Map building with ultrasonic sensors of indoor environments using neural networks

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Map Building with Ultrasonic Sensors of Indoor Environments Using Neural Networks

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Abstract

Map Building and Position Estimation are basic tasks in mobile robot navigation with path planning. A method to generate a global map of the vehicle work environment using ultrasonic sensors is developed in this paper. Depending on the physical properties of the walls that form the room where the robot is navigating, sonar sensors show different behaviours. A neural network is utilized to interpret the range readings of ultrasonic sensors in the different environments. A local map composed of squared cells is formed through the neural network that gives the occupancy probabilities for each cell. Finally, a global map is built achieving integration of different views of the environment using Bayes' rule. Results of the method implementation in the construction in specular environment as well as in rough wall environments are shown in this paper.

1 Introduction

Map building is an important matter in control architectures that employs planned motions, in the sense of not needing a priori knowledge of the environment. Through an exploration, the robot is able to make an internal representation of its work environment.

The choice of internal map representation depends on various characteristics but mainly of the environment itself [1]. For indoor high density environments, a metric map is a more compacted representation of the environment. The squared grid maps are the most widely used of this kind of environment models [2, 3, 4, 5]. Moreover, employing grid map, path planning is quite simple.

The grid map building philosophy shown in this paper was introduced by Thrun [6]. It was later used by other authors [7, 8]. This method basically consists of building a local map utilizing ultrasonic sensors, taking into account the cell probability concept introduced by Elfes [4], using a neural network to decide this probability values. A global map can be obtained integrating successively different local views of the environment interpreted as probabilities by the neural network.

The main contribution in this paper has been the development of a robust map building system for different nature environments, without having to train the neural network each time the room changes. To validate the approach two extreme cases have been tested: a full specular environment with smooth walls and another with rough walls where sensors work as almost ideal behaviour giving a range close to the real distance. Experimental results have been obtained with a Polaroid Ranging System with transducers 7000 and 600 series, and our robots RWI-B21 and Robuter II (see Fig 1).

Section two shows the sensor models adopted and results of the sonar measures obtained in our laboratories. Next, map building approach employed is explained in section three. Finally, section four presents the results obtained in different environments with this map building method.

2 Ultrasonic Range Sensors Response

In the external sensoring field used in mobile robotics, ultrasonic sensors for range measures have been widely employed in the last few years, mainly due to their simplicity, robustness and low cost. However sonar range readings are affected by many factors such as the wide angle of their radiation lobes, multiple reflections (specular reflections), diffuse reflections, fluctuations in the propagation medium and so on.

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Figure 1: One of our Robots:RWII B-21 (Univ. of Murcia).

One of the most common sources of error in range reading are multiple reflections that depend on object surfaces over which sonar wave is reflected. A classification between smooth wall environments (specular rooms) and rough wall environments is done by most of authors. For high incidence angles, multiple reflection are produced in the first type of walls (smooth walls) causing greater range readings than the real distances.

In one of our laboratories, various tests with Polaroid ultrasonic sensors (600 and 7000 series) were carried out in order to prove the specular reflection effects upon an environment with smooth walls made up of completely smooth veneered wood. Two positions of a plant corresponding to trials achieved in this laboratory is showed in figures 2 and 3. A Polaroid 7000 rotary transducer (one degree resolution) that transmits 16 cycles of a 52KHz squared wave was used in this experiment. Multiple reflections for high incidence angles can be observed in these figures as well as the plot of the range versus the transducer orientation which allows to show the first side-lobes effect at short distances (figure 3). It can also be observed in figures 2 and 3 (plot of range versus transducer orientation) how range readings in plants with specularities is composed of straight values, called by authors as Regions of Constant Depth [9, 1].

A bibliography review allows to realize that probability models are usually used by many authors when ultrasonic sensors is utilized to implement grid map building algorithms [2, 3, 4, 5, 10]. On the other hand, other authors model the sonar sensor taking into account its physical nature and the surrounding properties. Kuc and Siegel [11] model a round transducer with an impulse model, Kuc and Viard [12] model it with a Gaussian function. McKerrow and Hallam [13] propose a Bessel function considering also the side-

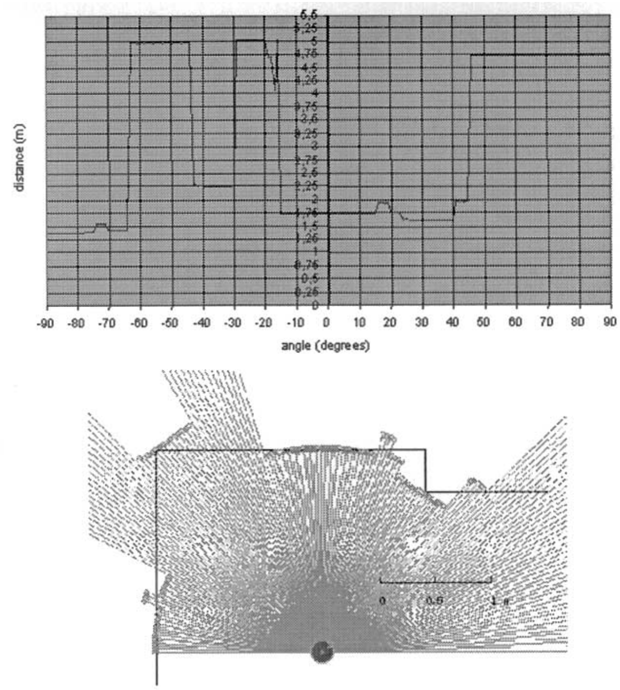

Figure 2: Range versus orientation and sonar scan of Plant1, Position A.

lobes apart from the main-lobe.

A geometric sensor model for specular surroundings is developed by Leonard [9]. In this model he differentiates between four classes of elements called targets: planes (walls), corners, edges and cylinders. This model is strictly geometrical and with low computational cost, simplifying enormously the Kuc and Siegel one [11], on which ideas it is based, obtaining a good simulation of sonar response.

For a plane, represented as a line in hessian normal form, its parameters can be defined as $p_{pl} = (p_R, p_\phi, p_V)$, with p_V +1 or -1 indicating the visible semiplane. The range and the bearing to target are defined according to,

$$r_{pl}(k) = p_V(p_R - x_s(k)cos(p_\theta) - y_s(k)sin(p_\theta)) \quad (1)$$
$$\phi_p l = p_\theta,$$

where (x_s, y_s) is the sensor position. Both the corners and edges are represented as points pc=(px,py) and the range and the bearing to target are calculated as

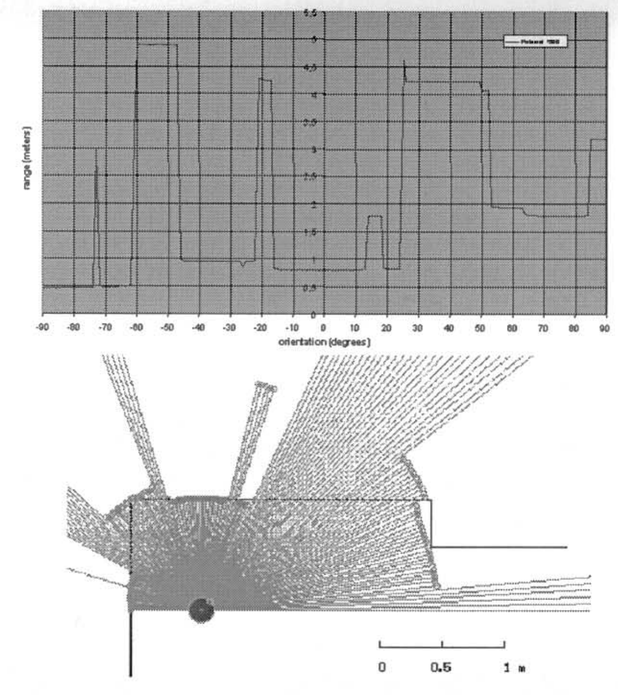

Figure 3: Range versus orientation and sonar scan of Plant1, Position C.

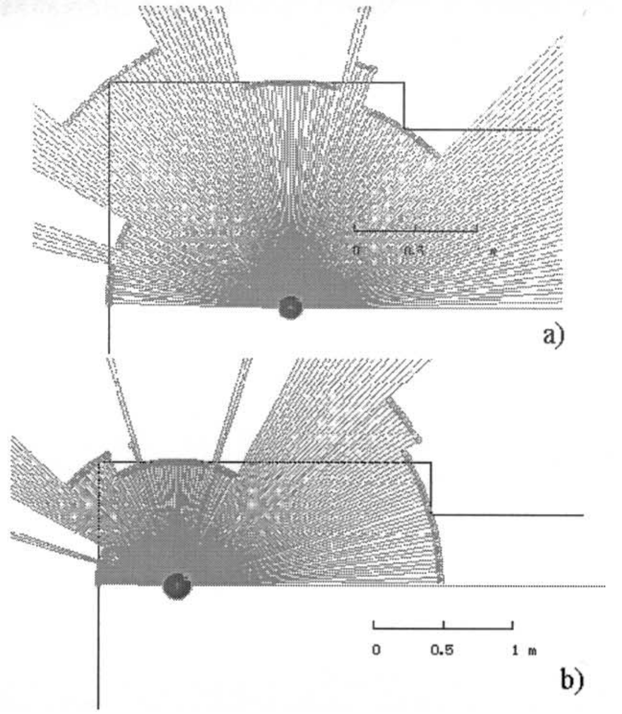

Figure 4: Simulated scan obtained with the proposed model:a)Plant 1,Position A b)Plant 1,Position C.

follows,

$$r_c(k) = \sqrt{(p_x - x_s(k))^2 + (p_y - y_s(k))^2} \quad (2)$$

$$\tan(\phi_c(k)) = \frac{p_y - y_s(k)}{P_x - x_s(k)}, \qquad p_x \neq x_s(k)$$

The cylinders are represented by its centre and radio pcy=(px,py,pR) and its range and bearing to target are defined as,

$$r_{cy}(k) = \sqrt{(p_x - x_s(k))^2 + (p_y - y_s(k))^2} - p_R \quad (3)$$

$$\tan(\phi_{cy}(k)) = \frac{p_y - y_s(k)}{p_x - x_s(k)} \qquad p_x \neq x_s(k)$$

All the previous ranges allow to obtain readings to targets as long as they are not occluded and the sensor orientation with respect to the object is within the visibility angle of target [9].

The model adopted in this research has been Leonard one, where the side-lobes effect at short distances has also been included. The use of this model allow not to lose the physical point of view of the system and therefore a more real physical sensorial interpretation of each kind of target can be done.

In figure 4, a representation of the sensor model behaviour in the specular environment is shown. These simulated scanners can be compared with the real ones obtained with Polaroid transducers (figures 2 and 3).

Second type of environments correspond to those with rough walls, where the specular reflection effect has very few probabilities, giving a range reading quite approximate to the real distance. Within this sort of walls, a more detailed classification ought to take into account the ridged wall grade associated with the sonar wavelength. A wall with sonar wavelength irregularities can cause an almost ideal behaviour of sonar sensors. Figure 5 illustrates the behaviour of a 7000 Polaroid sonar transducer in respect to a granulated paint wall at two various distances.

3 Map Building

A method with two main steps is employed to build an environment map: the interpretation of the sonar readings, and the integration of the different views of the surrounding and the global and local map matching.

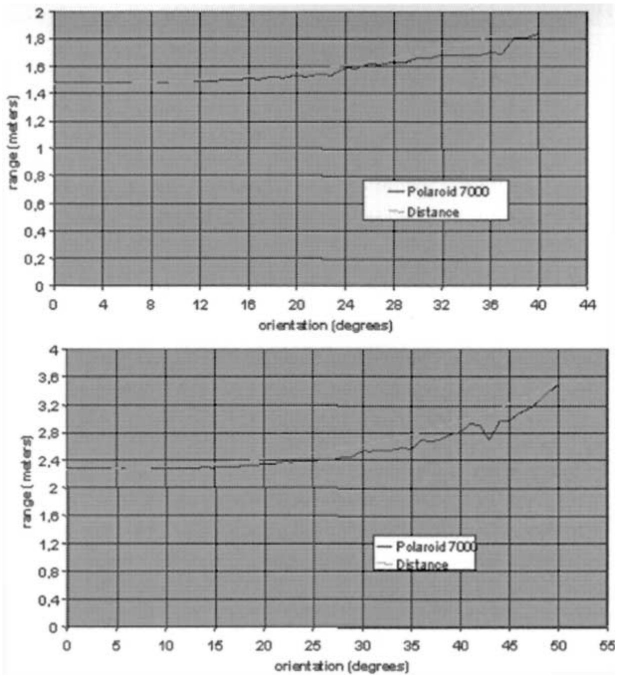

Figure 5: Range versus orientation in a rough wall for two distances.

The intepretation of sonar information is done using an artificial neural network. Its goal is to translate information obtained from sensor readings into probability of occupancy. We have developed an adaptation about philosophy proposed by Thrun [6].

The neural network is a multilayer perceptron one. It has an input layer, two hidden layers and an output one. The neural network inputs are the following:

The neural network output supplies the probability of occupancy of the point considered as input. Thus, the occupancy estimated value is realized bearing in mind the different sensors readings at the same time.

Neural network is trained using Back-propagation algorithm [14]. The neural network training is supervised and is carried out for a series of representative contours located into the four sensor zone. Each contour is composed of a set of points chosen as function of the different responses of the ultrasonic sensors in real environments. During training the output target for the network is 1 if the considered point is occupied and 0 if is not.

The highest uncertainty about the occupancy value of a point is indicated with 0.5. Once trained, the neural network output generates a value between 0 and 1 representing the probability of occupancy.

A local map centred on the robot is built using the neural network. The neural network interprets sonar readings obtained from a particular position of the robot and a local map is constructed on its nearest environment. This local map has 24x24 squared cells, 12 centimeters side each one, of which the 4x4 central cells are occupied by the robot.

The own robot's reference system is used to build the local map. Each cell is associated to its centre, i.e., the probability of occupancy of a cell is the probability of occupancy of its centre. This centre is the point used as the neural network input.

Since the robot can be orientated in any direction, most of the time a cell in the global map (in the global coordinate system) does not coincide exactly with just one cell in the local map (associated to the robot and relative to its own reference system). Instead of that, a cell in the global map is covered by several cells in the local map. Therefore depending on the robot's position and orientation, both global and local maps are overlapped. In order to calculate the probability of occupancy of a cell in the global map, probabilities of four cells in the local map are considered. The centres of the considered local map cells are the four nearest to the centre of the global map cell,

$$O_{gl}(x,y) = \frac{\sum_{i=1}^{4} \frac{1}{\sqrt{(x-x_i)^2+(y-y_i)^2}} O_l oc(x_i,y_i)}{\sum_{i=1}^{4} \frac{1}{\sqrt{(x-x_i)^2+(y-y_i)^2}}} \quad (4)$$

where (x_i, y_i) are the centres of local cells and $O(x_i, y_i)$ its occupancy probability.

Lastly, set of sensor readings generated by the robot in different positions supplies multiple environment views. The information of the different views of each cell (estimated probabilities of occupancy) is integrated incrementally using the Bayes' rule [4, 5, 6].

With map matching and integration, local information close to the robot is employed to decrease the uncertainty associated to the building of the global map and increase the estimation accuracy, reaching a coherent global map of the real environment.

4 Results

According to previous researchers which have used a neural network to build a local map [6, 7, 15], both exploration and path planning aspect had been taken more into account than sensor interpretation itself . However, this research has been precisely centred on this matter. In our previous research [8] we showed a

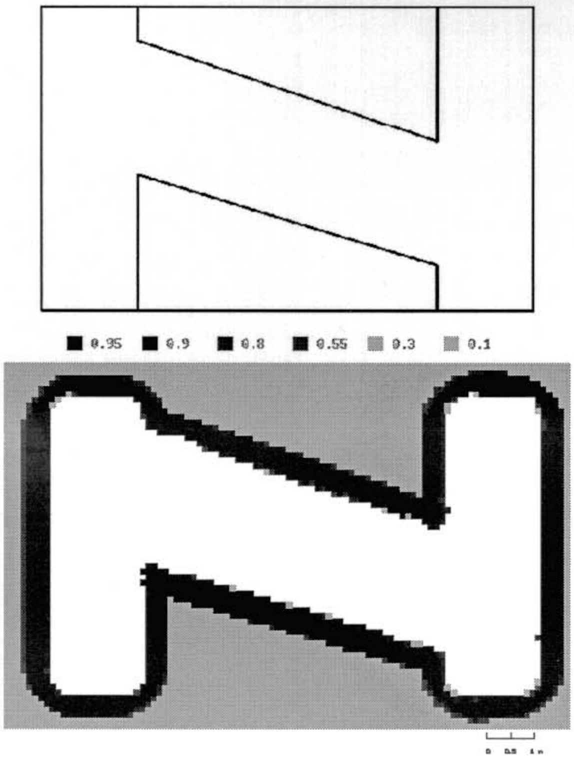

Figure 6: Plant 2, composed of smooth walls.

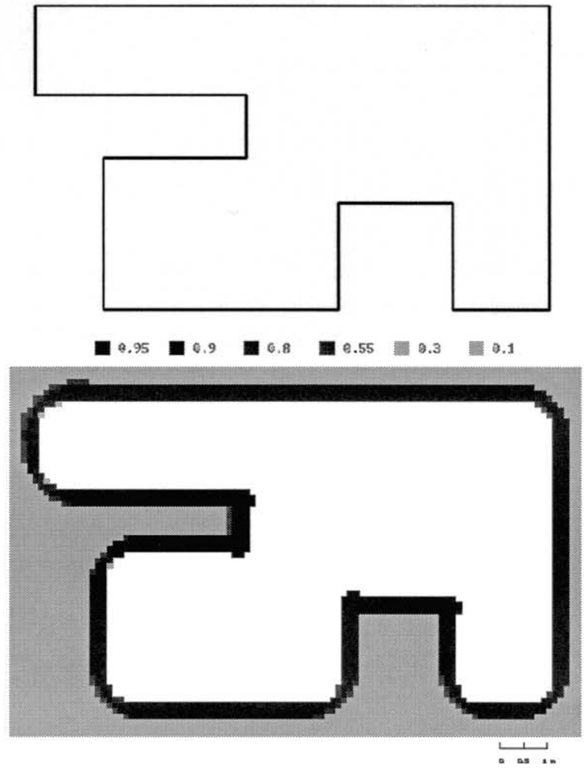

Figure 7: Plant 3, composed of rough walls.

system with a map final refinement using a neighborhood local mask. Through that method we achieved optimal results on high specular environments. Currently, using the same system without final filtering, we develop a system able to function in any type of indoor environment, with smooth walls or rough walls of any rugosity degree, simultaneously without needing to train the network or making changes in the rest method phases.

Moreover, examples utilized to train the network is a very important aspect for the good functioning of the system since it has to be able to learn different sensor responses filtering the specular reflections.

In figures 6, 7, 8 and 9 can be analyzed the results obtained when the method explained in previous section is applied on plants of different nature using exactly the same system without changes in parameters . Plant 2 is composed of simulated smooth walls with a high probability of specular reflections. On the contrary, plant 3 is composed of rough walls with a different sonar response with regard to plant 2. Figures 8 and 9 show the maps built using the B-21 robot in the corridors to our laboratory.

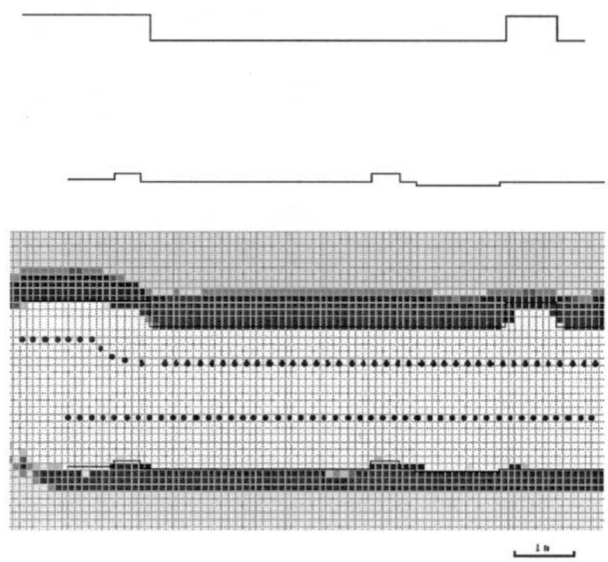

Figure 8: Corridor 1, composed of a painted wall and another one with tiles.

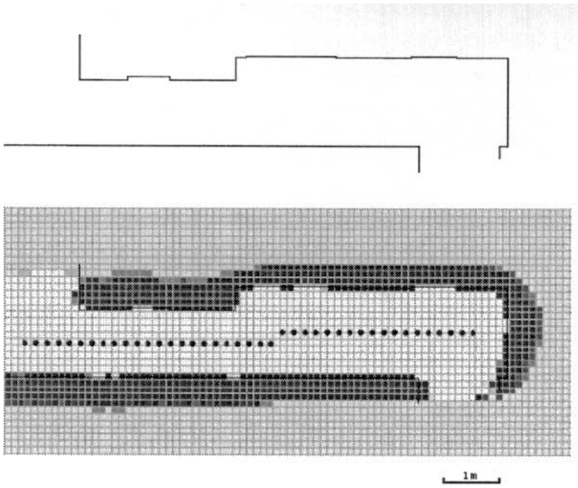

Figure 9: Corridor 2, with wooden walls.

5 Future Work and Conclusions

In this paper, it has been exposed the results obtained in relation to the experiments with Polaroid ultrasonic sensors and the map building method utilized, and its validation in any kind of indoor environments. These experiments have generated very acceptable results using sensor models as well as using the RWII B-21 robot.

However, the error associated to the robot's odometry has not been taken into account in this paper. Future works will be centred on this matter which will allow the system to be applied to great size plants without loosing the robot's position and therefore, accuracy in the map building process.

References

[1] D. Lee *The Map-Building and Exploration Strategies of a Simple Sonar-Equipped Robot*, Cambridge University Press, 1996.

[2] H.P. Moravec and A. Elfes " High resolution maps from wide angle sonar," *In. Proc. IEEE Int. Conf. Robot. Automat.*, pp. 116-121, 1985.

[3] J. Borenstein and Y. Koren "Obstacle avoidance with ultrasonic sensors," *IEEE J. Robot. Automat.*, Vol. 4, pp. 213-218, 1988.

[4] A. Elfes "Using Occupancy Grids for Mobile Robot Perception and Navigation," *Computer* 22(6), pp. 46-57, 1989.

[5] J.H. Lim and D.W. Cho "Physically Based Sensor Modeling for a Sonar Map in a Specular Environment," *In. Proc. IEEE Int. Conf. Robot. Automat*, pp. 1714-1719, 1992.

[6] S. Thrun and A. Bücken "Integrating Grid-Based and Topological Maps for Mobile Robot Navigation," *Proc. of the 3th National Conf. on Artificial Intelligence*, AAAAI, Portland, Oregon, 1996.

[7] José del R. Millán and A. Arleo "Neural Network Learning of Variable Grid-Based Maps for the Autonomous Navigation of Robots," *IEEE Int. Conf. on Robotics and Automation*, pp. 40-45, 1997.

[8] M.A. Zamora, F.J. Toledo, J.L. Muñoz, J. Tornero and L.M. Tomás "Sonar Grid Map of a Specular Environment using Artificial Neural Networks," *RAAD99*, 1999.

[9] J. Leonard and H.F. Durrant-Whyte *Directed Sonar Sensing for Mobile Robot Navigation*, Cambridge MA, Kluwer Academic Publishers, 1992.

[10] D. Pagac, E.M. Nebot and H. Durrant-Whyte "An Evidential Approach to Map-Building for Autonomous Vehicles," *IEEE Trans. on Robotics and Automation*, Vol. 14 n.4, 1998.

[11] R. Kuc and M.W. Siegel "Physically Based Simulation Model for Acoustic Sensor Robot Navigation," *IEEE Tansactions on Pattern Analysis and Machine Intelligence*, Vol PAMI-9 N6 Nov87, pp. 766-778, 1987.

[12] R. Kuc and V.B. Viard "A Physically Based Navigation Strategy for Sonar-Guided Vehicles," *Int. J. Robotics Research*, Vol10, n2, pp. 75-87, 1991.

[13] P.J. McKerrow and J.C.T. Hallam "An Introduction to the Physics of Echolocation," *Proc. 3th National Conf. on Robotics*, Melbourne, ARA90, 198-209, 1990.

[14] R.P. Lippman "An introduction to Computing with Neural Nets," *IEEE ASSP Magazine*, April 87, 4-22, 1987.

[15] V. Santos, J. Gonzalez and F. Vaz "Perception Maps for the Local Navigation of a Mobile Robot: A Neural Network Approach," *IEEE Int. Conf. on Robotics and Automation*, pp. 2193-2198, 1994.