Solving the Indoor SLAM Problem for a Low-Cost Robot using Sensor Data Fusion and Autonomous Feature-based Exploration

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Abstract: This article is concerned with the solution of the SLAM (Simultaneous Localization And Mapping) problem in an indoor environment using a low-cost mobile robot that autonomously explores the environment. The robot was constructed with a distance measurement subsystem composed of three types of sensors: a wireless webcam with a laser pointer (a visual sensor), two infrared sensors and an ultrasonic TOF (time-of-flight) sensor. Firstly, an algorithm that requires a small computational load is used to fuse the noisy raw data acquired by these sensors and generate the environment features. These features are then used by a particle filter to solve the SLAM problem. An autonomous feature-based exploration algorithm was implemented and is also presented. The results obtained in the experiments carried out in two small indoor environments show that the estimated environment map generated when the robot uses the autonomous exploration algorithm is very similar to the one generated when the robot poses were manually chosen.

1 INTRODUCTION

Nowadays it is highly desirable that a mobile robot is able to navigate in an unknown environment autonomously, which means that the robot needs to construct a map of the environment and at the same time locate itself within this map, a problem commonly referred as SLAM (Simultaneous Localization And Mapping) in the robotics literature.

Three software modules, which run in a cooperative form, were used (Figure 1): a) a sensor data fusion algorithm; b) an autonomous feature-based exploration algorithm; and c) a version of particle filter (Rao-Blackwellized). The two first modules were developed by the authors and are the main contributions of this article.

The robot, which was designed and built by the authors of this article, named SLAMVITA (final cost around US $ 2,100.00) employs three types of sensors: a wireless webcam with a laser pointer (a visual sensor), two infrared sensors and an ultrasonic TOF (time-of-flight) sensor or sonar. An algorithm was developed to transform the noisy data acquired by these sensors into features that geometrically represent the environment (walls).

A particle filter algorithm, known as Rao-Blackwellized or FastSLAM (Huge and Bailey, 2006), was implemented based on a proposal by (Thrun et al., 2005) which was modified to use the odometry motion model, such that the outputs of the encoders were computed as control information. This algorithm simultaneously estimate the robot poses and the environment map in solution of SLAM problem.

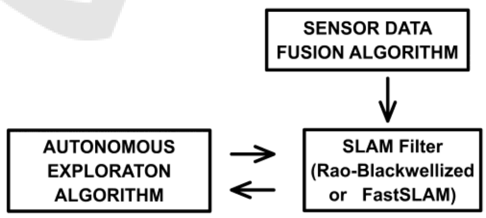

Figure 1: Algorithm modules to solve the indoor SLAM problem.

The autonomous exploration algorithm is structured as rules to perform two basic tasks: a) to decide the best target to explore in the environment in an incremental way; and b) to decide when to finish the exploration task.

This article is organized as follows. Section 2 introduces the SLAM problem and the approaches used to solve it. In Section 3 the proposed sensor data fusion algorithm is presented and shows the

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results of a simple experiment which was designed to measure its accuracy for environment mapping. Section 4 explains the autonomous exploration algorithm. Section 5 presents the experiment results obtained by the solution for the SLAM problem with and without using the proposed autonomous exploration algorithm in a small indoor environment. The same Section shows that the proposed solution fails if the raw data of any two SLAMVITA robot sensors are used by the fusion algorithm.

2 SLAM PROBLEM OVERVIEW

Some approaches employed to solve the SLAM problem were obtained using different techniques, such as fuzzy logic (Huge, 2001; Aguirre and González, 2002), artificial neural networks (Thrun, 1993), and the Dempster-Shafer theory (Milisavljević, Bloch and Acheroy, 2008). However, most of the literature employs the so-called probabilistic SLAM solutions (Thrun, Burgard and Fox, 2005), using different combinations of sensors, such as laser scanner and CCD camera (Castellanos, et al., 1998) or two sonars and six infrared sensors (Vazquez and Malcolm, 2005). Many other sensor combinations may be found in the literature.

Figure 2 shows a graphic representation of the two main forms of probabilistic SLAM problems (Thrun et al., 2005): online SLAM and full SLAM. In the solution of the SLAM problem the robot poses and environment map are unknown estimated variables (X and m, respectively) that must be computed at every time step t, and the accuracy of one variable is important to best estimate the other. This fact is referred in the literature as the “chicken and egg” problem.

This article uses a version of a particle filter known as Rao-Blackwellized or FastSLAM, where samples (particles) are employed to hold hypothesis of the robot poses along the EKF (Extended Kalman Filter) to estimate each feature extracted by the proposed sensor data fusion algorithm. Moreover, the choice for FastSLAM version 1.0, instead of version 2.0, is due to the high quality odometry

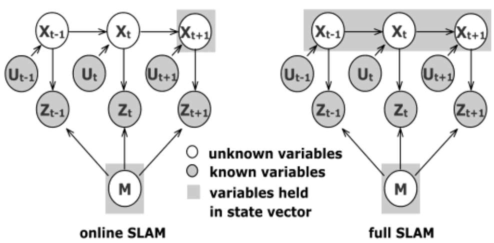


Figure 2: Forms of SLAM problems.

(Thrun et al., 2005) shown by the SLAMVITA robot in the experiments.

3 PROPOSED SENSOR DATA FUSION ALGORITHM

A single sensor hardly ever can provide enough information about the environment because of its limited field-of-view. The solution to overcome such shortcomings requires the use of two or more sensors whose information must be fused. Three-level architecture for robot sensor data fusion is presented by (Visser, 1999) in which three methods of data fusion may be applied: a) cooperative; b) competitive; and c) complementary.

The proposed sensor data fusion algorithm only uses competitive and complementary methods. In a competitive fusion each sensor produces its own estimated parameters, which are combined to generate a single set of parameters (in this case, the distance and the angle of the measured object). An example of competitive fusion occurs when the visual and infrared sensors measure the same object in the environment. Complementary fusion is applied when each sensor has only partial information about the environment. It aims to overcome the incompleteness of sensors being a classical example the array of several sonars attached around a mobile robot.

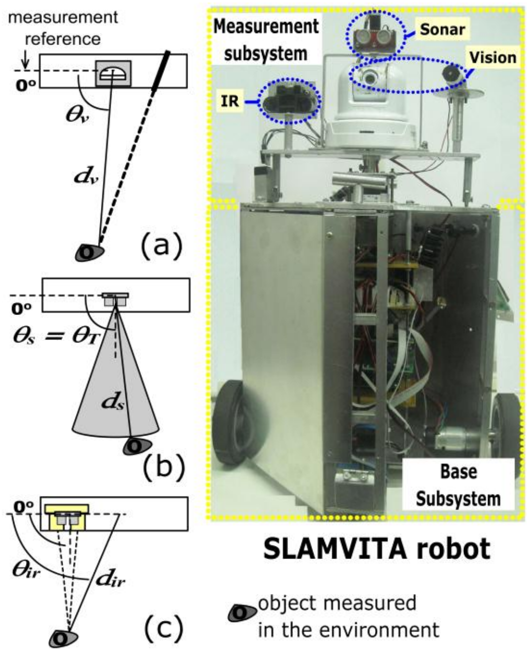


Figure 3: Measurement parameters (d, Θ) provided by the SLAMVITA sensors: (a) visual, (b) sonar and (c) infrared.

The SLAMVITA sensors are assembled on a panning turret located at top of the robot (Figure 3). The turret and the robot vertical axis are aligned and the turret can be turned around its axis to execute an 180° scan procedure.

The parameters supplied by the sensors are the distance (d) and angle (ϴ) of the object measured (details in Figure 3). These sensors were chosen in function of the complementary information provided by them. Due to their operating principles, the visual and infrared sensors provide reliable directional information (angle of the object), while the sonar is mainly a distance sensor, because of its accuracy in distance measurement (Ivanjko et al., 2009; Vazques and Malcolm, 2005).

The visual sensor employed in SLAMVITA robot uses active triangulation with calibration targets proposed by (Nguyen and Blackburn, 1995) and has never been used in the robotic literature for mapping purpose. The operating principle (laser center on image calculated in subpixel resolutions) and experimental results performed in distance measurements by the visual sensor are presented in (Buonocore et al., 2010).

The proposed sensor data fusion algorithm is informally described next to facilitate its comprehension, which flowchart is shown in Figure 4. It is based on the following considerations:

- It is assumed that the robot environment is composed of walls (they are always orthogonal to the floor but not necessarily to each other), and these walls can have openings (such as doors). Most structured indoor environments are composed by walls, doors, etc. that may be used as line segments into a compact map representation (Yap and Shelton, 2009).
- The occupancy grid (OG) and feature-based mapping techniques are employed to represent the environment in two dimensions.
- The RANSAC algorithm (Zuliani, 2009) is used to extract straight line segments from the directional (visual and IR) maps.
- The sonar measurements available in OG map (OGs) and in its vector raw data are used to eliminate noises in the directional OG maps and to adjust the feature distances in the directional fused feature-base map, respectively.
- The distance parameters in the visual and IR sensors are considered to have the same weights to compute the straight line segments to be fused.

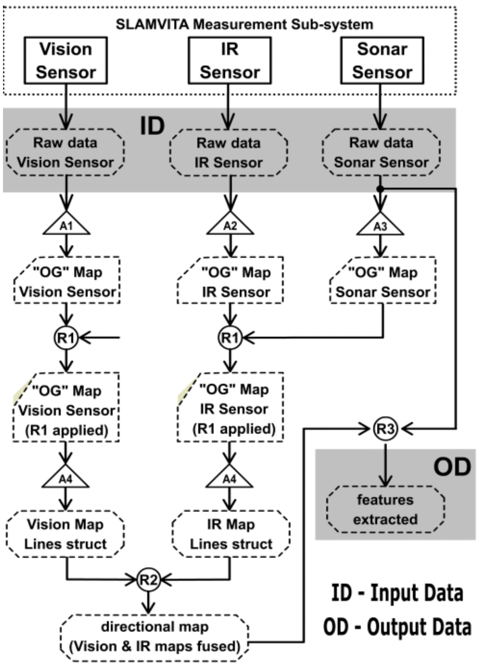


Figure 4: Flowchart of the proposed sensor data fusion algorithm.

The input data (ID) shown in Figure 4 are the distance/angle contained in each sensor raw data acquired in an 180^o scan, at each robot pose, with 1.8^o angular resolution. The algorithm generates the features extracted (output data, OD) as parameterzed lines. The proposed fusion algorithm is composed by 4 specific algorithms and 3 fusion rules. These rules (R1, R2 and R3) implement the data fusion method while the specific algorithms (A1 to A4) prepare the data to feed the rules. The pseudo-codes for these procedures are available at ftp: //labattmot.ele.ita.br/ele/luciano/My_Publications.

The basic concept in R1 rule is as follows: no object detected by the sonar cone must be perceived by the other two directional sensors. The application of R1 rule justifies the use of the OG representation, where the inverse sonar model is employed (Thrun et al., 2005). Due to the surface reflection that is not normal to the sonar acoustic wave, the sonar raw data must be pre-processed before being employed to remove these wrong data, keeping only those ones that mainly reveal the true RCD (Region of Constant Depth), reporting for walls in the environment (Pandey et al., 2007).

To extract line segments from directional maps, the proposed algorithm converts the OGv and OGir internal representation (after applying R1 rule) to *x-y* coordinates, which are held in separated vectors. Then, the RANSAC method is used in A4 algorithm to extract straight line segments (features) from those vectors, one map at a time. For each directional map, the A4 algorithm performs an interpretation on the data vector to break it in

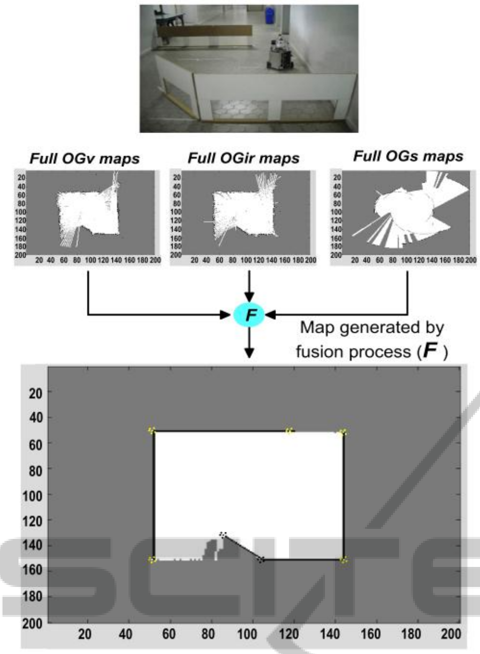


Figure 5: Comparison between OG maps computed from each sensor raw data and one generated by the proposed fusion algorithm.

segments that have significant variance in its data that point to different straight line slope or also gaps that may appear between line segments (environment openings). All vector segments are submitted to RANSAC trying to extract straight lines that represent the section features of the processing directional map.

The line segments extracted for each map are combined in R2 rule, applying competitive or complementary method. The competitive fusion is selected if both sensors have data at specific angular area. Otherwise, the complementary fusion takes place, such as the case in which the visual sensor is unable to define the laser spot at the camera image.

The R3 rule adjusts, if possible, the feature distances of the fused directional map (after applying R2 rule), searching for RCD in the angular area that contains the normal straight line of each feature in the map. Whenever the RCD is found, the feature distance is adjusted using the sonar measurement (RCD distance).

Figure 5 shows the geometrical representation of the actual environment (photo), which in comparison with each OG sensor map is more consistent and noise free. The error obtained in this mapping experiment was less than 1.5%. It is important to notice that the map constructed in this experiment is represented as full OG maps, instead of feature-base ones. However, in SLAM applications, the features for each robot pose must be processed and the environment representation outputted by the algorithm changed to feature-based map because of its computational cost in the particle filter.

4 AUTONOMOUS EXPLORATION ALGORITHM

The robot ability to explore an environment without human intervention ensures its real autonomy. The proposed sensor data fusion algorithm is nicely complemented by an autonomous exploration algorithm that uses the same environment map representation. The autonomous exploration algorithm developed in this article, from now on denoted by AEA, is based on concepts presented by (Newman, Bosse and Leonard, 2003) where hallways were mapped using two basic action criteria: a) goal generation and b) goal selection. Other concepts, such as visibility evaluation, were regarded in the AEA implementation.

It is important to note if no feature is extracted for a specific robot pose, the uncertainty in the estimated robot pose by the particle filter increases. The AEA deals with this case by using incremental exploration, avoiding the space-free analysis approach (e.g., Voronoi diagrams).

Figure 6 shows the flowchart of the proposed AEA. In the proposal presented in this article, only local context is relevant for the goal chosen, while in (Newman, Bosse and Leonard, 2003) local and global context are considered to goal selection. In the proposed AEA switching from local to global context is necessary only to define the goal that is located in the environment opening, which allows the robot to reach the selected global goal. This modification is necessary because the SLAMVITA robot must acquire the sensor measurements when it is stopped, after executing the movements between consecutive poses. Local to global context switches, such as presented in (Newman, Bosse and Leonard, 2003) would cause a large increase in the time necessary to finish the exploration task. In other words, the goals reached by the SLAMVITA robot are localized either locally (local context) or in an environment opening (global context evaluated).

Besides the definition of the best goal to explore in the environment, another important resource that the AEA performs is the decision of finishing the mapping task.

5 EXPERIMENTS AND RESULTS

Several experiments in distinct small environments were carried out, with or without AEA. In this Section, two of the experiments that use the same environment are presented, differing in the exploration forms (manual or autonomous). Figure 7 shows the environment (8.8 m x 2.80 m or 24.64m^2), where the two loops show the trajectory traveled by the robot when the exploration was manually planned. In this environment and with the robot starting at same pose, the second experiment was performed using AEA.

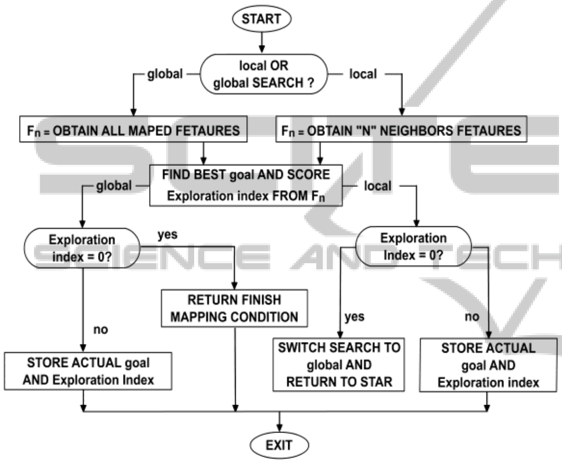


Figure 6: Flowchart of the proposed featured-based Autonomous Exploration Algorithm (AEA).

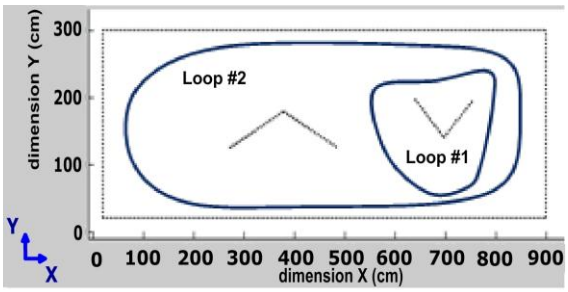


Figure 7: Indoor environment for the SLAM experiments.

Figure 8(a) shows the estimated map with the robot poses manually planned, while Figure 8(b) shows the estimated map using AEA. Table I informs the quantitative absolute difference between the estimated and real robot poses relative to both experiments. Some important considerations that can be mentioned in the experiment results, shown in Figure 8(a, b) and Table I are:

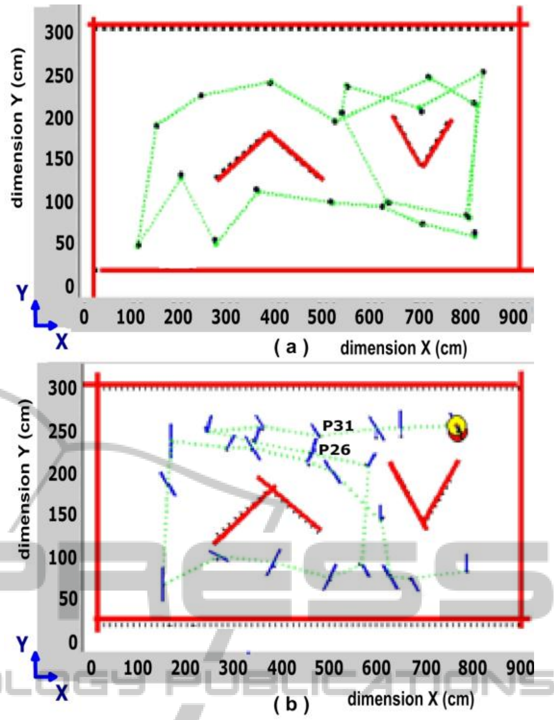


Figure 8: SLAM experiments with the robot using: (a) manually planned movements; and (b) autonomous exploration.

a) The absolute differences between the estimated and real robot poses (ΔX, ΔY and ΔΘ) in both experiments are kept small, less than 2%. However, in some robot poses, mainly in the experiment with AEA, the difference increased up to 3.5% (e.g., poses 32 and 33). The reason for this is the accuracy of the features acquired in some estimated poses where the robot made its measurements, that is, they were not associated with the proposed AEA.
b) The number of poses where the measures were taken is more than 50%, when using AEA (36 poses). Six robot poses (from 26 to 31 in Figure 8(b)) can be avoided, just evaluating the opening that has potential exploration to justify the movement of the robot to them. It is the case of two goals selected at environment opening in the experiment with AEA that led the robot to move in their directions.
c) The path followed by the robot in the experiment with AEA is not based in loop closing. The criterion in AEA is based just in goal scoring (locally and environment opening, the last using a global context).
d) The estimated maps for both experiments are consistent with the real environment contour for navigation purposes. Some segments are out of

Table I: Absolute differences between estimated and real robot poses (ΔX and ΔY in cm, ΔΘ in degree).

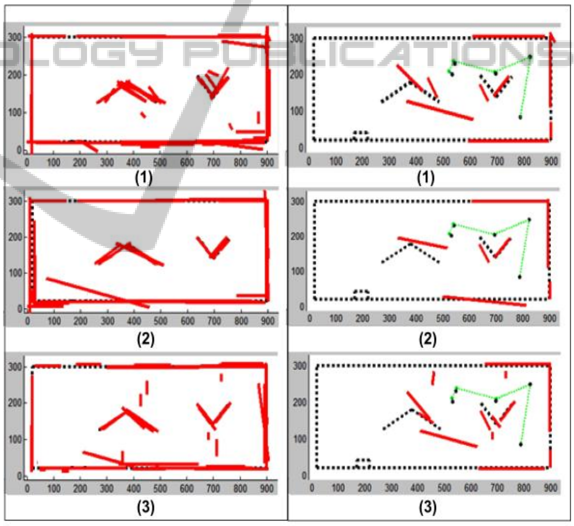
	Without AEA			With AEA		
POS	ΔX	ΔY	ΔΘ	ΔX	ΔY	ΔΘ
01	0.00	0.00	0.00	0.00	0.00	0.00
02	0.00	0.00	0.00	0.00	0.00	0.00
03	-1.00	-0.32	-2.00	0.51	0.15	1.85
04	-2.48	4.52	0.00	0.84	-2.72	1.47
05	-1.01	1.36	0.00	0.84	-2.72	1.42
06	-1.65	0.44	0.00	-3.29	-5.23	1.00
07	-3.33	0.81	-2.00	-0.21	0.85	2.98
08	1.85	-1.51	-3.04	-0.21	0.85	3.58
09	6.69	-1.63	0.00	-0.51	3.83	-1.85
10	2.86	-2.26	0.00	1.94	1.97	0.24
11	2.53	-0.20	-2.00	0.94	2.97	-0.24
12	2.94	1.92	3.00	0.28	2.96	-2.15
13	0.00	0.01	0.00	0.64	2.47	0.00
14	-0.67	1.99	0.00	0.64	2.47	0.00
15	-0.19	-0.70	-2.00	0.56	2.57	0.71
16	0.97	-4.01	0.00	0.56	2.57	0.10
17	2.86	-3.73	0.00	0.92	0.17	0.00
18	4.72	-2.97	0.00	0.92	0.17	1.00
19	4.50	-2.43	-1.00	2.36	3.77	3.03
20	0.07	0.05	0.43	2.36	3.77	1.77
21	-1.09	-0.04	-2.00	-1.76	4.84	2.99
22	1.36	-3.61	-1.84	-1.76	4.84	2.93
23				-2.39	2.91	3.12
24				-2.39	2.91	0.27
25				5.02	-1.83	0.99
26				6.35	-1.50	-0.06
27				4.44	-0.79	0.80
28				3.51	-2.20	-0.80
29				4.07	-4.05	3.39
30				1.62	3.22	3.13
31				-0.58	1.86	4.97
32				2.19	10.89	2.34
33				2.19	10.89	0.91
34				0.94	9.74	0.00
35				-1.43	7.67	0.99
36				-1.43	7.67	0.72

the actual environment area and others can be viewed more length than the respective walls inside the environment (Figure 8(b)). Once again, this is not associated to employing AEA and a possible solution to remove this mistakes is evaluating feature crossing (inside and on borders of the environment) based on the estimated robot poses. If the segment augmented in the feature crossing cannot be perceived in any estimated robot pose (border situations) or even if it occludes the previous ones that were viewed in other estimated robot poses (feature inside the environment), the feature excess may be removed accordingly.

Although the estimated map without AEA (Figure 8(a)) presents to be closer to the actual environment than the one with AEA (Figure8(b)), the fundamental reason to use the SLAM solution with AEA approach is the robot´s autonomy, avoiding human interventions as much as possible.

With some data produced in the experiment without AEA (robot commands and sensor raw data acquired in 22 position), one of the three sensors available in SLAMVITA was "withdrawn", just not involving its data in the fusion algorithm. So, the data (commands and raw data of the two "remained" sensors) are used to verify if it is possible to validate the solution to SLAM problem.

The experiments conducted for all combinations of two SLAMVITA sensors with the total features extracted by the proposed fusion algorithm considering the robot real poses are shown in Figure 9(a), while the estimated map outputted by the particle filter after the first six poses are presented in



(a) (b)

Figure 9: (a) The total feature acquired by two SLAMVITA sensors for all real robot poses; and (b) the estimated map by the filter until robot pose #6 (1-visual and sonar; 2- visual and infrared; and 3-infrared and sonar). (b) Just few poses were sufficient to show that the filter diverge for all cases.

When using the infrared and visual sensors (case 2, and so, not applying R1 and R3 rules) the overall features appears with some distortions of the real environment (Figure 9(a)), but with less feature mistakes related to the others sensors combinations. However, in all cases tested, the estimated map (Figure 9(b)) is not consistent with the real one. In the seventh robot pose the estimated and real ones presented larger difference, leading the filter to begin diverge for all tested cases. These experiments cannot be made using AEA, because it is based in an incremental way which would lead the robot to collide with the walls in the environment.

These experiments were important to show that the SLAMVITA sensors disposition in the panning turret and its simple types (visual, infrared and sonar) allow solving the SLAM problem using a low-cost mobile robot.

The proposed solution presented in this article in comparison to others works that deal with indoor SLAM using low-cost mobile robot, such as presented by (Vazquez and Malcolm, 2005), does not have restriction to navigate the robot nearby the environment walls in function of the short measurement range of the infrared sensors to build the mapping environment. Moreover, only 4 sensors are employed in SLAMVITA robot, and due to theirs different principle of operations, the measure noises can be solved by the proposed sensor data fusion algorithm, mainly considering the complementary fusion method. This is the case were one of two directional sensor (vision or infrared) has not measures at a specific angular area of the scan.

6 CONCLUSIONS

The environment mapping is an important task for many purposes that the mobile robots might perform, normally requiring sensor data fusion. A mobile robot was constructed employing three different sensor types: visual (wireless camera and laser pointer), infrared (two units) and sonar.

This paper presents the tests of three software modules that run in a cooperative way to solve the indoor SLAM problem: a) a sensor data fusion algorithm; b) a version of particle filter (FastSLAM 1.0); and c) an autonomous featured-based exploration algorithm.

The results experiments presented show that there are no significant differences when the environment exploration task is performed with or without autonomous exploration. In other word, choose better positions to acquire the environment measures are solved by proposed autonomous algorithm. The estimated maps constructed by the filter, which represent the environment, are consistent for robot navigation purpose.

Currently the solution for a larger environment, around 80 meters in length with some loop situations is under development with satisfactory partial results. The experiments in larger environments aim to consistently validate all software modules developed in this research. Both the estimated poses and map must hold the consistency obtained in the experiments presented in this article.

The main contribution of this research is to solve the indoor SLAM problem using a low-cost mobile platform that requires low computational load using the overall system intelligence running in a PC computer and embedded in the robot constructed with simplified hardware and software.

REFERENCES

Aguirre, E., González, A., 2002. Integrating fuzzy topological maps and fuzzy geometric maps for behavior-based robots. *International Journal of Intelligent Systems*, no. 17, pp. 333–368.

Buonocore, L., Nascimento Jr., C. L., Almeida Neto, A., 2010. Sistema de baixo custo para medição de distância em duas dimensões usando câmera IP sem fio. *18º. Congresso Brasileiro de Automática*, Bonito, MS, Brazil, pp. 2239 – 2246.

Castellanos, J. A., Martínez, J. M., Neira, J., Tardós, J. D., 1998. Simultaneous map building and localization for mobile robots: a multisensor fusion approach. *International Conference on Robotics & Automation*, vol. 2, pp. 1244–1249.

Huge, D-W., 2001. *Multi sensor data fusion*. [e-book] Available at: < http://www.acfr.usyd.edu.au/pdfs/ training/multiSensorDataFusion/dataFusionNotes.pdf> [Acessed 12 September 2009].

Huge, D-W., Bailey, T., 2006. Simultaneous localization and mapping: Part I. Tutorial. *Robotics & Automation Magazine*, vol. 13, no. 3, pp. 99–108.

Ivanjko, E., Petrović, I., Brezak, M., 2009. Experimental comparison of sonar based occupancy grid mapping methods. *AUTOMATIKA: Journal for Control, Measurement, Electronics, Computing and Communications*, vol. 50, no. 1-2, pp. 65–79.

Milisavljević, N., Bloch, I., Acheroy, M., 2008. Multi-sensor data fusion based on belief functions and possibility theory: close range antipersonnel mine detection and remote sensing mined area reduction. *I-Tech Education and Publishing*, pp. 95–120.

Nguyen, H. G., Blackburn, M. R. (1995). A simple method for range finding via laser triangulation, Technical Document 2734, Naval Command, Control and Ocean Surveillance Center RDT&E Division, San Diego, CA.

Newman, P., Bosse, M., Leonard, J, 2003. Autonomous feature-based exploration. *International Conference on Robotics and Automation*, vol. 1, pp. 1234–1240.

Pandey, A. K., Krishna, K. M., Nath, M., 2007. Feature based grid maps for sonar based safe-mapping. *International Joint Conferences on Artificial Intelligence*, pp. 2172–2177.

Thrun, S. B., 1993. Exploration and model building in mobile robot domains. *International Neural Networks*, vol. 1, pp. 175–180.

Thrun, S. B., Burgard, W., Fox, D., 2005. *Probabilistic Robotics*. Cambridge, USA: MIT Press.

Vazquez, J., Malcolm, C., 2005. Fusion of triangulated sonar plus infrared sensing for localization and mapping. *International Conference on Control and Automation*, vol. 2, pp. 1097–1102.

Visser, A., 1999. *Chapter 9 - Sensor Data Fusion.* [pdf] Available at: < http://www.science.uva.nl/~arnoud/education/OOAS/fwi/Chap9.pdf> [Acessed 12 September 2009].

Yap Jr., T. N., Shelton, C. R., 2009. SLAM in large indoor environments with low-cost, noisy and sparse sonars. *IEEE International Conference on Robotics and Automation*, Kobe, Japan, pp. 1395 – 1401.

Zuliani, M., 2009. *RANSAC for Dummies-Draft*. [pdf] Available at: < http://vision.ece.ucsb.edu/~zuliani/Research/RANSAC/docs/RANSAC4Dummies.pdf > [Accessed 15 August 2009].