CLASSIFICATION AND CHARACTERIZATION OF ENVIRONMENTS FOR INDOOR MAPS BASED MOBILE ROBOTS NAVIGATION

Mário Luiz Tronco, mariot@ibilce.unesp.br
Luciana Leal da Silva, lleals@gmail.com
Universidade Estadual Paulista – UNESP
Departamento de Ciências de Computação e Estatística
Rua Cristóvão Colombo, 2265 – Jardim Nazareth – CEP 15054-000 – São José do Rio Preto - SP

Arthur José Vieira Porto, ajvporto@sc.usp.br
Universidade de São Paulo – USP
Departamento de Engenharia Mecânica
Av. Trabalhador São-Carlense, 400 – Centro – CEP 13566-590 – São Carlos – SP

Abstract. *The The task of navigation in mobile robots´s context needs methods that use more efficiently the perceptual information collected about the external environment. A high autonomy degree is desirable to improve the mapping methods performance. One way to this is to increase the amount of sensory information available, using, for example, environment images collected by a câmera installed in the robot structure. Cameras are sensors potentially useful, since images have wealth information for maps construction. A vision system not widely used in traditional navigation of móbile robots is the omnivision system, composed by a camera and a catadioptric mirror. This system enables the robot collect images of 360º around it, thus increasing the amount of information available. Classically, research on mobile robot navigation has produced two major paradigms for mapping environments: geometrical and topological methods. Grid-based methods produce accurate metric maps, but their complexity often prohibits efficient planning and problem solving in large-scale indoor environments. Topological maps, on the other hand, can be used much more efficiently, yet accurate and consistent topological maps are often difficult to learn and maintain in large-scale environments, particularly if momentary sensor data is highly ambiguous. In this paper the topological approach is adopted: the environment is represented by a number of distinctive places [1] and the environment is represented by a graph, where places are vertices or nodes set and all links between each pair of nodes are edges set. Digital image processing and invariant patterns recognition techniques are used together with artificial neural networks to build a mapping and localization system for the LACE (Automation and Evolutive Computer Lab - UNESP) mobile robot. The system uses a robot on-board sensory system composed by ultrasound sensors and a omnivision system, to collect information about the exploited environment. The mapping module is composed by three sub modules, of which two will be presented in this paper: the characterizer and the classifier modules. The classifier module classifies the places explored by the robot among four default classes, using a Hierarchical Neural Network as the main tool of classification. The characterizer module, using image attributes extraction techniques and invariant patters recognition, characterise the nodes, that is, to storage their features in order to make each node unique and different from the others at the same class.*

Keywords*: mobile robots, neural networks, computer vision, environment mapping*

1. INTRODUCTION

The development of techniques for autonomous navigation of mobile robots is a trend in the robotic research area. The autonomy of the mobile robots is important and necessary so that they can detect and deviate from obstacles, auto-locate and to plan its trajectory. It also is essential when the robot needs quickly to react to changes of the environment or receives external stimulation. The key task during navigation of a mobile robot is your capacity of precise localization in its environment. It can do this task recognizing its position through information collected by a sensorial system and matching such information with a global map of the environment, which consists of a representation of its physical structure. In environment exploration tasks the robot navigates acquiring information for map building and in this case an additional task appears: the necessity of auto-locate the robot while it constructs the map. The robot can still navigate based on an existing map, thus solving the localization and planning of trajectories problems and to verify if the final position was reached. Tasks of local navigation, as obstacle avoidance, can be performed without the resource of environment maps. In global tasks, as navigation, the use of some type of description or representation of the space becomes necessary. Moreover, to efficiently play more complex missions, autonomous mobile robots need to be capable to acquire and to keep models of its environments.

The task of navigation in mobile robot´s context needs methods that use more efficiently the perceptual information collected about the external environment. Such information directly affects the autonomy degree of the robot, which is extremely necessary in the context of environments modeling and robot localization. A high autonomy degree is desirable to improve the mapping methods performance. One way to this is to increase the amount of sensory information available, using, for example, environment images collected by a camera installed in the robot structure.

Cameras are sensors potentially useful, since images have wealth information for maps construction. A vision system not widely used in traditional navigation of mobile robots is the omni vision system, which can be composed by a camera and a conical mirror. This system enables the robot collect images of 360º around it, thus increasing the amount of information available (Matsumoto et al., 1999). Classically, research on mobile robot navigation has produced two major paradigms for mapping environments: geometrical and topological methods. While grid-based methods produce accurate metric maps, their complexity often prohibits efficient problem planning and solving in large-scale indoor environments. Topological maps, on the other hand, can be used more efficiently, yet accurate and consistent topological maps are often difficult to learn and maintain in large-scale environments, particularly if sensor data is ambiguous.

In this paper the topological approach is adopted: the environment is represented by a number of distinctive places and represented by a graph, where places are vertices or nodes set and all links between each pair of nodes are edges set (Kuipers and Byun, 1991). Digital image processing and invariant patterns recognition techniques are used together with artificial neural networks to build a mapping and localization system to the LACE (Automation and Evolutive Computer Laboratory) mobile robot (Figure 1). This system uses a robot on-board sensory system composed by ultrasound sensors and an omni vision system, to collect information about the exploited environment. The mapping module is composed by three sub modules, where two will be presented in this paper: the characterizer and the classifier modules. The classifier module classifies the places explored by the robot among four default classes: lane, intersection, door and room, using for this a hierarchical artificial neural network (RNAH) as the main tool of classification. Beyond the nodes definition and classification, it is necessary to characterize them, that is, to storage their features in order to make each node unique and different from the others at the same class. This is implemented in the characterizer module through image attributes extraction techniques and invariant patterns recognition. (Zitovà and Flusser, 1999; Arsênio and Ribeiro, 1988; Betke and Gurvits, 1997; Marsland et al., 2001; Se et al.,2002).

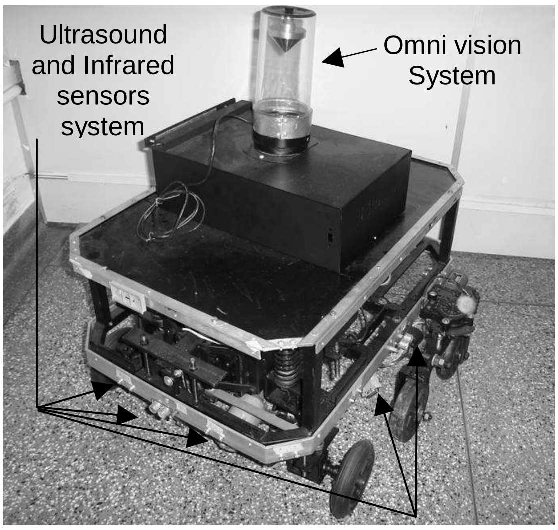


Figure 1. LACE Mobile Robot.

2. ENVIRONMENT MAPPING TECHNIQUES FOR MOBILE ROBOT NAVIGATION

Maps based navigation demands a process of recognition and analysis of high level, to interpret the map and to establish its correspondence with the real world. The first efforts in navigation of robots based in maps mainly had been inspired by the cognitive processes of the humans, assuming that the errors of sensors and actuators could be detected and be corrected by a process of higher level, or using some type of modification of the environment to become the navigation most easy. Basically, the navigation based on maps includes three processes (Balakrishnan et al., 1999):

- Map Learning – process to adequately represent the environment using data collected during its exploration;
- Localization - process that calculates the current position of the robot using for this the map;
- Path Planning – task to define a path until a destination place from a known initial position

The third process depends on the two first ones, since the current position of the robot as well as the environment map are necessary to calculate the path between two places. In a real-time map construction process the two first processes are closely linked, therefore the map is used to get the current position and this is used to construct the map. In this context, SLAMB (Simultaneous Localization And Map Building) appears. Such interdependence becomes difficult and complex the problem of learning of maps, therefore errors that appear from the calculation of the localization of the robot are incorporated to the map and need to be detected and corrected.

Moreover, the task of auto-localization during the learning of the map (SLAMB) are more difficult for a mobile robot if compared with the same task executed using a ready and know map of the environment; an additional problem appears: the robot needs to guarantee that the position currently explored not yet has been mapped.

The strategies of mobile robot navigation can be divided in two approaches (Filliat and Meyer, 2003):

(i) simultaneous treatment of the localization and map learning problems, together with a planning method analysis and; (II) localization strategies that uses a complete and already known map of the environment.

The map building process for mobile robots needs to receive information from the explored environment and of the robot movement and state. There are two distinct origins of information that can be used for navigation based on maps. The first origin is odometric, that supply internal information about the movements and current state of the robot, as for example, speed, acceleration, direction of the wheels. The second origin is sensorial, which supplies external information on the environment. In accordance with Filliat (Filliat and Meyer, 2003), the data proceeding from both origins can be used to: to directly locate a place or a situation; to create a bidimentional space representation of the environment through the fusion of both information, using for this a metric model (sensor model) that converts external information into a space representation of the environment. In this case, geometric properties of the environment, such as the position of objects, are inferred. The first consequence of the use of a metric model, or a sensor model, is the possibility of the fusion of different origins information in a common geometric representation, which is sufficiently natural and expressive for human operators. Another important consequence is that a sensorial model allows that external or sensorial information about not yet physically explored environment locals are inferred from other places already physically explored. The advantages and disadvantages of these two origins of information are complementary. The main problem with the information of odometric origin is its accumulating error, that are resulted of a integration process of different information collected from different resources or states of the robot. The consequence of this is the reduction of the quality of the information, which cannot be taken as true in full time period. The opposite happens with the quality of the sensorial information, which is stationary throughout the time. However, two main problems exist. The first one occurs when two distinct places are identified by the system as being the same place, that is, when two distinct places are confused and identified as only one. Such problem is called in literature as perceptual aliasing. The second problem occurs when a place seems different throughout the time, for example, with different illumination conditions.

The integration process of different information collected during the exploration of the environment can be used to create a representation of the explored environment, that is, the map building of the environment for the robot. Classically, the models of space representation are divided in two categories: geometric maps and topological maps. In geometric maps, the positions of some objects, mainly the obstacles that the robot can find, are stored in a global reference system. In topological maps, the places are defined as position that the robot can reach. Such definitions are stored together with some information on the relative position between them (Figure 2).

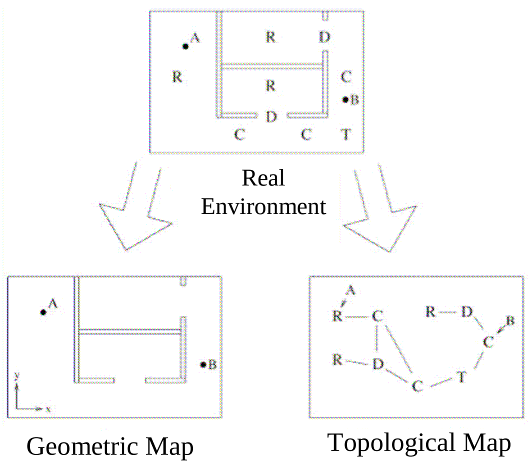
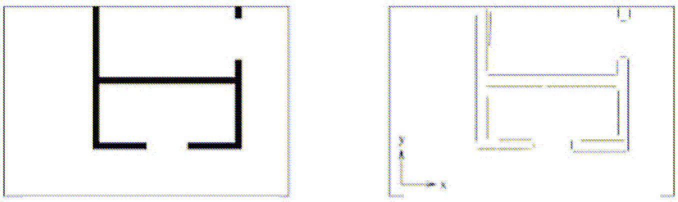


Figure 2. Geometric and Topological Map.

2.1 Geometric Maps

In geometric model, the environment is represented as a set of objects with its respective global coordinates in a two-dimensional space. The environment is represented through grids equally spaced, where each grid cell can, for example, to indicate the presence of an obstacle in the environment correspondent region. The odometric origin of information is very useful in this representation, therefore it becomes possible the direct management of the robot position in this space. The geometric map building process starts when the sensorial information are stored and later transformed into a two-dimensional representation of the environment, that is, in a geometric model. This transformation produces a set of objects, or obstacles and its respective position related to the robot. The difference key in relation to the topological approach is in the use of sensorial models, which allow the fusion of the sensors information with the odometric information in a common representation of the environment.

Geometric maps can store the characteristics perceived by the robot, together with its position (Figure 3). Such characteristics can be represented in diverse ways and using different levels of abstraction. Points, or point objects can be used, as a intuitive definition of a landmark, as a reference point (Levitt and Lawton, 1990; Prescott, 1995; Feder et al., 1999). The difficulty of this technique is in perceiving a single point and using it to estimate the robot position. An alternative would be to use some spread points on the surface of objects, so that the sensors data allows to define its space configuration (Lu and Milios, 1997; Gutmann and Konolige, 2000; Thrun et al.,2000).



Real Environment

Environment Characteristics Map

Figure 3. Example of environment characteristics mapping with detected segments detected on the obstacles edges.

2.2 Topological Maps

In the topological approach, the environment is represented by a set of distinct places, so that the robot can go of a place to other (Kuipers and Byun, 1991) This approach is based on the established geometric relation between the places identified and not in its respective absolute positions related to a global coordinate system, as with the geometric approach. The result is the representation of the environment in accordance with a graph, in way that the identified places form the set of vertices or nodes and all the existing links between each pair of vertices form the set. Kortenkamp (Kortenkamp and Weymouth, 1994) defined two basic functions of a topological map:

- Recognition of the places: through this function it is determined the current position of the robot in the environment. In general, each identified place, or defined node, is related to its respective description and the recognition process consists of matching the perceived sensorial data with the description of the node.

- Path Planning: definition of a path that binds a current position to one objective position.

The first advantage of the topological approach is that does not need a metric sensorial model capable to convert sensorial information into a two-dimensional representation of the environment, that is, does not need a process capable to fuse the information of both the origins. The necessity is of a method capable to store and to recognize the places from some sensorial input. Moreover, topological maps are closely related to the perceptual capacities of the robots and is unnecessary the extraction of the form of the environment objects, as it happens in the geometric modeling. Such representation of the environment allows the application of processes of high level with low computational cost. The main disadvantage of this approach is the necessity of physically explore all the places of the environment to acquire sensorial information about the places, whenever these are necessary to increase the precision of the position estimation. The result is a more exhausting exploration of the environment. Another difficulty is related to the process of definition of the places, that can be wronged if the reading of the sensors is not trustworthy or the environment is very dynamic. Such process can be still more difficult if to exist the possibility of distinct places to be confused (perceptual aliasing), or the same place to seem different depending, for example, of the viewpoint captured by the sensor (perceptual variability).

3. TOPOLOGICAL MAPPING

The environments mapping method proposed in this work aims to build a topological model of the environment exploited by the LACE mobile robot. To do this, it uses a sensory system composed by ultrasonic sensors and a omni vision system, that provide data to the system's modeling modules. The mapping procedure is runned during the environment exploitation. The data read by the sensors are pre-processed by modules with CAN (Controller Area Network) nodes network. This data pre-processing makes them appropriate to be used by robot navigation system, where is the map module. This system is composed of three modules: node classifier, node identifier/creator and node characterization modules. The main task of the node classifier module is to identify each place visited by robot, classifying them among four pre-defined classes, and so create the nodes of the map with their respective relations of adjacent (edges). A neural network hierarchically structured into two layers, reason and intuition, is used as the main tool of the node classifier module. Its structure and the classification procedures will be described in Section 4. The task of identification and creation of a new node is performed by a procedure that receives the information about the class of the place and creates a new node at this same class. Figure 4 illustrates the relation among the modules of the mapping system. In addition to identificate and to classificate nodes, it is necessary to characterizate them, that is, each created node needs to be identified in a unique way and different from the same class nodes. The node characterization module is responsible for this task. Its function is to select good landmarks from the robot point-of-view, using the nodes images.

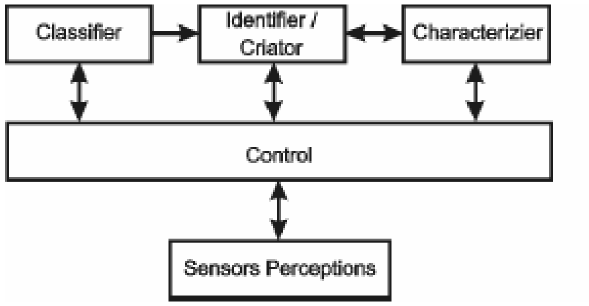


Figure 4. Functional diagram of the mapping system

Landmarks can be defined as objects of a scene that are found on a distinctive way by the robot. In this work, natural landmarks are defined using techniques of extraction of attributes of images and recognition of invariant patterns extracted from the nodes images set. The procedure adopted to implementation of this module will be further described.

3.1 Omni vision system of the LACE mobile robot

The omni vision system installed on the LACE mobile robot used to capture scenes of the exploited environment is present above. Figure 5 illustrates the procedure for capturing and processing images. The omni directional images are captured by a camera with its focus aligned to a conical mirror. These images are aligned in the omni vision module, and transformed into a panoramic image of the scene. They are preprocessed and, then, used by the classification and characterization procedures of the map nodes. The equations and the adopted procedure to capture and process the omni directional images are defined in Cavani (Cavani, 2004). Figures 6 and 7 illustrate examples of omni directional and panoramic images, respectively.

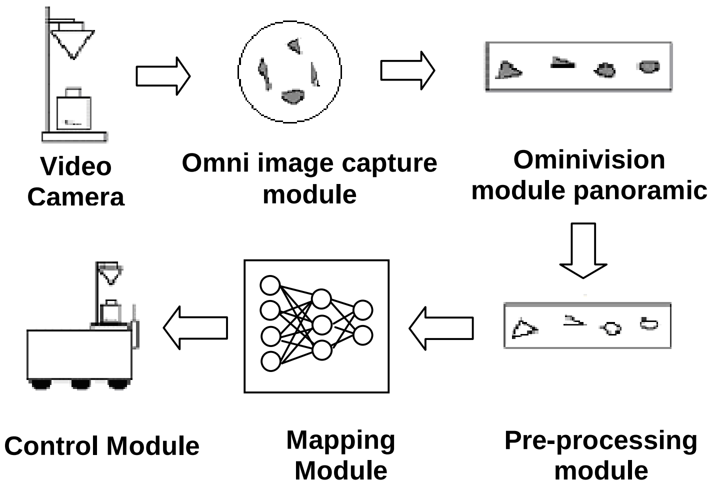


Figure 5. Processing stages of the LACE mobile robot omni vision system

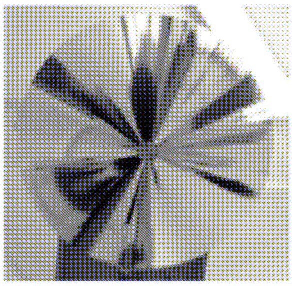


Figure 6. Omni directional image not preprocessed

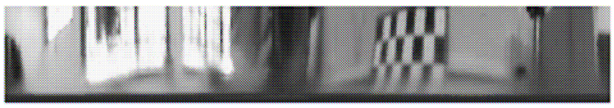


Figure 7. Panoramic image obtained from a omni image

3.2 Hierarchical Neural Network Structure

The hierarchical artificial neural network (RNAH) used in the project is structured into two layers, *reason* and *intuition*, and has the task of classifying the places exploited by the robot among four predefined classes: corridor, intersection, room and door. To accomplish this task, the network receives images and ultrasonic sensor readings as input data. The structure of the RNAH is schematized in Figures 8 to 11.

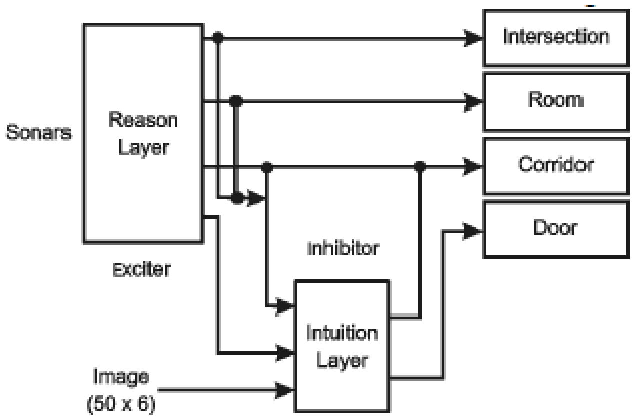


Figure 8. Hierarquical neural network.

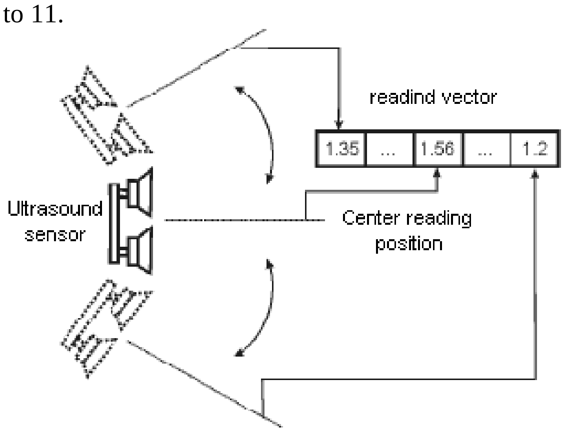


Figure 9 – Reading procedure of the side sonar.

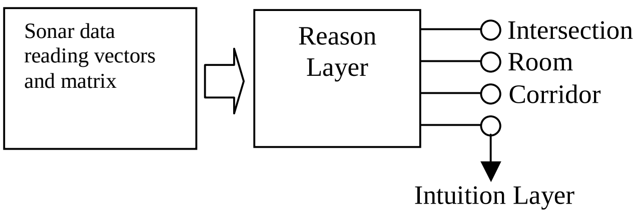


Figure 10. Reason Layer Structure

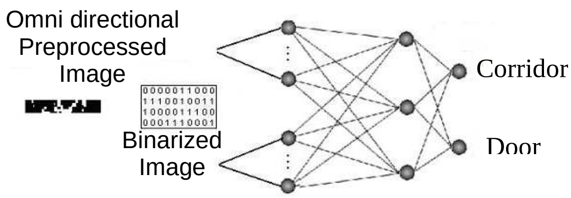


Figure 11. Intuition Layer Structure

The RNAH *reason* layer receives the values read by the ultra-sound sensors, which measure the distances of the robot to objects. The *intuition* layer takes an image of 50X6 pixels as input (this image is generated by the pre-processing module, translating a omni image in a panoramic image). The ultrasounds sensors are located in front and on the side of the robot. The side ultrasound sensors can to move in the horizontal direction. Thus, they create a real number vector, where each number represents the distance the robot on a object, calculated according to the angle formed between its reading direction and the central position reading. This procedure is illustrated in the Figure 9. The front sensor readings are executed following the same procedure, except that it is moving upright, resulting in a real number array. This is necessary to ensure that the robot detect the height of the free space to its front, avoiding possible collisions. Each input layer neuron of the first network receives the reading of one of the positions of vector and matrix. Thus, this layer has many neurons as the number of readings taken by the three sensors. This number is fixed during the procedure runned, which may, however, be changed.

Neural Network Training – Places Classification

To classify the places exploited by the robot, the RNAH needs to be trained to acquire the ability to recognize each of the four classes defined. Then, we attach to each class characteristics that make it distinct from the other, and such parameters are taken into account during the construction of the patterns set for network training. This patterns set is provided to the RNAH during its training phase. The subset provided to the first layer defines some of the characteristics of each class modeled taking into account distance measures the robot to the obstacles, such as a wall, while the subset provided for the *intuition* layer it is composed by images collected by the vision system. The *reason* layer learns to classify with some degree of certainty the classes whose parameters that characterize them are well defined and distinct from the others parameters. The *intuition* network is activated whenever there are any kind of confusion in the process of recognition of the first network. A class classified with no doubt is the corridor class. The parameters set used to definite this class are clear and only based on the distance between the robot and possible obstacles. Thus, the layer *reason* gets to recognize this class based on the sonar readings. The opposite happens in recognition of the door class. The pattern of a door and a narrow corridor identified by side sonar of the robot can result in conflicts of recognition. In this moment the layer *intuition* is activated. In this situation, the *reason* network is trained to enable a neuron of its output, which is the exciter neuron of the *intuition* network. In this moment the second network starts to be runned and classifies its input pattern, that is, the image of the place will be classified. Thus, the *intuition* network is trained using images of narrow corridors and doors, aiming to learn to distinguish them, thereby solving possible classification conflicts. The fact described above is what justifies the creation of a hierarchical neural network with the task of classifying exploited places by the robot The class *intersection* is defined as a place where the robot can possibly changes its journey direction. It should be mapped where there is a meeting between two or more corridors. Therefore, first the network must recognize the class *corridor* for after concluding that there is a intersection there. After the training stage, the RNAH is subject to a validation and testing phase, where a larger and different patterns set is presented it. The goal is to validate the previous phase and to test its performance faced different inputs patterns.

4. SELECTION AND RECOGNITION OF NATURAL LANDMARKS

In this section we describe the technique proposed to implement the node characterizer module of the mapping system. The function of this module is to characterize nodes that are identified by the classifier module, in order to make them unique and distinctive from the others nodes at the same class. The goal is to create natural landmarks for the nodes from scenes from a set of images. Thus, the scenes will be used as visual landmarks, which differs from approaches where landmarks are regarded as individual objects of the scene. In our approach, the landmarks are represented by attributes vectors and affine moment invariants extracted from the images of the nodes. The method used for extracting attributes vectors and decreasing their size is the PCA - Principal Component Analysis (Duda and Hart, 1973), whose application results in a smaller dimension image representation, taking into account the variance of attributes. The equations used to calculate affine moments were derived by Zitovà (Zitovà and Flusser, 1999), which are invariant under general affine transformations. The procedure described above select natural landmarks (vector of attributes and affine moments) in each node of the map. Thus, during the creation of the map, the landmarks of each node is used to train a neural network, creating a natural landmarks classifier used for mapping and localization tasks.

Selection of Visual Landmark s- Vectors of Attributes

The approach proposed for the PCA implementation is based on the work described in Martinez (Martinez and Costa, 2002), and is defined below. Consider the image I, provided by the omni vision system, represented by a matrix of m x n dimension, in which each element represents the level of gray intensity in that point. The image can be represented as a vector through the

reading column to column of the image matrix and storing each pixel in a column vector. Thus,

$$x(l) = I\,(i,j) \text{ to } i = 1,\ldots,n,\ j = 1,\ldots,m \text{ and } l = i + (j \times 1) \times m \quad (1)$$

The size of the array of attributes is given by $d = m \times n$. Consider t training standards are known, $x1, x2,\ldots, xt$. The training set can be seen as a matrix X, where each column contains a training standard,

$$X = \begin{bmatrix} x_1(1) & x_2(1) & . & . & x_t(1) \\ . & . & . & & \\ . & . & & . & \\ . & . & & & . \\ x_1(d) & x_2(d) & . & . & x_t(d) \end{bmatrix} \quad (2)$$

The covariance matrix Σ x of the training matrix X, can be defined as

$$\sum x = (X-\mu)(X-\mu)^T \quad (3)$$

where μ is the average matrix of $d \times t$ dimension, and each column of the matrix contains the expected value of the X patterns.

$$\mu(i,j) = \frac{1}{t}\sum_{j=1}^{t}(X\,(i,j)) \quad (4)$$

to $i = 1, . . . ,d$ and $j = 1, . . . ,t$. given the covariance matrix $\Sigma\, x$, it is estimated their eingen-vectors and eingen-values in a manner that:
where λi and vi, to $i = 1,. . . , d$, are the eigen-value and eigen-vectors of Σx, respectively.

The eigen-values indicate the eigen-vectors relevance. In the PCA case, if the eigen-vector has large eigen-value, means that the eigen-vector is in one direction with large variance in patterns. Thus, the eigen-vectors are arranged in descending order of eigen-values. The ordered set of eigen-vectors compose the transformation matrix H as follows,

$$H = [e_1, e_2, ..., e_d] \tag{5}$$

The vector of attributes transformation is accomplished through a change of base, where the matrix H is the matrix of change of base.

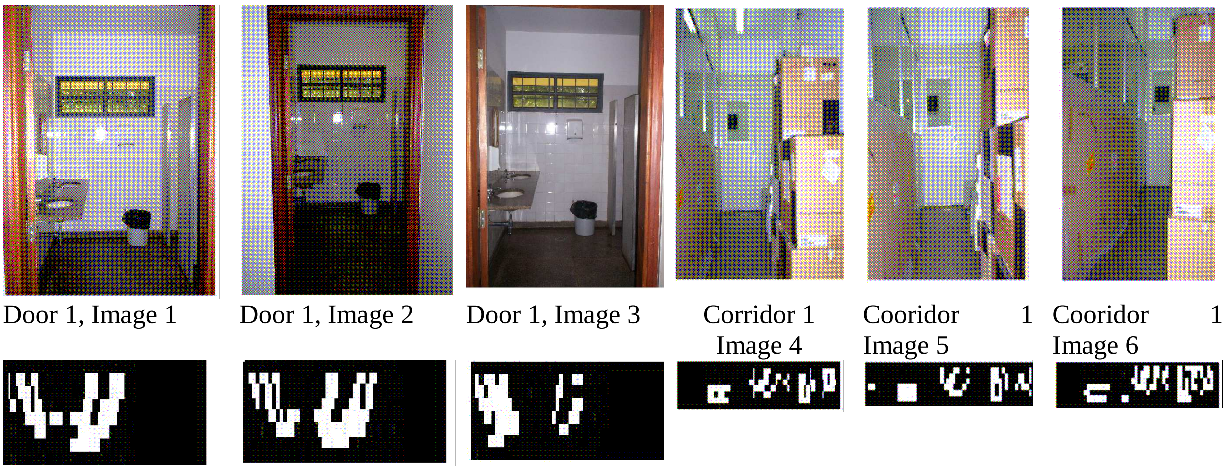
$$Y = H^T X \tag{6}$$

and is the transpose matrix of H.

The matrix of new attributes Y obtained presents no reduction in its dimension, being only a base changed in the attributes space. However, the H matrix can be built only with the self-vectors with the largest self-values. Thus, if it has been chosen k self-values, $k < d$, the attributes vector dimension is reduced to a k-dimension representation. In patterns recognition tasks, distinctive characteristics are searched, that is, we search for an attributes vector that doesn't have covariance between them. Through the covariance matrix Σx it's possible to check if there is covariance between the defined attributes. By making the transformation of X attributes for the new Y attributes using PCA, it is observed that the Y matrix has zero mean and Σy covariance matrix is diagonal, in which the main diagonal elements are the Σx self-values, and diagonal outside elements are zero. This means that the elements of the Y matrix are uncorrelated.

5. EXPERIMENTAL RESULTS

To create the two layers of the RNAH, as well the neural network that classify the landmarks, we use the neural network simulator SNNS (Stuttgart Neural Network Simulator), which also provides support for the training, validation and testing. phases. The reason layer created is one layer perceptron network, which has 35 neurons in its input layer, each that receives a position of the sonar readings vector. *Reason* output has four neurons, and the first three are on the *intersection*, *room* and *corridor* classes, and the last is the exciter neuron *intuition* network. The *intuition* layer was created using single layer and multilayer perceptron. That's why the results obtained in the first case were unsatisfactory, presenting a low rate of matches in the classification. This problem was solved with the use of a multilayer perceptron, whose results were still good and will be presented in this section. The input layer of the *intuition* network has 300 neurons, each of which receives the value stored in one of the pixels of 50 X 6 resolution image. Its output layer has two neurons that are the *corridor* and the *door* classes. The training set provided to the *reason* network has 95 pattern used to train the network for the recognition of corridors and intersections, and these classes are modeled taking into account the sonar readings. The *intuition* layer set has 65 images of doors and corridors. During the testing stage were presented 24 and 50 patterns for *reason* and *intuition* networks, respectively. All the 24 patterns provided the first network were completely unknown, that is, were situations never before presented to it. To the *intuition* network were presented 30 unknown patterns and the 20 others were images of doors and corridors presented in the earlier steps views, however, under different points-of-view or under different conditions of illumination. Figures 12 shows real images of corridors and doors used in simulation process.



Door 1, Image 1 | Door 1, Image 2 | Door 1, Image 3 | Corridor 1 Image 4 | Cooridor 1 Image 5 | Cooridor 1 Image 6

Image 1 Preprocessed | Image 2 Preprocessed | Image 3 Preprocessed | Image 4 Preprocessed | Image 5 Preprocessed | Image 6 Preprocessed

Figure 12. Real images from corridor and doors used on simulation process.

In figure 12, the preprocessed images are resulted of omni vision system module, and are used as input to the classification module.

To implement the characterizer module, we use a artificial neural network trained with the information about the landmarks extracted in each node. The tests were done with perceptrons with different numbers of neurons in their occult layer. Tables 1 to 5 summarizes the obtained results.

Table 1. General Classification percentage rate of the Reason and Intuition Layers

Layer	General Classification	Unknown Patterns	Modified Patterns
Reason	100%	0%	100%
Intuition	94%	96%	93%

Table 2. Corridor and Door Class Classification Intuition Layer

Class	Correct	Incorrect	Correct with low activation value
Door	93%	7%	7%
Corridor	93%	5%	0%

Table 3. General Classification percentage rate of the Reason and Intuition Layers – Test 2.

Layer	General Classification	Unknown Patterns	Modified Patterns
Reason	100%	100%	100%
Intuition	82%	77%	93%

Table 4. Corridor and Door Class Classification Intuition Layer – Lateral opening

Class	Correct	Incorrect	Correct with low activation value
Door	87%	13%	3%
Corridor	79%	21%	0%
Door or Corridor	100%	0%	8%

Table 5. General Classification Result of Reason and Intuition Layers in two test stages.

Layer	Unknown Patterns	Generalization	Performance	Test Stage
Reason	-	-	100%	Test 1
	30%	100%	100%	Test 2
Intuition	44%	96%	94%	Test 1
	70%	77%	82%	Test 2

Table 6. General Correct Classification Result of Intuition Layer - Test stage 3.

Layer	General Classification	Unknown Patterns	Modified Patterns
Intuition	84%	79%	95%

6. CONCLUSIONS

This work contemplates one mobile robot navigation technique based on environment modeling, used with the LACE mobile robot, which uses its omnivision system and sensors of ultrasound to acquire information on external environment and to supply the mapping system. We present two modules of the mapping system: node classifier module and node characterizer module. The classifier module uses as classification tool a hierarchical neural network structured in two layers: reason and intuition. The main use of the structured Artificial Neural Network is to decide possible conflicts in the classification process.

When the first neural network will not be able to distinguish the place to be classified using ultrasound information, the second network uses information extracted from images of the place to classify the same. The phase of tests, composed by three phases, had as objective to validate the training of the Neural Network. In this way, when necessary the networks had been re-training with different algorithms, parameters or amount of neurons in occult layer, in order to reach optimum performance in the classification of the tested patterns.

The use of one-layer perceptron network in the test phase of the reason network presented excellent results (100% of rightness). Such network architecture is adequate for the robot real mapping system implementation. The intuition network reached 84% of correct classification in the final tests phase. This value can be considered satisfactory because the proposal for the classification method is to base the final decision in a set of results from the classification of different situations of the same local, that is, to base the decision of classroom in a bigger sample space, and not only an one only situation of each place. Moreover, the generalization rate reached for the reason and intuition networks are 75% and 79%; values these considered satisfactory. Thus, the Hierarchical Artificial Neural Network reached the objective for which it was created: to decide possible conflicts in the process of classification of the first sub-net.

7. REFERENCES

Arsênio, A.; Ribeiro, M. I. “Absolute localization of mobile robots using natural landmarks”. IEEE International Conference on Electronics, Circuits and Systems, vol 2, 483-486, 1998.

Balakrishnan, K., Bousquet, O., Honavar, V. “Spatial learning and localization in rodents: a computation model of the for hippocampus and its implications for mobile robots”. Adaptive Behavior, 7(2), 173-216, 1999.

Betke, M.; Gurvits, L. “Mobile Robot Localization Using Landmarks”. IEEE Transactions on Robotics and Automation, Vol. 13, No. 2, 1997.

Cavani, F. “Sistema de Visão Omnidirecional para Robô Móvel”. Projeto Final de Graduação. UNESP, São José do Rio Preto, 2004.

Duda, R. O.; Hart, P. E. (1973). “Pattern Classification and Scene Analysis”. JohnWiley E Sons.

Feder, H., Leonard, J., Smith, C. “Adaptive mobile robot navigation and mapping”. International Journal of Robotics Research, 18(7), 650-668. 896-901, 1999.

Filliat, D.; Meyer, J. A. “Map-based navigation in mobile robots: I. A review of localization strategies”. Journal of Cognitive Systems Research, vol 4, pp. 243 - 282, 2003.

Gutmann, J., Konolige, K. “Incremental mapping of large cyclic environments”. Proceedings of the IEEE international symposium on computational intelligence in robotics and automation (CIRA- 2000). IEEE Press, 2000.

Kortenkamp, D., Weymouth, T. “Topological mapping for mobile robots using a combination of sonar and vision sensing”. Proceeding of the 12th National Conference on Artificial Intelligence. Vol. 2, p. 979-84. MIT Press, 1994.

Kuipers, B. J.; Byun, Y. T. “A robot exploration and mapping strategy based on a semantic hierarchy of spatial representations”. Robotics and Autonomous Systems, Vol. 8, 47–63, 1991.

Levitt, T. S., Lawton, D. T. “Qualitative navigation for mobile robots”. Artificial Intelligence, 44, 305-360. (SAB 02). MIT Press, 1990.

Lu, F., Milios, E. “Globally consistent range scan morpholoalignment for environment mapping”. Autonomous Robots 4, 333-349, 1997.

Marsland, S., Nehmzow, U., Duckett, T. “Learning to select distinctive landmarks for mobile robot navigation”. Robotics and Autonomous Systems, Vol. 37, pp. 241 – 260, 2001

Martinez, V. O.; Costa, A. H. R. (2005). “Reconhecimento de marcos visuais como cenas para localização de robôs móveis”I Workshop do Projeto AACROM, 2002, São Paulo. Anais do I Workshop do Projeto AACROM, 2002. p. 47-55..

Matsumoto, Y.; Ikeda, K.; Inaba, M.; Inoue, H. “Visual navigation using omni directional view sequence”. Proceeding of the IEEE International Conference on Intelligent Robots and Systems, pp. 317-322, 1999.

Moravec, H., Elfes, A. “High resolution maps from wide angular sensors”. Proceedings of the IEEE international conference on robotics and automation (ICRA- 85). IEEE Press, pp.116-121, 1985.

Prescott, T. J. “Spatial representation for navigation in animals”. Adaptive Behavior, 4(2), 85-123, 1995.

Se, S., Lowe, D., Little, J. “Mobile Robot Localization and Mapping with Uncertainty using Scale-Invariant Visual Landmarks”. The International Journal of Robotics Research, Vol. 21, pp. 735 – 758, 2002.

Thrun, S., Burgard, W., Fox, D. “A real-time algorithm for mobile robot mapping with applications to multi-robot and 3D mapping”. Proceedings of the IEEE international conference on robotics and automation (ICRA- 2000). IEEE Press, pp. 321-328, 2000.

Zitovà, B.; Flusser, J. “Landmark recognition using invariant features”. Pattern Recognition Letters, Vol 20, pp. 541-547, 1999.

8. RESPONSIBILITY NOTICE

The authors are the only responsible for the printed material included in this paper.