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Preface

CONTROLO 2014 – 11th Conference on Automatic Control in Porto, Portugal, July 21th to 23th, 2014, was organized by INESC TEC, in partnership with FEUP (Faculdade de Engenharia da Universidade de Porto), ISEP (Instituto Superior de Engenharia do Porto) and APCA the Portuguese Association of Automatic Control which is a national member organization of the International Federation of Automatic Control (IFAC).

The conference is Sponsored by APCA the Portuguese Association of Automatic Control with three partner institutions SBA - Sociedade Brasileira de Automática, CEA - Comité Español de Automática and SPR - Sociedade Portuguesa de Robótica.

We would like to thank the invaluable contribution of the International Program Committee Members, External Reviewers, Keynote Speakers, Sessions Chairs and Authors. We would also like to acknowledge Easychair for their Conference Management System, which was freely used for managing the paper submission and evaluation processes of CONTROLO 2014.

These proceedings present peer-reviewed papers from a wide range of topics including different areas of control compiled in the first 6 chapters, Decision, Estimation and Modelling in chapters 7, 8 and 9, Robotics and Sensing in Chapters 10 and 11 and finally Education in chapter 12.

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Part XI: Sensing

Part XII: Education

Robust Robot Localization Based on the Perfect Match Algorithm

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Abstract. Self-localization of a robot in an indoor plant is one of the most important requirement in mobile robotics. This paper addresses the application and improvement of a well known localization algorithm used in Robocup Midsize league competition in real service and industrial robots. This new robust approach is based on modeling the quality of several measures and minimizing the maching error. The presented innovative work applies the robotic football knowledge to other fields with high accuracy. Real and simulated results allow to validate the proposed methodology.

Keywords: AGV, Mobile Robot, Service Robots, 2D Matching, Laser Range Finder.

1 Introduction

Robust self-localization is one of the main requirements for autonomous mobile robots in industry. It can be defined as the task of estimating the robot's position and orientation in a map of the environment. This has been a research topic over the last years and many different solutions for these localization problems have been presented [1].

There are several localization systems already implemented on industries but usually they use a laser with artificial beacons [17]. It has a disadvantage of requiring a large number of beacons to be spread in the manufacturing plant. Besides the aesthetic, it can be a difficult and expensive task to spread those beacons over the manufacturing plant. Despite not getting aesthetic, it is sometimes a difficult and expensive task to implement those beacons spread over the manufacturing plant. Some problems arise from changes in the environment over time. These changes can be caused by dynamic obstacles like people or other vehicles across the floor. The main goal of this paper is to describe a localization system that does not require artificial beacons but, on the other hand uses natural features of the world. It was based on the robotic football algorithms [2] and implemented on industry and service robots. Moreover,

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estimated localization by the developed system is stable even with closer objects. Our example uses a precision and high range specifications laser scanner NAV 350 from SICK. It is desired to pick a palette of material from one side to another in a laboratory with 8 x 25 m. As further presented, precision is good enough to perform that task. The system is developed in ROS [3], a well known Robot Operating System that provides libraries and tools to help software developers create robot applications. The main topic of this work is the robustness of the algorithm to the obstacles (other robots, people and objects) that can affect the localization.

This paper is organized as follows: Section 1 presents a small introduction about laser scanner. Then, section 2, presents some related work in the community. Section 3, describes the algorithm whereas section 4 addresses the results of the developed tests. Finally, section 5 finishes the paper with conclusions and future work direction of the developed system.

2 Related Work

In the matching algorithms the pose estimation is commonly fused with dead reckoning data, using for that purpose, probabilistic methods such as the Kalman Filter family and the Particle Filters [6, 8, 15, 18].

There are matching algorithms that require prior knowledge on the navigation area. This prior knowledge can be an environment map, natural landmarks or artificial beacons.

There are other types of matching algorithms, which compute the overlapping zone between consecutive observations, to obtain the vehicle displacement. One possible matching algorithm to estimate the quantity of angular and linear displacement of a vehicle between two different and consecutive configurations is the Iterative Closest Point (ICP). This type of matching, known as point to point matching, analyses the contribution of each point of the laser scan, in the cost function.

The algorithm is composed of two fundamental steps, which are iterated until the solution convergence: the matching and optimization. The result is the distance between consecutive scans, corresponding to the vehicle configuration that minimizes the cost function.

The problem of this approach is the huge amount of data to be processed. The process of finding the correct correspondence between points (matching) is a difficult and time-consuming task.

Examples of works where the scan alignment is used to perform the registration between consecutive scans are described in the papers [12, 13, 14].

J. Minguez et al. [14], developed the metric-based ICP algorithm (MbICP), improving the standard ICP with a novel distance measure between corresponding points. This measure considers the translation and rotation displacements at the same time, in contrast to the standard ICP. This avoids two different minimization problems and consequently reduces the computational cost. Nevertheless, is still a heavy algorithm when compared with the present work.

The presented work was based on [4], with some different approaches, such as: stopping criteria, sensors, Kalman filter [5] and the application type (from RoboCup environments [7] to a shop floor automation field). Authors address the match algorithm, which is a time saver algorithm [6] and it has a large potential to be implemented in the service robots localization systems. By using a Kalman filter, it is possible to acquire signal from several sensors and implement a sensor fusion strategy [5]. Furthermore, the innovative algorithm approach improves the processing time, robustness and accuracy.

3 Algorithm

The developed localization system uses the result of a Matching algorithm as an observation measurement to be fused with the vehicle's odometry data. There are several sensors and techniques used in mobile robot positioning [11]. The presented work uses laser scanner information instead of image processing data [4].

This algorithm of Matching is based on the light computational Perfect Match algorithm, described by M. Lauer et al in [4]. In this algorithm the vehicle pose is computed using 2D distance points from the surrounding environment. These points are acquired with a Laser Range finder, and are matched with the map of the building previously computed. Therefore, the vehicle pose is calculated by trying to minimize the fitting error between the data acquired and the building's map.

The Perfect Match is based on the steps: 1) matching error and gradient computation; 2) optimisation routine Resilient Back-Propagation (RPROP); and 3) co-variance estimation using the second derivative.

Through the building occupancy grid (based in a SLAM algorithm [10, 19]) it is possible to obtain the distance and gradient matrices. The distance matrix at each cell gives the distance to the closest obstacle. There are two gradient matrices, in order to the x direction and in order to the y direction. The first gives the direction variation of the distance matrix with the variation of the x position. The second shows the direction variation with the y position variation. These three matrices, shown in the following figures (Figure 1, Figure 2 and Figure 3) for a corridor, can be pre computed and so they can speed up the completion of the Perfect Match algorithm. For more details about these matrices see [6] and [8].

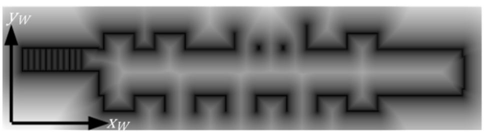

Fig. 1. Maps on a corridor where experiments were conducted: Distance Matrix

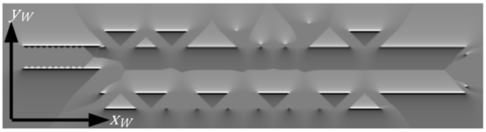

Fig. 2. Maps on a corridor where experiments were conducted: Gradient Matrix. Distance variation in direction y

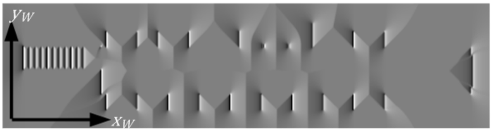

Fig. 3. Maps on a corridor where experiments were conducted: Gradient Matrix. Distance variation in direction x.

Consider now that the list of points of a Laser Range Finder scan $PntList$. The point i of this list in the world frame, is $PntList(i) = (x_i, y_i)$. The cost value is given by:

$$E = \sum_{i=1}^{PntList.Count} E_i \,, \quad E_i = 1 - \frac{L_c^2}{L_c^2 + d_i^2} \tag{1}$$

where d_i and E_i represent the distance matrix and cost function values of the point i.

The parameter L_c is used to discard points with large error E_i, increasing the robustness of the algorithm to the outliers. The resulting state/pose X_{Match} is given by the RPROP algorithm. The co-variance P_{Match} is computed using the second derivative of the algorithm of the quadratic matching error. For more details about the Perfect Match algorithm see [6].

Another improvement of the algorithm presented in this work, relatively to the authors' previous work [6] is the stop criterion used to stop the RPROP iterations. Instead of a fixed iterations number (ItN), the process can be stopped earlier if RPROP step is small enough meaning that a minimum has been reached.

In non-linear optimization problems, ItN depends on initial solution and cost function, among others. Furthermore, ItN shouldn't be a fixed value: on the one hand, increasing ItN increase processing time and the quality of solution. On the other hand, a few ItN decreases the solution quality. The criterion used is the RPROP step.

The limitation of the RPROP algorithm iterations guarantees that the time spent by the algorithm has ever a limit, that is ever lower than the algorithm cycle imposed by the observation module (Laser Range Finder). The limitation of the convergence guarantees that the minimization algorithm goes to a local minimum with the desired accuracy.

3.1 Kalman Filter Update

The Kalman filter [16] update stage combines the estimated state using the odometry, equal to $X_v(k+1|k)$ and the Perfect Match resultant state, $X_{Match}(k+1)$. The Kalman Filter equations can be seen in [5].

The observation model $h_v\ (X_v, r)$ in the update stage is equal to the vehicle state X_v:

$$h_v\ (X_v, r) = \begin{bmatrix} x_v + e_{rx} \\ y_v + e_{ry} \\ \theta_v + \varepsilon_{r\theta} \end{bmatrix} \tag{2}$$

where r is modeled as white noise, with a Gaussian distribution with zero mean ($\hat{r} = 0$) and covariance matrix R.

Therefore, in the update stage the observation is equal to the state obtained after the application of the Perfect Match:

$$Z_v(k+1) = X_{Match}(k+1) \tag{3}$$

The estimated observation is equal to the present estimative of the vehicle state, propagated during the Kalman Filter Prediction stage:

$$\hat{h}_v\ (X_v, \hat{r})(k+1) = X_v(k+1|k) \tag{4}$$

In that way, the innovation of the Kalman filter ($V(k+1)$) is equal to:

$$V(k+1) = Z_v(k+1) - \hat{h}_v\ (X_v, \hat{r})(k+1) \tag{5}$$

In this stage, the propagated covariance matrix, using odometry ($P(k+1|k)$), and the covariance matrix computed in the Perfect Match procedure ($P_{Match}(k+1)$), are used to determine the Kalman Filter gain ($W(k+1)$):

$$W(k+1) = P(k+1|k)\frac{\partial h_v}{\partial X_v}^T \left[\frac{\partial h_v}{\partial X_v} P(k+1|k)\frac{\partial h_v}{\partial X_v}^T + \frac{\partial h_v}{\partial r} P_{Match}(k+1)\frac{\partial h_v}{\partial r}^T\right]^{-1} \tag{6}$$

The gradient of the observation module, in order to the vehicle state and the observation noise, $\frac{\partial h_v}{\partial X_v}$ and $\frac{\partial h_v}{\partial r}$ respectively, are identity matrices. Therefore, the previous equation can be re-written as the following:

$$W(k+1) = P(k+1|k)[P(k+1|k) + P_{Match}(k+1)]^{-1} \tag{7}$$

Therefore, after the update stage the new estimated state ($X_v(k+1|k+1)$), is given by the expression:

$$X_v(k+1|k+1) = X_v(k+1|k) + W(k+1) \cdot V(k+1) \tag{8}$$

The new covariance matrix, decreases with the following equation:

$$P(k+1|k+1) = [I^{3x3} - W(k+1)] \cdot P(k+1|k) \quad (9)$$

where I^{3x3} is the square identity matrix with the dimension 3x3.

The rejection of data from obstacles that are not present in the map is a key to the localization algorithm robustness. A histogram of measures errors is processed and a threshold allows to select the valid data to the localization algorithm.

4 Results

Firstly, the time requirements are validated: 7 ms to process 1440 beams of laser with an Intel T4300 processor with 1.2 GHz clock speed. This is a compatible time to perform decision tasks and control. Robot could reach a repeatability of position in stop procedures of 5 mm (in the laboratory environment).

The assembled robot was used to perform all measurements and tests. The tests were conducted in the laboratories of the Faculty of Engineering of Porto, as presented in next subsection 4.1, and in the EMAF exposition in Exponor (Porto International Fair), as presented in next subsection 4.2. As it can be seen in next subsection, the developed filter allows rejecting closest objects that could interfere in localization. Moreover, the presented algorithm ensures precision and fast computation time (4 ms).

As we can see in [15], with a number of points acquired by the LRF equal to 682 points, the maximum time spent in the matching localization algorithm is limited. This limit time was measured and is equal to 17 milliseconds. The average execution time is about 12 milliseconds. Both the maximum and mean time spent, allows the algorithm to be used online, in a low computational power computer (these tests were executed in a Mini ITX, EPIA M10000G with a processor of 1.0GHz).

The ROS platform provides a package of mapping called gmapping. Using this package, a 2D grid map can be obtained. Another ROS' package, the adaptive Monte Carlo localization (amcl) algorithm, uses the 2D map grid built by the gmapping package to locate the vehicle, using 2D data. In comparative tests (same conditions than the last referred test), the execution time of the localization provided by the amcl package (with 1000 particles, the accuracy is similar to the proposed algorithm) has a maximum value of 42 ms and an average time of 32ms, almost 3 times more than the proposed algorithm.

4.1 Laboratory

The laboratory tests consists in achieving the localization of the robot in a space composed by 3 rooms (with an average dimension of 9x7 meters), a corridor (with a length of 20 meters) and a larger room with dimension 20x7 meters, as presented in Figure 4. The robot is moving and the obstacle interferes in the localization. The closest the object is, more error will be introduced in localization, as it can be seen in

Figure 5. This Figure is an example of a bad localization. The robot localizes itself in a wrong position of the map. The developed threshold method allows the robot to be correctly localized in the map as further presented in this paper.

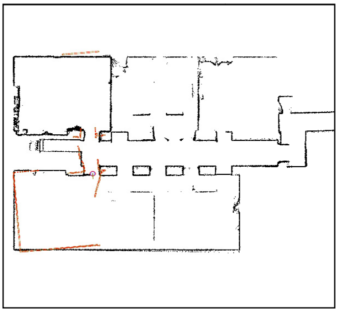

Fig. 4. Algorithm estimated location

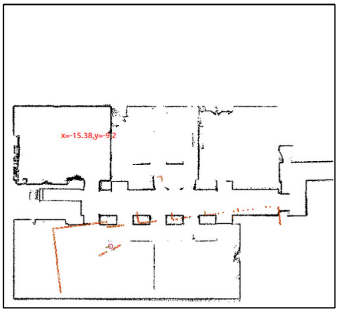

Fig. 5. Robot localization failure

Red colored dots are the measures used for localization. The graphic presented in Figure 6 shows the laser error in measurements for the map presented in Figure 4. In other words, the distance between laser measure and the closest obstacle that doesn't match with robot posture.

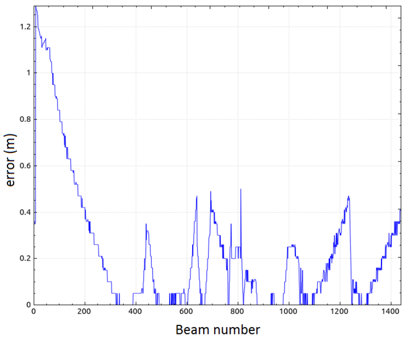

Fig. 6. Error in measure (without thresholding)

With the developed algorithm to reject error measures and as a good demonstration of our algorithm it is shown in Figure 7 green beams that are rejected and makes possible the robot to be localized.

The rejection of data from some obstacles that are not present in the map can be modeled as a function (see Equation (1)) with a threshold (A) operation as presented in Figure 8 (adapted from [4]). By this way, it is possible to drop completely outliers that are present in the measures. Threshold value depends on several map conditions like the number and dimensions of the expected objects that can generate outliers and the maximum dimension of the map.

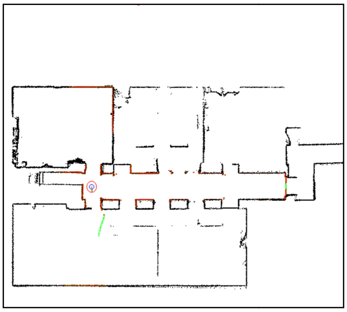

Fig. 7. Algorithm estimated location (with threshold, position 1)

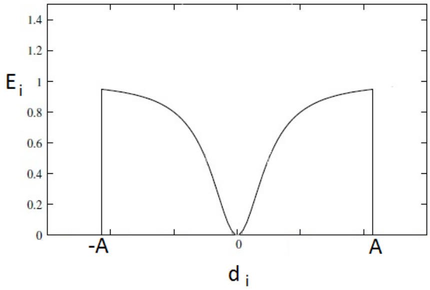

Fig. 8. Error function with threshold (A)

Figure 9 shows the error in measurements, with an error limitation of 0.5 for the map presented in the Figure 7.

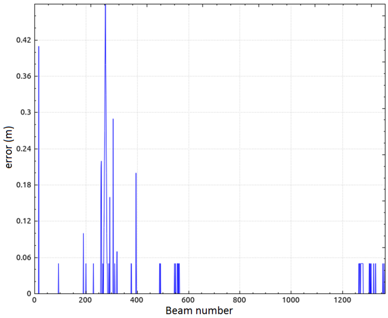

Fig. 9. Error in measure (with 0.5 thresholding filter)

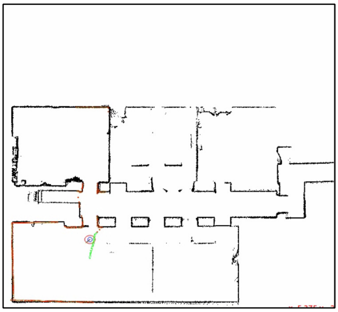

Fig. 10. Algorithm estimated location (with threshold, position 2)

It is possible to notice that our algorithm rejects the fault measurements. Moreover, with the lean object, it is possible to notice that algorithm obtains the localization without error, as presented in Figure 10.

4.2 Professional Robotics Event

The experiments executed in the EMAF event were the final test of our algorithm. The robot navigated during three days, with several people moving around it and the path was planned so that the robot should cross areas with 1 cm of gap. The EMAF environment becomes a validation place different from laboratory with larger areas and far walls.

Figure 11 shows the developed robot moving around the EMAF fair (see map of Figure 12). Of course, there was security plans to avoid collision with humans. The same experiments were done (as subsection 4.1) and the results were compatible. Figure 12 shows the acquired map to plan the path.

Fig. 11. Robot moving in the EMAF

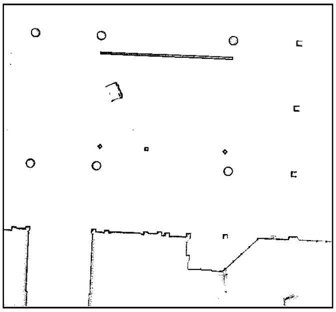

Fig. 12. Acquired map of EMAF

5 Conclusions and Future Work

The localization method is applied in the AGV of test from the robotics laboratory. The localization method used the occupancy grid of indoor environments.

The experiments conducted made it possible to confirm that there are advantages to the proposed localization algorithm: the used observation modules are affordable and the localization algorithm used here works in structured mapped environments, without the need for any kind of artificial landmarks – this is the main advantage of this work.

The Extended Kalman Filter was applied as a multi fusion sensor system in order to combine the odometry information and the result of the Perfect Match. The experiments conducted by M. Lauer *et al* [4], which elects the Perfect Match as the faster algorithm comparatively to the Particle Filter algorithm [9][12], remain valid. As conclusion, the presented algorithm ensures precision and fast computation time (4 ms).

As a future work direction, enhancing the outlier's rejection is a promising research area since robot moves in a map with several obstacles. Moreover, handling more outliers and with bigger dimensions (such as people moving or layout changing) is a challenge to future work.

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