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SLAM with Slow Rotating Range Sensors. Evaluation of Lined-based Map Quality.

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Abstract—This paper is concerned with the Simultaneous Localization And Mapping (SLAM) application with a mobile robot moving in a structured environment using data obtained from rotating sensors such as radars or lasers. A line-based EKF-SLAM algorithm is presented, which is able to deal with data that cannot be considered instantaneous when compared with the dynamics of the vehicle. When the sensor motion is fast relative to the measurement time, scans become locally distorted. A mapping solution is presented, that includes sensor motion in observation model by taking into account the dynamics of the system. Experimental results on real-world with 2D-laser scanner data are presented. Moreover a performance evaluation of the results is carried out. A quantitative performance evaluation method is proposed when dealing with a 2D line map and when a ground truth is available. It is based on the bipartite graph matching and combines several criteria that are described. A comparative study is made between the output data of the proposed method and the data processed without taking into account distortion phenomena.

Index Terms—SLAM, distortion, rotating range sensor, map quality.

I. INTRODUCTION

In order to act in an environment, autonomous mobile robots have to be able to know their position and orientation but also the structure of the environment. This problem is known by the acronym SLAM standing for Simultaneous Localization and Mapping. The problem we want to solve is SLAM with a mobile robot potentially moving at high-speed in a structured environment and using rotating range sensors such as radars or laser scanners. In the SLAM problem, it is usually assumed that the scan of a range sensor is a collection of depth measurements taken from a single robot position. This can be done when working with lasers that are much faster than radar sensors and can be considered instantaneous when compared with the dynamics of the vehicle. But, when the robot is moving at high speed, this assumption is unacceptable. Important distortion phenomena appear and cannot be ignored any more. For example, in a radar mapping application [1], [2], the sensor delivers one panoramic radar image per second. When the robot is going straight ahead, at the low speed of 5 m/s, the panoramic image includes a 5 meter distortion. In the case of a laser range finder with a scanning rate of 75 Hz, distortion exists but is not considered. This assumption is valid for low speed applications (when still moving straight forward at a 5 m/s speed, a 7 cm distortion effect appears). For classical road vehicle speed (in cities, on roads or highways)

more important distortions can be observed. Of course, the rotation of the vehicle during the measurement acquisition is an other source of disturbance which cannot be neglected for high speed displacement or with slow sensors (See Fig. 1). Finally, let us note that when the sensor is really too slow, a “stop & scan” method is often applied [3].

In this paper, a line-based EKF-SLAM technique is presented using data from rotating sensors such as radars and lasers. Line-based maps represent a middle ground between highly reduced feature maps and massively redundant raw sensor-data maps. These maps are most suited for structured outdoor applications, where straight-edged objects comprise many of the environmental features [4], [5]. The idea of fitting lines to range data is not a new one (for instance see [4] for a large review). But, on the contrary to methods such as those developed in [4], the proposed approach does not wait until a full range scan is taken to extract a set of features, it does it on the fly. In a way, our On-The-Fly SLAM algorithm is an extension to lines of the work described in [6] dealing with beacons and taking into account the dynamics of the vehicle. However, our goal is to perform SLAM in urban and semi-urban environments without cooperative reflectors. Experimental results on real-world data provided by laser sensors are presented. The article does not restrict itself to another presentation of a new SLAM algorithm. A quantitative performance evaluation method is proposed when dealing with a line-based map and when a ground truth is available. An analysis about the trajectory is conducted too. A comparative study between the output data of the proposed SLAM algorithm and the data processed without taking into account distortion phenomena is achieved. The performance evaluation method is based on the bipartite graph matching applied to two distinct sets of nodes –the segments in the ground truth and the segments in the obtained map– where the graph edges are weighted according to cost functions. The method is completely automated and can be modulated according to the needs of the user.

The paper is organized as follows: in Section II, a review of articles related to our research interests is carried out in order to position our work in relation to previous studies. Section III presents the line-based SLAM algorithm. Section IV is illustrated with results of experiments on real data. Section V explains the SLAM evaluation method we have used to score the different results. Conclusions and future work are presented

in Section VI.

II. RELATED WORK

A. In The Field Of High Speed Robotics

Few research works have been carried out over the last ten years concerning localization and mapping with a vehicle moving at high speed using rotating sensors. In fact, it is the complementary problem that has been studied. Since the rotation speed of the scanner is relatively slow, the idea has been to process the landmarks when they become available and not at the completion of the scan. This concept has been described in a range and bearing navigation application using radar [6] where the vehicle might be traveling at speeds up to 10 *m/s*. The sensor scans through 360° at approximately 3 *Hz*, providing range and bearing information to a number of well separated, highly reflective beacons. Interestingly, this kind of sensor was used to provide a solution to the SLAM problem [7] using an extended Kalman filter framework and a landmark based approach. Lingemann et al. [8] also addressed the problem of high-speed localization for mobile robots. They developed a laser-based approach for tracking the pose and evaluated their algorithm with the high-speed robot Kurt3D (4 *m/s*).

The SLAM algorithm presented here is based on the concept introduced in [6] but builds a line-based map without using cooperative reflectors that are placed in the outdoor environment. The structured environment explored is an urban environment. The goal we are aiming at is to reach a SLAM solution that will ultimately work with a vehicle moving beyond 10 *m/s* whatever the rotation speed of the used sensor is.

B. In The Field Of Evaluation Of Map Quality

Performance evaluation of SLAM algorithms has received increasing attention recently (e.g., [9], [10], [11], [12], [13]).

Experimental comparisons of algorithms have already been attempted in numerous areas of computer vision. Today, this effort is carried out by researchers in the field of mobile robotics. Several tracks are explored. The framework for comparison which is itself a research issue [13] can be summarized by these three elements: problem definition, performance evaluation and data set. In this paper, our purpose is not to provide complete answers (if they exist) to these items but to discuss some points important for us and to underline a deficiency among the solutions already proposed.

As mentioned by previous authors, we agree with the fact that the evaluation procedure should be automated, and based upon objective performance measures. Moreover, thorough and challenging public data sets should be developed as proposed by [14], [15], even if we haven't yet made our own data sets available. Metrics are needed for error measurement, in addition to correct/valid performance. Just as accuracy and precision error measurements can each be useful in certain situations, there is usually more than one way to measure algorithmic performance. A potential consumer of an algorithm's output needs to know what types of incorrect/invalid results to expect, as some types of results might be acceptable while

others are not. Thus multiple metrics are necessary for potential consumers to make intelligent decisions.

Evaluating and comparing SLAM algorithms need quantitative performance metrics like robustness, rate of convergence, computational complexity, quality of the results (error of the trajectory) and specially of the maps. Thus, solutions have been proposed in [9], [10], [11], [12]. In order to measure the error of the trajectory, we will use one of these metrics [11], [12]. But, no article proposes a way to evaluate line segment-based maps. So, this last point is addressed in Section V.

III. ON-THE-FLY LINE BASED SLAM

In our approach, sensor data is used on the fly during the measurement acquisition taking into account the vehicle and the sensor movements at each step. We use the rotating rate of the sensor and the velocity of the robot to include distortion effect in observation model.

A. Feature-based EKF-SLAM

In order to take into account sensor data distortion during the measurement acquisition, the vehicle pose has to be estimated at each measurement time but localization data is not always available at these precise moments. Because the time interval between two successive sensor data acquisitions is short, a simple Extended Kalman Filter (EKF) has been used. Thanks to the knowledge of both the sensor scanning rate and the robot state, each pose of the system is estimated based on a constant velocity model. This model is simple but realistic in order to describe the robot movement. We limited the study to two dimensions, the pose of the robot is (x, y) and its orientation θ . The state of the robot for time k is:

$$\mathbf{X}_{v_k}^T = [X_k, Y_k, V_k, \dot{\theta}_k, \theta_k]$$

with V_k and $\dot{\theta}_k$ respectively the linear and angular velocities.

The exteroceptive data, provided by the sensor, allows the robot to detect the presence of features with respect to its local coordinate frame.

The formulation of the SLAM problem used to estimate the vehicle pose and the map is defined by the estimated state $\mathbf{X}_k = [\mathbf{X}_{v_k}^T, \mathbf{X}_{m_k}^T]^T$, where $\mathbf{X}_{v_k}^T$ is the robot state vector described before. $\mathbf{X}_{m_k}^T$ is the map state vector defined by $\mathbf{X}_{m_k}^T = [\mathbf{X}_{L1_k}, \mathbf{X}_{L2_k}, \dots, \mathbf{X}_{Ln_k}]$. Each \mathbf{X}_{Li_k} represents the pose and the characteristics of a landmark Li at time k in the global coordinate frame. It is assumed that the world could reasonably be modeled as a set of simple discrete landmarks described by geometric primitives.

B. On-The-Fly Sensed Data Processing

In the case of a high-speed application or an application with slow sensors, sensor rotation and vehicle displacement distort the exteroceptive data. In Fig. 1, the distortion effect on laser data is shown. The idea is not to wait for the entire rotation of the acquisition system but to use each measurement as soon as possible. The combined movements of the sensor and the robot have to be taken into account when a range scan

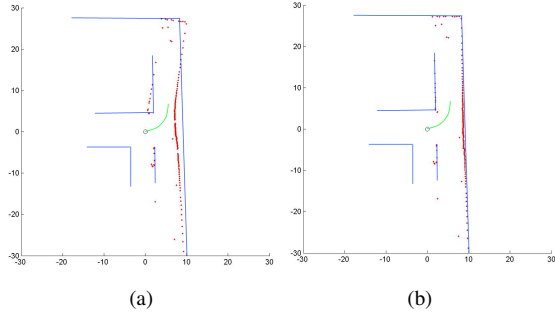


Fig. 1. Laser data with distortion effect (a) Laser data with On-The-Fly propagation (b). Blue lines represent the ground truth, red dots are laser detections, the green line represents the trajectory of the vehicle during the measurement acquisition; the starting point is circled in blue.

is acquired. Each data measurement has to be propagated in the current robot frame taking into account the system dynamics.

For example, at time k , a new observation of a point is done in the vehicle centered coordinate frame (See Fig. 2):

$$\mathbf{z}_k = \begin{pmatrix} z_{x_k} \\ z_{y_k} \end{pmatrix} = \begin{pmatrix} \rho_k \cos(\Phi_k) + d \\ \rho_k \sin(\Phi_k) \end{pmatrix}$$

where d is the longitudinal offset between the sensor and the robot centered coordinate system.

Because the vehicle is moving and the sensor data acquisition is not instantaneous, each measurement has to be propagated in the current robot frame. This propagation can be done using information about the robot displacement and the sensor movement. This displacement occurs during the time δt between two successive detections. δt depends on the sensor movement. It is a function of scanning rate and of angular resolution:

$$\delta t = \frac{\text{Angular resolution}}{\text{Scanning rate}}$$

Robot displacement, processed thanks to the evolution model, can be represented classically by a rigid-transformation between the initial and the final pose.

$$\Gamma_k^{k+\delta t} = \begin{pmatrix} \cos(\beta) & -\sin(\beta) & Tv_x \\ \sin(\beta) & \cos(\beta) & Tv_y \\ 0 & 0 & 1 \end{pmatrix}$$

Where:

$$Tv_x = \delta t V_k \cos(\theta_k)$$

$$Tv_y = \delta t V_k \sin(\theta_k)$$

$$\beta = \dot{\theta}_k \delta t$$

Finally, each measurement \mathbf{z}_k taken at time k can be propagated in the current robot frame. The observation of the detection \mathbf{z}_k at time $k + \delta t$ can be obtained as follows:

$$\mathbf{z}_k^{k+\delta t} = (\Gamma_k^{k+\delta t})^{-1} \mathbf{z}_k$$

This principle is illustrated in Fig. 2.

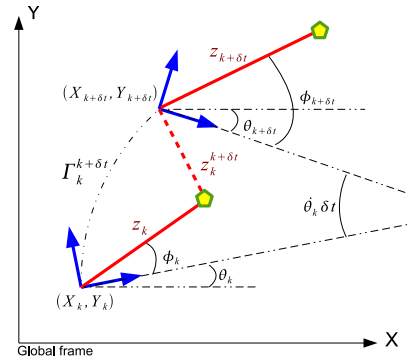


Fig. 2. Detection propagation taking into account robot and sensor dynamics. In red line, two successive sensor beams. In blue the vehicle frame at respective acquisition times. In yellow the detection to propagate.

Because we are working in structured outdoor environments, where straight-edged objects comprise many of the environmental features, a line-based SLAM has been developed. The advantages and drawbacks of such a kind of landmark representation are well described in [5], [4]. For sensors like radars, lines are much easier to observe than punctual measurements which are very sensitive to multi-reflection and interferences. Moreover, data association between one point of a line and an other one is problematic. As a consequence, hybrid mapping has been discarded. A line to line association is used because we want this On-The-Fly SLAM to be also well adapted to different kinds of sensors. As a consequence, in order to detect geometric features, more than one measurement is required.

Indeed, too few points can imply a landmark detection with a huge uncertainty. So data association will be sensitive for this new detected feature. Moreover, the use of a small quantity of points makes outliers detected as a line.

In order to do localization and to build the map, only representative lines should be detected. A minimum number of points is required, let us denote this number N . While the measurement acquisition is under way, the successive detections are propagated at each time step in the vehicle frame. Once the N detections are over, a geometric landmark extraction is performed. N is defined according to the angular resolution of the sensor: we choose to observe the environment in successive 25° angular sectors. For example, a five step propagation is presented in Fig. 3.

C. Geometric Features Extraction

Sensor data is provided as (ρ, Φ) associated with its covariance matrix P .

Depending on the sensor used, several detections can be done for a same “beam” (it is the case for a radar). The first step consists in a segmentation of data on-the-fly. Each measurement acquisition is compared to the previous one and grouped thanks to a simple distance criterion. At the end of this step, we have point groups called objects as represented in Fig. 3.

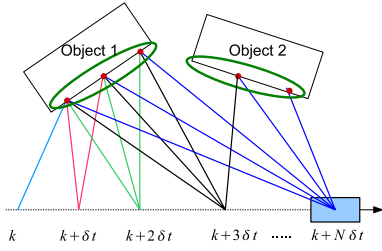


Fig. 3. On-The-Fly propagation and segmentation principle.

During the construction of these objects, at each step, previous measurement acquisitions are propagated in the current vehicle frame according to the process described in Section III-B.

Once the acquisition of N points is done, for each object, the lines are extracted as well as their respective covariance matrix and are represented using the Normal form (d, α) :

$$-\sin(\alpha) \times x + \cos(\alpha) \times y = d$$

Landmark $L_{i_{k+N\delta t}}$ extracted from the object i at time $k + N\delta t$ is represented by its state vector as follows:

$$\mathbf{X}_{L_{i_{k+N\delta t}}} = [d_{L_{i_{k+N\delta t}}}, \alpha_{L_{i_{k+N\delta t}}}]^T$$

The line parameters $d_{L_{i_{k+N\delta t}}}$ and $\alpha_{L_{i_{k+N\delta t}}}$ are functions of measurements $\mathbf{z}_p^{k+N\delta t}$ taken at time $p = k + n\delta t$ with $n \in \{1, \dots, N\}$.

In case of extraction failure, the N points are ignored. Otherwise, this observation $\mathbf{X}_{L_{i_{k+N\delta t}}}$ is provided at time $k + N\delta t$ to the SLAM process without waiting for the entire revolution of the sensor.

Based on a classical EKF approach, the system vector state at time k , $\mathbf{X}_k = [\mathbf{X}_{v_k}^T, \mathbf{X}_{m_k}^T]^T$ described in Section III-A can be predicted and updated at time $k + N\delta t$.

An overview of the algorithm is presented in Fig. 4.

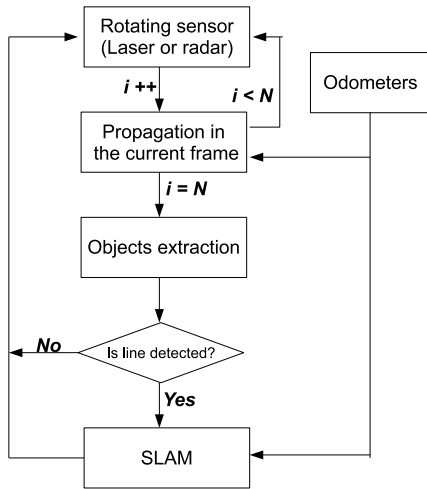


Fig. 4. On-The-Fly SLAM scheme.

In this approach, it is not a correction of the global scan which is applied but distortion is taken into account in the

observation formulation. Moreover, the completion of the sensor rotation is not waited as in scan-matching approach [16] or recent line-based SLAM [17], [18]. Line extraction is performed on-the-fly with undistorted observed data when enough detections are available.

IV. EXPERIMENTAL RESULTS

A. On-The-Fly SLAM In Classical Conditions

First our On-the-fly SLAM has been applied to a data set realized on the experimental “PAVIN” platform (Fig. 5) thanks to a Robucab vehicle equipped with odometers and a laser range finder with a scanning rate of 75 Hz . The velocity of the vehicle is limited to 3 m/s so distortion can be neglected. The purpose of this experiment is to show that our approach is also working in classical conditions, namely at low speed with high scanning rate sensors.



(a)



(b)

Fig. 5. (a) Aerial image of the experimental area called “PAVIN”, (b) Architectural blueprint of “PAVIN”.

The algorithm has been applied to laser data without any previous treatment or filtering. Rolling and pitching movements of the vehicle are not compensated. Moreover the planar environment assumption is not verified on our experimental site: there are 5% to 10% slopes. These conditions explain false line detections resulting from ground laser measurements. The localization error is presented in Fig. 6. It is calculated from the ground truth, provided by a RTK GPS, and from the final map of this SLAM process.

Around the iterations 4000 and 8000, loop closures occur. The large distance error around the iteration 7000 is due to the fact that the experimental ground is not flat in this area, so ground detection causes erroneous associations.

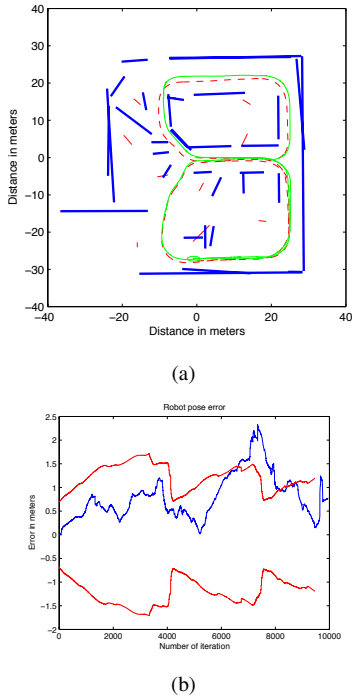


Fig. 6. (a) Map obtained with the On-the-fly method in classical conditions. The red landmarks are considered a posteriori as noise. The blue landmarks represent the walls of the environment. (b) Localization error with its 2σ bounds.

B. On-the-fly SLAM With A Slow Artificial Sensor (0.2 Hz) at Low Speed

In order to evaluate our algorithm with a slow sensor, we used a SICK LMS221 laser range finder with a 75 Hz scanning rate. Only one beam per entire rotation has been taken; so the scanning rate has been artificially reduced to 0.2 Hz (one acquisition every 4.8 s). The experiment has been realized in the same condition and with the same data set as the previous one.

Results without and with consideration of the distortion are presented (See Fig. 7 and Fig. 8).

The map and localization without taking into account the distortion look erroneous with a trajectory maximal error of 4 meters to the ground truth. In the curves, we can see that the detections are submitted to a rotation shown in the map. In the same way, in a straight line, wall apertures are not detected. As a consequence, localization based on these detections is not accurate. Moreover, distortions cause over-segmentation.

In our On-The-Fly approach, the localization is accurate except during displacement in the slopy area of the environment where false ground detections cause erroneous data associations. Comparing Fig. 7 and Fig. 8, wall apertures are detected with the On-The-Fly approach and less geometric landmarks are created to represent the environment.

Comparing the two On-the-Fly approaches (Fig. 6 and 8), the obtained map, with 180 times less sensor measurements shows that the data is sufficient in order to do accurate

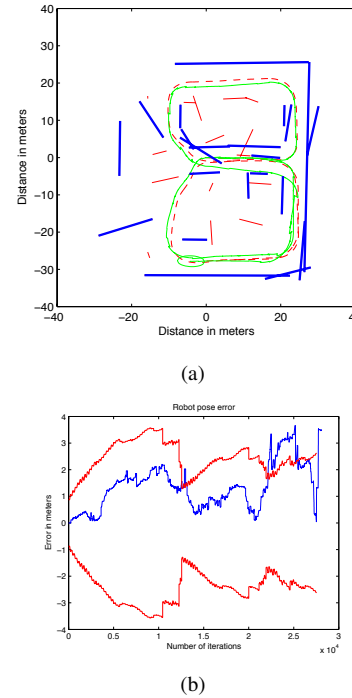


Fig. 7. On-The-Fly SLAM without distortion consideration (a) and its respective 2σ bounds (b).

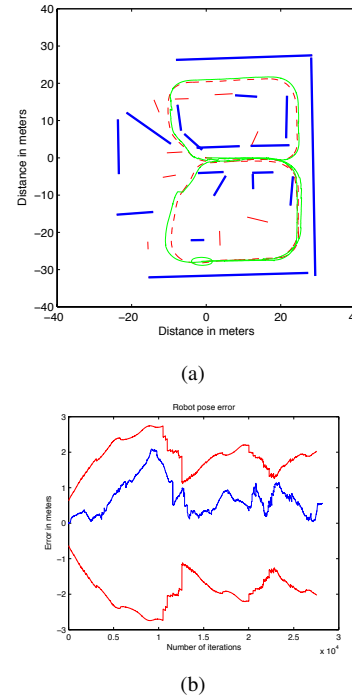


Fig. 8. On-The-Fly SLAM with distortion consideration (a) and its respective 2σ bounds (b).

localization. Moreover, we can observe that the map looks better than the previous one obtained with a 75 Hz sensor. This is the consequence of the use of a slow sensor. The applied

under-sampling behaves as a filtering process. Fewer detections are done and distances between sensor measurements are larger, so geometric feature detection is more selective and fewer wrong detections occur.

In order to show the contributions of the On-The-Fly method, we need to characterize the obtained results thanks to metric criteria.

V. SLAM PERFORMANCE EVALUATION

A. Map Quality Evaluation

1) *How to evaluate a 2D line map?*: The proposed quantitative performance evaluation method is concerned with 2D line maps and is relevant when a ground truth is available. The same global reference frame between the output of SLAM algorithm and the ground truth is used. This off-line process is based on a bipartite graph matching which is a well studied topic in Graph Theory [19].

Such matching relates pairs of nodes from two distinct sets by selecting a subset of the graph edges connecting them. Each edge selected has no common node as its end points to any other edge within the subset. An objective function associates weights to the graph edges, semantically related to some benefit or cost of the application. In that case, the weighted graph matching optimization goal is to maximize (or minimize) the sum of the weights of the matched edges.

When applying this technique to our map quality evaluation problem (see Fig. 9), it can be defined as: given a graph G , its set of edges E and its two distinct sets of nodes N_{GT} and N_{SLAM} , a matching M is a set of edges, subset of E , such that no two edges in M are incident to the same node. N_{GT} and N_{SLAM} respectively refer to the landmarks L_j from the ground truth map and L_i from SLAM map. Fig. 9 presents on simple cases the ground truth maps and the possible SLAM maps. Each corresponding matching M is displayed in Fig. 9. This automated procedure can be easily implemented using the well-known Hungarian algorithm [20]. The criteria used to compute the weights of the graph edges are presented in Section V-A2.

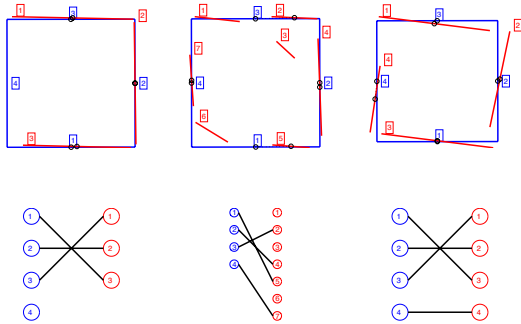


Fig. 9. Principle of the evaluation. The segments of the ground truth are in blue and the output of the SLAM algorithm is displayed in red. Below, the max-weight matchings respectively obtained.

2) *Map Geometry Quality*: In order to evaluate our line-based SLAM, we used several metrics.

First, dissimilarity between two lines is required. The difference in the parameters of two landmarks L_i from the SLAM map and L_j from the ground truth is calculated as follows:

$$\Delta\rho = \rho_i - \rho_j$$

$$\Delta\theta = \min(|\theta_i - \theta_j|, 2\pi - |\theta_i - \theta_j|)$$

A weighted absolute difference metric between ρ and θ is obtained by calculating the dissimilarity metric $\mathcal{D}_{d(i,j)}$:

$$\mathcal{D}_{d(i,j)} = c_{w1} \times |\Delta\rho| + c_{w2} \times |\Delta\theta|$$

where $c_{w1} = 1$ and $c_{w2} = 1.5$ are the weights applied respectively to the distance to the origin and angle as in [21].

Once that matching is obtained, a first score is calculated based on this metric; it measures the global line dissimilarity and so characterises the global geometry of the final map compared to a reference:

$$Score_d = \sum_{i,j} \mathcal{D}_{d(i,j)}$$

This score does not take into account the uncertainties attached to the detected lines. It can be completed by a metric based on Mahalanobis distance. It measures the dissimilarity between the line parameters weighted by the uncertainties.

The Mahalanobis distance between two landmarks is calculated classically as follows:

$$\mathcal{D}_{m(i,j)} = (\Delta\rho \quad \Delta\theta) \times (P_i + P_j)^{-1} \times \begin{pmatrix} \Delta\rho \\ \Delta\theta \end{pmatrix}$$

where P_i and P_j are the respective covariance matrix of the compared landmarks.

The resulting score of this metric is given by:

$$Score_m = \sum_{i,j} \mathcal{D}_{m(i,j)}$$

3) *Segment length quality*: Landmarks are not only represented by their line orientation but also by their length. So, each detected landmark L_k is represented by (ρ_k, θ_k) but also by two extremal points $A_k(x, y)$ and $B_k(x, y)$. When comparing two maps composed of basic geometric shapes or objects, such as lines, walls, and so on, the overlapping distance of the associated features is important.

Two overlapping rates have been calculated with respect to the associated segments after the matching and the segments defined in the ground truth:

$$R_{OverlapAssoSeg} = \frac{\sum_{i,j} \overrightarrow{D_{overlap(i,j)}}}{\sum_j \overrightarrow{\|A_j B_j\|}}$$

$$R_{OverlapGT} = \frac{\sum_{i,j} \overrightarrow{D_{overlap(i,j)}}}{\sum_n \overrightarrow{\|GTSeg_n\|}}$$

TABLE I
MAP QUALITY EVALUATION RELATED TO EXAMPLES PRESENTED IN FIG. 9.

	(a)	(b)	(c)
$Score_d$	0.27719	0.88124	1.4974
$Score_m$	0.18611	1.9447	12.9393
$R_{OverlapAssoSeg}$	91.6325%	45.2584%	80.6126%
$R_{OverlapGT}$	68.7244%	45.2584%	80.6126%
% Unmatched Segt. in map	0%	42.8571%	0%
% Undetected Segt. in GT	25%	0%	0%

4) *Over- or Under-segmentation*: Another very obvious criterion to estimate the quality of a map is the over or under segmentation rate of the environment. They are respectively calculated as the percentage of unmatched features in the SLAM map and as the percentage of undetected segments in the ground truth.

The different rates related to the examples presented in Fig. 9 are provided and discussed in Section V-C.

B. Trajectory Evaluation

In order to score trajectory results, we use a metric proposed by Kümmerle et al. [11] based on the relative displacement between robot poses. Instead of comparing the poses \mathbf{x} of the trajectory to the poses of the ground truth \mathbf{x}^* (in the global reference frame), the comparison is made between δ and δ^* with $\delta_{i,j} = x_j \ominus x_i$ which is the relative transformation that moves the node x_i onto x_j (and accordingly $\delta_{i,j}^* = x_j^* \ominus x_i^*$). \ominus is the inverse standard motion composition operator.

$$\epsilon(\delta)_{trans} = \frac{1}{N} \sum_{i,j} trans(|\delta_{i,j} \ominus \delta_{i,j}^*|)$$

$$\epsilon(\delta)_{rot} = \frac{1}{N} \sum_{i,j} rot(|\delta_{i,j} \ominus \delta_{i,j}^*|)$$

where N is the number of relative relations. $trans(\cdot)$ and $rot(\cdot)$ are used to separate the translational and rotational components.

C. Evaluation Results

1) *Evaluation on simulated results*: Table I summarizes the different values of rates presented above applied to the cases shown in Fig. 9.

We can see that for simulated data (a) both $Score_d$ and $Score_m$ are good; moreover the detected lines are well suited to the ground truth (GT). As expected when comparing tests (b) and (c), associated lines are closer to the GT for (b). $R_{OverlapAssoSeg}$ shows that considering only the associated features, result (a) is the best one as it presents an overlap of 91%. Comparing (b) and (c), result (c) represents more adequately the length of the GT landmarks. The score $R_{OverlapGT}$ (c) is the best one for global length overlapping. Over- or under- segmentations can complete these scores. Result (b) presents over-segmentation effect, it represents 43% of the map. (a) is the test where segment 4 in the GT has not been detected. To conclude on simulation, result (a) is globally the best one even if the complete environment has not been

TABLE II
MAP QUALITY EVALUATION RELATED TO EXPERIMENTAL RESULTS OBTAINED ON REAL DATA (SEE SECTION IV-B).

	Map in Fig. 8	Map in Fig. 7
$Score_d$	2.9573	6.7929
$Score_m$	293.9655	353.0831
$R_{OverlapAssoSeg}$	77.6345%	80.8545%
$R_{OverlapGT}$	60.6518%	61.7381%
% Unmatched Segt. in map	33.3333%	51.3514%
% Undetected Segt. in GT	35.7143%	35.7143%

observed; yet results concerning the observed part are accurate. Thanks to the scores we can see that result (b) indicates an over-segmentation of the environment but provides good estimates of the lines. Result (c) detects the entire GT but with poor accuracy. Of course, the interpretation of each score depends on the final application.

2) *Evaluation on real-world data*: The performance evaluation method is now applied to the experiments presented in Section IV-B. The results are summarized in Table II.

Comparing the score given by the evaluation of the two maps, we can see that both $Score_d$ and $Score_m$ are better for the map in Fig. 8. Landmarks detected thanks to this algorithm are closer to the ground truth and present fewer uncertainties. Both maps represent the same detected rate of the environment but the one obtained without taking into account the distortion (map in Fig. 7) is more over-segmented. Looking at the overlap rates, we can see that both algorithms give the same results. Based on these criteria, we can conclude that the quality of the map is better when taking distortion into account.

To complete this observation, a trajectory evaluation has been applied to these experiments. Table III shows the results.

TABLE III
TRAJECTORY EVALUATION.

	Trajectory in Fig. 8	Trajectory in Fig. 7
Translational Error	0.00099347	0.0017407
Tx et Ty (in meters)	0.00091117	0.0014697
Rotational Error (in radians)	0.066087	0.072469

Based on the trajectory evaluation, the mean transformation error is better for both translation and rotation for the experiment when taking distortion into account.

Thanks to the metrics used, we have evaluated the map quality of the approach with and without consideration of the distortion. These criteria complete the classical visual evaluation and quantify both of the map and the trajectory quality.

Looking at these two evaluations, distortion has an important impact both on map and localization quality. On-The-Fly method improves SLAM results by avoiding distortion on data and providing detections as soon as possible to the process.

VI. CONCLUSION

In this paper, we have presented a version of a line-based On-The-Fly SLAM algorithm taking into account sensor rotation and vehicle displacements in order to build and extract on-the-fly lines. The non-instantaneous aspect of the measurement

acquisition is considered in order to take into account distortion in the observation model rather than to globally correct a scan. As a consequence, detection can be provided to the SLAM process without waiting for the completion of the sensor rotation. The proposed approach has been applied to a set of laser data. The necessity of operating in this way has been demonstrated by illustrating the errors which appear if distortion phenomena are not taken into account. To give quantitative evidence of the quality of the obtained results, a performance evaluation has been carried out based on a process and criteria specifically developed for line-based maps.

Based on these evaluations, we can conclude that distortion phenomena cannot be neglected. On-The-Fly principle increases SLAM results quality for robot with low scanning rate sensor.

Experiments with a 1 Hz radar sensor have also been realized but not presented in this paper for the sake of concision and clarity about the method.

Future work will address the issue of SLAM with a robot moving at high-speed with a slow rotating radar sensor in semi-urban dynamic environments. This radar called IMPALA [22] will provide native Doppler information which will make the classification, segmentation and filtering or tracking of mobile objects much easier.

Moreover, our evaluation method will be compared with other existing metrics.

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