ICP-SLAM Methods Implementation on a Bi-steerable Mobile Robot

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***Abstract*—Scan matching is a popular way of recovering a mobile robot's motion and constitutes the basis of many localization and mapping approaches. The work presented in this paper consists in the implementation of a SLAM method (Simultaneous Localization and Mapping) based on the Iterative Closest Points (ICP) algorithm on the Robucar, a car-like mobile robot. Two variants are considered related to the error metric minimization. These variants of ICP-SLAM have been implemented and tested on the robot for performance's comparison.**

***Keywords*—scan matching; ICP-SLAM; measures alignment; Robucar.**

I. INTRODUCTION

Nowadays, Simultaneous Localization and Mapping (SLAM) is a well-defined problem in mobile robotics and has been extensively studied for indoor and outdoor environments. In fact, the last two decades have seen extensive work in the development of SLAM approaches where the most popular ones are probabilistic techniques [1, 2, 3, 4] and scan matching techniques [5, 6, 8, 9, 10] which allow to define landmarks without resorting to geometric feature models.

One of the most used approaches for scan matching is the Iterative Closest Point (ICP) algorithm [9]. Many SLAM solutions rely on ICP algorithms to estimate the relative transformation between two overlapping point clouds. ICP was independently introduced by Besl and McKay [7], Chen and Medioni [8], and Zhang [9]. The ICP algorithm attempts to find transform parameters that minimize the Euclidean distance of corresponding points, which are assumed to be the nearest neighbor points.

Several variants of ICP have been proposed corresponding to all steps of the algorithm from the points selection to the minimization strategy. A good survey can be found in [10] where a comparison relating to the speed of convergence is made among different variants. According to the six steps of the algorithm, Rusinskiewicz and Levoy [10] have classified them as:

1. Selection of the set of points.
2. Matching the points to the samples.
3. Weighting corresponding pairs appropriately.
4. Rejecting certain pairs.
5. Assigning an error metric.
6. Minimizing the error metric.

For instance, in [11] to overcome the problem of false selection of corresponding points, a new method is proposed which introduces rotation-invariant descriptors for robust correspondence. In Segal, Haehnel, and Thrun [12], to take into account the underlying surface structure of the point cloud, they introduced the idea of generalized-ICP. This approach calculates surface structure using local neighborhoods of points and uses this additional information in the optimization process to generate higher quality scan matches. In Rowekamper, Sprunk, Tipaldi, Stachniss, Pfaff, and Burgard [13], a highly accurate motion capture system, to precisely determine the error in the robot's pose, is used. This system is constituted by a combination of Monte-Carlo localization, KLD sampling, and ICP-scan matching; an accuracy of a few millimeters at taught-in reference locations has been achieved. In [6], two methods are proposed; one is based on a Genetic Algorithm (GA) and the other on the combination of GA and ICP. Their performance in terms of real-time applicability and accuracy has been compared in outdoor experiments showing that the last method outperforms the pure methods. Reference [14] presents a method which solves data association by matching scan segments across scans. They use a modified version of the ICP algorithm where the search for point-to-point correspondences is constrained to associated segments to generate accurate segment associations. The novelty of the proposed approach is in the segment matching process which takes into account the proximity of segments, their shape, and the consistency of their relative locations in each scan. The method is tested on seven sequences of Velodyne scans acquired in urban environments.

The aim of this work is the evaluation of a scan matching SLAM method based on the ICP algorithm. Two variants of this algorithm are implemented and compared. The focus is set on the minimization strategy of the Rusinkiewicz classification [10]. The first one uses the mean squared error of the Euclidian distance metric (classical ICP) while the second introduces a test on pairs of outliers which are deleted and their effect on the error metric (Boolean ICP) considered.

In this paper, the ICP-SLAM technique is presented in section II where the ICP algorithm is given. The two methods, namely Boolean and classical ICP, are explained as well as the map building. In Section III, the experiments on the Robucar which is a bi-steerable mobile robot are shown. Then, a comparison between the two variants of ICP-SLAM is given. Finally, the conclusion and future work are outlined in section IV.

II. ICP-SLAM TECHNIQUE

In this section, we present the principle of ICP-SLAM technique, by explaining several sub-tasks like the measures alignment and the robot configuration (position and orientation) estimation. Other aspects such as map building and management step are also developed.

A. The ICP algorithm

The ICP algorithm is the most applied algorithm concerning the automatic registration between two models of geometric data regardless of their types (points, curves of different degree, surfaces). It does not impose prior conditions and its convergence is demonstrated for the majority of cases. In ICP, the transformation between scans is found iteratively by assuming that every point in the first scan corresponds to its closest point in the second scan, and by calculating a closed form solution using these correspondences.

The ICP algorithm is composed of three main steps [15]. Each step is described where the corresponding formulations are given.

Step 1: Projection of laser scan

To make a comparison between two points represented in two different markers, they must be represented in the same coordinates system or frame. A laser scan S is defined by local coordinates in the mobile robot frame, where the robot position P, given by the odometry, is expressed in the global frame. Each new scan S_{new} is then projected in the global frame, and noted S'_{new}. This can easily be done using the homogeneous transformation matrix between the two frames.

Let P_1 and P_2 being two points belonging to two different scans S_{ref} taken at the beginning, and S_{new} taken in motion. Using the following equations, P'_2 which is the projection of P_2 in the global frame is obtained by:

$$P_2' = \mathrm{T} \times P_2 \tag{1}$$

$$T = \begin{bmatrix} \cos(\theta) & -\sin(\theta) & t_x \\ \sin(\theta) & \cos(\theta) & t_y \\ 0 & 0 & 1 \end{bmatrix} \tag{2}$$

Where T is the homogeneous transformation matrix.

Step2: Data Association

In this step, called also Matching step, we should compute for each point of the new scan S'_{new} its correspondent in the reference scan S_{ref}, as shown in Figures 1 and 2. The Euclidean distances between one point of S'_{new} and all the points of S_{ref} are calculated and the point of S_{ref} corresponding to the smallest distance is chosen to be the corresponding point.

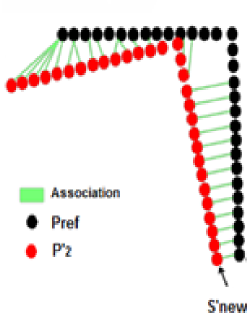

Fig. 1. The matching principal

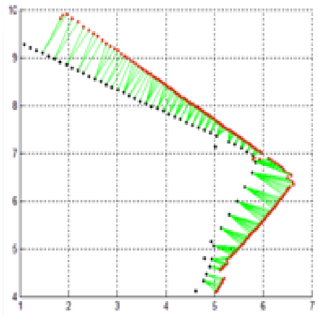

Fig. 2. Real exemple of matching

Figure 3 shows the pseudo code used in the association step:

for $i=1$ *à* N
  for $k=1$ *à* N_0
    $d_x = X'_{new}(i) - X_{ref}(k)$
    $d_y = Y'_{new}(i) - Y_{ref}(k)$
    $d(k) = \sqrt[2]{d_x^2 + d_y^2}$
    if $(d_{min}(i) > d(k))$ $d_{min}(i) = d(k)$
  end for
    $c(i) = k$
end for

Fig.3 Pseudo code of the association

Where:

- N: size of S'_{new}.
- N_0: size of S_{ref}.
- X'_{new} : abscissas of S'_{new} points.
- X_{ref} : abscissas of S_{ref} points.
- Y'_{new} : ordinates of S'_{new} points.
- Y_{ref} : ordinates of S_{new} points
- d_{min} : minimal distance between S'_{new} points and S_{ref} points.
- c(i): rank of a point of S_{ref} which corresponds to the i^{th} point in S'_{new}.

Step3: Position estimation

3.1) Scan alignment criteria

The criteria used for alignment is formulated as the minimization of the mean squared error of the distance defined between the associated points:

$$\mathrm{J} = \frac{1}{N}\sum_{\mathrm{i}=1}^{N} \|\mathrm{S}_{\mathrm{ref}}\left(\mathrm{c(i)}\right) - S'_{new}(\mathrm{i})\|^2 \tag{3}$$

We have then:

$$P'_{new} = \mathrm{T} * P_{new} \tag{4}$$

Therefore:

$$\mathrm{J} = \frac{1}{N}\sum_{\mathrm{i}=1}^{N}\|\mathrm{S}_{\mathrm{ref}}\big(\mathrm{c(i)}\big) - \mathrm{TS}_{\mathrm{new}}(\mathrm{i})\|^2 \tag{5}$$

$$\mathrm{J} = \frac{1}{N}\sum_{\mathrm{i}=1}^{N}[(\mathrm{X}_{\mathrm{ref}}\big(\mathrm{c(i)}\big) - X'_{new}(\mathrm{i}))^2 + (\mathrm{Y}_{\mathrm{ref}}\big(\mathrm{c(i)}\big) - Y'_{new}(\mathrm{i}))^2] \tag{6}$$

With:

$$X'_{new}(\mathrm{i}) = \mathrm{X}_{new}(\mathrm{i}) * \cos\theta - \mathrm{Y}_{new}(\mathrm{i}) * \sin\theta + \mathrm{t}_x \tag{7}$$

$$Y'_{new}(\mathrm{i}) = \mathrm{X}_{new}(\mathrm{i}) * \sin\theta + \mathrm{Y}_{new}(\mathrm{i}) * \cos\theta + \mathrm{t}_y \tag{8}$$

Finally, (7) and (8) are replaced in (6).

3.2) Homogeneous transformation estimation

The weighting of the associated pair of points reinforces the contribution of correct associations and decreases the effect of false associations during the estimation phase. Two types of weighting are considered [16]: A binary weighting (Boolean) where the weight assigned is 1 when the association is considered correct and it takes zero value if the association is considered false. The second type of weighting doesn't consider associations as either exclusively "correct" or only "false", but consider the pairs of points between these two categories.

a) Boolean weighting estimation

To determine the parameters of the transformation T (t_x,t_y,θ), the squared error of the distance between the two associated scans is minimized. Unmatchable points can be discarded by defining a Boolean function for outliers detection[6]:

$$p_T(i) = \begin{cases} 0 & if \;\; |J_b(i)| \geq E \\ 1 & otherwise \end{cases} \tag{9}$$

With:

$$J_b(\mathrm{i}) = (X_{ref}\big(\mathrm{c(i)}\big) - X'_{new}(\mathrm{i}))^2 + (\mathrm{Y}_{\mathrm{ref}}\big(\mathrm{c(i)}\big) - Y'_{new}(\mathrm{i}))^2$$

E is the outlier threshold calculated experimentally. Consequently, the number n_T of valid correspondences is given by:

$$n_T = \sum_{i=0}^{N} p_T(i) \tag{10}$$

The ratio that shows the degree of overlap of any possible transformation is:

$$P_T = \frac{n_T}{N+1} \tag{11}$$

Authors in [6] have noticed that having an exact correspondence of points from different scans is impossible, due to a number of parameters like deformation caused by robot motion, random noise, terrain unevenness, etc. Then, scan matching can be thought of as an optimization problem for determining a 2D transformation that minimizes a well-grounded matching criterion I_T. So for a given transformation T, a general matching index I_T can be formulated by accumulating the matching errors and dividing this sum by n_T, to normalize and by Erreur ! Signet non défini. P_T to penalize low correspondence rates that are [6]:

$$\mathrm{I_T} = \frac{\sum_{\mathrm{i}=0}^{\mathrm{N}}[\mathrm{p_T(i)}\; J_b(\mathrm{i})]}{\mathrm{n_T P_T}} \tag{12}$$

This expression represents the cost function to be iteratively minimized by point matching methods.

Finally, motion parameters are updated by minimizing I_T in (12) with the error definition of (6).

This optimization can be solved analytically (when the term $\frac{\partial I_T}{\partial(\theta,x,y)} = 0$) as follows [6]:

$$\begin{cases} \breve{\theta} = \arctan\left(\frac{\mathrm{S_{X_{ref}} * S_{Y_{new}} + n_T * S_{Y_{ref}X_{new}} - n_T * S_{X_{ref}Y_{new}} - S_{X_{new}} * S_{Y_{ref}}}}{\mathrm{n_T * S_{X_{ref}X_{new}} + n_T * S_{Y_{ref}Y_{new}} - S_{X_{ref}} * S_{X_{new}} - S_{Y_{ref}} * S_{Y_{new}}}}\right) \\ \breve{t}_x = \frac{S_{X_{ref}} - \cos(\breve{\theta}) * S_{X_{new}} + \sin(\breve{\theta}) * S_{Y_{new}}}{n_T} \\ \breve{t}_y = \frac{S_{Y_{ref}} - \sin(\breve{\theta}) * S_{X_{new}} - cos\;(\breve{\theta}) * S_{Y_{new}}}{n_T} \end{cases} \tag{13}$$

Where the S terms stand for the following sums:

$$S_{X_{ref}} = \sum_{i=0}^{N}[p_T\,(i) X_{ref}\big(c(i)\big)] \tag{14}$$

$$S_{Y_{ref}} = \sum_{i=0}^{N}[p_T\,(i) Y_{ref}\big(c(i)\big)] \tag{15}$$

$$S_{X_{new}} = \sum_{i=0}^{N}[p_T\,(i) X_{new}\,(i)] \tag{16}$$

$$S_{Y_{new}} = \sum_{i=0}^{N}[p_T\,(i) Y_{new}\,(i)] \tag{17}$$

$$S_{X_{ref}X_{new}} = \sum_{i=0}^{N}[p_T\,(i) X_{ref}\big(c(i)\big)\, X_{new}\,(i)] \tag{18}$$

$$S_{X_{ref}Y_{new}} = \sum_{i=0}^{N}[p_T\,(i) X_{ref}\big(c(i)\big)\, Y_{new}\,(i)] \tag{19}$$

$$S_{Y_{ref}X_{new}} = \sum_{i=0}^{N}[p_T\,(j) Y_{ref}\big(c(i)\big)\, X_{new}\,(i)] \tag{20}$$

$$S_{Y_{ref}Y_{new}} = \sum_{i=0}^{N}[p_T\,(i) Y_{ref}\big(c(i)\big)\, Y_{new}\,(i)] \tag{21}$$

b) Estimate by weighting pairs of points

For this variant, in parameters computation of the transformation TErreur ! Signet non défini. , the squared error of the distance between the two associated scans is minimized by deriving (6) according to the three parameters (t_x,t_y,θ). The following system of equations is obtained:

$$\begin{cases} \frac{\partial J}{\partial t_x} = t_x - \bar{X}_{ref} + \bar{X}_{new} * \cos(\theta) - \bar{Y}_{new} * \sin(\theta) \\ \frac{\partial J}{\partial t_y} = t_y - \bar{Y}_{ref} + \bar{X}_{new} * \sin(\theta) + \bar{Y}_{new} * \sin(\theta) \\ \frac{\partial J}{\partial \theta} = \theta - atan2\left(\frac{-A_1 + t_x * \bar{Y}_{new} - t_y * \bar{X}_{new}}{A_2 - t_x * \bar{X}_{new} - t_y * \bar{Y}_{new}}\right) \end{cases} \quad (22)$$

With:

$$\bar{X}_{ref} = \frac{1}{N_0} \sum_{i=1}^{N_0} X_{ref}\big(c(i)\big) \quad (23)$$

$$\bar{Y}_{ref} = \frac{1}{N_0} \sum_{i=1}^{N_0} Y_{ref}\big(c(i)\big) \quad (24)$$

$$\bar{X}_{new} = \frac{1}{N_1} \sum_{i=1}^{N_1} X_{new}(i) \quad (25)$$

$$\bar{Y}_{new} = \frac{1}{N_1} \sum_{i=1}^{N_1} Y_{new}(i) \quad (26)$$

A1 and A2 are given by:

$$A_1 = \frac{1}{N}\left(\sum_{i=1}^{N} X_{ref}\big(c(i)\big) * Y_{new}(i) - \sum_{i=1}^{N} Y_{ref}\big(c(i)\big) * X_{new}(i)\right) (27)$$

$$A_2 = \frac{1}{N}\left(\sum_{i=1}^{N} X_{ref}\big(c(i)\big) * X_{new}(i) - \sum_{i=1}^{N} Y_{ref}\big(c(i)\big) * Y_{new}(i)\right) (28)$$

The criteria "J" is optimal when the term $\frac{\partial J}{\partial (t_x, t_y, \theta)}$ is equal to 0. Then, we obtain a coupled nonlinear equations system:

$$S = \begin{cases} t_x - \bar{X}_{ref} + \bar{X}_{new} * \cos(\theta) - \bar{Y}_{new} * \sin(\theta) = 0 \\ t_y - \bar{Y}_{ref} + \bar{X}_{new} * \sin(\theta) + \bar{Y}_{new} * \sin(\theta) \ = 0 \\ \theta - atan2\left(\frac{-A_1 + t_x * \bar{Y}_{new} - t_y * \bar{X}_{new}}{A_2 - t_x * \bar{X}_{new} - t_y * \bar{Y}_{new}}\right) \qquad = 0 \end{cases} \quad (29)$$

To solve (29), an iterative method defined as follows is used:

1. Take initial condition given by odometry.
2. Fix $\theta = \check{\theta}$ and find t_x and t_y from the first two equations of the system, resulting in a new estimate $(\check{t}_x, \check{t}_y)$.
3. From$(\check{t}_x, \check{t}_y)$, the new $\check{\theta}$ of θ is determined from the third equation of the system. Re-using this value in the previous step will recalculate the estimates $(\check{t}_x, \check{t}_y)$.
4. Repeat Steps 2 and 3 until the triplet converges to a fixed value.

In general, the convergence depends on the initial transformation estimate of the used point clouds. In this paper, the odometry parameters are chosen to be the initial conditions.

B. The ICP-SLAM principals

The ICP-SLAM is performed following the cited steps below:

1. Initialize robot configuration P(x,y,θ) to (0m,0m,0°) and push first Scan S_0 in the map.
2. Move robot to a configuration P_{new} and acquire S_{new}.
3. Compute corrected configuration by ICP algorithm.
4. Project, associate & push S_{new} in the map.
5. Return to step 2 until the robot stop.

For the map building step in this work, the chosen representation is the geometric one based on points. But map building must be incremental, by merging successive data acquired by the laser range finder. For this aim, in the association step, the new acquired scan S_{new} is compared to the global map of the already built environment as shown in Figure 4.

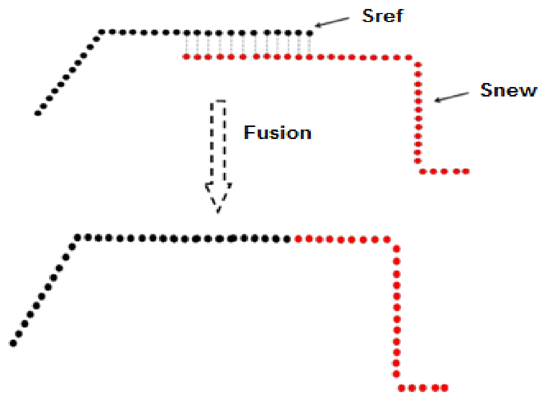

Fig.4. Data fusion in the map

The associated parts of S_{new} and the global map represent the same point in the environment. The non-associated parts of S_{new} represent a new part of the environment that is not yet modeled, and it will be pushed into the map.

III. EXPERIMENTAL RESULTS

Experiments were performed on the mobile robot prototype called Robucar shown in Figure 5. Robucar is a bi-steerable mobile robot, which has been recently equipped with a new obstacles detection system based on the laser range finder sensor *LMS511* with 65m detection range.

Fig. 5. The Robucar

Sensors acquisition and actuators management are performed within a novel Linux modular architecture based on the LAAS-CNRS tool called "Genom2", and using C/C++ interfacing scheme. Genom is a software environment allowing to define, produce and control modules that encapsulate algorithms [17]. The system architecture used in this work is presented in Figure 6. It shows that the software layer, implemented on an embedded laptop, contains three perception modules, as explained below:

- **Lms** : laser sensing module
- **Communication** : internal robot data acquisition module (odometry)
- **Localization** : SLAM module

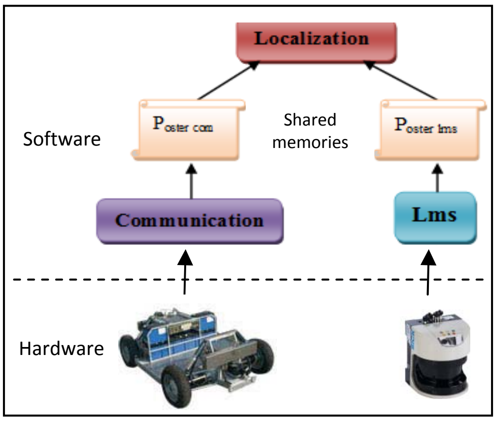

Fig. 6. SLAM architecture

The "Localization" module performs a SLAM using internal robot data provided by "Communication" module, and environment data extracted from "Lms" module. Experimental tests were carried out in a static environment, as follows: The robot is moved manually by joystick from a starting point to a finish point. The two cited techniques are tested with the same scenario: Initially, the robot is from point A, driven manually throw environment corridor to point B then turned right to reach point C, and finally stopped at point D. Figure 7.a shows the map and the robot trajectories provided by the odometry (blue) and Boolean ICP (green), while Figure 7.b shows those related to classical ICP (red). We notice that both environments maps are quite descriptive, even if the first map is more accurate since the walls appear clearly.

Based on obtained results, a comparison between the two variants is performed according to the algorithm convergence, number of points in the map and speed of convergence.

- In the classical ICP method, the parameters t_x, t_y, and θ are calculated by solving a nonlinear equations system, where a wrong initialization can lead to algorithm divergence. Instead, the Boolean method does not require an initialization step, which betters its convergence.

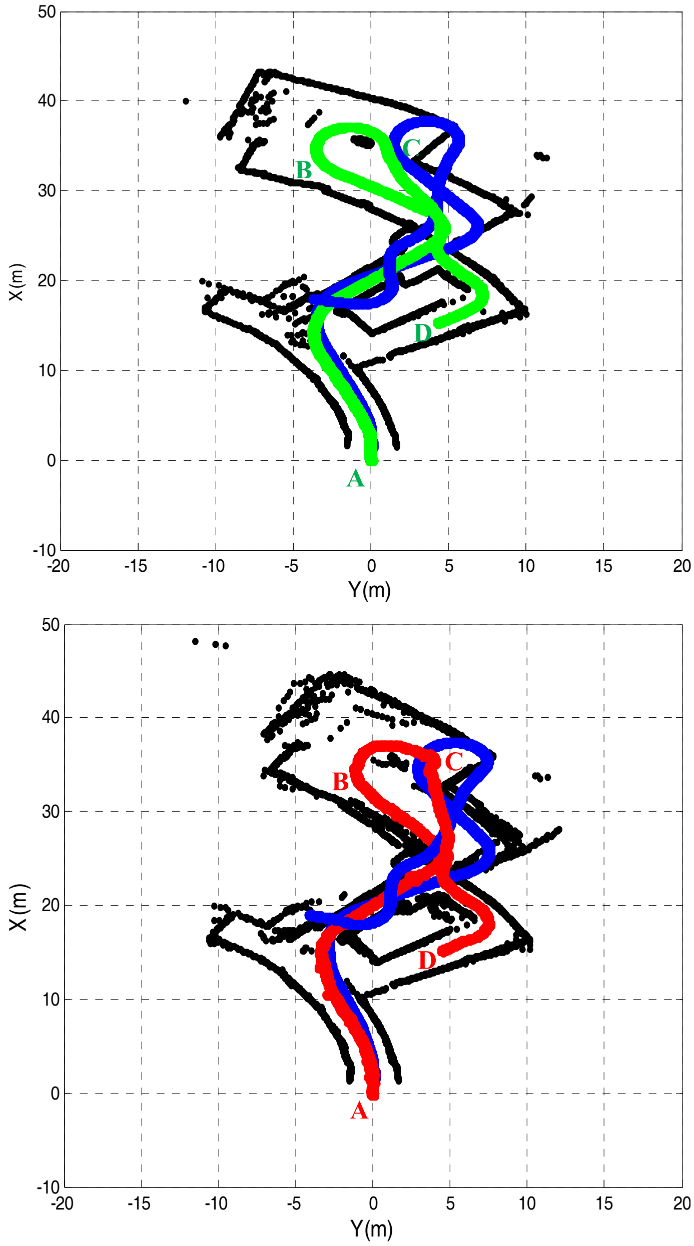

Fig. 7. ICP-SLAM maps and robot trajectories

- During the map building, Boolean method ignores the encountered outliers while in the classical ICP, all points are considered. Then, the number of points being more important leads to bigger computation time even if both variants are time consuming as it is argued in the literature.

- Boolean variant provides a better accuracy with more sensor data (smaller laser resolution), even if the computation time is then increased. On the contrary, classical ICP variant converges less when using more points.

IV. CONCLUSION

This work has treated the problem of simultaneous localization and mapping in a static environment. The goal is to provide an accurate environment's map for safe robot navigation. We have implemented two variants of the ICP-SLAM algorithm. Experimental tests have been performed on a bi-steerable mobile robot to allow comparison between the two variants. Obtained results show the effectiveness of both variants in map construction, even if they are time consuming.

In fact, one of the shortcomings of these approaches is the generation of the nearest neighbor correspondences. This step is generally computationally expensive and has been shown to be the bottleneck of the ICP algorithm. A possible solution is to use ICP cluster to cluster to reduce execution time by accelerating the association step.

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