Exploration of Unknown Environments Using Learned Representations

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Abstract

This study addresses the problem of performing robotic missions where an **unknown** region must be surveyed. We address this problem under two fundamental assumptions:

H_1: The robot has **no a priori knowledge** about the environment;

H_2: The robot is equipped only with perception (distance) sensors and odometric sensors. More precisely, it has **no access** to information about its position in the **global** coordinate system.

Under these constraints, the robot must survey the unknown region resorting basically to dead-reckoning positioning, which, as it is well known, leads to a divergent error behavior that may eventually result in the robot getting lost.

The mapping problem has been studied by several researchers in the last years. Our work differs from the makority of these studies in that we explicitly address the effect of navigation errors in the execution of survey missions, and evaluating the ability of using perceptual information to guarantee that a coherent representation of thesurveyed region is obtained.

In this paper, we present a perception-based navigation approach to the realization of mapping missions in unknown regions. Our approach is based on the iterative construction of an internal representation of the perceptual information acquired by the robot, which, conviently fused with the odometry information, can be used to contrariate the constant error growth of dead-reckoning navigation. During its exploration, the robot constantly updates this internal representation, trying to maximize the coherency of the topological relations between its elements. We use distinct uncertainty representation formalisms to represent the morphological properties of the environment (which are essentially dependent on the perception sensors) and position/orientation information, which is fundamentally related to odometry data. While the former is based on fuzzy set theory, the latter uses a conventional probabilistic framework.

In the paper, we show how the algorithm IFSHADES [2, 3] is used for producing an environment representation. Although IFSHADES has been defined in a general context, its current implementation considers the use of short-range distance sensors, and iteratively produces a representation of the (2D) shape of the objects present in the environment as a concatenation of fuzzy line segments and arcs of circle.

The spatial coherency of the representation produced by IFSHADES is optimized by a data fusion procedure that combines the stored representation with the current perceptual data. This fusion, which is performed when an association between perceived and learned objects is successfully made,

(a) (b)

Figure 1: (a) Detecting termination condition (b) Corrected representation.

yields a new (better) estimate of the robot's position and orientation. This new estimate is then backpropagated, enabling the correction of the topological relations between the objects perceived between the previous observation of the associated object and the time at which association is established. The paper presents a robust association procedure that uses the approximate shape representation provided by IFSHADES and that is based on possibility theory. The backwards correction procedure is inspired on techniques of optimal smoothing theory, and uses an analytical approximation to the error evolution of optimal filters to keep to a minimum computational requirements [4].

Figures 1–3 illustrate the evolution of an exploration of a region delimited by a closed contour. These experimental results were obtained using a mini-robotic platform equipped of odometric counters and a belt of proximity (infra-red) sensors.

The robot has been initially positioned near the external closed contour. It follows the wall, iteratively building a representation of its shape, using the algorithm IFSHADES, approximating the closed curved shape of the contour by a concatenation of fuzzy arcs of circle and segments of line. The observation of the wall is continued until completion of the external contour is detected. The detection of this termination (completion) is made by using the shape of the contour, and is based on the association of the shape elements observed twice. Figure 1(a) shows the simplified representation of the closed curved boundary obtained at the end of contour observation during one experiment with the Khepera. We also display the estimate of the robot's trajectory. The point at which the robot stopped is indicated by a small circle.

The transition between the two element shapes that produce a best match is used as a reference point in the backwards correction procedure. Figure 1(b) shows the corrected version of the exterior contour shown in Figure 1.

Once a corrected representation of the outside wall was finished, the robot started exploration of its interior, making a sequence of linear motions that take it in a randomly chosen direction until it finds another object. In this experiment, no objects were placed in the inside region, so the robot found the oposite region of the external contour. It then entered a trajectory parallel to it, producing a description of the part of the wall that it sees (using IFSHADES). Wall observation is continued until the association procedure establishes the association between elements of the new representation and the stored description. Figure 2 shows the trajectory of the robot during one exploration, and the shape elements generated during its subsequent observation of the exterior

(a) (b)

Figure 2: (a) Exploratory segment and repositioning (b) Correction of explored region.

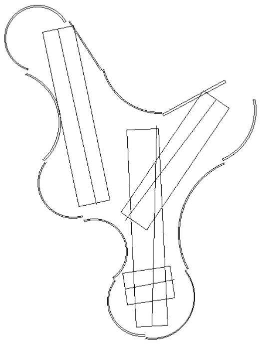

Figure 3: Outside contour and explored regions.

wall, for the same experiment as in the previous figures

At this point, a translation and rotation of the contact point are computed, enabling the correction of the traveled trajectory, as shown in Figure 2(a). Note that a correction of the estimated trajectory to the left side has been introduced, as a result of the association between perceived and stored wall shape.

Figure 3(b) shows the internal representation after a certain number of trajectories. The estimated exploratory trajectories are displayed along with the estimated regions that were actually covered by the robot (after correction), allowing appreciation of the corrections introduced.

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