



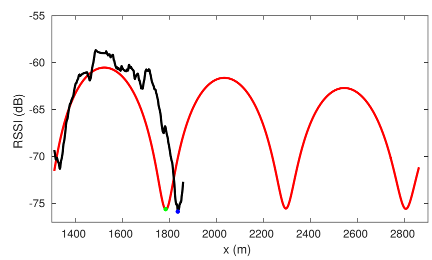
(c) Zero referenced models



(d) Inlier/outlier classification



(e) Minimum detection



(f) Estimated and reference minimum pose

Fig. 2. RF signal minima detection steps:(a) Theoretical model (green points inside the dashed green square A) extracted from the RF signal model (red). (b) Real model generation during the displacement of the vehicle from the real RF signal. (c) Both models referenced to the same system coordinates. (d) Point classification depending on the Mahalanobis distance between the real data and the closest neighbors from the theoretical model (e) Minimum detection if the number and proportion of inliers satisfy the threshold. (f) Estimated position by the odometry (black point) and position reference from the RF Map (green point) of the detected minimum

The resulting data are the estimated position provided by the odometry (x_{T-k}) and the position reference of the RF map (z_i), both corresponding to a minimum of the RF signal. The uncertainty of the position reference (δ) is a measure of the RF signal model fidelity with respect to the ground truth. This process is repeated iteratively using a sliding window to generate the discrete real model (dashed blue area in Fig. 2(b)). It is worthy to notice that the information provided by the virtual sensor corresponds to delayed measurements, i.e., the position of the minimum is detected at a timestamp after its appearance. The strategy followed to add these measurements to the pose-graph is explained in the following section.

4 Graph-based localization using RF Fadings

In our approach we model the robot localization problem as a graph-based pose optimization problem. The trajectory of the robot $\mathbf{x}_{0:T} = \{\mathbf{x}_0, ..., \mathbf{x}_T\}$ is represented as a graph where nodes symbolize discrete robot positions $\mathbf{x}_t$ at time step t. Nodes in the graph are related by *binary* measurements encoding relative position constraints between two nodes $(\mathbf{x}_i, \mathbf{x}_j)$ characterized by a mean $\mathbf{z}_{ij}$ and information matrix $\mathbf{\Omega}_{ij}$. These relative measurements are typically obtained through odometry or scan matching. Furthermore, it is possible to incorporate into the graph global or prior information associated only to one robot position $\mathbf{x}_i$ by means of *unary* measurements $\mathbf{z}_i$ with information matrix $\mathbf{\Omega}_i$. These unary measurements typically come from sensors providing direct absolute information about the robot pose such as GPS or IMU. Let $\hat{\mathbf{z}}_i = \mathbf{h}(\mathbf{x}_i)$ and $\hat{\mathbf{z}}_{ij} = \mathbf{h}(\mathbf{x}_i, \mathbf{x}_j)$ be the expected unary and binary measurements given the current estimation of the nodes. The errors committed in the estimation can be obtained as:

$$\mathbf{e}_i = \mathbf{z}_i - \hat{\mathbf{z}}_i, \ \mathbf{e}_{ij} = \mathbf{z}_{ij} - \hat{\mathbf{z}}_{ij} \tag{1}$$

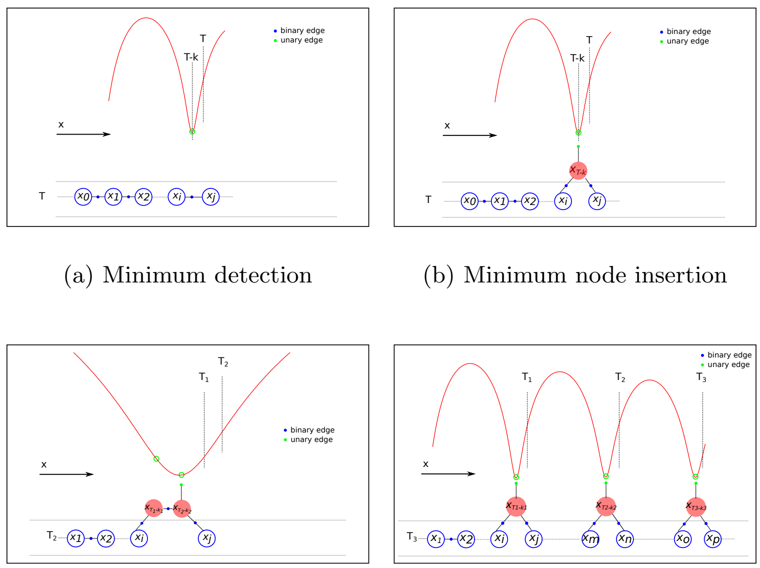
The goal of a graph-based approach is to find the configuration of nodes that minimizes the sum of the errors introduced by the measurements, formulated as:

$$\mathbf{x}^* = \underset{\mathbf{x}}{\operatorname{argmin}} \sum_{i,j} \mathbf{e}_{ij}^T \mathbf{\Omega}_{ij} \mathbf{e}_{ij} + \sum_i \mathbf{e}_i^T \mathbf{\Omega}_i \mathbf{e}_i \tag{2}$$

The above Eq. 2 poses a non-linear least-squares problem that can be solved iteratively using the Gauss-Newton algorithm.

Our approach for localization inside tunnels considers measurements coming from two sources of information: odometry data and RF signal minima detection using the procedure described in previous Section 3. Odometry measurements are straightforwardly introduced into the graph as binary constraints encoding relative displacement between consecutive nodes $(\mathbf{x}_{t-1}, \mathbf{x}_t)$. Additionally, the output provided by the minima detection mechanism can be considered as an absolute positioning system inside the tunnel which can be used as a unary measurement during the graph optimization process.

As previously mentioned, RF signal minima detection is obtained on a posterior time T in which it actually occurred. This implies incorporating in the estimation process information referred to a past position $\mathbf{x}_{T-k}$. This can be handled thanks to the use of a graph representation, having an impact on the current pose estimation after the optimization process. Next subsection 4.1 describes the proposed mechanism to incorporate the RF signal minima measurements into the graph.



(a) Minimum detection

(b) Minimum node insertion

(c) False positive case

(d) Final graph

Fig. 3. Pose-graph creation steps: (a) Minimum identification at time T. (b) Insertion of the node and the unary constraint corresponding to the detected minimum. (c) False positive case detail, deactivation of the previous unary edge. (d) Resulting pose-graph after three minimums.

4.1 Management of RF fadings minima detection in the pose-graph

As introduced in the previous section, the graph based localization approach consists in the representation of a set of discretized robot poses from the robot trajectory as nodes in the graph. Once the constraints derived from the measurements are introduced into the graph the error minimization process takes place, where the optimization time depends directly on the number of nodes.

Graph-based localization and mapping systems usually perform a rich discretization of the robot trajectory, where the separation between nodes ranges from few centimeters to few meters. This type of dense discretization would be intractable in a tunnel-like environment with few distinguishable features where the length of the robot trajectory is measured in the order of magnitude of kilometers. It is therefore necessary to maintain a greater distance between nodes to manage a sparser and more efficient graph.

Under an RF signal minimum detection event we need to associate a unary constraint to the past robot position where the minimum occurred. In view of the need to maintain a sparse graph, it can happen that the referred robot position is not represented in the graph as a node, having to modify the current graph structure to include it.

The procedure to include the unary measurement corresponding to a past robot position $\mathbf{x}_{T-k}$, is illustrated in Fig. 3 and described in the following:

- At timestamp T, a RF signal minimum corresponding to timestamp $T-k$ is identified. Since robot position $\mathbf{x}_{T-k}$ is not present in the graph, we determine between which two nodes $\mathbf{x}_i$ and $\mathbf{x}_j$ it should be included, based on the timestamps stored in each node. We also maintain a buffer containing the odometry information associated to each timestamp (Fig. 3(a)).
- Once the two nodes are identified, the new node $\mathbf{x}_{T-k}$ is inserted into the graph connected to nodes $\mathbf{x}_i$ and $\mathbf{x}_j$ by taking into account their original relative odometry information and the unary edge is associated to the node $\mathbf{x}_{T-k}$. Previous odometry measurement connecting $\mathbf{x}_i$ and $\mathbf{x}_j$ is removed to prevent double-counting of information (Fig. 3(b)).
- In the event of detecting another minimum corresponding to the same minimum in the RF map, the unary constraint of the previous minimum is deactivated and same procedure is followed (Fig. 3(c)). This can be the case of false positives or improved detections after the accumulation of more data.

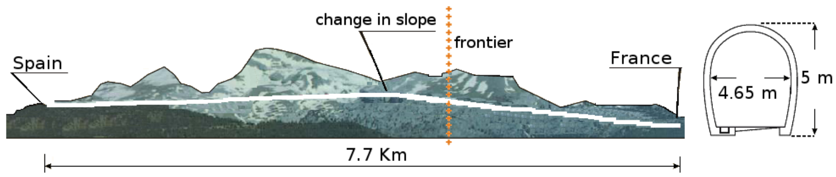
5 Experimental results

In order to validate the proposed graph-based localization approach, all the algorithms involved in the process were implemented in $MATLAB^{TM}$ and tested with real data collected during an experiment developed in the Somport tunnel.

5.1 Scenario and Experimental Setup

The old out-of-service Somport railway tunnel was selected to carry out the experiments. It is a 7.7 km long tunnel connecting Spain with France with a change in slope at approximately 4 km from the Spanish entrance. It has a horseshoe-shape cross section, around 5 m high and 4.65 m wide.

An all-terrain vehicle was used as the mobile platform simulating a service routine. It was equipped with two SICK DSF60 0.036 deg resolution encoders and a SICK LMS200 LIDAR. Due to the specific characteristics of this tunnel, with lateral galleries and emergency shelters, it is possible to obtain the real localization of the platform (ground truth) along the tunnel fusing all the data



(a) The Somport tunnel

(b) Encoder (c) Laser sensor (d) RF receivers

Fig. 4. Experimental setup

sensor using the algorithm described in [11] with a previously built map. Without these landmarks, it would not be feasible to apply this method because of the lack of relevant features along the tunnel. The ground truth is only used for comparison purposes.

The platform was also equipped with two RF Alpha receivers placed at 2.25 m in height from the ground and with the antennas spaced 1.40 m apart. The transmitter, a TPLINK tl-wn7200md wireless adapter with Ralink chipset, was placed at approximately 850 m from the entrance of the tunnel, 3.50 m above the ground and 1.50 m from the right wall. Using a 2.412 GHz working frequency and under this receiver-transmitter setup, the expected fadings period is around 512 m. Fig. 4 shows the experimental setup.

The mobile platform moved up to about 3000 meters from the transmitter position along the center of the tunnel in straight line with almost negligible heading variations. This behaviour during the experiment makes feasible the simplification of the general formulation of our approach, where $\mathbf{x}$ refers to (x, y, θ), to a one dimension problem where $\mathbf{x}$ corresponds to the longitudinal distance from the transmitter. During the displacement of the vehicle, the data provided by the sensors were streaming and logging with a laptop running Robot Operating System (ROS) [12] on Ubuntu.

The RF data used to validate the proposed method are the RSSI values provided by the rightmost antenna. It should be noted that the proposed graph-based approach is intended to solve the localization problem in the area of the tunnel where the periodic fadings are observable (far sector). For this reason, the data corresponding to the near sector have been removed from the data set.

5.2 Algorithm implementation

As stated before, the nodes are added to the graph each time the platform travels a certain distance, which in this case is 40 meters. The selected value provides sufficient discretization of the total distance travelled avoiding the complexity of a more dense graph guaranteeing enough resolution between minima. The binary edges $\mathbf{e}_{ij}$ model the constraints between two consecutive nodes $(\mathbf{x}_i, \mathbf{x}_j)$ with the relative position between them calculated using the odometry data: $\mathbf{z}_{ij} = (x_j^{odom} - x_i^{odom})$, $\mathbf{\Omega}_{ij} = [\epsilon]^{-1}$, where x^{odom} is the position estimated by the odometry and ϵ represents the uncertainty of the odometry with a value of 0.02.

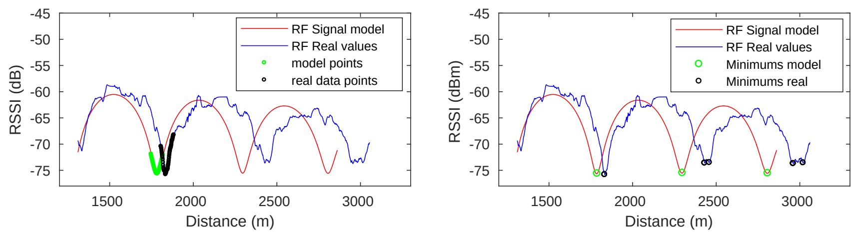
If a minimum is detected at time T, the estimated position $\mathbf{x}_m$ of this minimum provided by the odometry (x_m^{odom}) is added as a new node in the pose-graph. The position reference of the minimum $(x_m^{RF_{map}})$ provided by the RF map is considered as the measurement $\mathbf{z}_m$ and it is included as a global information with a unary edge $\mathbf{e}_m$ associated to this new minimum node, being $\mathbf{\Omega}_m = [\delta]^{-1}$ the information matrix. δ corresponds to the uncertainty of the measurement and, due to the fact that the positions provided by the RF map closely represent the ground truth, it has a very low value (10^{-4}).

The strategy explained in Section 4.1 is used to introduce this delayed measurement into the graph. Each time a new node or measurement is added to the graph, the optimization process takes place. Even if nodes separation is large in the graph, our approach guarantees continuous robot localization by accumulating the odometry data to the last estimated robot position in the graph.

5.3 Results

Minima detection Fig. 5 shows the results of the minima detection method. The number of points accumulated to create the real model corresponds to a distance D of 80 m. This value is selected based on the distance corresponding to the theoretical minimum model. The RSSI data provided by the RF receiver is represented related to the position estimated by the odometry and the RF signal model related to the ground truth (Fig. 5(a)). The results shows the ability of the proposed algorithm to identify the minima of the signal although the real signal waveform does not exactly match with the RF signal model due to the noisy nature of the real signal and the odometry errors. As can be seen in Fig. 5(b), two different values have been identified corresponding to the same RF map minimum (second and third). The mechanism explained in Section 4.1 is used to handle this situation.

Graph-based localization results Although the pose-graph generation and optimization take place online during the displacement of the vehicle, the results



(a) Theoretical and real model

(b) Minimums detected

Fig. 5. Results of the mimima detection process

presented in this section correspond not only to the vehicle localization along the tunnel but also to the position correction after the service routine.

Fig. 6(a) shows the initial graph with the odometry and the minimum nodes, and the resultant graph after the optimization process. It is clearly seen how the vehicle positions represented by the nodes are corrected after the optimization.

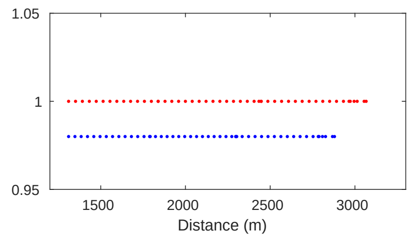
The position error during the movement of the robot is shown in Fig. 6(b). Each time a minimum is detected, the position of the vehicle is corrected and therefore, the error is reset. As previously mentioned, the detection of the minimum is delayed with respect to the instant at which the minimum appears. The effect in the position correction can also be observed in Fig. 6(c) and in Fig. 6(d) in detail.

As stated before, one of the main benefits of the proposed approach is the ability to modify the location of some features observed during the route of the vehicle. Fig. 7 shows the results when the position and the error are calculated once the tunnel has been traversed. The position error along the tunnel remains limited under acceptable values in comparison with the error using only the odometry which increases along the time as shown (Fig. 7(a)). The estimated position obtained through our proposed method follows closely the real position of the vehicle as can be seen in Fig. 7(b).

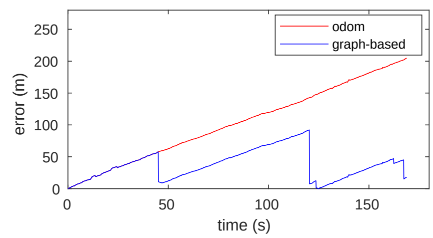
6 Conclusions

This paper have presented a graph-based localization approach for tunnel-like environments using two main sources of information: the odometry data and the absolute positions provided by an RF signal minima detector based on a theoretical fadings model that acts as an RF map. The feasibility of the proposed approach has been validated with the data collected during experiments developed in a real tunnel scenario.

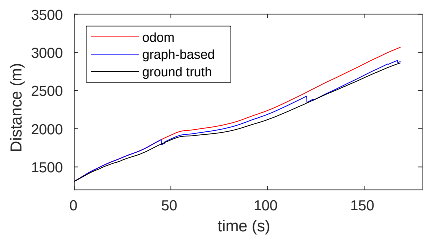
The empirical results demonstrate the validity of the proposed minima detection method even when the RF actual signal and the RF signal model differs due mainly to odometry uncertainty and amplitude differences in the RSSI signal



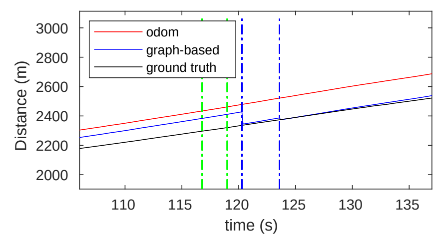
(a) Graph before and after optimization



(b) Error pose

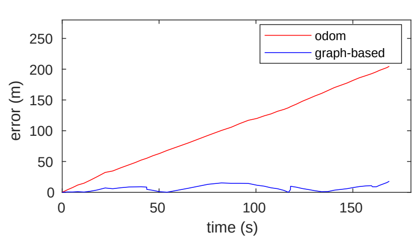


(c) Pose estimation

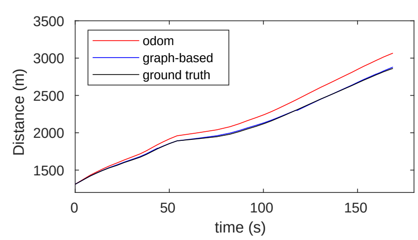


(d) Minimum detection

Fig. 6. Results of the online pose-graph localization approach. (a) Node graph before (red) and after (blue) the graph-optimization process. The y axis values have been set only for visualization purposes to avoid overlapping of the trajectories. (b) Pose error during the displacement of the vehicle. (c) Estimated position along the tunnel provided by the odometry and our proposed method. (d) Detail corresponding to a detected minimum. The dashed blue line represents the minimum detection instant and the dashed green line the previous time when the minimum occurs



(a) Error pose



(b) Pose estimation

Fig. 7. Results of the pose-graph approach after the service routine of the vehicle

values. Additionaly we prove the robustness of the method against scale differences in the signal. The results also show that the localization error is greatly reduced after the graph optimization. As a consequence, it is possible to locate features of interest observed during the inspection task more accurately.

Future work will be aimed at improving the continuous localization in the tunnel by incorporating into the graph additional sources of information such as galleries detection or the results of a scan matching process.

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