Fast 3D Map Matching Localisation Algorithm

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***Abstract* — A new and fast methodology is discussed as a solution to pinpointing the location of a robot, in a robust way, without environment preparation, even in dynamic scenarios. This solution does not require a high computational power.**
The methodology is a three-dimensional map based approach, which uses the 3D map of the surrounding environment and data acquired by a tilting Laser Range Finder (LRF), to pinpoint the robot pose. Experimental results about the accuracy of the proposed method are presented in this paper.

Index Terms— **Robot localisation, 3D matching, EKF-SLAM, Laser Range Finder**

I. Introduction

To be truly autonomous, a robot must be able to pinpoint their location inside dynamic environments, moving in an unlimited area, without preparation needs. In order to fulfil this definition of autonomy, the fundamental motivation and opportunity of this work, was the implementation of a robust strategy of localisation that runs online in a short execution time.

The developed approach is a three-dimensional map based localisation method, with the objective of solve the problem of accumulative error when the odometry is used, using the environment infrastructure, without constraints in terms of the navigation area and with no need of prepare the environment with artificial landmarks or beacons.

The localisation methodology is divided in the following steps: 1) *pre-localisation* and *mapping*, performed offline and only once, to obtain the map of an indoor environment; here it is intended to navigate with a vehicle equipped with an tilting LRF acquiring three-dimensional data; and 2) *localisation*, which execute the vehicle self-localisation during its normal operation; this is used online using a matching algorithm and the obtained previous map.

It is applied to the RobVigil robot, a differential drive vehicle, shown in Figure 1 called RobVigil.

The RobVigil is equipped with sensors to detect dangerous situations, like fires, floods or gas leaks. It is equipped as well with three surveillance cameras. The main application of the RobVigil is the surveillance of public facilities, i.e. dynamic environments, allowing systematic and uninterruptable inspection routines, with minimum human intervention.

The RobVigil, performing a surveillance routine, in a shopping mall is shown in **Erro! A origem da referência não foi encontrada.**.

The LRF – Hokuyo URG-04LX-UG01 – was used to perceive the environment. To obtain a three-dimensional sensor, a rotating platform was created based on the dc servo motor, the AX-12 Dynamixel Bioloid. The complete tilting LRF solution is shown in Figure 2. The tilting LRF has a distance range of 5 metres and acquires 769 points at every 100 milliseconds.

Figure 1 Left: the RobVigil robot equipped with the tilting LRF at top. Right: the robot performing a surveillance routine..

As the localisation algorithm is applied in the RobVigil, which navigates in public facilities, with people an dynamic objects crossing the navigation area, only data and the map about the headroom of the building (upper side-remains static during large periods of time), is used aiming to improve the methodology accuracy and robustness. Videos and downloads about this three-dimensional map based methodology can be found at [1].

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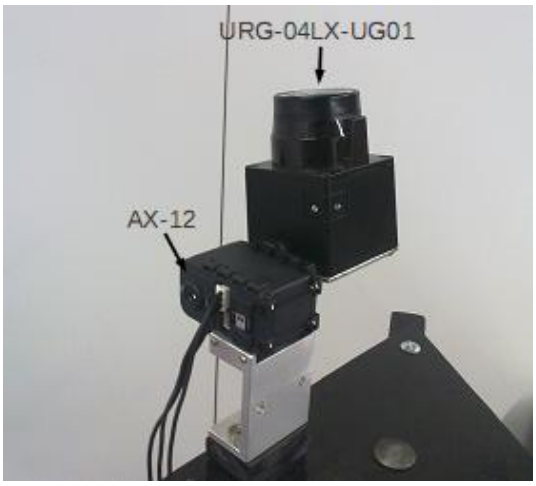

Figure 2 The tilting LRF developed.

II. Literature Review

Different sensors and techniques for the localisation of vehicles are described in [1]. These sensors and techniques are divided into absolute and relative localisation.

The dead-reckoning are sensors of relative localisation leading to an increase of the error over time. The most commonly used is the odometry.

Due to their high frequency rate, the dead-reckoning are commonly fused with more complex localisation techniques or sensors, through probabilistic methods as is example the Kalman Filters and the Particle Filters, [3].

Examples of sensors and techniques of absolute localisation are the attitude sensors, digital compasses, the GPS and passive or active beacons. The two essential localisation techniques based on active or passive beacons are: triangulation and trilateration, [4]. Unfortunately, this methods require environment preparation.

The algorithms concerning the localisation of mobile robots can be divided in two large areas: the matching and the Simultaneous Localisation and Mapping (SLAM) algorithms.

There are matching algorithms that need a prior knowledge about the navigation area, as is example [5]. Another example of a matching algorithm is the Perfect Match described by M. Lauren *et al.* [6], used in the Robotic Soccer Middle Size League (MSL) at RoboCup. The Perfect Match is a time saver algorithm.

There are other types of matching algorithms, which compute the overlapping zone between consecutive observations to obtain the vehicle displacement, [7].

The most common SLAM's solutions are: the Extended Kalman Filter (EKF-SLAM) [8], and the FastSlam/Rao-Blackwellized Particle Filters [9].

The EKF-SLAM computationally complexity is $O(N^2)$, while the FastSlam has a lower computational complexity, $O(M \log N)$, with M particles and where N landmarks.

III. Pre-Localisation & Mapping

This phase is performed offline and only once, aiming to obtain the 3D occupancy grid of the building where it is intended the RobVigil navigation.

The obtained 3D occupancy grid is used before, during the vehicle normal operation, to pinpoint its self-location, in a fast way and on-line.

This phase has two crucial steps, the *pre-localisation* and *mapping*. The *pre-localisation* implements a SLAM solution. Once the SLAM has been applied, the 2D feature map with linear segments and points is obtained. The same map is after used to determine the vehicle's location (*pre-localisation*). The SLAM solution is based in the state of art EKF-SLAM algorithms, as the described in [3].

Finally, still offline and with the vehicle's position obtained, the three-dimensional map can be built and the respective distance and gradient matrices can be created and stored (*mapping* procedure)

To create the distance matrix, the distance transform is applied in the 3D space, on the occupancy grid of the building. Furthermore, the Sobel filter, again in the 3D space, is applied to obtain the gradient matrices, in both the directions x and y. The stored distance and gradient matrices are used as look-up tables for the localisation procedure, in the normal vehicle operation, as described in the next section.

IV. Localisation

The light computational Perfect Match algorithm described in [6] by M.Lauren *et al.*, was adapted from 2D to the 3D space, using Laser Range Finder data, maintaining the low computational requirements.

Therefore, the developed 3D Perfect Match is based on the steps: 1) matching error; 2) optimisation routine Resilient Back-Propagation (RPROP); and 3) second derivative.

The distance matrix, stored in memory is used to compute the matching error. The gradient matrices also stored in memory, are used to find convergence direction of the RPROP algorithm and compute the resulting covariance estimation.

The RPROP algorithm takes the previous state of the vehicle $X_{Match}(n-1)$ and estimates a new vehicle position $X_{Match}(n)$, which is used in the next iteration.

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

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

in which, d_i and E_i represent the distance matrix and cost function values.

The parameter L_c is used to negligect points with and error E_i, higher than itself. The used value was 1 meter. The resulting state X_{Match} is given by the RPROP

algorithm. The match P_{Match} covariance is given by the following matrix:

$$P_{Match} = diag\left(K_{XY}/\frac{\partial^2 E}{\partial x_v^2}, K_{XY}/\frac{\partial^2 E}{\partial y_v^2}, K_\theta/\frac{\partial^2 E}{\partial \theta_v^2}\right) \quad (2)$$

in which, $\mathrm{diag}(.,.,.)$ is the diagonal matrix 3x3.

The parameters in the equation 2, K_{XY} and K_θ, are normalized values. The algorithm was tested with values of K_{XY} and K_θ in the gap between $[10^{-6},\ 10^{-1}]$. The best performance achieved was $K_{XY} = 10^{-3}$ and $K_\theta = 10^{-3}$. To more details about the Perfect Match algorithm see [6].

The localisation procedure uses the result of the 3D Perfect Match in a position tracking algorithm, which has three fundamental stages: 1) the Kalman Filter Prediction, 2) the 3D Perfect Match procedure, and 3) the Kalman Filter Update. The Kalman Filter equations can be seen in more detail in [3].

The Kalman filter prediction stage takes the previously estimated vehicle state X_v and, using odometry, it estimates the next vehicle state X_{Odo}.

The 3D Perfect Match algorithm takes the state X_{Odo} given by the Kalman Filter Prediction, and outputs the resulting state X_{Match} and covariance P_{Match}.

The Kalman Filter Update stage combines the estimated states X_{odo} and the X_{Match} using the EKF Update equations, [3].

V. Experimental Results

The Figure 1 shows the architects' plant about a building on the Faculty of Engineering of the University Porto, in Portugal. The solid black colour on the Figure 1, shows the zone where the *pre-localisation & mapping*, described on section III, was applied becoming possible to obtain the 3D occupancy grid used during the *localisation*, described on section IV.

The map was obtained with success. The Figure 4 and Figure 5, with two different perspectives of view, shows the 3D occupancy grid of this large indoor environment.

In the Figure 4 and Figure 5, the red points represent the upper side of the building (above 1.8 metres of height), almost static, used to perform the 3D matching.

Aiming to evaluate the accuracy of the localisation algorithm based on the 3D matching presented in this paper, experiments were made with the high precision Ground Truth (GND) positioning system, the SICK Nav350, a commercial solution for autonomous guided vehicles (AGV).

The SICK Nav350 uses reflectors to output its self location, with a sample rate of 125 milliseconds and an accuracy of 4 millimetres to 25 millimetres.

The Figure 6 shows the trajectory in a corridor of the building, whose map is shown in Figure 4 and Figure 5. Only in this part of the building it is available the GND system. Therefore, only in this corridor are shown accuracy results.

Figure 3 Architects' plant of the mapped environment.

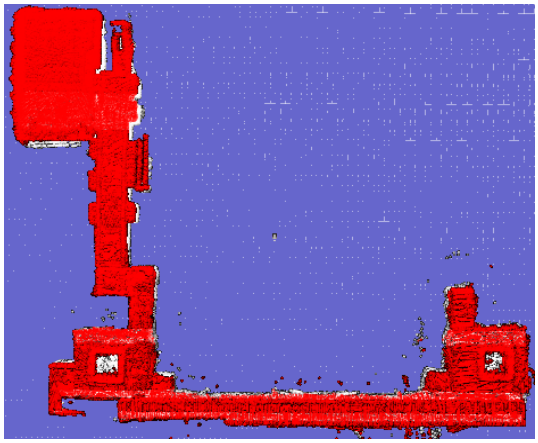
Figure 4 Occupancy grid of the scenario, with square shape of 60x60 metres.

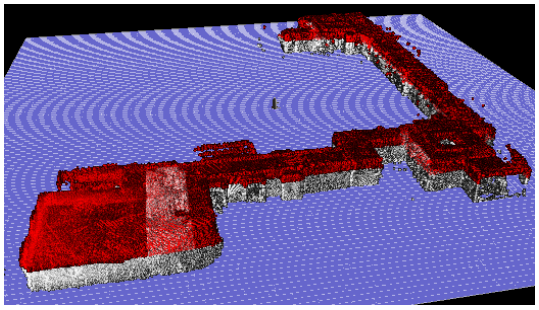
Figure 5 Occupancy grid of the scenario. Other perspective of view.

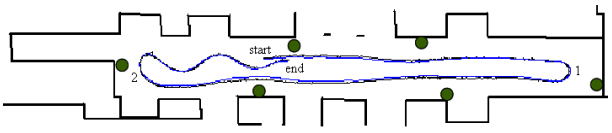

Figure 6 SICK Nav350 Vs estimated location. The corridor has 25 x 8 metres.

In the figure (Figure 6), the black line is the trajectory obtained with the Nav350, while the blue line is the

trajectory estimated by the localisation algorithm (3D matching).

The Figure 7 shows the architects' plant about another building, in the Faculty of Engineering of the University Porto, in Portugal, where the methodology described in this paper was applied, aiming the vehicle's normal operation in this building. The solid black colour shows the zone where the methodology was applied.

The 3D occupancy grid about this building, obtained after applied the *pre-localisation & mapping*, described on section III, used in the vehicle normal operation, aiming its *localisation*, as described on section IV, is shown in Figure 8 and Figure 9.

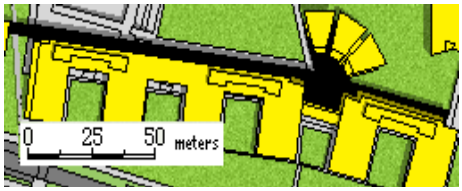

Figure 7 Architects' plant of the mapped environment.

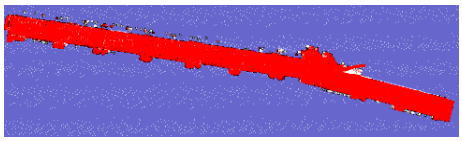

Figure 8 Occupancy grid of the scenario, with square shape of 60x60 metres.

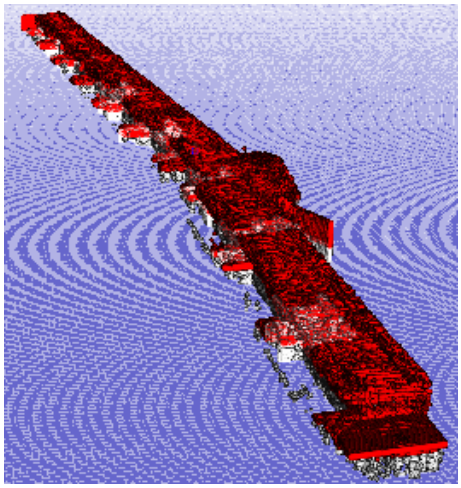

Figure 9 Occupancy grid of the scenario. Other perspective of view.

In this scenario, also the red points represent the upper side of the building (above 1.8 metres of height), almost static, used to perform the 3D matching.

Again, in this scenario the ground truth sensor (Sick Nav350) is available to perform the characterization of the accuracy of the proposed 3D Matching method. The Figure 10 shows the trajectory in a part of the building, whose map is shown in Figure 8 and Figure 9.

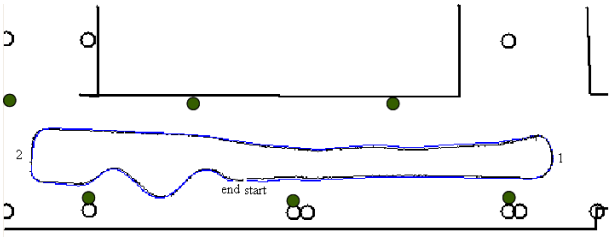

Figure 10 SICK Nav350 Vs estimated location. The corridor has 25 x 8 metres.

In the figure, the black line is the ground truth trajectory, while the blue line is the trajectory estimated by the localisation algorithm (3D matching).

In the experiments of Figure 6 and Figure 10, the average of the Euclidian distance error between the 3D matching and the Nav350 position is 0.08 metres, with a standard deviation of 0.086 metres. The absolute average orientation difference is 1.18º, with a standard deviation of 1.72º.

This experiments helped to realize that the localisation proposed here is sufficient accurate to be used in the surveillance task of the RobVigil robot.

The RobVigil moved in these experiments at an average speed of 0.4 m/s. The localisation algorithm takes an average execution time of 12 milliseconds, with 769 points of the tilting LRF in a Mini ITX, EPIA M10000G with a 1.0GHz processor. In this experiment the tilting LRF rotates at a speed of 10 rpm.

The ICP algorithm described in [7] takes an average time of 76 milliseconds (can be higher) to find the optimal solution, using only 361 Laser Range Finder points, in a cycle of 200 milliseconds, in a Pentium IV 1.8GHz.

VI. CONCLUSIONS

The contributes made in this work were: adaptation of a light computational matching algorithm, the Perfect Match, to be used in the 3D space instead 2D, using Laser Range Finder data, maintaining the low computational requirements. Improvement of the fusion system between the matching algorithm described in [6] by M.Lauren *et al*. and odometry data, using an EKF. Only 3D data about the upper side of a building (almost a static scenario) is used, becoming the localisation more robust and reliable, since in dynamic scenarios. The localisation methodology can be used with any observation module, which acquires 3D data: Kinect, 3D camera (MESA), stereo vision or commercial 3D LRF. Development of a localisation methodology that becomes the robot RobVigil an economically practicable robotic platform.

The three-dimensional map based localisation algorithm presented here, improves computational requirement comparatively to 2D and 3D Simultaneous Localisation and Mapping (SLAM) algorithms. Furthermore, the time necessary to locate the robot is also reduced comparatively to ICP algorithms.

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