Shape Recognition: a Fuzzy Approach

Stefan Rolfes[1]
rolfes@isr.ist.utl.pt

Maria-João Rendas[2]
rendas@estrela.unice.fr

August 3, 2000

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, the robot is able to periodically decrease the uncertainty with respect to its position. In this way, the information provided by its perception sensors results in an effective extension of the robot's autonomy.

1 Introduction

The design of autonomous navigation systems for mobile robots in unknown environments requires 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 dead reckoning navigation, the robot builds a representation of the objects present in the environment, using it later as reference for relocalisation purposes. Our approach to the problem of robot navigation in uncertain environments is, to some extent, analogous to that of humans, used for instance by ancient times navigators when exploring the world in the XVI-*th* century. We rely, not on a precise and detailed environment description of the environment, and accurate knowledge of the position of the platform, but rather on a *topologically coherent* workspace representation, and on, each time, being able to situate the robot in this rough representation.

As the experiments presented in the paper show, with this approach the robot is able to displace itself in a previously unknown region, and use an acquired imprecise representation to infer its position with respect to the known part of the environment.

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 elementary "fuzzy geometrical shapes", based on the theory of fuzzy sets [2]. This algorithm has been presented in [1] and we just remember here (section 2) its fundamental characteristics that differ largely from other fuzzy clustering methods as described in [3], [4], [5], [6]. Opposite to IFSHADES these methods search for an optimal shape description and need the storage of all measurements, working e.g. on images. The paper presents a new procedure for robot repositioning (section 3), ad-

[1]ISR, Instituto Superior Técnico, Torre Norte Piso 7, Av. Rovisco Pais 1, P 1096 Lisboa Codex = Portugal.

[2]I3S CNRS URA 1376, Université de Nice Sophia Antipolis, Ave. Albert Einstein, Les Lucioles 1, 06560 VALBONNE, France.

dressing the problem of associating the currently perceived object to existing elements of the environment representation. The algorithm iteratively updates a graph whose *arcs* express the degree of confidence on pairwise associations of individual elementary shapes. Global correspondence is established on the basis of a similarity measure computed over the *paths* of this graph. 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.

Each elementary fuzzy shape λ is characterized by: *(i)* its *geometry*, described by a membership function $\mu_\lambda(x, y)$ that, at each point (x, y) of the space assigns a degree of membership of the point to the shape λ; *(ii)* uncertain *global position* p and orientation θ, described by membership functions $\mu_{\lambda_p}(p)$ and $\mu_{\lambda_\theta}(\theta)$, and that express the uncertainty in the robot's position and orientation when it first detected the shape.

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

$$\Lambda^0 = \emptyset, \quad \Lambda^{k+1} = \Lambda^k \cup \lambda_k, \quad k = 0, \ldots \qquad (1)$$

where Λ^k is the complete internal representation at the $k-th$ iteration, and λ_k is the most recently created shape element. The shape elements that are manipulated by IFSHADES are line segments and arc of circles, see figure 1.

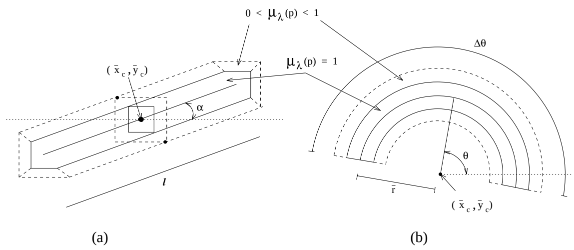

Figure 1: Example of (a) a fuzzy line segment and (b) a fuzzy arc of circle. The size of the shapes indicates the uncertainty in position of points that may belong to the shape

Detailed presentation of IFSHADES can be found in [1]. Here, we concentrate on *recognizing* the objects whose shape has been coded, by this algorithm, as a concatenation of elementary fuzzy shapes.

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

$$\lambda_k \text{ codes the same object as } \lambda_n, \quad n = 1, \ldots, k-1.$$

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

$$A(\theta, P) = T_P \circ R_\theta, \qquad (2)$$

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

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

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

with θ and P compatible with the position and orientations of λ_k.

For each possible 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 [2]:

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

The plausibility that the two shapes are related through a rotation by θ and a translation by P is measured by:

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

weighting in this way the compatibility of P and θ with the uncertainty associated to the position and orientation of λ_k.

Finally the desired degree of association between two shape elements is given by

$$\mu_{kn} = \max_{P,\theta} \mu_{kn}(P,\theta). \qquad (4)$$

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

Let Λ^k be the collection of all shape elements created before λ_k is produced, and $\lambda_k, \lambda_{k-1}, \ldots, \lambda_{k-\ell}$ be the $\ell+1$ most recent 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 :

$$\mu_{kn} > 0 \Rightarrow \lambda_n \in L_k,$$

where μ_{kn} is defined by (4). L_k collects *all* the shape elements that successfully associate with λ_k. A graph G^k is built whose nodes are the elements of the 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. Note that each node of this graph codes the association of one recently acquired shape element λ_k to an older shape element $\lambda_n, n < k$. We associate to such 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 pair of associations coded by the source and sink nodes. This compatibility is coded by a membership function that indicates the range of translations and rotations that are plausible for both associations:

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

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. Simple pairwise analysis of the associations would yield over optimistic evaluation of the plausibility of associating a complete chain of shape elements. A more adequate evaluation of the plausibility of the sequence of associations implied by each path $p = \{a^{k-n}_{i_n j_n}, i_n \in L_k, j_n \in L_{k+1}, i_{n+1} = j_n\}_{n=0}^{\ell}$, of G^k is obtained by the following recursive computation:

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

This membership function associates to each path, for a given affine map, the lowest value of the set of pairwise associations that it defines. Finally, a degree of confidence on the sequence of associations is computed by

$$\mu_p = \max_{P,\theta} \mu_p(P,\theta). \quad (5)$$

The plausibility of a path may decrease when new arcs are added to it by observation of new shape elements. This fact enables deletion of arcs from G, eliminating ambiguities in the association. In fact, whenever $\mu_p \simeq 0$, the nodes of p that are not nodes of another plausible path are removed from the graph.

Note that the fact that the algorithm does not require that adjacent nodes in G are consecutive elements of Λ increases the robustness of the algorithm with respect to wrong shape segmentation during the coding process, and to partial or spurious observations.

If more than one distinct paths exist in G^k, multiple associations are possible, flagging *ambiguity* in the recognition process. The algorithm terminates, and 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. (6)

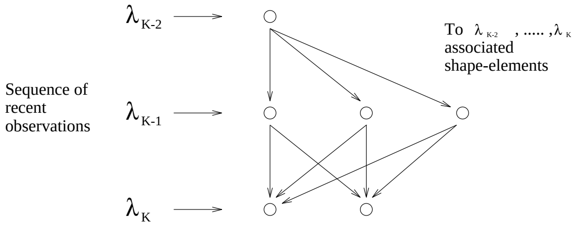

Figure 2: Example of ambiguous graph G_k.

$$A^* = T_{P^\star} \circ R_{\theta^\star}, \quad (P^\star, \theta^\star) = \arg\max_{P,\theta} \mu_{p^\star}(P,\theta). \quad (6)$$

Direct computation of the membership functions and degrees of confidence for all paths, as presented above, is computationally demanding. We implemented approximate expressions, which can be shown to yield upper bounds on the degrees of confidence of the paths of G. Lack of space prevents detailed presentation of these expressions here, and will be done elsewhere.

The next section presents experimental results which demonstrate the reliability of the associations produced by the recognition algorithm.

4 Experimental results

We let a small circular (52mm diameter) two-wheeled mobile robot (khepera [7]), equipped with odometric counters and infra-red proximity sensors, run in a closed environment. Figure 3 illustrates the utilization of the association algorithm presented in the paper during an exploration that consists of 6 exploration phases.

For each phase we plot the robot's estimate of its own trajectory as inferred from the odometric counters (solid lines), the internal representation of the shape of the objects detected by the robot in its workspace (sequence of rectangles and circular sections) and the final position estimate after recognition of an object (with a $\oplus$). The confidence ellipsis at the beginning (corrected position) and at the end (uncorrected position) of each exploration phase are also displayed.

The robot followed the border of the environment, figure 3(a), using the IFSHADES algorithm to generate a set of fuzzy line segments and arcs of circle, which are its internal representation of the shape of the contour.

Using the association algorithm presented in this communication, the robot recognizes the two first shape elements produced (arc of circle and line segment) the second time it observes them, knowing at that point that it finished the observation of a closed contour. The robustness of the association procedure with respect to the length of each individual shape element can be seen, by noting that the initial observation started in the interior of the curved portion coded by the second arc of circle.

The ellipsis shown in this figure shows the final position uncertainty of the robot with respect to its initial position. Note that this error region is entirely determined by the dynamic characteristics of the robot and by the noise in the odometric measures, no a priori constraints being assumed by the positioning filter, since the environment is assumed completely unknown.

The recognition of the first two elementary shapes produced allows: *(i)* the generation of a *corrected representation* of the shape of the contour, by fusing the information in the two separate observations of the same wall segment [8]; *(ii)* the generation of a *new estimate* of the robot's position - as explained at the end of the previous section – which is coherent with the corrected representation.The result of these two steps can be appreciated in (b), by noting that a single arc of circle and line segment code the region of the wall observed initially, and that uncertainty has been considerably reduced – since the robot is close to its position at the beginning of the exploration.

Having finished the acquisition of the contour shape, the robot starts, in a random direction, exploration of its interior, see (b). It detects a polygonal object, and moves around it to produce a chain of fuzzy line segments. After having repeated the observation of 3 of its sides, it successfully associates them with the first 3 line segments of the object, in spite of the small arc of circle that has been generated during the observation of the object's corner. The two steps performed in the transition (a)$\rightarrow$(b) are again executed, resulting in the initial configuration for figure (c), where the robot moved back to the contour to reposition itself again (twice, see (c) and (d)) by recognizing two distinct sequences of a line and an arc. In (e) the robot does a second exploration, finding a second polygonal object, performing the same operations as in (b). In this case, a second observation of only two of its sides were enough to establish the association.

In (f), similar to (c), the robot refers again to the external contour, to reposition itself – after the recognition of a sequence of a curved and linear part of the contour – with small uncertainty since this portion of the contour is close to the initial position, and thus accumulated uncertainty was small when it acquired its representation for the first time. This uncertainty decrease is evident in (g) where the robot's position estimate before (+) and after ($\oplus$) repositioning are shown, along with the corresponding error reduction.

5 Conclusions

We presented an algorithm for association of learned shape representations based on 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 best maps one representation into the other one. Experimental results are presented, demonstrating the usefulness of the proposed technique for periodic repositioning of a mobile robot in an unknown environment.

Acknowledgments

This work has been partially funded by the European Union through the ESPRIT (Long Term Research) project no. 20185 NARVAL (Navigation of Autonomous Robots via Active Environment Perception).

References

[1] M. João Rendas and S. Rolfes, "Incremental Fuzzy Shape Description," submitted to *IEEE Trans. Fuzzy Systems*, 1997.

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

[3] H. Timm and F. Klawonn, "Object recognition with fuzzy shell cluster analysis," in *Proc. of the EUFIT'97*, 1997, pp. 1039–1043.

[4] R. Krishnapuram, H. Frigui, and O. Nasraoui, "The Fuzzy C Quadratic Shell clustering algorithm and the detection of second-degree

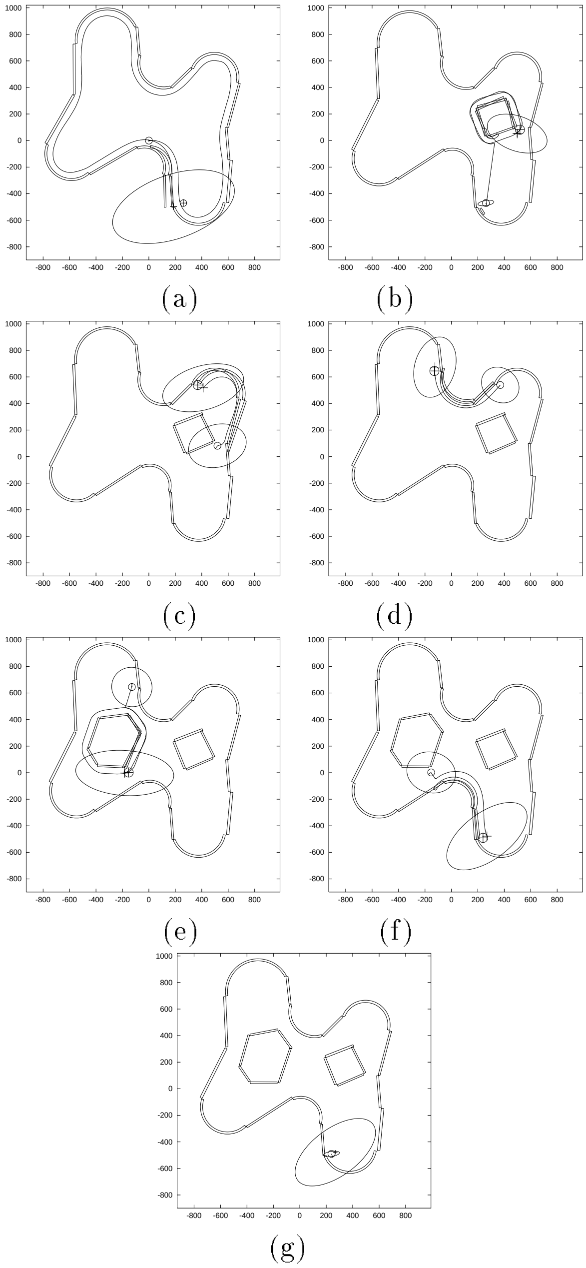

Figure 3: Exploration of the border and the interior of a closed environment

curves," *Pattern Recognition Letters*, vol. 14, pp. 545–552, 1993.

[5] I. Gath and A.B. Geva, "Unsupervised Optimal Fuzzy Clustering," *IEEE Transactions on Pattern Analysis and Machine Intelligence*, vol. 11, pp. 773–781, 1989.

[6] R. Krishnapuram, H. Frigui, and O. Nasraoui, "Fuzzy and Possibilistic Shell Clustering Algorithms and Their Application to Boundary Detection and Surface Approximation - Part 1 & 2," *IEEE Transactions on Fuzzy Systems*, vol. 3, pp. 29–60, 1995.

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

[8] F. Bouvier and M.J. Rendas, "Estimation et correction statistique de trajectoires en robotique mobile par intégration d'informations globales," Tech. Rep. (96-44), CNRS, Laboratoire I3S, September 1996.