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POSSIBILISTIC POSITION ESTIMATION IN MOBILE ROBOTICS

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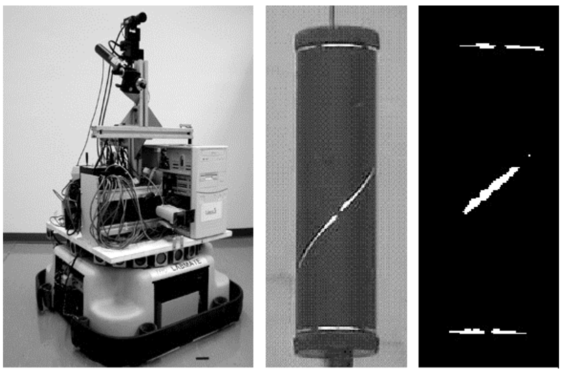
Abstract: Using an enhanced version of possibility theory, we propose a logic-based position estimation method, fusing symbolic knowledge and interpretations of uncertain sensor data. The method is tested on a mobile robot using an annotated topological map of an indoor environment.
Keywords: Mobile robotics, Management of uncertainty, Localization

1 INTRODUCTION

We propose a technique for estimating the position of a mobile robot, based on a combination of sensor fusion and symbolic reasoning. The robot moves in an ordinary office environment and position estimation (localization) is made against a topological map, consisting of relevant **places** (corners, doorways) connected by **paths**, annotated with approximate metrics. Each place is labeled by a set of logical formulae (**sequents**), which relate an abstract structural description of the place with the perceptual picture provided by the sensors. The formalism adopted for the sequents is based on an enhanced version, called Local Possibilistic Logic (**LPL**) [1], of the Possibilistic Logic of Dubois, Lang and Prade [2], which provides the formal basis for fuzzy techniques. LPL allows to code uncertainty by attaching a **degree of confidence** in [0,1] to each sentence expressing sensory information. Sentences expressing “crisp” symbolic knowledge have a degree of 1. All the available information about a place is then fused and a resulting degree for each place P_i in the map is found. Using the terminology of possibility theory, this corresponds to calculating the **necessity value** of a predicate like ***at_place(P_i)***. Localization in the map consists then in choosing the place with necessity of the predicate above a threshold (or in acknowledging disorientation).

The treatment of uncertainty in robotics is the subject of a lively debate, reflecting a variety of cultural attitudes [3]. The possibilistic perspective seems more appropriate than other approaches to autonomous mobile robotics, in the absence of accurate models of the world; in particular, possibilities naturally capture the idea of **similarity** [4] between actual percepts and prototypical configurations or expected observations. A measure of similarity between percepts and prototypes may either come from a heuristic algorithm proposed by an expert, or from a neural learning process, or from accurate analytical modeling.



a) b) c)

Figure 1. a) The robot used in the experiments. b) The structured beacon. c) A binary image of the light pattern.

2 EXPERIMENTAL SETUP

The robot consists of a TRC Labmate (fig. 1a), equipped with a belt of twelve sonar sensors, a laser-beam projector generating a horizontal line in front of the robot, and two cameras. The sonars are used to detect obstacles and to identify walls. One of the cameras monitors the changes in the laser-beam line and allows to compare the current shape with the one expected at each place.

The other camera tracks a visual beacon (fig. 1b) developed by the authors [5]. This consists of a small vertical cylinder with two horizontal cuts and a helicoidal one, producing a light pattern (fig. 1c), that can be used both as a visual signature for each place, and as a source of approximate metric information. The beacon is currently positioned manually at key points in the environment, but it is meant to be mounted on a second smaller robot for experiments in cooperative navigation. Odometric measurements are also used for consistency checks with the metrics contained in the map.

3 POSITION ESTIMATION OUTLINE

Our approach is based on the idea that even though each piece of information available at each time instant is heavily affected by uncertainty, a proper fusion technique can provide a correct estimate. As explained more formally in [6], the technique consists of the following steps: **i**) a set of **logical formulae** in LPL is associated to each place P_i, describing how predicate *at_place*(P_i) is related to specific percepts, like, e.g., *wall_at_north*, and to symbolic knowledge; **ii**) using Sequent Calculus, a technique borrowed from Proof Theory, a **proof** is found for predicate *at_place*(P_i); **iii**) from the proof, an **algorithm** is constructed, that calculates the degree of the predicate as a function of the degrees of the percepts; **iv**) during navigation, at each time cycle, sensor measurements are interpreted as **percepts with a degree**, expressing, for example, that: “sonar readings suggest that there is a wall at North, with a degree of 0.8”; **v**) the degree of *at_place*(P_i) for each P_i is calculated and the place, if it exists and it is unique, with degree above a threshold, is chosen as the current place.

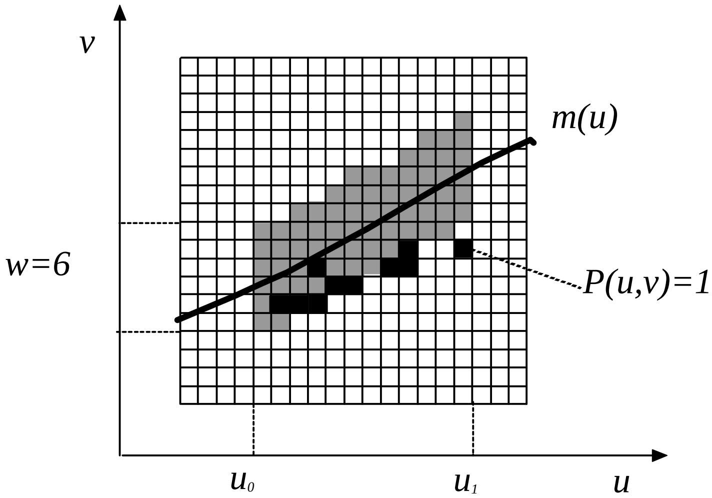


Figure 2. Matching the beacon image (black pixels) with the geometric model m(u). The match area is shown in gray.

4 CALCULATING THE DEGREES OF PERCEPTS

As mentioned in the introduction, percepts are weighted according to their similarity to a model. For example, in the case of the **structured beacon**, by analyzing the binary image obtained by the tracking camera, the approximate distance and orientation of the beacon are computed. To do this, the white patches, like in fig. 1c, are least-squares interpolated by segments.

Then the best match is found between an appropriate portion of the image and a geometric model of the cylinder, and a matching degree M is calculated, that accounts for the dispersion of the pixels around the ideal image, as in fig. 2. M is given by:

$$M = \frac{\sum_{u=u_0}^{u_1} \sum_{v=m(u)-w/2}^{m(u)+w/2} \left(m(u)-v\right)^2 P(u,v)}{N^2} \tag{1}$$

where u_0 and u_1 are, respectively, the left and right margins of the beacon image, <u,m(u)> is the generic point of the projection of the helix, w is the height of the match portion, P(u,v) is 1 if pixel <u,v> is “on”, 0 if it is “off”, and N is the number of pixels that are “on” in the match portion. Two percepts are then produced: *beacon_angle* and *beacon_distance*, weighted by degrees β_θ and β_d, respectively, calculated as follows:

$$b_q = \frac{\mathrm{MN}}{(\mathrm{w}/2)^2}, \; b_d = \max(d_{s1}, d_{s2}) \tag{2}$$

where d_{s_1} and d_{s_2} are the dispersions of pixels around the ideal segments representing the horizontal cuts in the cylinder.

Two additional percepts, called *laser_wall* and *laser_corner*, are provided by the **structured-light system**. The binary image of the projected line is treated as a visual cue for establishing whether the robot is facing a wall or a corner. First of all, three lines are least-squares fitted to the image. The first line, L_1, encompasses all points; the other two lines are computed assuming the lowest point in the image as a pivot point and fitting the points on its left with line L_2, and those on its right with line L_3. The values δ_f and δ_c represent the degrees of similarity between the visual pattern and, respectively, the prototypical images of a front wall or a corner, i.e. a V-shaped figure or a horizontal line. They are computed by the following formulae, which are functions of the parameters of the fitted lines:

$$d_f = \min\left(|M| + \frac{S_1}{10}, 1\right), \quad d_c = \min\left(1 - \min\left(\frac{|M_2 - M_3|}{1.1}, 1\right) + \frac{S_2 + S_3}{20}, 1\right) \tag{3}$$

where M_i and S_i, with i = 1,2,3, are the slope and the standard deviation of the i-th line. d_f and d_c are used as the degrees of the *laser_wall* and *laser_corner* percepts.

A further percept, *sonar_wall*, is extracted from **sonar readings**. The sonar belt consists of 16 sensors arranged in a ring, and it is used to avoid obstacles during navigation and to detect walls for localization. Wall detection is done using the sonars mounted on the lateral sides of the robot: for each sonar, the last 8 readings, taken at significantly different robot positions, are passed to a least-squares line-fitting algorithm, which returns the best-fitting line for each side, with the associated dispersion value Δ, normalized to [0,1], to obtain d_w, the degree of similarity between the observed points and the collinear points representing an ideal wall:

$$d_w = \min\left(\frac{\Delta}{\Delta_{\max}}, 1\right) \tag{4}$$

$\Delta_{\max}$ is a threshold for dispersion values, beyond which the fitted lines are considered completely unreliable. When d_w is close to 0, the fitted line is considered a very good approximation of a real wall.

5 EVALUATING SYMBOLIC KNOWLEDGE

Once the degrees of the percepts have been evaluated, the information they provide is fused to calculate the degrees of higher-level pieces of symbolic knowledge. To do this, the dependencies among the various elements of the knowledge base are expressed as LPL formulae, for which a powerful set of logical connectives is available, including the classical and/or (&/⊕), implication (→), and T-norms.

As a simple example, consider the beacon information. We may want to use the individual percepts, *beacon_angle* and *beacon_distance*, to build a higher-level predicate called *beacon_signature*. In the LPL formalism, this is expressed, for each place P_i, by the following sequent:

$$\vdash \left(\left(beacon\_angle\,(a, A_i, t)\,\&\, beacon\_distance\,\,(l, L_i, t)\right) \rightarrow beacon\_signature\,\left(\langle a, l\rangle, \langle A_i, L_i\rangle, t\right)\right) \tag{5}$$

where the A_i and L_i are the values of angle and distance corresponding to the pre-defined signatures of each place. Using Sequent Calculus, a proof is found for the formula, which provides the function that calculates the degree β of the *beacon_signature* predicate. In this case, such function is simply:

$$b = \max(b_q, b_d) \tag{6}$$

To give a more complex example, suppose we want to express the fact that the robot is detecting a corner in a certain direction. We define a corner predicate as a logical combination of percepts *sonar_wall*, *laser_wall*, *at_wall*, *laser_corner*, *at_corner*:

$$\begin{aligned}\vdash\ & ((sonar\_wall(p_1,d_1,t)\ \&\ at\_wall(p_1,t)\ \&\ laser\_wall(p_2,d_2,t)\ \&\ at\_wall(p_2,t)) \oplus \\ & (sonar\_wall(p_3,d_2,t)\ \&\ at\_wall(p_3,t)\ \&\ laser\_wall(p_4,d_1,t)\ \&\ at\_wall(p_4,t)) \oplus \\ & (laser\_corner(p_5,d_1,d_2,t)\ \&\ at\_corner(p_5,t))) \\ & \quad \rightarrow corner(d_1,d_2,t) \\ & \text{for all pairs } (d_1,d_2) \in \{(North,East),(North,West),(South,East),(South,West)\}\end{aligned} \tag{7}$$

where the p's are parameters of the percepts. The sequent says that a corner is detected, at time t, if either the robot recognizes a lateral wall using the sonars and a front wall using the structured light, or it recognizes directly a corner using the structured light.

Again, using Sequent Calculus, the function is determined that calculates the degree of the *corner* predicate. In a similar way, even higher-level predicates, like, eventually, the *at_place* predicates, are evaluated.

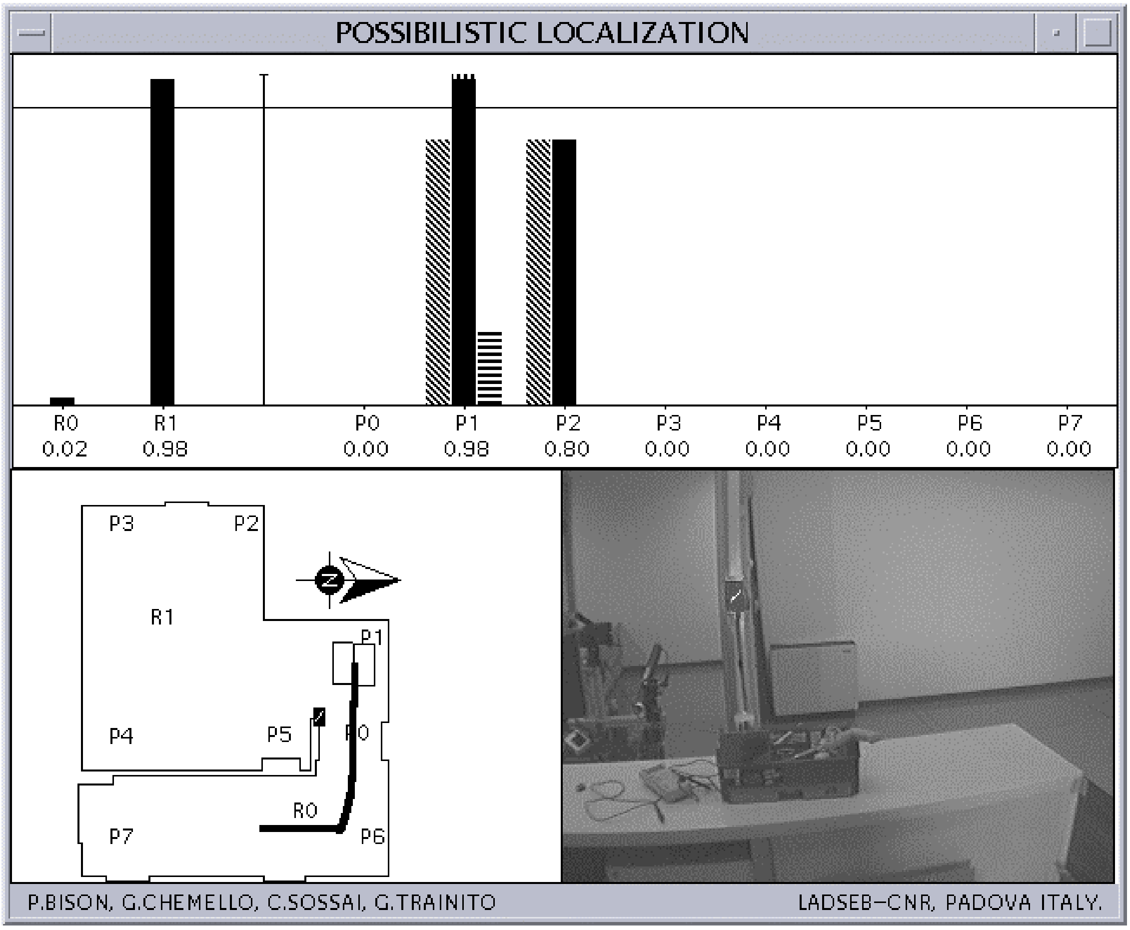


Figure 3. A typical run-time display, showing degree distributions.

6 EXPERIMENTAL RESULTS

The method was successfully applied to several navigation runs. Fig. 3 shows a typical run-time display. In the lower part, a map of the workplace is shown, with two rooms, R_0 and R_1, connected by a door, and with 8 places, P_0 to P_7; the beacon is located by the door. In the upper-right part, the distribution of degrees of *at_place* is shown, over the set of places. For each place, the black bar indicates the overall degree, while the striped bars give the contributions of the individual percepts that are involved in the evaluation: the diagonally-striped bars give the cumulative contribution of structured-light and sonars, whereas the horizontally-striped bars denote the evidence provided by the beacon. The current place P_1 is discriminated from place P_2 because of the difference in the beacon signatures, while the other percepts give similar contributions. An additional predicate *in_room* is also evaluated, that tells which room the robot is currently in, and its degree distribution over $\{R_0, R_1\}$ is shown in the upper-left part of the display.

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