Landmark Recognition for Autonomous Navigation Using Odometric Information and a Network of Perceptrons

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Abstract In this paper two methods for the detection and recognition of landmarks to be used in topological modeling for autonomous mobile robots are presented. The first method is based on odometric information and the distance between the estimated position of the robot and the already existing landmarks. Due to significant errors arising in the robot's position measurements, the distance-based recognition method performs quite poorly. For such reason a much more robust method, which is based on a neural network formed by perceptrons as the basic neural unit is proposed. Apart from performing very satisfactorily in the detection and recognition of landmarks, the simplicity of the selected ANN architecture makes its implementation very attractive from the computational standpoint and guarantees its application to real-time autonomous navigation.

1 Introduction

Autonomous navigation is a hot topic in the field of advanced robotics, with a relative long existence since the first prototypes of mobile robots developed in the mid sixties. Through all these years two main approaches can be considered as consolidated paradigms for the design and implementation of autonomous navigation systems. The first one, chronologically speaking and undoubtedly the dominant approach, is based on the use of models of the environment in which the robot navigates. The second one has appeared as the field has matured and it has become an evidence the impossibility of building completely autonomous robots by relying exclusively on models or maps of the environments, mainly due to two reasons: (1) the lack of the required perceptual abilities from the part

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of the robots themselves and (2) the lack of appropiate formal and mathematical tools for environment's modelling. As a consequence, the so-called reactive paradigm [1,2] has emerged as a theoretical and practical alternative, or rather as a complement, to the conventional model-based approach. Confining our discussion to the model-based autonomous navigation, one key issue is to detect and recognize the so-called reference places or landmarks, which are basic elements for the map building endeavor [3,4,5]. In this paper we present a contribution to the landmark detection and recognition problem.

The detection of the reference places allows the creation of environment landmarks for use in the exploration, planning and navigation tasks. Besides the detection ability, in the exploration and navigation tasks the distinction between a new and an already created landmark —i.e. landmark recognition— is also required.

In [6] we propose a method for the detection of reference places that does not employ sensory information but the information provided by the robot's control subsystem. The changes in the behavior modes of the control subsystem generated by the presence of obstacles allow the creation of reference places.

In the sequel we describe two methods for the recognition of the reference places. In the first and more primitive method, the current distances of the robot to the already known landmarks are used for recognition purposes; in the second and much more powerful method a network of perceptrons recognizes the landmarks.

2 Distance-based Recognition of Reference Places

In this method the robot's position and those of the existing landmarks are utilized for recognition purposes. Then, let p_n be the current reference place to be recognized, with cartesian coordinates $\boldsymbol{p}_n = (x_n, y_n)$ and angular coordinate θ_n and let $P = \{p_0, ..., p_m\}$ be the set of existing landmarks with coordinates $\boldsymbol{p}_i = (x_i, y_i)$ and θ_i for each $p_i \in P$ as computed in the robot's reference system. If the euclidean distance between two landmarks p_i and p_n is:

$$d(\boldsymbol{p}_i, \boldsymbol{p}_n) = \sqrt{(x_i - x_n)^2 + (y_i - y_n)^2} \tag{1}$$

then the nearest reference place p_c to the current landmark p_n is $p_i \in P$ such that minimizes (1); that is:

$$p_c \mid d_c = \min[d(\boldsymbol{p}_i, \boldsymbol{p}_n)] \ \forall p_i \in P \tag{2}$$

in which d_c is the euclidean distance between p_c and p_n. The relationship between the orientation of both reference places is:

$$\delta_c = |\theta_c - \theta_n| \tag{3}$$

The recognizer will classify the current landmark p_n as unknown if its distance to the nearest existing landmark is greater than a certain threshold t_d and if their orientation differs at least in some threshold t_δ. In a formal way:

$$p = \begin{cases} p_c \text{ iff } d_c < t_d \text{ and } \delta_c < t_\delta \\ p_n \text{ otherwise} \end{cases} \tag{4}$$

The thresholds t_d and t_δ permit a posterior refinement in the recognition process in order to identify the landmarks with a greater exactness. Threshold t_d depends on the available precision in the estimation of the robot's position. Threshold t_δ determines the precision in the orientation of the robot's approach to a landmark. Obviously, $t_\delta = 2\pi$ means that the robot's orientation has no influence on the recognition process.

3 Landmark Recognition Using a Network of Perceptrons

The recognition of reference places by means of distance-based information works appropiately for highly structured environments and when the exact position of the robot is available, which unfortunately is not very common. Therefore, more robust methods for landmark recognition are necessary.

In the sequel we present an algorithm that employs a network of perceptrons for the landmark recognition task. The only information injected into the perceprons —i.e. the basic neural units— is the readings of the sonar sensors on-board the robot. This information is extremely simple making the method very attractive from the computational standpoint. A raw estimation of the robot's position can be used as well for the final recognition in case of a draw among several perceptrons.

Let $p_i \in P$ be a concrete, existing reference place. We define s_i as the sensory register of landmark p_i, with s_i being a vector of dimension M and formed by the M robot's sonar sensors measurements at place p_i.

The training set $S = \{s_1, ..., s_n\}$ is formed by the sensory registers taken during different visits to each individual landmark. Every reference place has at least one sensory register in the training set. We also define a function $f : P \times S \to [0, 1]$ that associates each landmark $p_i \in P$ with the sensory registers $s_i \in S$.

A perceptron with M inputs and a single output is associated with each landmark. Graphically, we can represent the network of perceptrons as in the Figure 1. Each landmark holds information related to its position in the environment, links to other connected landmarks and the perceptron.

Every perceptron is trained with the complete training set S in order to be properly activated whenever the input corresponds to a sensory register of the associated landmark. Formally stated, for each perceptron Π_i adscribed to landmark p_i, it holds:

$$\Pi_i = f(p_i, s_j)\ \forall s_j \in S \tag{5}$$

Therefore, when a new reference place p_n is detected during the recognition process, the perceptrons activated by the current sensory register are associated with the most similar existing landmarks:

$$P_c = \{p_i\}\ \forall\, \Pi_i = 1 \tag{6}$$

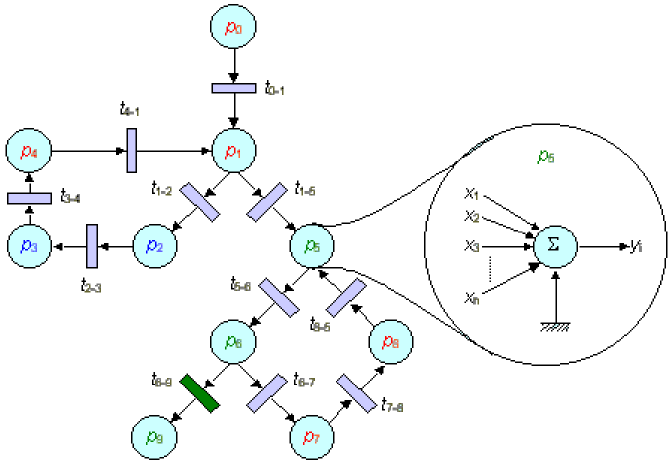

Figure 1. Net of landmaks with detailed information about a node

Afterwards, the landmark $p_c \in P_c$ nearest to the currently detected place p_n is selected:

$$p_c \mid d_c = min[d(\boldsymbol{p}_i, \boldsymbol{p}_n)] \; \forall p_i \in P_c \tag{7}$$

Finally, a test is carried out to decide whether or not both landmarks, the detected one and the existing one, are the same. This test is performed by applying a distance threshold t_d on d_c.

A positive test indicates that the current landmark is actually one of the already existing landmarks, i.e. p_c, and a negative test means that the current landmark p_n is a new reference place. In a formal way:

$$p = \begin{cases} p_c \text{ iff } d_c < t_d \\ p_n \text{ otherwise} \end{cases} \tag{8}$$

The t_d threshold can be made significantly greater than the threshold used in the distance-based recognition phase as the sensory information used by the networks of perceptrons has been able to dramatically refine the landmark recognition by a strong reduction of the search region.

4 Application to Autonomous Navigation of Mobile Robots

In our simulation and development environment the exact position of the robot is obviously available —unless we introduce simulated errors— and the distance-based recognition guarantees a perfect recognition of the reference places. Such accuracy permits an excellent validation of the model-building process and a reliable quality test of the neural network-based recognition method. The thresholds used in the distance-based recognition are $t_d = 15$ inches, that gives a slightly higher tolerance than the robot's radius of 10 inches and $t_\delta = \pi/4$ that guarantees a suitable rank of orientations for the type of landmarks occurring in our experiments —indoors environments—.

In Figure 2 are displayed several reference places that have been detected and recognized by just applying the distance-based recognizer. For this example, the threshold relative to the robot orientation has not been applied.

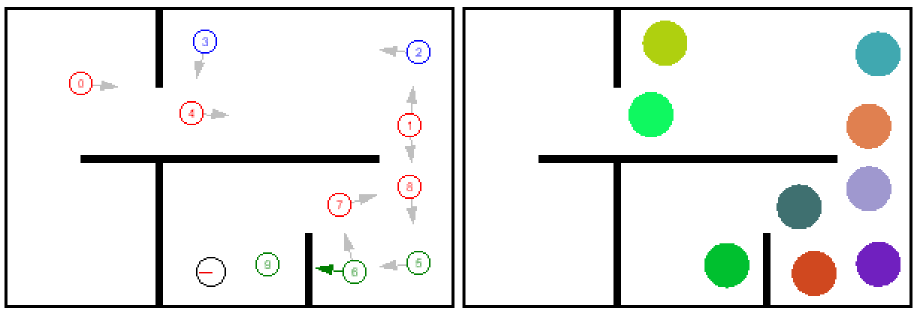

Figure 2. An example of landmarks detection and recognition employing only the distance-based method

In principle, the recognition of landmarks using the network of perceptrons has the important advantage of being almost independent on the errors of the estimated robot's position as it is based on the sensors readings. However, in our first experiments the results were unsatisfactory, even for simulated environments; the reason being quite obvious: the resemblance of the sensors readings for landmarks of similar shape: walls, corners, doors and so on. Concerning such problem, just observe landmarks p_2 and p_3 in Figure 3. Both reference places are of the same type —i.e. corners— although they are different physical landmarks. The sensory register for both landmarks are extremely similar: small magnitudes on the front side and on the right side and big magnitudes for the rest. In a similar fashion, landmarks p_1 and p_4 are of the same kind —i.e. bifurcations— and therefore present the same problem. In such situations, even with a sophisticated recognition algorithm, different physical landmarks of the same type cannot be correctly discriminated.

In order to overcome this serious problem and to increase the difference among the measurements produced by the set of landmarks, the coordinates of the robot's sensors are rotated to coincide with the robot's orientation θ_R. The formal expression of this base change is:

$$s_j = s'_i \mid j = \left(\frac{\theta_r}{2\pi/M} + i\right) \mod M \tag{9}$$

where s_j is the sensor readings after transforming the original readings s'_i; M is the number of sensors —which in our case have been placed in a totally sim-

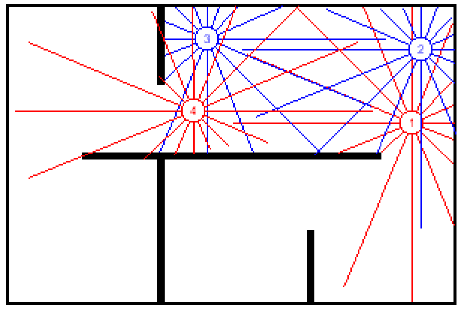

Figure 3. Average sensory register for two similar landmarks

metrical radial configuration— and $i, j \in [0, M)$ are indexes for each particular sensor.

In Figure 4 are displayed the landmarks detected and recognized by a network of perceptrons with thresholds $u_d = 30$ inches —i.e. three times the robot's radius— for the environment of Figure 2. During the exploration of this particular environment a 100% success ratio was obtained, for both new landmarks and already existing —i.e. revisited— landmarks: reference places p_1, p_5 and p_6.

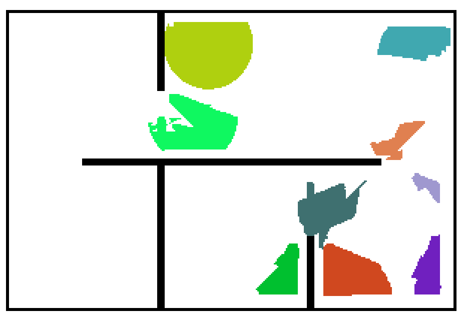

Figure 4. Regions corresponding to the landmarks detected and recognized using the perceptron network

Whenever a landmark cannot be recognized with absolute accuracy using the perceptron network, it is advisable to simultaneously employ the distance-based method in order to get an estimation of the robot's physical position and its distance to the nearest existing landmark. In spite of the position errors, the distance-based recognizer provides a valuable second vote for landmark detection and recognition. Eventually, in the worst case of the robot not being able to recognize a particular landmark, the only consequence is that the environment model will create a new landmark instead of employing the existing landmark associated with the corresponding region.

If a successful recognition has been performed when using the distance-based method as the background recognition process, then the corresponding sensory register has to be incorporated to the training set of the perceptron network. This new training element is incorporated inmediately after the distance-based landmark recognition has been accomplished in order (a) to avoid future errors in the landmark recognition by the perceptron network and (b) to update all the perceptrons with the new element. As the number of both the training instances and perceptrons is relatively small, the training duration is almost insignificant.

The formal description of the algorithm for the combined recognition process —i.e. the perceptron network and the distance-based recognizer— for both (1) recognition of a new landmark p_n and (2) the introduction of new instances in the training set S, is as follows.

1. If the reference place or landmark p_n can be recognized by means of expression (8), then the recognized landmark corresponds to landmark p_c, i.e. $p = p_c$.
2. Else, determine whether or not the reference place p_n can be recognized using expression (4).
   (a) If the recognition is performed, then the reference place is $p = p_c$ and the training set is consequently augmented $S = S \cup s_n$ with $f(p_c, s_n) = 1$ y $f(p_i, s_n) = 0 \ \forall p_i \neq p_c$ and the set of perceptrons Π_i are trained according to expression (5).
   (b) Else, the new landmark is $p = p_n$ and the training set is accordingly updated $S = S \cup s_n$ with $f(p_n, s_n) = 1$ and $f(p_i, s_n) = 0 \ \forall p_i \neq p_n$ and the set of perceptrons are trained according to expression (5).

5 Conclusions

Two methods have been proposed for the detection and recognition of landmarks in the creation of environment's models or maps, a fundamental issue in the autonomous navigation of mobile robots. The first method for landmark recognition employs the distance between the estimated position of the robot and the already existing landmarks. Due to the significant errors arising in the robot's position measurement, the distance-based recognition method performs quite poorly. For this reason we have introduced a much more robust and reliable second method, which is based on a neural network formed by perceptrons as the basic neuronal units. In order to optimize the success ratio in the detection and recognition of reference places we have combined both methods, with the distance-based recognizer acting as a background option.

The justification of a rather simple neuron prototype as the perceptron is twofold. In the first place, we have found through experimentation that more complex neural structures, for instance the multilayer perceptron trained with a well-tested learning algorithm, perform quite similarly to the network of perceptrons used in our work. The advantages in implementation, mainly storage requirements and computation time, for the simplest neural network are evident.

In the second place, the computation burden in the training phase is almost insignificant. For environments with say 50 reference places and two samples in average for each landmark, the total computation time is always lower than 50 ms. Such fast performance is absolutely crucial for real-time navigation as the training phase can be executed under a low priority process, which for the architecture implemented in our mobile robot is almost compulsory [6,7]. Last but not least, the reconfiguration process in the number of neuron units due to the incorporation of a new landmark is immediate, as a new perceptron is added to the network whenever a new landmark is detected and the augmented neural network is easily re-trained. For any other neural network architecture different than the one used in our work, a maximum number of outputs should be defined at the beginning of an exploratory mission —i.e. the phase in which the robot creates the map of the environment by detecting landmarks— or it should be necessary to dynamically modify the outputs of the neural network. For multilayer perceptron networks the process could be even more involved because the hidden layers are much more difficult to update for each new neuron unit added to the output layer. An additional advantage of the network of perceptrons is the straightforward updating of the network parameters whenever a new landmark is introduced in the environment's model.

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