MERGING TOPOLOGICAL DATA INTO KALMAN BASED SLAM

S. Panzieri, F. Pascucci, I. Santinelli, G. Ulivi
Dipartimento di Informatica e Automazione, Università "Roma Tre"
Via della Vasca Navale, 79, 00146 Roma, Italy
{panzieri,pascucci,ulivi}@dia.uniroma3.it

ABSTRACT

The paper presents an application of a well-known SLAM algorithm, based on an augmented state Kalman estimator, to self-localise the robot and build a fuzzy gridmap of the environment at the same time. In an office-like environment, a vision system is used to single-out on the ceiling some lamps, that are considered as natural landmarks and included in the state of the filter. Information provided at each step by ultrasonic range finders is used to build the gridmap. Sonar uncertainties are modeled using the theory of fuzzy measures for its ability to highlight contradiction arising from an imperfect localisation. A rather interesting point is the use of the acquired gridmap itself (beside the lamps) as an input for the SLAM algorithm, in particular for the robot orientation. Some simulations conclude the paper and show the effectiveness of the approach.

KEYWORDS: SLAM, EKF, Fuzzy measures, Mapping, Hough transform

1 INTRODUCTION

The development of techniques for autonomous robot navigation in unstructured environments is one of the major challenges in the current research on robotics. Purposeful robot navigation requires both reliable localisation and mapping systems; various approaches have been proposed in literature to cope with localisation and mapping problems severally, while in the last few years the trend of solving those problems simultaneously (Simultaneous Localisation And Mapping, SLAM) had a great success [1].

Most of the algorithms suggested for localisation, mapping, and SLAM problems have one common feature: they are probabilistic. They employ stochastic equation to model robot systems and uncertainty arising in the interactions between the robot and its environment. In this framework Bayesian filter are applied to estimate mobile platform pose (i.e., position and orientation) and map, merging data from different sensors. A classical approach is based on Extended Kalman Filter (EKF): this mathematical formulation is still widely used today, although it comes up with several limitations due to the unimodal Gaussian noise assumption and the strong nonlinearities that characterise robotic systems.

Among other problems, the representation of the environment has been often discussed and both abstract (*topological*) representations [2, 3], and metric ones [1, 4, 5] have been proposed. Techniques based on topological maps have less requirements in terms of modeling and computational needing, but metric maps provide a more precise localisation. In this paper we present a double approach that makes use of two different metric maps.

Consider a mobile robot navigating in an office-like environment with an encoder based odometry, a ring of ultrasonic range finders and a web cam focusing the ceiling [6] to detect

and use the lamps as natural landmarks (beacons with no orientation property located in unknown positions).

First, an EKF is used in a SLAM scheme to improve odometric data and build a geometric map including robot pose and beacons locations. Second, exploiting fuzzy measures theory to modeling sonar uncertainties better than its probabilistic counterpart does, a fuzzy *global* map (FGM) [7] is computed using ultrasonic range finders while exploring the environment. After a refinement period, the FGM can be employed to further improve (robustify) the estimation, thanks to the extraction of a quantitative information about the absolute orientation of the robot. This is obtained comparing the mapped environment with a fuzzy *local* map (FLM): a kind of artificial visual perception (FLM vision) of the surroundings of the robot computed from actual sonar readings and commonly used for topological localisation [8, 9].

The paper is organised as follows: first the EKF for SLAM is introduced, then a description of the gridmaps (FGM and FLM) is given, finally several experimental results are reported.

2 VISION BASED SLAM

The solution for the SLAM problem adopted in this work is based on the estimation theory. In this framework we try to compute the probability density $p(x|z)$ that provide the maximum like-hood estimate, using stochastic equations to model the vehicle, the beacon positions, and the sensors. The mobile platform considered is a robot with the kinematics of an unicycle. The robot is equipped with encoders as proprioceptive sensors, while uses a vision system as exteroceptive sensor [6]. The measurements provided by the exteroceptive sensory system are expressed in the robot coordinates and represent the position of the spot lights in the viewing windows of the web cam.

The structure of the SLAM filter proceeds directly from the EKF equations: as we considered uncertainty having a unimodal Gaussian distribution and linearised model for the robot, only the moments of the first two orders have to be computed in order to completely describe $p(x|z)$. At the k-th step, the kinematic model of the robot and the measurements from encoders are used to form an odometric and map prediction $\hat{x}_{k|k-1}$ with an associated covariance matrix $P_{k|k-1}$. An observation prediction $\hat{z}_k$ is then calculated and compared with the real measure z_k provided by the vision system. The result is the innovation term v_k and its covariance matrix S_k, that is used by the EKF to produce the new state estimate $\hat{x}_k$ and the associated covariance P_k.

Under the SLAM framework, the filter is able to localise the robot and concurrently build a map (a list of beacons position) [6]. During the navigation task, the system detects new features when exploring new areas. Once those features become reliable, they are included into the map.

3 MAP BUILDING VIA FUZZY MEASURES AND ULTRASONIC RANGE FINDERS

Ultrasonic sensor performance may be rather poor due to various phenomena [10] (multiple reflections, wide radiation cone, etc.). As a consequence, the ultrasonic sensing process is affected by a large amount of uncertainty that is quite difficult to model. A range reading r provides the information that one or more obstacles are located somewhere along an arc of circumference of radius r. Hence, there is evidence that cells located in the proximity of

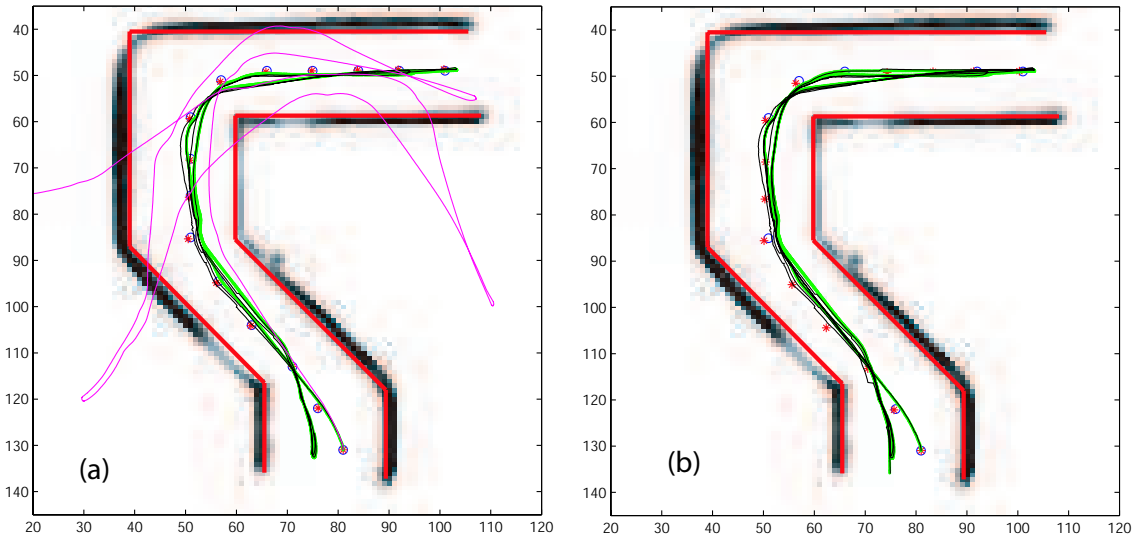

Figure 1: *Fuzzy global maps: estimated paths and beacons positions 4-th run (a) and 6-th run (b)*

this arc are *occupied*. On the other hand, cells well inside the circular sector of radius r are likely to be *empty*. A description on how to model those evidences that make use of fuzzy measures theory [13] can be found in [11, 7, 9]. In those papers the Smets [12] uncertainty calculus is applied to fuse different pieces of evidence.

Consider now an unknown environment and assume a discretisation with a grid made of 10cm cells: define the FGM as fuzzy representation of the whole environment and the FLM as the 41×41 cells fuzzy map describing only the surroundings of the robot. As a consequence of the SLAM algorithm, the pose estimation of the robot reaches its convergence only after a navigation period depending on the odometry errors and on the number of recognised beacons. The more the beacons seen at the same time, the better the obtained estimate, and the FGM, deployed using the estimated pose, can retain uncorrect information until this refinement process reaches its end. As long as the pose become more reliable, and due to a forgetting factor, related to the contradiction that can be computed along the mapping process thanks to the fuzzy measures theory, most recent acquisitions have enough influence to refine the map during the navigation task. For example, see Fig. 1 where a FGM has been computed during a robot navigation task. Once the convergence of the SLAM has been guaranteed, also FGM reaches its steady state and its update is suspended to use the map itself, as will be explained in the following section, as a reference for future navigation. On the contrary, the FLM, obtained with a single set of sonar acquisitions, has no odometry dependency and displays the shape of environment around the robot at each time (see Fig. 2d up).

4 MERGING FUZZY MAPS INTO SLAM

The idea of using a comparison between some selected spots of the FGM (see Figs. 2a/b/c) and the FLM available at each sonar reading has two kinds of motivations. First of all, to allow a robust navigation, that means having more than one source of localisation data to feed the SLAM algorithm. We have supposed, in fact, that the beacons could fail in

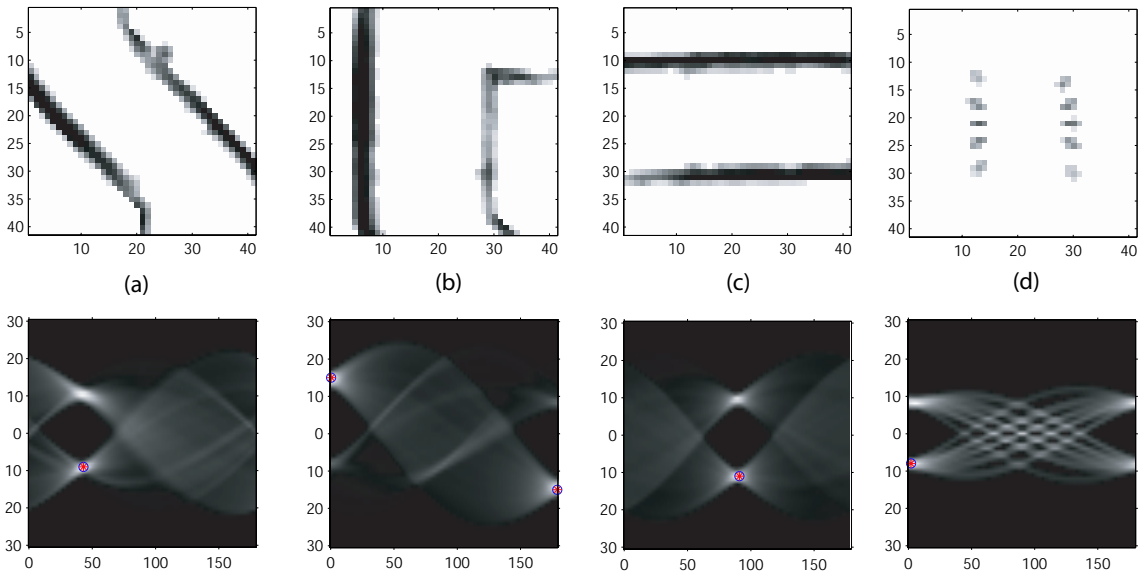

Figure 2: *FGM reference spots (a,b,c) and FLM (d) with their respective Hough transforms*

their function, i.e., lamps could break at any time leaving the robot without the necessary headlights. Second, such map could be used to detect unusual obstacles or people walking down the corridors and alerts the robot to switch into a different, perhaps more conservative, behaviour. In any case, the fuzzy map is a spatial context for the mobile robot, providing a better interaction with the environment to give the right meaning to new facts and, possibly, establishing new relations, in order to facilitate a learning phase.

In our experimentation, after the refinement phase, the FGM of Fig. 1 has been divided into segments to identify three corridors (see Figs. 2a/b/c) whose orientations have been computed to be successively compared with the robot orientation w.r.t. the walls calculated through the FLM. The comparison can be easily done using the Hough transform [14, 15] through the simple mapping

$$r = x \cos\theta + y \sin\theta, \tag{1}$$

that, for each point (x, y) of the initial image, reinforce a point in the transformed plane belonging to a straight line with a distance r from the origin and an orientation θ.

In the second row of Fig. 2 the Hough transforms are shown and the red dots point out the relative maximums associated to linear shapes (walls). There is no difficulty in computing the three reference angles (a, b, c) and the robot orientation (d) with a simple analysis of the four transformed planes. The mean angular error for the comparison is 1 degree, with a standard deviation of 0.66 degrees.

5 SIMULATION RESULTS

Many experiments have been carried on using the Nomad 200 mobile robot simulator and the Matlab environment. In all of them, having a sufficient number of beacons (at least two in each frame captured from the webcam), the convergence of the SLAM algorithm was guaranteed. The experiment reported consists in letting the robot to navigate six times back and forth in a four corridors environment. At the end of the 4-th run the map building process is stopped and, as it could see in Fig. 1a, the map is considered a reliable

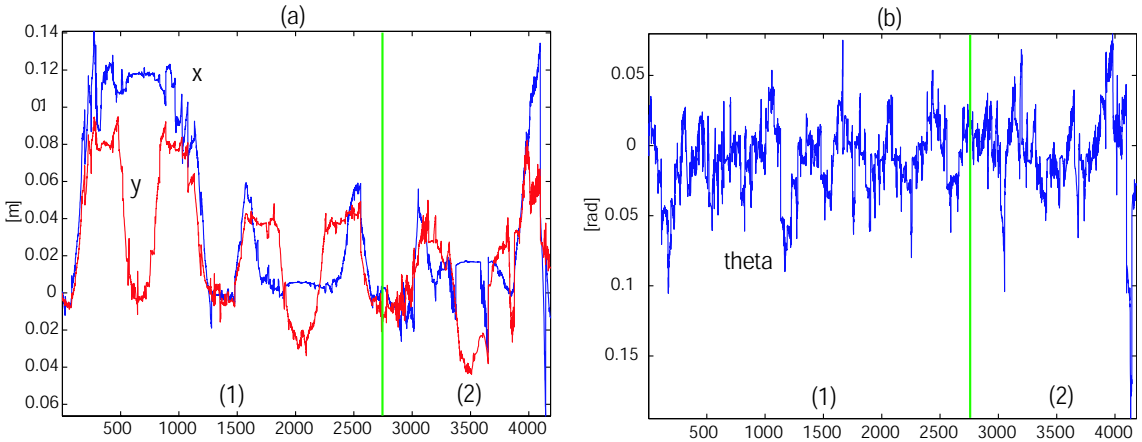

Figure 3: *Cartesian and angular errors: (1) 15 active beacons (runs 1..4); (2) 8 active beacons plus Hough localisation (runs 5,6)*

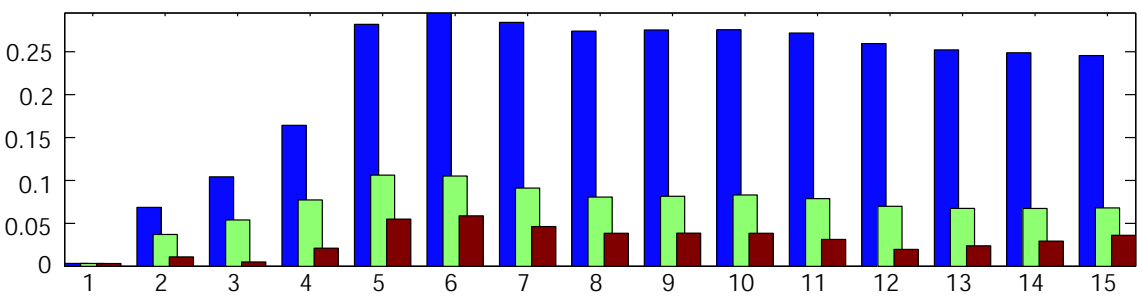

Figure 4: *Beacons positions estimation error in meters at 4-th run (lower), 6-th run (middle), with perturbation (higher)*

representation of the four corridors (in red). The x, y and θ robot position errors are reported in parts 1 of Figs. 3a and 3b, while beacons position errors are displayed in Fig. 4 (lower). Less then 5cm is the average error reached in this phase. Note that the odometric prediction would lead to the wandering path showed in Fig. 1a. Now, we deactivate some beacons (7/15) and, during runs 5-th and 6-th the robot get lost, i.e., all the estimated variables diverge inexorably. One of the dangers coming from SLAM algorithms is the poor ability to recognise old beacons when newly seen: this creates new unnecessary state variables and makes easier the divergence. To restore the convergence, and to show the effectiveness of information extracted from the fuzzy map, we report the 5-th and 6-th runs obtained using the Hough approach to the orientation estimation problem. The accuracy is slightly lost in the passage but the errors remain bounded (almost doubled) as it could se in Fig. 4 (medium) for beacons positions.

A final test has been performed to verify the robustness of the algorithm: some disturbances have been added to the robot real position (with no effect on the odometry) making the robot turning of 10 degrees in one step at each run like it would have encounter a stone on the floor or it was bumped. The convergence was preserved but errors went to 25 and 18 cm for x and y and 15 degrees for the angle. The errors on beacons positions are reported in Fig. 4 (higher).

6 CONCLUSIONS

The effectiveness of a vision based SLAM algorithm, merging natural landmarks information and quantitative data coming from the comparison of a fuzzy global map with a local representation of the surroundings of a mobile robot, has been shown. Results are good and encouraging but some steps ahead have to be done. A more sophisticated pattern matching, able to manage rotations and translations, could allow a more extensive use of FLMs, not only along corridors. Then, the use of a reliable, beacons based, pose estimator like the SLAM presented, would allow the implementation of composite motion strategies on the fuzzy map to more efficiently explore the environment, or single out the perceived differences as previously hinted at.

REFERENCES

1. Clark S., Dissanayake G., Newman P. and Durrant-Whyte H., "A Solution to Simultaneous Localization and Map Building (SLAM) Problem," *IEEE Transaction of Robotics and Automation*, Vol. 17, No 3. pp. 229-241, 2001.
2. Levitt T.S., Lautwon D.T., "Qualitative navigation for mobile robots," *Artificial Intelligence Journal*, Vol. 44, No 3. pp. 305-360, 1990.
3. Kuipers B., Byun Y.T., "A robot exploration and mapping strategy based on semantic hierarchy of spatial representation", *Journal of Robotics and Autonomous Systems*, Vol. 8, pp. 47-63, 1991.
4. Guivant J., Nebot E., "Optimization of Simultaneous Localization and Map Building Algorithm for Real Time Implementation" *IEEE Transaction of Robotics and Automation*, Vol. 17, No 3. pp. 242-256, 2001.
5. Thrun S., Fox D., Burgard W., "A probabilistic approach to concurrent mapping and localization for mobile robots," *Mach. learning Autonom. Robots*, Vol. 31, pp. 29-53, 1998.
6. S. Panzieri, F. Pascucci, G. Ulivi, "Vision based navigation using Kalman approach for SLAM," *11th Int. Conf. on Advanced Robotics*, Coimbra, Portugal, 2003
7. Gambino, F., Ulivi, G. and Vendittelli, M., "The Transferable Belief Model in Ultrasonic Map Building," *IEEE Int. Conf. on Fuzzy Systems*, pp. 601-608, Barcelona, ES,1997.
8. Fabrizi E., Panzieri S., Ulivi G., "Extracting topological feature of indoor environment from sonar-based fuzzy maps" *Intelligent Autonomous Systems 6*, Pagello E., Groen F., Arai T., Dillmann R., Stenz A.(eds), IOS press, Amsterdam, 2000
9. L. Longega, S. Panzieri, F. Pascucci, G. Ulivi, "Indoor robot navigation using log-polar local maps," *Prep. of 7th Int. IFAC Symp. on Robot Control*, pp. 229-234, Wroclaw, Poland, 2003.
10. J. J. Leonard and H. F. Durrant-Whyte, *Directed Sonar Sensing for Mobile Robot Navigation*. Kluwer Academic Publishers, 1992.
11. Oriolo, Ulivi, G. and, Vendittelli, M., "Fuzzy Maps: A New Tool for Mobile Robot Perception and Planning," *Journal of Robotic Systems*, **14**(3), pp. 179-197, 1997.
12. P. Smets, "The combination of evidence in the transferable believe model," *IEEE Trans. on Pattern Analisys and Machine Intelligence,* vol. 12, n. 5, pp. 447–458, 1990.
13. G. J. Klir and T. A. Folger, *Fuzzy sets*. Kluwer Academic Publishers, 1988.
14. H. Koshimizu, K. Muakami, M. Numada, Global Feature extraction using efficent Hough transform, *International workshop on industrial applications of machine intelligence and vision,* pp. 298–303, Tokyo, 1989.
15. X. Yun, K. Latt, J.S. Glennon, Mobile robot Localization using the Hough Transform and neural networks, *IEEE International Symposium on Computational Intelligence in Robotics and Automation,* pp. 393–400, Gaithersburg, MD, 1998.