Autonomous Robot Navigation using Unsupervised Shape Description and Recognition

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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 based on fuzzy measures of association for object recognition, which is able to establish the association of a learned fuzzy internal representation of the object's shape and currently perceived objects. Using this procedure, the robot is able to periodically decrease the uncertainty with respect to its position, effectively using the information provided by its perception sensors in order to extend its autonomy.

1 Problem statement: Autonomous navigation

The design of autonomous navigation systems for mobile robots is still a challenge, requiring the definition of procedures that allow a robot to explore unknown environments without getting lost. In our work we consider a robot moving in an unknown environment, without access to global position information, the only means to estimate its position being on-board odometric sensors. To overcome the characteristic error growth associated to deadreckoning navigation, the robot builts a representation of the objects present in the environment, using it later as reference for relocalisation purposes.

In this paper we use the algorithm IFSHADES [1] to build an uncertain description of the shape of *each object* in the workspace of the robot. An *environment description* is obtained by describing the relative positions of all detected objects. IFSHADES represents shapes by using the concept of "fuzzy geometrical shapes", based on the theory of fuzzy sets [2]. This algorithhm has been presented in [1] and we just remember here (section 2) its fundamental characteristics. 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. Object recognition uses the fuzzy description provided by IFSHADES, and is also based on fuzzy measures of similarity and degrees of association. Section 4 presents preliminary results using a mini-robotic platform, showing the feasibility of the approach.

2 Fuzzy environment description (IFSHADES)

IFSHADES describes the shape of arbitrary objects as a sequence of basic geometric shape elements (in the current implementation fuzzy line segments and arcs of circle). These basic shape elements are formally defined as fuzzy subsets of the parameter space defining their usual (strict) counterparts, i.e., by considering as fuzzy entities parameters such as radius, arc length, orientation, etc.

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The algorithm operates in a completely iterative manner. For each new input point, the internal representation of all elementary shapes to which it can be successfully associated is updated. New (multiple) hypothesis are created when the input point does not belong to any shape element already existing. The definition of a fuzzy binary relation (generalized inclusion) between all the elements of the representation allows the deletion and recombination of spurious or redundant elements. As the robot progresses it creates a sequence of fuzzy shape elements that describe adjacent parts of the observed objects and adds them to its internal environment representation

$$\Lambda^0 = \emptyset, \quad \Lambda^K = \Lambda^{K-1} \cup \lambda_K \Rightarrow \Lambda^K = \{\lambda_k\}_{k=1}^K, \tag{1}$$

where Λ^k is the complete internal representation at the k-th$iteration, and \lambda_K$ is the most recently created shape element.

3 Object recognition

We describe the procedure that enables the establishement of an association between the most recent shape element, λ_K, and previously generated elements. More formally, this procedure checks whether λ_K corresponds to a new description of a shape for which a representation λ_i has already been generated ($i < K$). The robot searches in Λ^{K-1} for plausible descriptions of the same object as λ_K, building the list L_K:

$$\lambda_K \rightarrow L_K = \{\lambda_1^K, \ldots, \lambda_{n_K}^K\} \subset \Lambda^{K-1}, \tag{2}$$

using the following criterion:

$$\lambda_i \cap \lambda_K \neq \emptyset \Rightarrow \lambda_i \in \mathrm{L}_K, \tag{3}$$

i.e., L_K gathers all shape elements previously generated that have a non-empty intersection with λ_K. Notice that, due to odometry errrors and to the uncertainty of the representation, L_K can contain more than one element, flagging ambiguities in the association procedure. Using consecutive association lists, $L_{K-l}, \ldots, L_K$, a cycle-free weighted directed graph $G^K = (N_K, A_K)$ is constructed, where the nodes are the pairs of recent associations

$$N_K = \left\{(\lambda_i, \lambda_j^i); \quad i = K-l, \ldots, K; j = 1, \ldots, n_i\right\}, \tag{4}$$

and the set of arcs

$$A_K = \left\{a_{i,j,k} = (\lambda_i, \lambda_j^i) \rightarrow (\lambda_{i+1}, \lambda_k^{i+1}); \quad i = K-l, \ldots, K-1; j = 1, \ldots, n_i; k = 1, \ldots, n_{i+1}\right\} \tag{5}$$

join elements in consecutive association lists. An example is shown in figure 1. Each node in graph G_K corresponds to the identification of shape elements which are (individually) plausible distinct representations of the same object. If at least one of the association lists has more than one element, several distinct

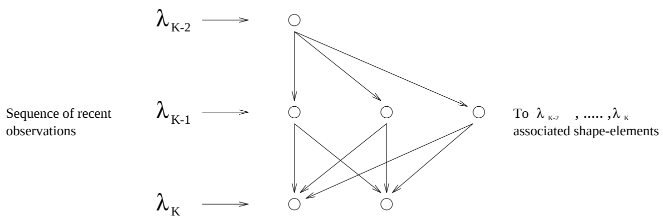


Figure 1: Example of ambiguous graph G_K.

paths exist in G_K, denoting ambigous identifications of some of the $l+1$ most recently perceived objects $(\lambda_{K-l}, \ldots, \lambda_K)$. Let p be a path in G_K, defined by a list of arcs:

$$p = (a_{K-l, j_{K-l}, k_{K-l+1}}, \ldots, a_{K-1, j_{K-1}, k_K}). \tag{6}$$

The arc weights $\mu(a_{i,j,k})$ in the graph G_k allow te determination of the plausibility of the corresponding associations. We evaluate a measure of correspondence of two sequences of shape elements using their pair-wise relative orientation and displacement, under the following two constraints:

- Invariance to rotation and translation.
- Consideration of the uncertainty of the shape description.

As we will see, in addition to a degree of plausibility of the association of the two sequences, an overall orientation change and displacement are also determined, allowing repositioning of the robot.

We remember that line segments and arcs of circles, the algebraic forms manipulated IFSHADES are defined by

Line segments: orientation α; middle point $P_M = (x_m, y_m)$; and length l.

Arcs of circle: radius r; center (x_c, y_c); orientation α (orientation of the line joining the center and the middle point $P_M = (x_m, y_m)$ of the arc; and angular aperture $\Delta\Theta$.

The (non-fuzzy) rotation, $\Delta\alpha$, and translation, ΔP, of a shape element λ_j with respect to another shape element λ_i are given by:

$$\Delta\alpha = \alpha(\lambda_j) - \alpha(\lambda_i) \qquad \Delta P = P_M(\lambda_j) - P_M(\lambda_i). \tag{7}$$

Using the measures of uncertainty produced by IFSHADES we associate to the orientation α and middle points P_M of each shape element membership functions $\mu_o^{\lambda_i}(\alpha)$ and $\mu_M^{\lambda_i}(P)$ given by

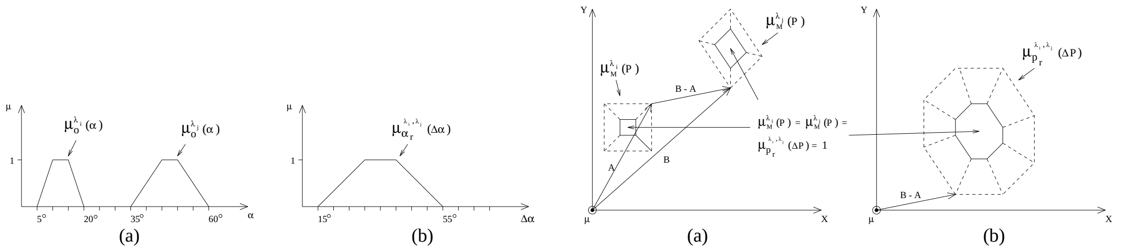
$$\begin{array}{rcccl} \mu_o^{\lambda_i}(\alpha) & : & \mathcal{R} & \to & [0,1] \\ & & \alpha & \leadsto & \mu_o^{\lambda_i}(\alpha) \end{array} \qquad \begin{array}{rcccl} \mu_M^{\lambda_i}(P) & : & \mathcal{R}^2 & \to & [0,1] \\ & & P & \leadsto & \mu_M^{\lambda_i}(P) \end{array} .$$

The definition of the fuzzy sets $\mu_{\alpha_r}^{\lambda_i,\lambda_j}(\Delta\alpha)$ and $\mu_{P_r}^{\lambda_i,\lambda_j}(\Delta P)$, that describe the fuzzy orientation change and displacement of the middle points implied by one association are, see figure 2,

$$\begin{aligned} \mu_{\alpha_r}^{i,j}(\Delta\alpha) &= \max_{\alpha,\beta:\Delta\alpha=\beta-\alpha} \left[\mu_o^{\lambda_i}(\alpha) \wedge \mu_o^{\lambda_j}(\beta)\right] \\ &= \max_{\alpha} \left[\mu_o^{\lambda_i}(\alpha) \wedge \mu_o^{\lambda_j}(\Delta\alpha + \alpha)\right], \quad \lambda_i \in L_j \end{aligned} \tag{8}$$

$$\begin{aligned} \mu_{P_r}^{i,j}(\Delta P) &= \max_{P,Q:\Delta P=Q-P} \left[\mu_M^{\lambda_i}(P) \wedge \mu_M^{\lambda_j}(Q)\right] \\ &= \max_{P} \left[\mu_M^{\lambda_i}(P) \wedge \mu_M^{\lambda_j}(\Delta P + P)\right], \quad \lambda_i \in L_j \end{aligned} \tag{9}$$

where we used the standard connective $a \wedge b = min(a, b)$.



(a) (b)

Figure 2: (a) Orientation change $\Delta\alpha$ implied by the association of λ_j with λ_i. (b) Displacement of the middle points ΔP implied by the association of λ_j with λ_i.

We can now compare the displacements of orientation and position of the middle points of consecutive associations based on the fuzzy sets computed in eq. (8) and eq. (9), computing the final two fuzzy sets, μ_α and μ_P, that label the arcs of the graph G_K:

$$\mu_\alpha^{i,j,k}(\Delta\alpha) = \mu_{\alpha_r}^{i,j}(\Delta\alpha) \wedge \mu_{\alpha_r}^{i+1,k}(\Delta\alpha) \tag{10}$$
$$\mu_P^{i,j,k}(\Delta P) = \mu_{P_r}^{i,j}(\Delta P) \wedge \mu_{P_r}^{i+1,k}(\Delta P) \tag{11}$$

The comparison of the displacement of the middle points is not independent of rotation. But, since $\mu_{\alpha_r}^{i,j}(\Delta\alpha)$ using the orientation of λ_j with respect to λ_i we can make the comparison of ΔP invariant to rotation by computing a new fuzzy set

$$\mu_M^{\lambda_i}(P_{new}) = \forall_{\Delta\alpha} \max_{P_{new}=R_{\Delta\alpha}P} \left(\mu_{\alpha_r}^{i,j}(\Delta\alpha) \wedge \mu_M^{\lambda_i}(P)\right), \qquad R_{\Delta\alpha} = \begin{bmatrix} \cos(\Delta\alpha) & -\sin(\Delta\alpha) \\ \sin(\Delta\alpha) & cos(\Delta\alpha) \end{bmatrix}. \tag{12}$$

Replacement of $\mu_M^{\lambda_i}(P)$ of eq. (9) by $\mu_M^{\lambda_i}(P_{new})$ yields comparison of the global displacement of the middle points invariant to the rotation.

Since simple pair-wise comparison of consecutive shape elements can lead to an optimistic evaluation of the overall plausibility of associating a sequence of shapes, we define, for each path $p \in G^K$, two fuzzy measures of the compatibility of the corresponding associations, $\mu_p(\Delta\alpha)$ and $\mu_p(\Delta P)$:

$$\mu_p(\Delta\alpha) = \min\left(\mu_\alpha^{K-l,j_{K-l},k_{K-l+1}}(\Delta\alpha), \mu_\alpha^{K-l+1,j_{K-l+1},k_{K-l+2}}(\Delta\alpha), \ldots, \mu_\alpha^{K-1,j_{K-1},k_K}(\Delta\alpha)\right) \tag{13}$$

$$\mu_p(\Delta P) = \min\left(\mu_P^{K-l,j_{K-l},k_{K-l+1}}(\Delta P), \mu_P^{K-l+1,j_{K-l+1},k_{K-l+2}}(\Delta P), \ldots, \mu_P^{K-1,j_{K-1},k_K}(\Delta P)\right) \tag{14}$$

Finally, the degree of plausibility of a path $p \in G^K$ is given by

$$\mu(p) = \min\left(\max_{\Delta\alpha}(\mu_p(\Delta\alpha)), \max_{\Delta P}(\mu_p(\Delta P))\right). \tag{15}$$

i.e., by checking the existence of an orientation change and global displacement that can make all the pair-wise associations plausible, Note that for plausible paths, the two fuzzy measures presented above directly give the rotation and translation that must be aplied to one of the sequences to make it correspond to the other one, i.e., the correction that must be applied to the robot's position and orientation. Paths with a low value of $\mu(p)$ are removed from G_K, by deleting all the corresponding arcs. Notice that two distinct paths may differ in just one arc. If all arcs descending from a node are deleted the node too can be deleted, implying a deletion of the arriving arcs and thus to the potential deletion of previous nodes. However, all nodes that are connected downwards to nodes by plausible arcs are kept as plausible associations. The robot continues its observations, augmenting the graph G_K, until a unique (plausible) path exist in the graph. In the current implementation the robot must recognize at least two shape elements that describe the object to be able to compute the deviation in position and orientation accumulated during the exploration.

4 Preliminary results

We let a small circular (52mm diameter) two-wheeled mobile robot (Khepera [3]), equipped with odometric counters and infra-red proximity sensors, run in a closed environment. Figure 3 illustrates the utilisation of the association algorithm presented in the paper. In this figure, we show the robot's estimation of its own trajectory, as infered from the odometric counters, as well as the internal representation of the shape of the objects detected by the robot in its workspace. In this figure, the positions indicated by $\oplus$ correspond to position estimates before correction (obtained by dead-reckoning), the corrected positions, using the association between previous and current observations being denoted by $\oplus$. The confidence ellipsis before and after correction are also displayed, showing the decrease in positioning uncertainty gained through use of perception information. The arrows indicate the direction of the robot.

The robot followed the border of the environment, using the IFSHADES algorithm to generate a set of fuzzy line segments, which are its internal representation of the shape of the contour wall. Using the association algorithm presented in this communication, it recognizes a part of the border that it already observed, knowing at that point that it finished the description of a closed contour. Using the associations established between current current and previous representations, it relocalises itself, by using the first (less uncertain) element of its representation of the contour, at position indicated as (1) in the figure. It subsequently explored the interior of the contour, generating a description of a polygonal object found in its interior. Using the association algorithm, the robot was able to relocalize again at position (2), and continued the exploration. Then, it started a new description of the border, recognized it, and relocalized at point (3), using its previous description of the border.

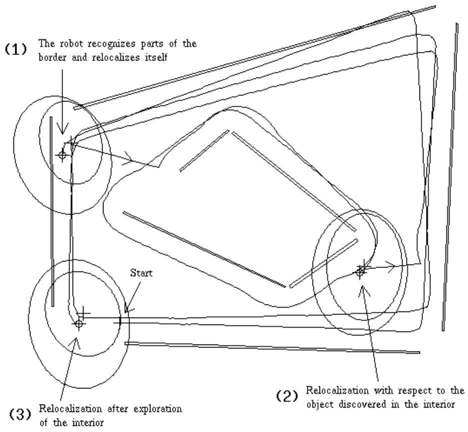


Figure 3: Exploration of the border and the interior of a closed environment

In the experiment shown, the description of the shapes is not corrected when the robot detects that it finished the acquisition of its constituing elements. Future work, will integrate a procedure that allows the correction of relative positions and orientations of the shape elements.

5 Conclusions

We presented an algorithm for association of learned shape representations based the propagation of fuzzy measures of the plausibility of a sequence of partial pairwise associations of the elements describing each representation. The algorithm derives a global measure of correspondence of two independently acquired shape representations by constructing fuzzy sets that identify the global rotation and displacement that can apply one representation into the other one. Experimental results in the context of mobile robotics are presented, demonstrating the usefulness of the proposed technique for periodic repositioning of a mobile robot in an unknown environment.

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References

[1] M.J. Rendas, S. Rolfes, "Incremental Fuzzy Shape Description", submitted to IEEE Trans. on Fuzzy Systems, May 1997.

[2] S. Gottwald. Fuzzy Sets and Fuzzy Logic: Foundations of Application from a Mathematical point of view, Wiebaden, Vieweg Verlag, 1993.

[3] Khepera: Users manual, K-Team, Laboratoire de microinformatique, Swiss Federal Institute of Technology (EPFL), INF - Ecublens, 1015 Lausanne/Switzerland