Local Perception Maps and Navigation for a Mobile Robot

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Resumo - **Este artigo descreve um sistema robótico móvel realmente implementado e que é capaz de construir representações instantâneas do espaço livre circundante e de as usar para fazer navegação. As representações do espaço livre são feitas usando mapas de percepção especialmente concebidos para conter e combinar dados de ultra-som. Os mapas são construídos usando redes neuronais treinadas para minimizar erros de medição devidos a reflexões especulares; isso é conseguido tirando partido da redundância dos dados sensoriais. O conceito de navegação local é desenvolvido como uma nova abordagem da navegação completamente independente do ambiente contando simplesmente com os dados sensoriais. O movimento local é gerado de acordo com simples descrições de comportamento: as estratégias de navegação local. O sistema implementado garante movimento local no ambiente com segurança e sem qualquer informação a priori ou qualquer trajectória pré-definida. Uma arquitectura de navegação integra todo um conjunto de módulos, entre os quais a navegação local, de forma a permitir tarefas completas de navegação. Os resultados obtidos são muito prometedores para o desenvolvimento de sistemas autónomos.**

Abstract - **This paper describes a mobile robotics system that was implemented and is capable of building instantaneous representations of the free space available, and use those representations to perform navigation. The free space representations are done by means of perception maps specially designed to hold and combine ultrasonic data. The maps are built by neural networks appropriately trained to minimise undesired ranging errors due to specular reflections; that is achieved by taking advantage of the redundancy of sensorial data. The concept of local navigation is developed as a new navigation approach, and is based on full independence on the environment, relying purely on sensorial perception. Local motion is generated according to simple generic behaviour descriptions: the local navigation strategies. The system, which was implemented, guarantees a safe local motion throughout the environment, requiring no a priori information nor any pre-defined path to follow. An adequate navigation architecture integrates the local navigation module within a framework of other several modules for more complete navigation tasks. The results obtained are quite promising in pointing the way to an autonomous system.**

I. INTRODUCTION

Traditional navigation of mobile robots does not clearly separate local actions from global concerns. Motion commands, namely those intended for obstacle avoidance always take into account the final target, hence the current point in space and the location of the goal [1, 2, 3, 4, 5]. In those approaches, the problem of obstacle avoidance is dealt with the caution of keeping motion toward the navigation goal. This means that the component performing the obstacle avoidance must have a permanent and continuous knowledge of the robot position in the environment. That information may not be always available considering that the localisation procedures may not provide a correct positioning and the dead-reckoning system is not reliable enough to count on (as it often occurs). During these conditions motion has to be suspended. Furthermore, most traditional methods seek to avoid obstacles in robot path; some others try to follow walls, such as in [6], or the simpler approach in [7], but no significant integrated approach, meeting all conditions, has been developed, to our knowledge.

The idea is then to develop a concept of navigation requiring no *a priori* knowledge of the environment nor any pre-defined path, and capable of doing motion simply interpreting the free space around the robot. Moreover, the module responsible for this type of navigation should be easily integrated in a global navigation scheme (architecture) in order to allow virtually all types of task execution a mobile platform can do. These specifications lead to what we call the Local Navigation concept, which consists of two main components: the perception and representation of the free space around the robot by means of perception maps, and a set of navigation strategies, which are simple primitive behaviours for reacting to free/occupied space.

In this approach, the obstacle avoidance problem is managed as a sort of reflex behaviour. It should be noted that the local navigation concept needs no distinctions between obstacles and the environment: they all represent occupied space.

This work uses and improves previous results on perception map construction with neural networks [8]. The ideas left open by then for actual robot navigation are now developed and carried out with very good practical results as it will be described.

The work has been developed as part of a larger project on mobile robotics for remote verification of storage areas [9]. The perception equipment for this component of the project is mainly a belt of 24 ultrasound sensors of the Polaroid™ type carried by a Robuter™ platform.

II. SONAR PERCEPTION MAPS

In spite of the very well known and sometimes misleading problems that characterise the use of ultrasound sensors [10, 11], the popularity of sonar as a ranging method in robotics is undeniable. Matters of cost and ease of use overwhelm the specularity and cross-talk risks, as well as the speed limitations of ultrasonic perception. As individual sensor reading do not guarantee correct measurements, a possible solution is to try to combine multiple values of range, preferably from different sensors [8].

The idea is to conceive perception maps to represent accurately, to the maximum extent possible, the free space in the surroundings of robot, as opposed to a global map of the environment where the robot moves.

To represent the space around the robot an appropriate concept of perception map was used and adapted to this application. The main idea is to conceive a special grid (Generalised Geometry Grid—GGG) adapted to the nature of ultrasonic ranging that will serve as the skeleton for the map (fig. 1). It is worth remarking that this type of grid is centred on the robot and is suited to constructing maps from the robot viewpoint (i.e. “perceived” by the on-board sensors), and not a view of the environment such as the occupancy grids developed by Moravec and Elfes [12, 13].

Reduced versions of entire are of greater utility for navigation (fig. 3); when moving forward, there is little need of wasting resources trying to map the back of robot. If there is the need of moving backwards, map orientation can simply be swapped and algorithms of cells and sensor selection are adjusted for the new configuration. The properties of this type of grid are discussed and explained in [8].

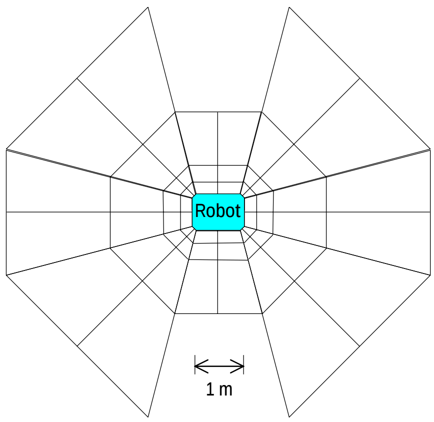

Fig. 1 - A generalised geometry grid with robot in centre. The grid is adapted to sensors' and data characteristics.

III. NEURAL NETWORKS AND PERCEPTION MAPS

The task of building a map (of cell occupancies) after raw ultrasound data should take into account, among others, data redundancy. For that, a neural network has been found to be good method.

The reasons for choosing a neural network to map raw ultrasonic data into cell occupancy include the following:

- neural networks have proved to give very good results in complex mapping problems [14, 15];
- neural networks are a flexible tool in the sense that distorted data can still be successfully processed;
- neural networks provide faster outputs, when compared to most geometric algorithms.

The global mapping problem can be stated as a process of transforming complex (perhaps also erroneous) ultrasonic data (ultrasound measurements) into a relatively simple description of the environment (occupancy of cells on a special map). The well known feed-forward architecture with back-propagation training algorithm can be used in the formulation given to the problem. Being of the supervised type, this network requires training pairs of data: the raw ultrasound data as input and cell occupancy as output.

Early results [8] were obtained with an interpolating network (that is, a continuous function approximation network), which was capable of building the entire map at each set of 24 data measurements. The limitations found by then persisted for a while, namely the difficulty in creating correct maps when the robot was closer to the obstacles. The solution was to divide the map in several sub-maps, each covered by its own (smaller in size) neural net [16].

The fragmentation of the entire map into smaller sub-maps implies the need of smaller nets. Furthermore, it was also decided to use networks as pattern classifiers rather than as interpolating systems. This means that an intermediate representation of the output data is used. That is, the network will not have to find individual cell occupancies, but patterns of occupied and free cells, instead. The most convenient fragmentation resulted in groups of 6 or 8 cells covered by 3 sensors each.

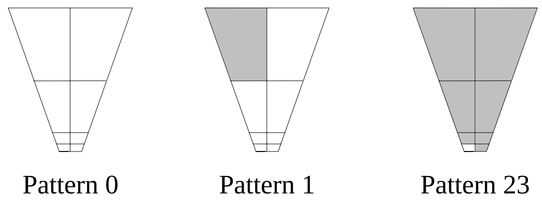

Fig. 2 - Examples of occupancy patterns for one type of sub-region on the perception map.

When compared to early networks and maps of 24 sensors for 60 cells, it is clear how simpler representations became. This intermediate representation demands more from the neural net (more complex mapping), but on the other hand it always ensures coherent results of occupancy. In summary, the net is now trained to determine a pattern number (from a set of 25 for 4-layered regions and 16 for 3-layered ones).

Performance and generalisation with pattern classifiers improved when compared to the early interpolating networks. Results of convergence are given at the end.

IV. LOCAL NAVIGATION

The local navigation can be viewed as a two component procedure: the evaluation of occupancy perception maps, and the generation of local motion commands taking into account some behaviour. The behaviours are simple and intuitive, for example, move by “following the free space” or move by “following the environment on the side (right or left)”. The behaviours can be set by a higher level module which is aware of eventual directions to take or goals to reach. In the absence of such module, the system can still subsist in a sort of wandering mode, or endless environment following.

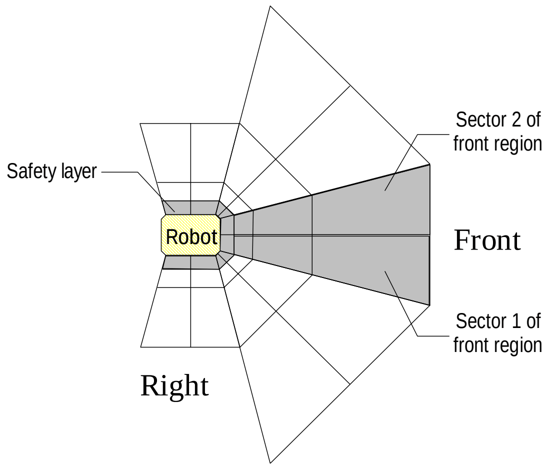

Fig. 3 - Reduced GGG and some details taken into account by the local navigation algorithm.

A. Navigation strategies

The behaviours mentioned above are the actual kernel of the local navigation, and are designated as Strategies of Local Navigation. Executing motion under a strategy consists in evaluating the amount of free cells and their location on the map and compute a new **direction** and **speed** for the robot.

The number of strategies is not vast, mainly because behaviours are qualitative and their number quite limited. In fact, the base actions that can be taken relative to the perceived environment are to look for obstacles or to avoid them.

When following the environment on one side, the local navigation algorithm tries to maintain distances to environment in a way that a given number of layers counting from the robot (1 or 2 layers as in the map of figure 3, and depending on algorithm status) is kept free.

As mentioned, the navigation algorithm must take into account the free cell distribution, but also some special circumstances of navigation such as dead-locks or oscillations in the new direction to take. There, simple counting of cells is not sufficient. The algorithm must possess some short-term memory, or some sort of hysteresis: it cannot simply be a simple reflex. Figure 4 shows a simplified flowchart for the local navigation algorithm.

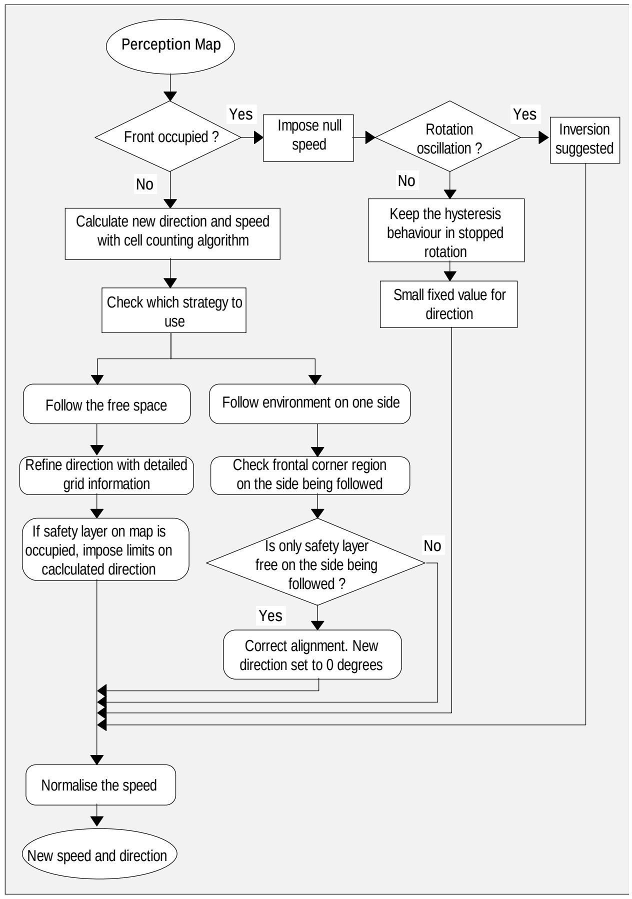

Fig. 4 - Main steps of local navigation algorithm.

V. TOWARDS FULL NAVIGATION

A higher level module may select combinations or sequences of strategies in order to perform some navigation task, or simply try to follow a pre-planned path until an unexpected obstacle appears in path and switch to local navigation mode to avoid or contour it. Further path recovery or path re-planning may be needed once the obstacle is avoided. For those actions to be possible, the architecture will require components of localisation and path planning in a global navigation structure.

Navigation architectures have evolved from “serial reasonings between sensors and actuators” to the layered arrangements proposed by Brooks in his *subsumption* model [17]. The term *reactive* also emerged to stress the behaviour of system in presence of decisive sensorial data: decisions can be taken at the level of the sensing, before reaching the actual perception and higher analysis levels. The architecture proposed (fig. 5) acts at the sensing level for collision avoidance, at the perception level for Local Navigation and at higher levels for more complex navigation tasks.

The architecture contains several loops regulating the navigation itself: the first, at the lowest level, can be classified as “reflex” and is related to imminent collision detection based on continuous analysis upon ultrasound data. The second loop can be classified “reactive”, and is mainly composed of the local navigation module. Motion commands are generated as reactions to free space only without any superior reasoning interference. Finally, we have the last loop (of highest level) whose functions include those of trying to follow a given trajectory or find alternatives to one turned impossible by the presence of unknown obstacles dealt by the local navigator.

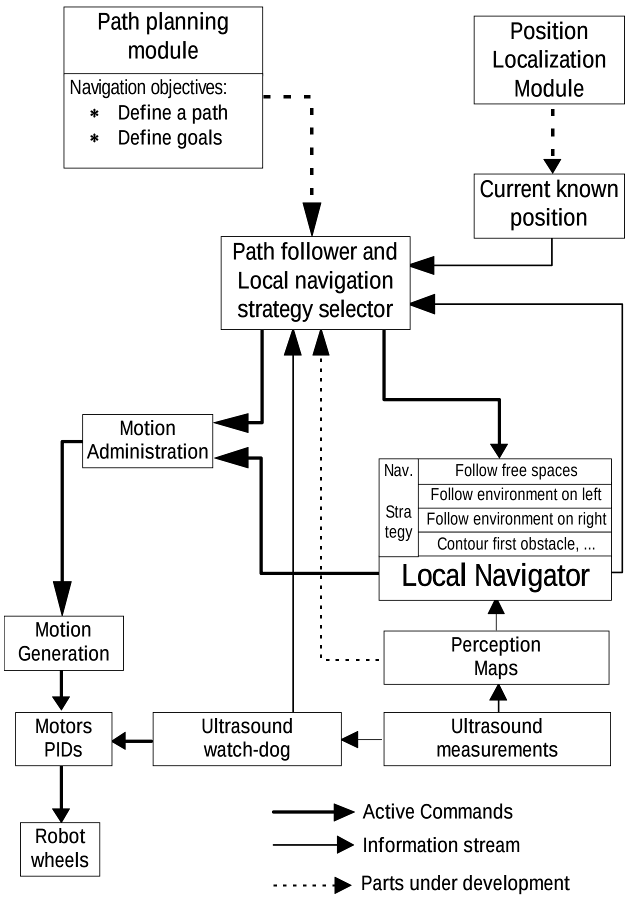

Fig. 5 - Complete architecture for navigation including a collision prevention watch-dog.

VI. RESULTS

The results are quite abundant and in multiple components, so follows a summary of the most significant. The first results are related to the neural network convergence, that is the ability of neural net to learn the training pairs and also its generalisation capabilities. Neural net classifiers converged well: for example, a 3::15::25 neural net (15 hidden units) trained with back-propagation with momentum (a=0.05, i=0.2) learned 99% of the 910 training pairs with a maximal recognition error of 20% on every pattern. Patterns are binary, and an error of 20% means that an output of 0.8 is considered to be a 1 and an output of 0.2 is considered to be a 0. Anyway, the average convergence error often dropped below 5%. It must be said that training data was pre-filtered in order to eliminate contradictory samples/occupancy pairs that sometimes occur with real ultrasound measurements, and complemented with synthesised (theoretically expected) training pairs for those situations impossible or very difficult to obtain in practice.

In the operation phase, neural nets were able to build correct maps using ultrasound data never seen before. About 95% of the generated maps were correct, even when one sensor on a group of 3 failed due to specular reflection.

A second set of results compares the neural net to two specially developed alternative methods for calculating the perception map: one of them, named Intersection with the Polygon of Free Space (IPFS) is purely geometric, and the other which is a rule based approach, is very simple and fast, but not general enough once it is difficult to provide all the rules governing the behaviour of ultrasound measurements. The method of the neural net performs better than both alternatives in most parameters except the speed when compared to the rule based method: on a Motorola 68020@20 MHz, the neural net system managed to calculate a little less than 2.5 maps/second, and the rule based method achieved more than 10 maps/second. Considering that this is higher than the actual ultrasound data rate (which reached at most 3 Hz for full scans), it can thus be said that map construction speed if of secondary importance.

The third important set of results concerns the algorithm that implemented the local navigation strategies. Two examples of real robot behaviour can be seen in figure 6. The robot was left to follow the free space as it appeared on its path. Maximal speeds were limited to 0.3–0.4 m/s for safety reasons, though 0.5 m/s was also tried without any collisions. More complex paths were also performed.

VII. DISCUSSION AND FUTURE WORK

The differences between some existing wall-following systems, as mentioned earlier, and these strategies for local navigation lays at more than one level. First, there is a coherent representation of the free space resulting from the natural combination of multiple sensors as opposed to individual sensor ranging; this property has further advantages because of the absence of "gaps" on the perception map. Secondly, the local navigation module is conceived in such a way that it can actuate with or without a master selector of strategies. This property allows the development of a navigation architecture with several levels of decision making.

Still, the proposed approach, though being different from most existing navigating and obstacle avoidance methods, shows similar or better performance.

For what has been said, perception maps keep their reliability if the speed of robot does not increase. Maps' smallest cell is 12 cm long, allowing therefore measurement errors of that magnitude. As the top ultrasound data rate (in our set-up) barely reaches 3 Hz, it can be said that the robot is allowed to move up to 3×12=36 cm/s for maps to remain valid. For the angular motion, measurements are more sensitive but the angular aperture of ultrasonic beams have here a useful role of spatial integration; assuming an aperture of 20° [11], the robot can rotate at a maximal angular speed of 3×20=60°/s (π/3 rad/s) without invalidating the perception maps.

Future developments of this work will involve several essential issues: i) higher ultrasonic data rate and more maps per second, allow larger robot speeds (possibly up to 0.8 m/s) ii) The development of the remainder modules of the architecture, in particular the path follower, will allow very high level robot control, hence complete autonomous navigation tasks. ii) Extending the principles and methods for another type of robot, a circular platform, for example.

VIII. CONCLUSIONS

The main conclusions of this work can be summarised as follows.

The perception maps are suited for ultrasonic data representation because they follow physically based principles and their use for navigation was successful.

The method of the neural net to map raw ultrasound data into occupancy maps gave very good results. Neural nets seem to be able of coping with sensorial data failure.

The Local Navigation concept proved to be adequate both for standalone activity (robot wandering in the environment), and as part of a global architecture of navigation, with the successful role of automatic obstacle avoidance and contouring.

Besides these, it is worth mentioning that the proposed modular navigation architecture is a valid approach that eases individual module development, and provides robustness to the tasks of mobile robot navigation. This has a second consequence which is the possibility of separating processing from the hardware point of view, which was also done in practice [16]. These distributed processing capabilities push further the limits of parallel module development and the expansion and implementation of the architecture itself.

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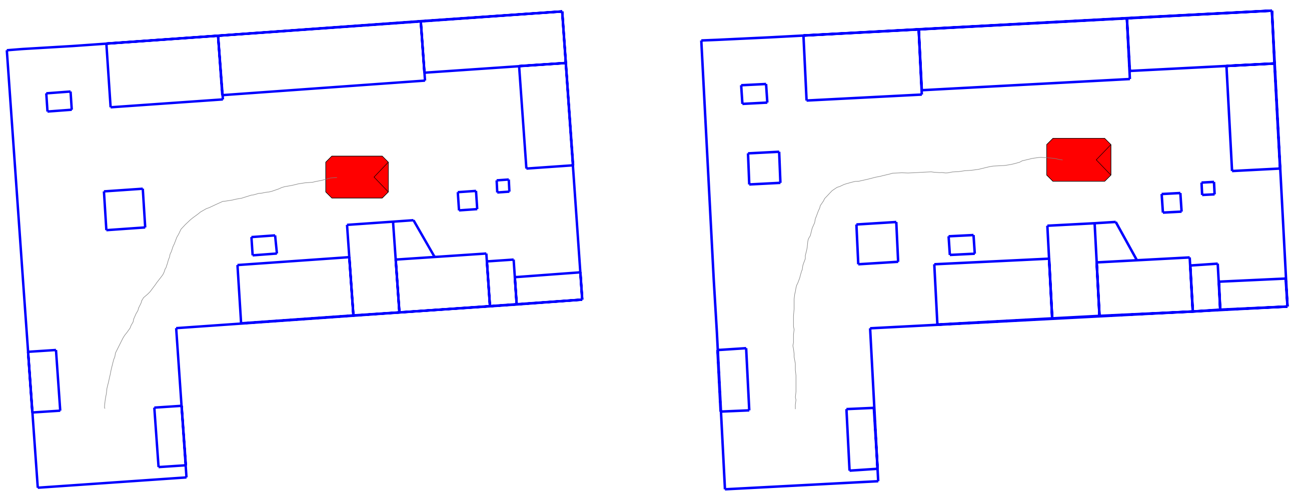

Fig. 6 - Real paths executed by the robot under a strategy of following the free space. In both cases the robot started on the same location, but the environment was slightly modified by moving a box in the robot's path.

X. REFERENCES

[1] O. Kathib - Real-Time Obstacle Avoidance for Manipulators and Mobile Robots, *Proc. of the IEEE Int. Conf. on Robotics and Automation*, St. Louis, May 1985, pp. 500-505.

[2] B. H. Krogh - A Generalized Potential Field Approach to Obstacle Avoidance Control, *Robotics International Robotics Research Conference*, Bethlehem,PA, August 1984.

[3] J. Borenstein , Yorem Koren - Real-Time Obstacle Avoidance for Fast Mobile Robots, *IEEE Trans. on Systems, Man and Cybernetics*, vol. 19, n. 5, September/October 1989.

[4] Bruce H. Krogh , Charles E. Thorpe - Integrated Path Planning and Dynamic Steering Control for Autonomous Vehicles, *Proc. IEEE Int. Conf. on Robotics and Automation*, pp. 1664-1669, 1986.

[5] J. Borenstein, Yoram Koren - The Vector Field Histogram-Fast Obstacle Avoidance for Mobile Robots, *IEEE Trans. on Robotics and Automation*, vol. 7, n. 3, June 1991.

[6] P. van Turennout, G. Honderd , L. J. van Schelven - Wall-following Control of a Mobile Robot, *Proc. of the 1992 IEEE Inter. Conference on Robotics and Automation*, May 1992.

[7] Uwe Wienkop - Robot Hallway Travelling using Sonar Information, *Intelligent Robotics Systems-IRS94*, Grenoble, France, Edited by A. Borkowsky and J. L. Crowley, pp. 30-36, July 1994.

[8] V. Santos, J. Gonçalves, F. Vaz - Perception Maps for the Local Navigation of a Mobile Robot: a Neural Network Approach, *IEEE Int. Conf. on Robotics and Automation*, San Diego, USA, pp. 2193-2198, May 1994.

[9] J. Gonçalves, G. Campos, V. Santos, V. Sequeira, F. Silva - Mobile Robotics Applied to the Remote Verification of Storage Areas, *Proc. of 15th ESARDA Symposium on Safeguards and Nuclear Material Management*, Rome, May 1993.

[10] J. Borenstein, Yoram Koren - Obstacle Avoidance with Ultrasonic Sensors, *IEEE Journal of Robotics and Automation*, vol. RA-4, n. 2, April 1988.

[11] V. Santos, J. Gonçalves, F. Vaz - Ultrasound Sensors for Environment Perception, *JRC Technical Note No. I.93.128*, October 1993.

[12] Hans P. Moravec, Alberto Elfes - High Resolution Maps from Wide Angle Sonar, *Proc. IEEE Int. Conference on Robotics and Automation*, Washington D.C., pp. 116-121, March 1985.

[13] Alberto Elfes - Using Occupancy Grids For Mobile Robot Perception and Navigation, *IEEE Computer*, pp. 46-57, June 1989.

[14] R. P. Gorman , T. J. Sejnowski - Analysis of Hidden Units in a Layered Network Trained to Classify Sonar Targets, *Neural Networks*, vol. 1, 1988.

[15] D. A. Pomerleau - Efficient Training of Artificial Neural Networks for Autonomous Navigation, *Neural Computation*, vol. 3, n. 1, 1991.

[16] V. Santos - Navegação Autónoma de Robots: Interpretação dos Dados Sensoriais e Navegação Local, *Tese de Doutoramento*, Universidade de Aveiro, Portugal, 1995

[17] R. A. Brooks - A Robust Layered Control System for a Mobile Robot, *IEEE Journal of Robotics and Automation*, vol. 2, n. 1, Mar 1986, pp.14-23.