Probabilistic Localization of a Mobile Robot Based on the Sensor Fusion of a Laser Scanner and a Monocular Camera

Lucas Costa, Larissa Da Silva and Antonio Lima

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Lucas F. A. Costa * **Larissa T. Da Silva** ** **Antonio M. N. Lima** **

* *Graduate Program in Electrical Engineering, Federal University of Campina Grande, (e-mail: lucas.costa@ee.ufcg.edu.br).*
** *Departament of Electrical Engineering, Federal University of Campina Grande, (e-mails: larissa.silva@ee.ufcg.edu.br, amnlima@dee.ufcg.edu.br).*

Abstract: In the context of indoor localization, due to the popularization of the laser scanner, there is a massive use of LiDAR-based approaches due to their real-time performance and high accuracy, and it was perceived that these methods present difficulties in symmetrical environments and environments with lack of longitudinal reference. This paper deals with the proposition of a localization problem approach for a mobile robot in indoor environments using scanning and image sensory. Considering the existence of a map of the environment containing fiducial markers, it brings the monocular camera to overcome LiDAR exteroceptive perception limitations. The results obtained indicated gains of up to 19.35% in the accuracy of determining the location of the system in relation to LiDAR-based methods in scenarios with low range LiDAR.

Keywords: Indoor Localization; Particle Filter; Autonomous Vehicle Navigation; Sensor Fusion; Fiducial Marks.

1. INTRODUCTION

Indoor localization refers to the estimation of the pose of a mobile robot in the motion area, which is a prerequisite for autonomous navigation, which requires constant update of robot pose in a dynamic environment. To determine the current location on the known map, various techniques and algorithms have been developed. Radio frequency (RF) technology based on indoor localization systems such as Wireless-Sensor-Network (WSN)-based methods utilizing Ultra Wide Band (UWB), WiFi, and Bluetooth Low Energy (BLE) can localize the robot with the Received Signal Strength Indicator (RSSI), which is unique at specific location. Such methods rely on Access Point (AP) deployment, the accuracy is not high, orientation is not covered and further optimization is required. Exteroceptive-sensor-based methods determine the robot's pose by perceiving the surroundings with sensors mounted on the robot. Perceptual data is fused with algorithms such as the Kalman Filter (KF) and its extensions (extended Kalman filter and unscented Kalman filter), grid localization, and the Particle Filter (PF). Among them, the PF implemented in Monte Carlo Localization (MCL) is a widely used technique with a multi-modal probabilistic density function. It is a prevalent approach to nonlinear and non-Gaussian state estimation.

Normally, the localization problem is solved at three levels, position tracking, global localization, and the robot kidnapping problem. As far as practical application is concerned, besides solving the three sub-problems, real-time performance and accuracy also need to be considered. Approaches applying various sensor modalities are challenged by specific problems.

The high accuracy of indoor localization is the key point of modern robotics applications, mainly in complex and dynamic environments such as factories, distribution centers or hospitals, since the ability of the mobile robot to locate itself accurately on the map is essential to guarantee the efficient execution of tasks, while ensuring the safety of the environment in human-machine interaction. In a typical problem of robot localization tracking, a map of the environment is available and the robot has sensors that observe the environment and monitor its own movement. The challenge of localization is defined by estimating the pose of the robot within the map, using the information collected by the sensors. Therefore, the techniques applied for robot localization must be able to deal with inaccurate sensor measurements, dynamic environments, in addition to providing an accurate estimate of the robot's pose, but also a measure of uncertainty associated with this estimate. Restricted navigation cases generate the need for increasingly accurate localization systems, as is the case with (Azpúrua et al., 2021).

New approaches based on the current particle filter standard (Fox, 2001) have been proposed for localization improvements in the effectiveness of solving the three classic localization problems, as well as the performance

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evaluation of the current standard, such as the AMCL (Talwar and Jung, 2019).

Some of these approaches presented soft modifications of the original AMCL present in the navigation package (Marder-Eppstein et al., 2010), as in Chung and Lin (2022) that tries to address the problem of environments with high similarity and symmetry, using the same inputs as the traditional AMCL: scanning sensor and odometry.

The inclusion of new sources of information is also addressed Yuan-Heng Huang (2022), Shi et al. (2022) and Shi et al. (2018), where in general, additional sensors arrive as a way to increase the accuracy of the localization system by suppressing noise and as a way to get around the limitations that a type of sensor may have, adding another type that can overcome this limitation. In the case of the inclusion of visual information, it is observed that compared to the use of the laser, it is robust to the environment homogeneity.

In Yuan-Heng Huang (2022), this inclusion is observed as a robot localization system using LiDAR and two AprilTags. In this study, a different approach was observed, where two reference points are generated through a pair of neighboring tags, offering restrictions to estimate the robot's pose. It is also said that the use of a single tag for such alignment is possible. However, the uncertainty would cause errors in the estimation of the robot's pose.

Various approaches have been previously employed to tackle the problem of robot kidnapping in specific environments. In Shi et al. (2022), the focus is on the combination of visual and probabilistic localization, with LiDAR 2D and enhanced AMCL being responsible, respectively. The objective of this study is to address the challenge of robot kidnapping and global localization in a symmetrical environment. The research aims to solve issues such as imprecise pose estimations, location ambiguity, and robot reorientation difficulties, which are caused by premature convergence. Another technique used to handle these problems is the application of multi-objective particle swarm optimization, as demonstrated in Chien et al. (2017).

To address the general case of robot kidnapping, Campbell and Whitty (2013) presents a metric-based technique for real-time detection using a set of binary classifiers to identify all events during an autonomous operation.

Other approaches were further explored in Su et al. (2017), Li et al. (2020), and Yu et al. (2021).

The target environment of the study are places with high topological similarity, with places without longitudinal reference for distance sensors, where there may be interference from the addition of fiduciary marks and the demonstration of the need for the proposed approach occurs in the increase of its proportions. The robot must have at least one LiDAR and one camera, and the LiDAR range is a performance impact factor to be mitigated.

The aforementioned articles highlight the paucity of studies on the application of commercially available off-the-shelf (COTS) vision sensors in AMCL.

Based on previous studies, this work proposes an approach to the problem of localization of a mobile robot in indoor environments, since it has knowledge of the environment map, and fusion of information provided by a single LiDAR that feeds the AMCL, in addition to the use of fiducial markers with known localization. In this scenario, contributions are:

(1) Explore advantages in partial re-sampling in the particle filter
(2) Address the problem of tag detection uncertainty with one tag by increasing particle swarm variance
(3) Enable the use of COTS while maintaining performance

The remainder of this paper is organized as follows. Section 2 introduces the proposed approach. Experiments are presented in Section 3. Finally, Section 4 concludes this work.

2. PROPOSED APPROACH

Given the detection of a fiducial mark through an image and the location information of that mark on the map, it is necessary to develop the problem of how to include this information in the location system used. The present work proposes to include the information as a particle cloud resample using the localization given by the measured data.

The main improvement of this approach is the assurance of correct global localization, which is not guaranteed in homogeneous environments. This brings a more reliable and secure localization estimate, maintaining the local precision that is proportioned by AMCL. In some cases the fusion even improves local precision.

In the proposed arrangement, the map of the environment was previously generated (localization-only problem), and the pose of the tags on the map was defined (ξ_T), the transform from robot to camera (${}^R\xi_C$) is fixed transform that is considered known and when occurs the detection of a tag (${}^C\xi_T$) the robot localization (ξ_R) can be found by equation 1.

With the localization of the robot (ξ_R), the particle swarm can be partially resampled around the new localization estimate. The purpose of such inclusion is to use the AMCL ecosystem as a form of sensor fusion.

$$\xi_R = \xi_T \ominus ({}^R\xi_C \oplus^C \xi_T) \qquad (1)$$

2.1 Modified AMCL

The proposed improvement to the original structure of the AMCL (Marder-Eppstein et al., 2010) available in open source code, a *subscriber* ROS was created that executes a routine in which every detection generated by AprilTag runs:

- The record of tags is cleared to fill in a new one;
- The detection performed in the camera's coordinate frame is transformed to the robot's reference coordinate frame, commonly called base link in the ROS environment;
- The global location of the previously cataloged tag is obtained from the individual id of the tag;

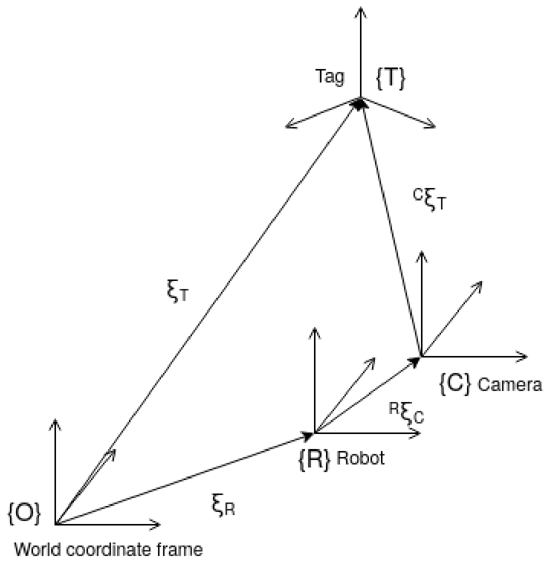

Figure 1. The transforms ξ_T, $^C\xi_T$, $^R\xi_C$ are known, so ξ_R can be found by operations on the known transforms.

- The global location of the tag is used as a transform and the transformation of the localization pose of the detection of the tag in the frame of coordinates of the base link is performed to the global pose of the robot;
- Using the covariance from the AprilTag system, a part of the swarm of particles around the estimate generated in the previous steps is re-sampled.

This improvement resulted in the algorithm described in Algorithm 1.

Algorithm 1 Modified AMCL

while navigating **do**
  $pose_i \leftarrow odometry()$
  if $pose_i - pose_{i-1} \geq$ treshold **then**
    tags ← consult_tags()
    tag_bl ← camera_transform(tags.localization)
    localization_estimate ← tag_to_map(tag_bl)
    resample(localization_estimate)
    tags ← []
    $i \leftarrow i + 1$
  end if
end while

The diagram shown in Figure 2 shows all the modules involved in the experiment, which are the AMCL with its original systems, the AMCL systems that were modified to work with the solution, the blocks external elements that are the fiducial tag detector (AprilTag) and the system responsible for computing the transforms. The components that provide information to the system are also represented. They are the robot sensors and the map.

The resulting source code uses ROS environment (Quigley et al., 2009). The fiducial marker detection algorithm used was AprilTag (Wang and Olson, 2016) so the tags placed in the environment must be AprilTag type.

2.2 Sensor Fusion

Using the properties of the particle filter, it is possible to use the estimated covariance to calculate the dispersion of the dispersed particle swarm.

One of the biggest advantages of this approach is the correction of errors at the end of the corridors, because as shown in the figure, when creating more points in the cloud of points together on the wall at the end of the corridor, error correction is prioritized in this sense.

AMCL can not correct this type of error if it's magnitude is above the frontal dispersion of the particle swarm.

3. EXPERIMENTAL STUDY

To verify the performance of the proposed system against the pure AMCL, a simulation world was used with degradation of the quality of signals of interest, such as the laser signal, in order to make the experiment closer to reality and to allow the evaluation of the algorithm, proposed for its fault correction purpose.

The experiment was run under two conditions that were determined by the range of laser used, the first condition using a 5 m range laser as a low-range scanning laser, and the second condition using a 20 m range laser as a high-range scanning laser.

The test cases were composed of each condition employing the standard AMCL and the modified one with one test, always initialized at the same position and executing the same trajectory. The results are displayed in Figures 5-8.

The four tests were carried out and the error of the pose provided as output by the proposed system was cataloged in relation to the real location, commonly referred to as *ground truth* in the literature, provided by the Gazebo simulation software Koenig and Howard (2004).

Figure 4 presents a visualization of the trajectory adopted for the tests. One of the cases of interest in the present study was chosen: places similar to corridors where, if the laser does not reach the end, the movement reference in the parallel direction to the side is lost.

The adopted trajectory generates a situation with two stages to the experiment using the modified algorithm: the first, before the turn, when the camera sees the tag, and the second, after the turn, when it doesn't. After the turn, the typical AMCL assumes the operation and this can demonstrate the return to typical AMCL working.

In test case 1 (Fig. 5)with the low-range scanning laser and using the AMCL for localization, an average error of 0.31 m in position and in orientation of 0.053 radians was found, which represents high-precision localization for most mobile robotics applications.

In test case 2 (Fig. 6) with the low-range scanning laser and using the proposed approach, an average error of 0.25 m in position and in orientation of 0.055 radians was found. In this case, it is possible to notice a significant improvement in the accuracy of the position, and the orientation error remained.

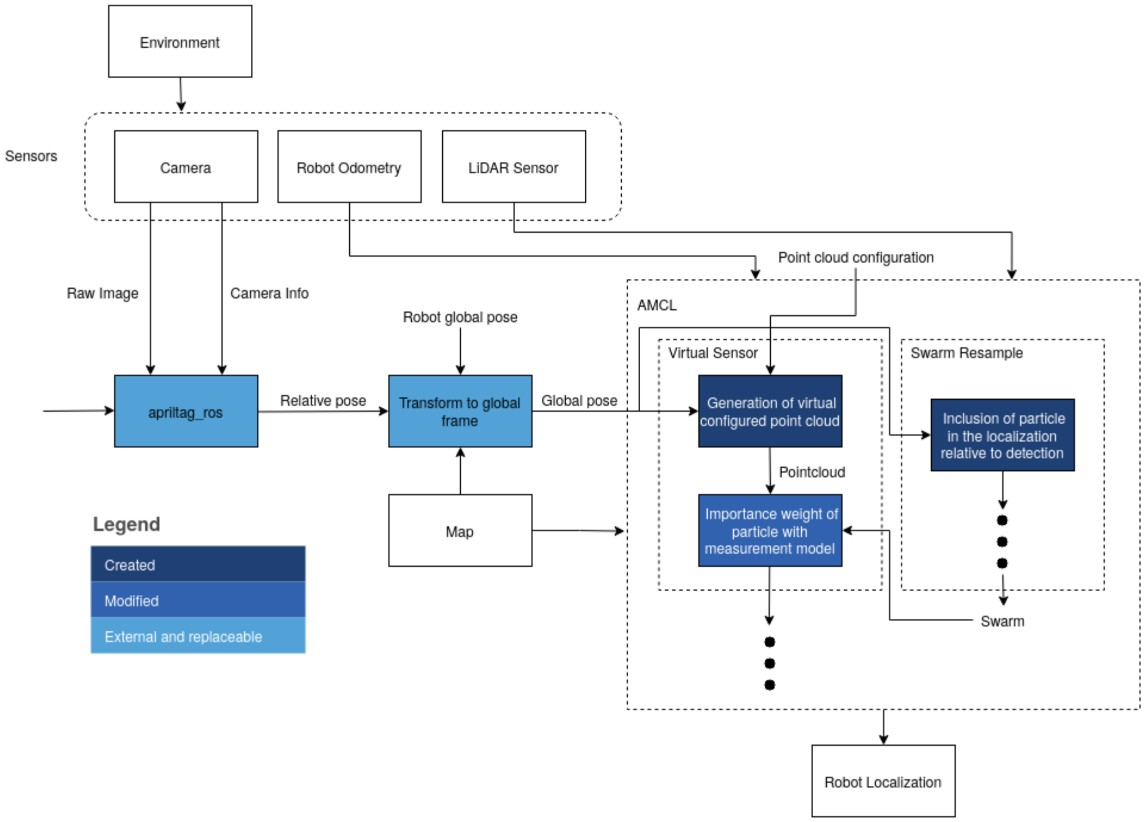

Figure 2. Proposed modification of the AMCL structure

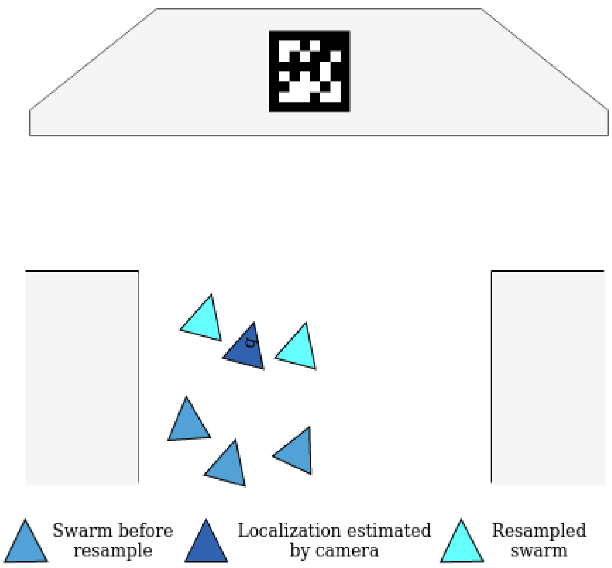

Figure 3. Particle swarm after a tag detection.

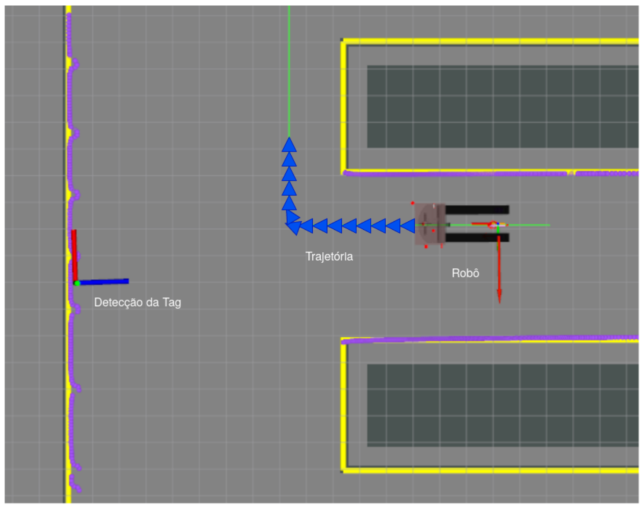

Figure 4. Trajectory used in the tests.

In test case 3 (Fig. 7) with a high-range scanning laser and using the AMCL, an average error of 0.29 m in position and in orientation of 0.054 radians was found. The orientation error was maintained again, but the position error is now smaller in relation to the case with a low-range laser, which was expected, but still higher than the error using a low-range laser with the proposed localization system.

In test case 4 (Fig. 8) with the high-range scanning laser and using the proposed approach, an average error of 0.254 m in position and in orientation of 0.055 radians was found. The position error remains close to the case with a low-range laser with the proposed localization system, which indicates that the quality of the laser starts to influence less the accuracy of the system's position definition.

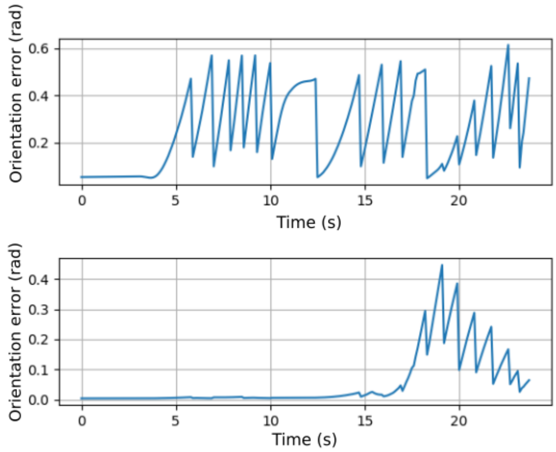

Figure 5. Error magnitude with low-range scanning laser and AMCL - case 1.

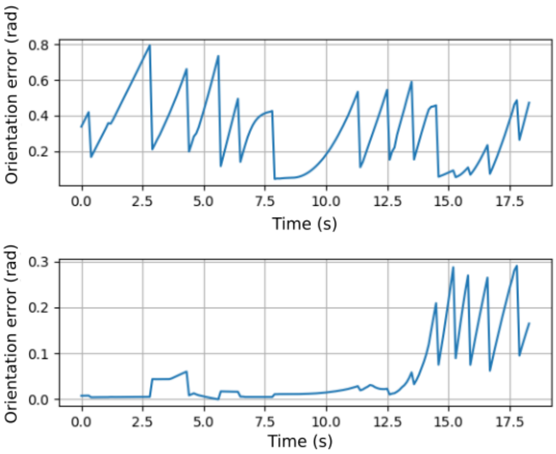

Figure 6. Error magnitude with low-range scanning laser and propo - case 2.

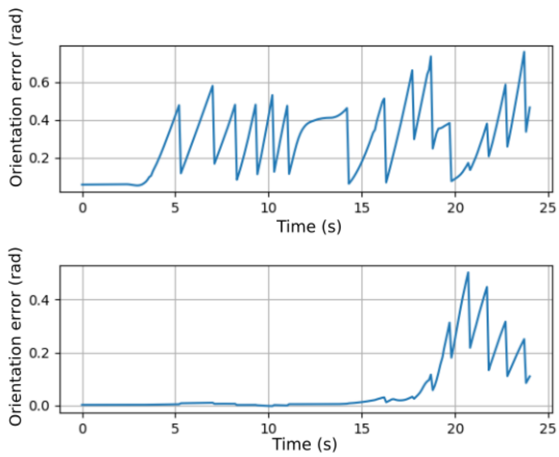

Figure 7. Error magnitude with high-range scanning laser and AMCL - case 3.

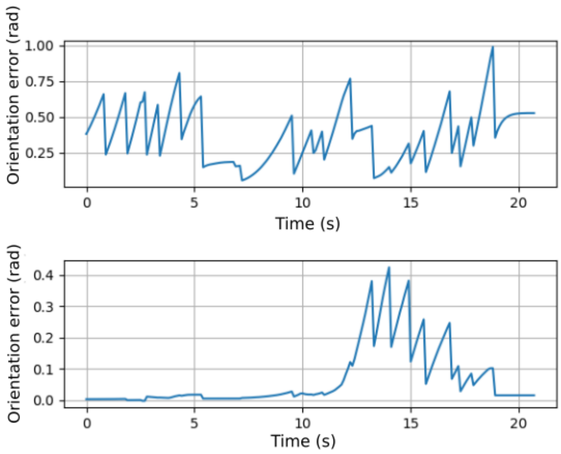

Figure 8. Error magnitude with high-range scanning laser and hte proposed approach - case 4.

Table 1. Test results.

Technique	Laser Range	Pos. Error (m)	Yaw Error (rad)
AMCL	Low	0.31	0.053
AMCL	High	0.28	0.054
Proposed	Low	0.25	0.055
Proposed	High	0.24	0.053

4. CONCLUSION AND FUTURE WORK

The presented and described system contemplated the main objective of performing the fusion of scanning and image sensors in computing the location of a mobile robot.

It was possible to verify the need for a new exteroceptive sensor, considering the problems inherent to a robot with only a scanning sensor using the AMCL to compute its global location in homogeneous topology environments, in order to enable the resolution of the three traditional location problems , whereas with the inclusion of the image sensor, the system demonstrated effectiveness in solving them.

The approach used was successful in using multiple marks simultaneously in the location computation, through the partial re-sampling of the swarm of particles that can be performed for any number of marks disposed of in the environment.

During the development of the re-sampling solution, possible limitations were identified, such as: Continuous resampling inhibits the convergence of the AMCL, which stops computing the next state of the particles if a re-sampling occurs at each cycle due to the frequency of publication of AprilTag detections, which may cause a location that contains a low contribution from the AMCL itself and provide a drop in accuracy by failing to detect the fiducial mark, giving greater weight to the detection of marks; for large updates of the swarm of particles it is necessary to reinitialize all the weights used by the adaptive part of the algorithm, thus, for the proposed implementation to work it is necessary that the resampling is always done in small parts of the swarm.

As the next steps can be listed find a better representation for the error, repeat the experiments more times; and validate in a real environment.

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