Fuzzy Shape Recognition for Robot Repositioning

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Abstract

In this communication we address the problem of shape recognition in the context of autonomous navigation of mobile robots. We present an association procedure which is able to establish the correspondence between elements of a learned fuzzy internal representation of the environment and currently perceived objects. Using this procedure, a mobile robot is able to periodically decrease the uncertainty affecting its position.

1. Introduction

The aim of our work is to design procedures that allow a robot to explore unknown environments without getting lost, under the constraint that no global position information is available. If the range of the robots sensors is short compared to the distance between objects in the workspace, the robot needs to perform deliberate (blind) motions in order to navigate between objects. During this blind motion it can only rely on its on-board odometric sensors to estimate its position and orientation. To overcome the error growth associated to dead reckoning, the robot builts an internal representation of all objects that it encounters in the environment, using it later as reference for relocalisation purposes.

We use the algorithm IFSHADES that has been presented in [7] to build an uncertain description of the position and shape of the objects. IFSHADES is based on the theory of fuzzy sets [3], but differs largely from other fuzzy clustering methods as described in [8], [5], [2], that search for an optimal shape description. The paper presents a new procedure for robot repositioning (section 3), addressing the problem of associating the currently perceived object to existing elements of the environment representation. Section 4 presents results using a mini-robotic platform.

2. Fuzzy shape description (IFSHADES)

The algorithm is based on the notion of *fuzzy geometrical shapes* and operates in a completely iterative manner by updating existing shape elements with each new input point that can be successfully associated to them. New (multiple) hypothesis are created when no correspondance to any of the existing shape elements exist. Similar/redundant shape elements are recombined by definition of a fuzzy binary relation (generalized inclusion) between shape elements. As the robot progresses it creates a sequence of fuzzy shape elements that describe adjacent parts of the observed object and adds them to its internal environment representation

$$\Lambda^0 = \emptyset, \quad \Lambda^{k+1} = \Lambda^k \cup \lambda_k, \;\; k = 0, \ldots \tag{1}$$

where Λ^k is the complete internal representation at the $k-th$ iteration (see example in figure 1, based on fuzzy line segments and arcs), and λ_k is the most recently created shape element.

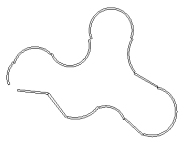

Figure 1. Fuzzy shape description

3. Object recognition

Before we address the problem of recognizing a complete shape coded by IFSHADES, i.e., a chain of elementary shape elements, we treat the simpler problem of defining a function that measures the degree of plausibility of the propositions

$$\lambda_k \text{ codes the same object as } \lambda_n, \quad \lambda_n \in \Lambda^{k-1}.$$

Let $A(\theta, P)$ be the affine map:

$$A(\theta, P) = T_P \circ R_\theta, \tag{2}$$

where R_θ denotes rotation by an angle θ around a fixed reference point (taken as the center of one of the first associated shape elements) and T_P translation by the vector $P^{(1)}$.

We say that *association* of λ_k to λ_n is *plausible* if there exists at least one pair (θ, P) such that

$$\lambda_n = T_P\left[R_\theta\left[\lambda_k\right]\right] \triangleq \lambda_{k,P,\theta}. \tag{3}$$

For each pair (θ, P) we measure the truth value of eq. (3) by the generalized inclusion of $\mu_{\lambda_{k,P,\theta}}$ in λ_n, see [3]:

$$S_{kn}(P,\theta) = \frac{\int \mu_{\lambda_n}(x,y) \wedge \mu_{\lambda_{k,P,\theta}}(x,y)\, dxdy}{\int \mu_{\lambda_k}(x,y)\, dxdy}. \tag{4}$$

Moreover each pair (P, θ) must be compatible with the current uncertainty in the robot's position and orientation, expressed by the fuzzy set $\mu_R(P,\theta)$, such that the plausibility that the two shapes are related through a rotation by θ and a translation by P is measured by:

$$\mu_{kn}(P,\theta) = \min\left(S_{kn}(P,\theta), \mu_R(P,\theta)\right),$$

Simplified expressions to compute equation (4) are implemented to reduce the compexity of the computation.

Having established how the association between two shape elements is determined, we can return to the problem of associating one chain of shape elements to other chains of shape elements.

Our algorithm works recursively. For each new λ_k, it builds an *association list* $L_k \subset \Lambda^k$, using the following rule

$$\max_{P,\theta} \mu_{kn}(P,\theta) > \epsilon \Rightarrow \lambda_n \in L_k,$$

where ϵ is a fixed treshold. L_k collects *all* shape elements that successfully associate with λ_k. A graph G^k is built, whose nodes (coding one association) are lists $\{L_{k-i}\}_{i=0}^{\ell}$, and whose arcs join all the elements of one list L_k to *all* the elements of the next list L_{k+1}, see figure 2. We associate to each *node* of G^k the membership function $\mu_{kn}(P,\theta)$.

Each *arc* has associated to it a membership function that expresses the compatibility of the source and sink nodes.

$$\begin{aligned} a^k_{n,m}(P,\theta) &= \min\left(\mu_{k-1,n}(P,\theta), \mu_{k,m}(P,\theta)\right), \\ & \quad \lambda_n \in L_{k-1}, \lambda_m \in L_k. \end{aligned}$$

The paths of G^k determine all the sequences of pairwise plausible associations of the elements of the recent chain with pre-existing shape elements in the representation. The evaluation of the plausibility of the sequence of associations implied by each path $p = \{a^{k-n}_{i_n j_n}, i_n \in L_{k-n}, j_n \in L_{k-n+1}, i_n = j_{n-1}\}_{n=0}^{\ell-1}$, of G^k is obtained by the following recursive computation:

[1] $\circ$ denotes operator composition

$$\begin{aligned} \mu_p(P,\theta)^0 &= a^k_{i_0,j_0}(P,\theta); \\ \mu_p(P,\theta)^n &= \min\left(\mu_p(P,\theta)^{n-1}, a^k_{i_{\ell-n},j_{\ell-n}}(P,\theta)\right), \\ & \quad n = 1,\ldots,\ell. \end{aligned}$$

This membership function associates to each path p, for a given affine map, the degree of compatibility of all nodes that belong to p.

A path with low degree of confidence $\max_{P,\theta} \mu_p(P,\theta) \simeq 0$ is no longer updated by new associations. Arcs that do not belong to any plausible path are removed from G.

Ambiguity in the recognition process is flagged if more than one distinct paths exist in G^k. Recognition is declared, if an unambiguous plausible maximum length path $p^\star$ is found. Note also that the algorithm automatically generates the required correction in the robot orientation and position, which are obtained by applying the affine map A^* that yields maximum plausibility of $p^\star$, see eq. (5)

$$A^* = T_{P^\star} \circ R_{\theta^\star}, \quad (P^\star, \theta^\star) = \arg\max_{P,\theta} \mu_{p^\star}(P,\theta). \tag{5}$$

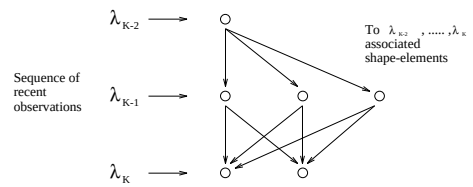

Figure 2. Example of ambiguous graph G_k.

4. Experimental results

We used the mini robot Khepera [4], equipped with odometric counters and infra-red proximity sensors, to validate the association procedure presented in the paper. Figure 3 illustrates the utilization of the association algorithm presented in the paper during an exploration of an a-priori unknown environment with the mission of returning home after having reached a predefined goal (indicated by $\oplus$).

The robot followed the border of a first object O_1, figure 3(a), using the IFSHADES algorithm to generate a set of fuzzy line segments, which are its internal representation of the shape of the object.

Using the association algorithm presented in this communication, the robot recognizes the two first shape elements produced, the second time it observes them, knowing at that point that it finished the observation of the object. The recognition of the first two elementary shapes produced allows: *(i)* the generation of a *corrected representation* of the shape of the object [1]; *(ii)* the generation of a *new estimate* of the robot's position according to equation 5.

Having finished the acquisition of the shape of object O_1, the robot starts exploration of the environment in direction of the goal, see (b). During the deliberate motion a on-line control of the autonomy (which is not a subject of this paper) [6] signals the robot that it should return to the object, preventing it from getting lost. As shown in (b) the robot returned to O_1, produced a new description and stopped after having recognized the object. The corrected position is shown in (c) where the robot continued the exploration in a distinct direction and encountered a new object O_2. Similarly to (a) the robot produced a description of the new object and repositioned itself with respect to the correct shape after having recognized two elementary shapes of the same object. The exploration procedure is repeated, resulting in the detection and observation of a last object O_3, see (d).

During the observation of O_3, the robot reached the goal and returns to the initial object O_1. The return trajectory is illustrated in (e,f). Figure 3(g) shows the robot's position after having reached object O_1 along with the complete environment description and the area of free space that was observed by the robot during periods of deliberate motion.

The usefulness of the approach is well illustrated by figure 3(h) where the same exploration is executed, without performing any correction of the robot's pose, yielding large errors accumulated both in position and orientation.

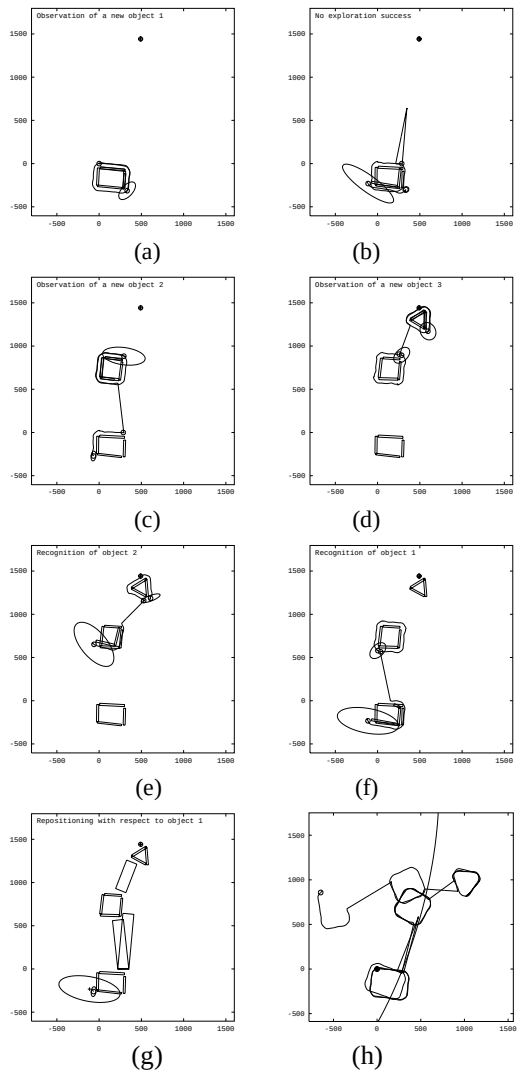

Figure 3. Goal driven exploration

5. Conclusions

We presented an algorithm for association of learned shape representations that derives a global measure of correspondence of two independently acquired shape representations by constructing fuzzy sets that identify the global rotation and displacement that best maps one representation into the other one. The feasibility of the approach was demonstrated during an exploration performed by the mini robot Khepera.

Acknowledgments

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