SELF-ORGANIZING MAPS FOR ENVIRONMENTS AND STATES MAPPING OF AN AUTONOMOUS NAVIGATION SYSTEM BASED ON MONOCULAR VISION

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Abstract. *Helping humans with automated, semi-autonomous and autonomous systems is the trend that results of technological developments. Mobile robots and driver assistance are some examples of such systems. From an explicit or emerging need, the autonomous or semi-autonomous systems have come to replace or assist drivers. In this paper, the study of Kohonen Self-organizing Maps for Environments and States Mapping of an Autonomous Navigation System based on Monocular Vision is proposed. With the aim of mapping the environment to further aid the completion of tasks, in an exploration-training stage supervised by the user, a neural network was trained for internal representation of the environment, taking as input information from a local sensing system (monocular system) aggregating global information (time information), collected by the TH Finder algorithm (Threshold and Horizon Finder), and the time sequence of events/commands related to each stage of the original route. This visual memory results into the autonomy of the navigation system to support the completion of tasks. It uses a robust system which is inherent to the simplicity of a monocular-based solution. Whether for the exploring/training stage or for the task, the Discarding Redundant Information process was used as controller and weight to the states of the system (stationary or moving) and also as a tool to reduce the computational cost.*

Keywords*: Mobile Robots, Driver-assistance Systems, Neural Networks, Self-organizing Maps, Monocular Vision.*

1. INTRODUCTION

Helping humans from automated, semi-autonomous and autonomous systems is a trend which results in technological developments. However, in fulfilling the task, there is a variable of great importance and impact that is the environment. Because, even if an environment is previously mapped by a global positioning system, the constant randomness and repositioning on the course of time partially or totally undistinguishes it.

Currently, research in the area of autonomous and semi-autonomous navigation has motivated many researchers from different groups because of the challenge it represents. Several proposals have been studied, mainly based on the multidisciplinary and development of computer systems with biological inspiration. The number of publications in recent years is noteworthy, incorporating the developments in the area of telematics (Miranda Neto, 2007).

In this scenario, the role of the environment in the task completion is highlighted, so the generation of macro routes may be classified into two broad categories, having the environment as the main element: deterministic and known; or unknown and dynamic (Mendeleck et al., 2005).

Common to the autonomous and semi-autonomous systems, in order to obtain information about the environment, sensors and actuators are needed, which in many cases may be limited in scope and subject to noise. However, when incorporating several types of sensors, there is an increase of autonomy and "intelligence" degrees, especially in relation to navigation in unknown environments. On the other hand, the type and quantity of sensors determine the volume of data for processing and composition of the "image" of the environment, requiring, in most cases, a high computational cost. This cost may often rule out projects that use equipment that has little capacity and/or real-time applications.

Regarding the task performance, if the navigation task is carried out in a static and known environment, problems may be first reduced for the environment modeling and search for roads following some optimization criterion, e.g., distance, energy, processing, number of movements, quality of travel, and so on. For unstructured environments, the scenario for study is dynamic, with several elements in motion. Thus, running an automated or semi-autonomous navigation system from a starting point to a destination, or assisting a driver with this task, involves carrying out complex and non-deterministic operations, such as: interaction with the environment, identification of environmental elements and decision making. In this case, the route generation requires that a number of unknown factors by the planning software be addressed, such as the volume of the work area as well as the mobile and fixed elements. Without this information, the computational cost for generating the route becomes quite high, especially considering the conventional ways of programming robots (Mendeleck et al., 2005).

For some years, interested in the individual study of sensors, fusion of sensors, completion of tasks, etc., a research agency known as DARPA (Defense Advanced Research Projects Agency) has been promoting excellent results in the area of autonomous navigation. Within this objective, since 2002, they have been stimulating universities, colleges and businesses from within and outside the U.S.A. to develop autonomous vehicles, since one of the objectives that the U.S. government has is to turn a third of its military fleet into autonomous vehicles before 2015.

As a consequence, in 2004 and 2005, a challenge was held, known as the Grand Challenge. However, in 2004 none of the teams completed the course set out for the competition. But in 2005 five teams completed the challenge. During the 2005 Grand Challenge, the challenge was to cross the Mojave Desert. The winning team completed the race with an average speed of 30.7 km/h. The last challenge was held in November 2007. Known as the DARPA Urban Challenge, it was characterized by autonomous vehicles which managed their tasks in a fake urban area.

In recent years, research on Human Factors has merged with research of intelligent vehicles, but it aims to create a new generation of Driver-Assistance Systems, which goes beyond the automated control to attempt to work harmoniously with a human operator. Emerging systems, which monitor the state of the driver, foresee the driver's intention, warn and help them to drive the vehicle (Mccall and Trivedi, 2006).

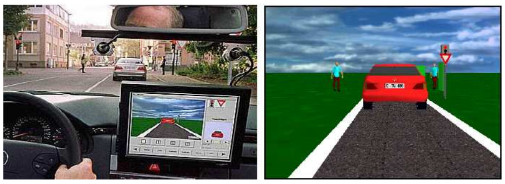

Figure 1 – UTA II - Mercedes-Benz E-class (Franke et al., 2000).

Especially with the use of the self-organizing maps in navigation systems, Nagrath et al. (1997) have proposed a navigation method for mobile robots using the Kohonen self-organizing maps for the topology conservation for navigation in unknown environments. The mobile robot localization was discretely kept using a two-dimensional Kohonen network. The network was used for planning routes and was well suited to solve the problem of navigation in real time. The authors point out that, once the space was discretized in weight and was tuned to the mobile robot orientation, the system was able to navigate successfully in new tasks. For the experiments, a robot with 7 ultrasound sensors was used, divided into three subgroups: Right, Center, Left. The tasks were carried out in a real environment of 4m x 6m. In figure 2 the layout of the environment and the topological map generated are shown.

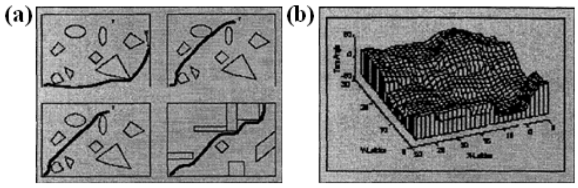

Figure 2 – (a) Environment Layout; (b) Topological map generated (Nagrath et al., 1997).

In Huosheng and Dongbing (1999), a navigation system based on landmarks was shown. From the identification of landmarks by a laser scanner sensor, for each robot repositioning in the environment, its manual re-calibration was necessary, which, according to the authors, was not something that should be used for a practical application. For this, they used a Kohonen self-organizing map, which had, as input, the laser measurements, which, in turn, could only measure the angles of different milestones and could not distinguish among them. Thus, the network should determine the correlation between angles and landmarks in order to provide coordinate triangulation.

In Dimakov and Golovko (2000), a common problem for mobile robots was discussed, which, according to the authors, usually require prior and detailed information about the route map, requiring a detailed description of all possible roads. So, they describe a neural network architecture to solve the problem of shortest routes. This architecture has a Kohonen network as the only single memory level of the storage system of the environment main points. As the system inputs, Current Robot Coordinate, Direction of Movement; Nearest Point from the current robot position were used. Figure 3 shows the results of the experiments in a simulated environment.

Yamada (2004) presents a mobile robot that uses a non-supervised learning system for recognition of environments from the sequence of actions. The sequence of actions performed were converted into vectors and used as input to self-organizing the map. According to the author, the learning enabled the robot to identify different environments. For the experiments, a robot with an infrared proximity sensor was used. Figure 4 shows the robot, an environment and the outcome of a sensing vector.

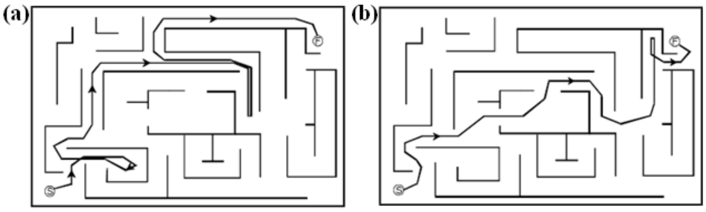

Figure 3 – (a) Route 1; (b) Route 2 (Dimakov and Golovko, 2000).

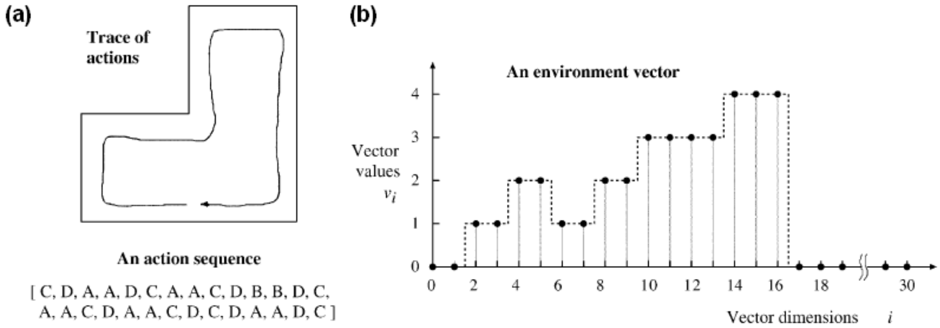

Figure 4 – (a) Environment; (b) Generated Vector (Yamada, 2004).

Finally, Ishikawa et al. (2007) classifies the problem to teach each action to a mobile robot as being difficult and suggests, as an option, to apply the technologies which has the brain as inspiration. Figure 5 shows the outcomes of a route mapped in movements in a self-organizing map.

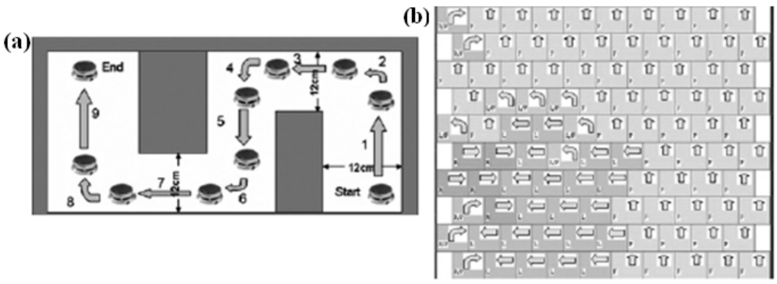

Figure 5 – (a) Environment; (b) Mapping of movements Ishikawa (2007).

Basically, the problem of autonomous or semi-autonomous navigation systems involves the recognition of the environment, self-location, trajectory planning and control of movements of the system in the space. As previously mentioned, a series of sensors can be used to create and maintain an environment representation, through which the navigation system, with some level of autonomy, decide by a movement. In this context, with a self-organizing map, a phase of exploration-supervised training can store (save) the information inherent to the explored environment, contributing at a later stage, named as task completion.

Regarding the characterization of a system as autonomous or (semi)-autonomous, it should be in mind that each system has its own level of autonomy. Different of the previously applications (above), the robotic platform and the monocular vision system selected characterize the system with a low level of autonomy. However, the Kohonen neural network model is applied as an autonomous and semi-autonomous navigation aid tool bringing greater robustness to the system.

The research written here is limited to the development of internal topological maps generated from the neural network. Furthermore, this project does not address aspects which are inherent to different types of sensors applicable to current robotics, but is limited to extract information from images captured by the camera sensor, turning them into neural network input. The information extracted from images, using the TH Finder (Threshold and Horizon Finder) method of segmentation offered by Miranda Neto and Rittner (2006), is limited to identifying the navigation area.

However, the different states of navigation system, such as stationary or in movement, and the performance of tasks in real time are highlighted. For this, the Discarding Redundant Information method was proposed by Miranda Neto et al. (2007) and Miranda Neto et al. (2008).

2. AUTONOMOUS AND SEMI-AUTONOMOUS NAVIGATION SYSTEM AND THE ROBOT PROTOTYPE

Here the use of self-organizing maps is proposed to assist the task completion, for autonomous or semi-autonomous navigation systems. In this case, it is highlighted that, in many occasions, it will not be possible to dispose of human beings, which leads to autonomous and semi-autonomous systems having the same relevance. Accordingly, figure 6 emphasizes that, on the threshold of the autonomous navigation systems research, the semi-autonomous systems (SAC) may be found, where, basically, the main difference is that, for an autonomous system, it is necessary that the kinematic and dynamic model of the vehicle be known, while for a SAC, it is a Human-Machine Interface and/or a Virtual Reality System. Thus, for an autonomous system, the result of the sensory analysis generates movement commands to the vehicle actuators, while for a SAC warnings to the driver are generated, which, in turn, interacts with the vehicle actuator (Miranda Neto and Zampieri, 2008). Therefore, it can be concluded that both systems operate autonomously, differing only in the performance of movements, which is executed either by a robot actuator or by a human user, which would allow the implementation of what is proposed in this document.

Still it is important to notice that for both autonomous and semi-autonomous navigation systems, for a task completion in general, one seeks to know the world map world from information that identifies a global positioning, including the information that allows the recognition of the local space. This sequence of perception and control is presented in figure 7. From the extraction of information of the environment, the localization map is then formed, from a sequence of learned commands, which intervene with the robot decisions through commands sent to actuators or for the driver's decision. After these movements are generated, the cycle restarts so that, through perception, a new image and positioning is formed in the navigation process.

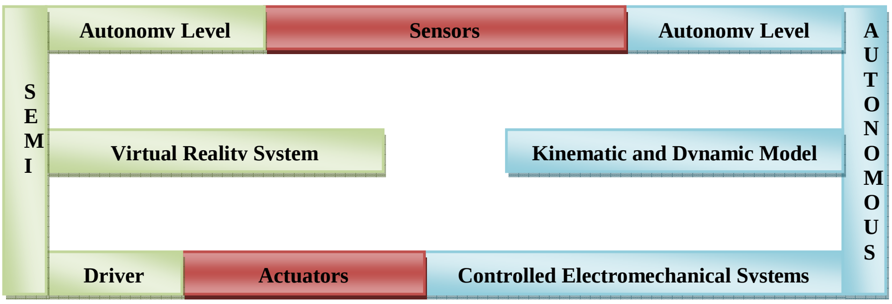

Figure 6 – Main components of the Autonomous and Semi-autonomous Systems (Miranda Neto and Zampieri, 2008).

The robot shown in figure 7, used in Miranda Neto (2007), is classified as non-holonomic in this paper, which, along with its embedded system of monocular vision, has a level of autonomy below expected for autonomous navigation. As for the sensing system (video camera), it is classified as being exteroceptive and passive, once it has already captured external information from a camera.

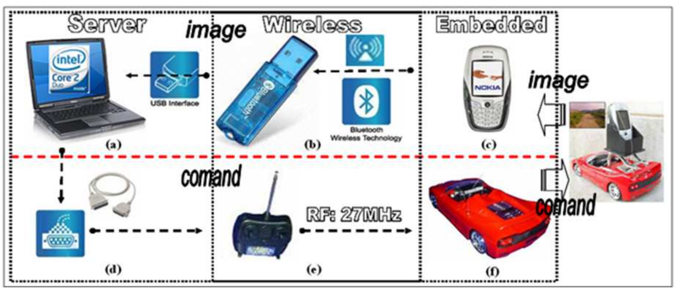

Figure 7 – Prototype: (a) Computer-Server; (b) Wireless-Bluetooth Communication; (c) Video Camera-Mobile phone; (d) Computer connection-Control; (e) Remote Control; (e) Original Remote Control Car (Miranda Neto, 2007).

3. SEGMENTATION AND DISCARDING REDUNDANT INFORMATION METHOD

3.1. The Segmentation Method - TH Finder

In Miranda Neto and Rittner (2006), a technique of images segmentation called Threshold and Horizon Finder (TH Finder) was presented, based on the method proposed by Otsu (1978). This algorithm searches a threshold that discards the image above of the horizon line. For this, the image is divided into two parts. The division does not necessarily occur in equal parts, but in two complementary images. Figure 8 shows an example of this division in Up and Down, respectively, the vision of the horizon (which may contribute for future decisions) and the vision of proximity or closed vision (which contributes for the instantaneous decision-movements). For the study in question, the main objective of using the TH Finder method is the extraction of the data from the segmented images to the neural network input.

Figure 8 – Original Image (Up and Down); Result of TH Finder segmentation (Miranda Neto et al., 2007).

3.2. Discarding Redundant Information

In Miranda Neto et al. (2007), an automatic method of Discarding Redundant Information based on Pearson's Coefficient of Correlation method was considered (PCC). According to Eugene and Johnston (1996), the PCC,the coefficient r, is used for statistical analysis, recognition of standards pattern and image processing. With this intention, it includes the comparison between two images, the calculation of disparity and the object recognition. For monochromatic digital images, the PCC is described in the Equation (1):

$$r = \frac{\sum_i (x_i - x_m)(y_i - y_m)}{\sqrt{\sum_i (x_i - x_m)^2}\sqrt{\sum_i (y_i - y_m)^2}} \qquad (1)$$

where x_i is the intensity of an i^{th} pixel in image 1, y_i is the intensity of an i^{th} pixel in image 2, x_m is the average of intensities of image 1, and y_m is the average of intensities in image 2. The PCC takes value 1 if images are absolutely identical, 0 if they are completely uncorrelated, and -1 if they are completely anti-correlated.

Miranda Neto et al. (2008) propose to replace the empirical search to find a suitable PCC threshold with a threshold value found from the non-deterministic criterion. For this task, the Discarding Redundant Information process uses information from the TH Finder segmentation method.

For this study, and as shown in figure 9, the discard process will act as a weight for the task completion, because it allows the disposal of images during exploratory navigation, regardless of the robot state, stationary or in motion (be it at different speeds). For further performance of the same or very similar task, preserving the main characteristics of the environment, it is expected a similar number of images to be found, which, in turn, will suggest the composition of the route already performed. In the chart of figure 9 is represented the number of selected frames of the DARPA video versus the correlation coefficient (PCC) between the first image with its subsequent until the last. For each image analyzed, a lower value of correlation is achieved when it is closer to the vehicle (obstacle detection). Once a vehicle pass occurs, there is a return to the stabilization.

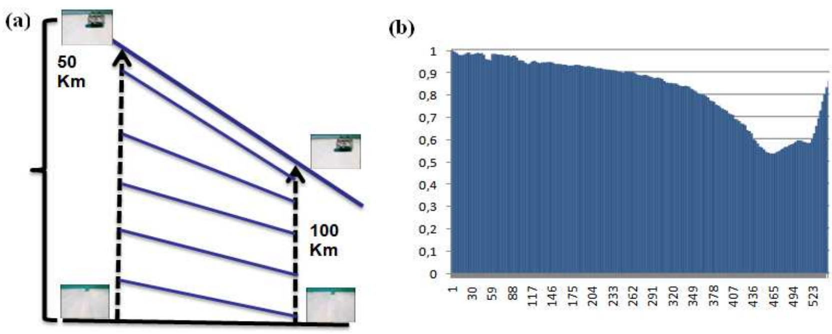

Figure 9 – (a) Discarding Redundant Information Non-deterministic process with weight of system states for task completion. (b) Number of selected frames of the DARPA video versus the correlation coefficient (PCC).

4. KOHONEN SELF-ORGANIZING MAPS

In addition to what has already been shown in the introduction of this paper, the choice of the self-organizing maps to navigation tasks or sub-tasks was made in contrast to the supervised training and the training by strengthening, since there is not any explicit desired output for the system or any external evaluation of the output for each input data, even during the exploration/training stage. Furthermore, the system does not have a feedback data, which does not allow, for example, the use of a Genetic Algorithms & Classifier Systems or others neural networks models.

According to Haykin (2001), the main objective of a self-organizing map is to turn an incident signal standard of arbitrary dimension into a discrete map, in this in case, two-dimensional, and perform this transformation in an adaptative form and in topological order.

Characteristics of the map used in this paper are presented herebelow, as well as the composition of the input data.

4.1. Map Characteristics

As it may be seen in figure 10 (a) and (b), the neural structure used in this paper has, respectively, a two-dimensional arrangement of 5x5 neurons, with neighboring of 2. Each neuron of the grid is totally connected with all knots at entry layer. This grid represents a feedfoward structure, with a single computational layer consisting of neurons arranged in lines and columns.

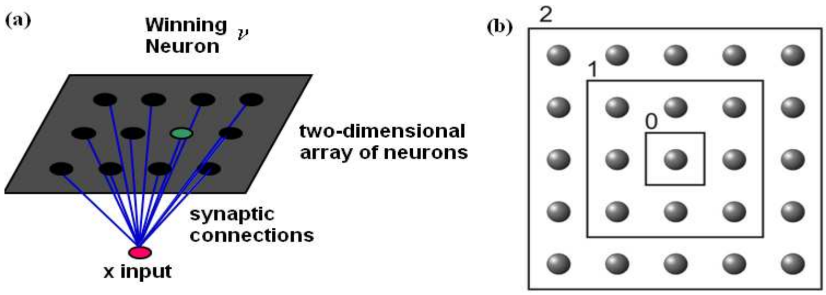

Figure 10 – (a) Two-dimensional array of neurons; (b) Update of weights by windowing of neighboring 2.

For each input pattern, the network neurons calculate their respective values from a discriminating function, which provides the basis for competition among neurons. The neuron with the largest discriminating function value is declared the winner of the competition. In this paper, the Euclidean distance was used for this competition.

Looking at the neighboring 2, using a Gaussian function, figure 11 (b), a winning neuron determines the location of neighboring neurons, figure 11 (a), thus providing the basis for cooperation among them.

According to Haykin (2001), Equations (2) and (3), presented below, allow excited neurons to increase their individual values of the discriminant function in relation to the pattern of the input through appropriate adjustments applied to their synaptic weights. The adjustments made are such that the winning neuron response to subsequent application of a pattern with similar input is improved.

The known discriminant function is written as,

$$\mathbf{w}_j(t+1) = \mathbf{w}_j(t) + \alpha(t) h_{vj}(t)[\mathbf{x} - \mathbf{w}_j(t)] \tag{2}$$

where $\mathbf{w}_j$ (t+1) is the updated weight vector, $\mathbf{w}_j$ (t) is the previous weight vector, α(t) is the rate of learning, h_{vj} (t) is the neighborhood and [$\mathbf{x}$ - $\mathbf{w}_j$ (t)] is the adjustment.

The rate of learning is written as,

$$\alpha(t) = \alpha_0 \exp\left(-\frac{t}{\tau_2}\right), \tag{3}$$

where τ2 is the total number of iterations.

For the performance of the algorithm, other important information is cited:

- At Start Up : vector of weights **w** initiated with values = 0;
- Vector of weights **w** with values between [- 1, 1];
- 2 stages of iteration – 1st: number of standards * 15; 2nd: number of standards * 5;
- Tax of learning: 0.8/phase (defined above);
- 50 steps by iteration - adapting process of topological ordinance;

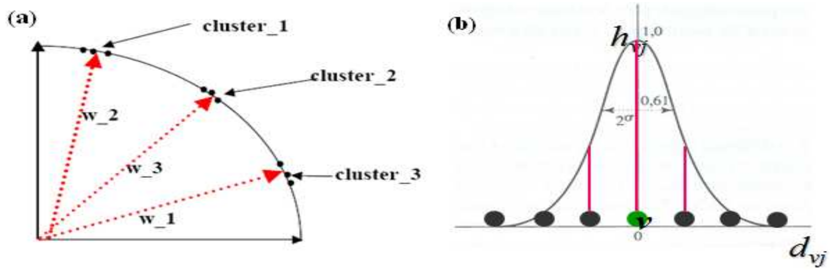

Figure 11 – (a) Clustering of Neurons; (b) Gaussian function based on cooperation.

4.2. Input Data

Input data of the neural network are extracted from the results of the TH Finder segmentation of each image obtained from the sensory camera. The data are:

- Maximization vector: Equation (4): See Maximization Vector - representation of the distribution of navigation points versus not navigable points in the image, Equation (3.21) in Section 3.5 in Miranda Neto (2007);
- Depth and Depth Vector: Equations (5) and (6): See Speed v – speed calculated from Depth Vector, Equation (3.19) in Section 3.4; Depth Vector - variable for analysis of the depth of the navigation area, Equation (3.9) in Section 3.2 in Miranda Neto (2007);
- Center of Mass: Equation (7): See Alignment Angle to the Navigation Area Center - angle of direction correction to the navigation area center, Equation (3.17) in Section 3.3.3 in Miranda Neto (2007);

$$\vec{VM}_i = \sum_{j=1}^{n} M(x_i, y_j) \tag{4}$$

$$v = \sum_{i=1}^{10} \frac{(\vec{VP}_i / i)*10}{VMI} \tag{5}$$

$$\vec{VP}_i = \frac{NP_i * 100}{(H*W)_i} \tag{6}$$

$$a = ((arc.\cos(\frac{|(yo_{c1} - y)|}{\sqrt{(xo_{c1} - x)^2 + (yo_{c1} - y)^2}}))*180)/PI \tag{7}$$

Given the adequacies, the values must be within an interval [- 1, 1], as previously mentioned. Equations (4) to (7) allow the generation of the input data of the neural network. Making a parallel thought with figure 12, it could be said that: Equation (4) generates the values represented in figure 12 (b); Equation (5) generates the values represented in figure 12 (c); Equation (7) generates the values represented in figure 12 (d), thus forming the input data of the neural network, represented in figure 12 (e). The figure 13 is the final composition of the input data presented to neural network for each interaction with the environment. In this case, as global information, one can understand the time of information in which the sensing system acquires the images of the environment. The main purpose of this procedure is to aggregate sequencing information for each network input, making this information to work for further completion of tasks. It would be emphasize the predominance of local information with the global one, which ensures that the immediate features of the environment prevail in relation to the task.

5. RESULTS

The experiments were performed using sets of images from videos, one from the team of Stanford in the DARPA Gran Challenge, and other generated from the video camera embedded in the robot shown in figure 7. To understand the system sequence, see the macro-flowchart shown in figure 14.

For the exploration-training stage, whether it is by a set of images from a video that is ready, or during the robot navigation shown here, by observing figure 14, the sequence for mapping the environment was: (b) Environment; (c) Discard Redundant Information; (d) TH Finder; (e) Kohonen; (f) Movement.

It may be noticed that in the exploration-training stage the Movement was not included (f), since, if the sequence of images were obtained from the camera of the robot, it would being led by a human operator through a remote control.

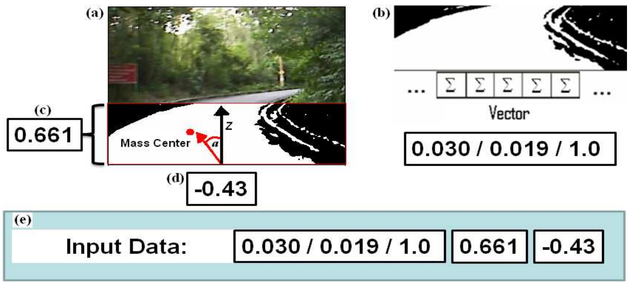

Figure 12 – (a) Original Image; (b) *TH Finder* Result; (c) Calculated Depth; (d) Calculated Center of Mass; (e) 1st stage of generation of Input data from the Neural Network.

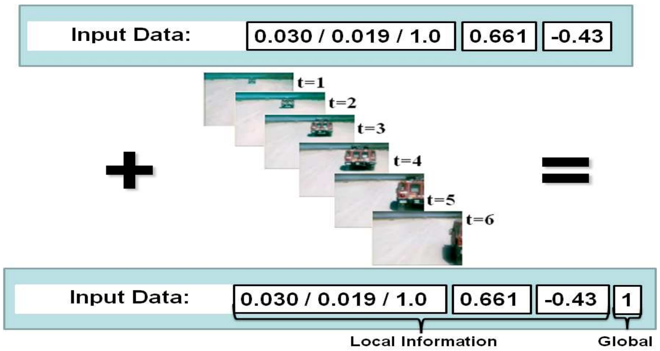

Figure 13 – Input Data of 1st stage of generation, in figure 12, aggregate global information.

Since the Kohonen map has been generated, that is, the exploring/training stage has already been completed and, consequently, the system has memorized the main structures of the environment, then, the sequence for performing the task is presented. It is important to know that the map will be frozen, except for the competition function, which will seek to find, in the map, the neuron that best fits to each data (image + sequence) of the environment where the task is being performed.

Now it is noticed that the Movement (f) was inserted to perform the task. So, it is important to highlight that, whether the task is autonomously accomplished by the robot or semi-autonomously driven by the user, the output of the commands will always be generated from the winning neuron of the Kohonen map (environment), regardless of how much this information is similar to the original input data. Therefore, (b) to (d) are defined as the implementation stage of the task, in which the input data for the network are prepared. In (e), however, there is a competition among all the neurons, and in (f) there is the movement for a winning neuron.

In the first case of the experiment, shown in figure 15, (a) introduces the mapping of the environment by Kohonen for the sequence of images. In (a), there is the exploration/training stage, what demonstrates good grouping for the input data. For figure 15 (b) the task is performed, an optimal case. Suppose that the robot runs exactly the same task performed during the exploration/training stage. It is observed that the same set of images of the training was used to simulate the task performance. In this case, the neural network output yielded 100% of hits for the task completion, allowing that the trajectory shown in (b), in the exploration/training stage, be exactly the same at the end of the task performance.

For figure 16, there has been a task performance for a semi-optimal case, which reflects a set of images generated by the camera of the robot, during navigation in an indoor environment. Suppose that the robot had carried out exactly the same task performed during the exploration/training stage. It is observed that a similar set of images in the training was used to simulate the task performance. Notice: similar, except for the number of images, since the Discard Redundant Information module was disabled. In this case, the neural network output produced 88% of hits for the task completion, allowing that, for the route shown in (a. Red) in the exploration/training stage, it is similar to the final route of the task carried out which is shown in (a. Green). (a. Blue) shows the preferential route of the monocular vision system without the neural network.

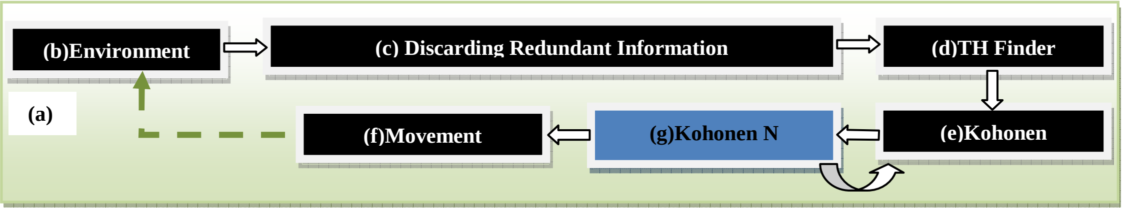

Figure 14 - (a) Macro flowchart of the considered Navigation System; (b) Environment representing the input of images; (c) Discarding Redundant Information; (d) TH Finder; (e) Neural Network: Kohonen self-organizing map; (f) Movements generated from the Neural Network output; (g) Continued learning - not implemented.

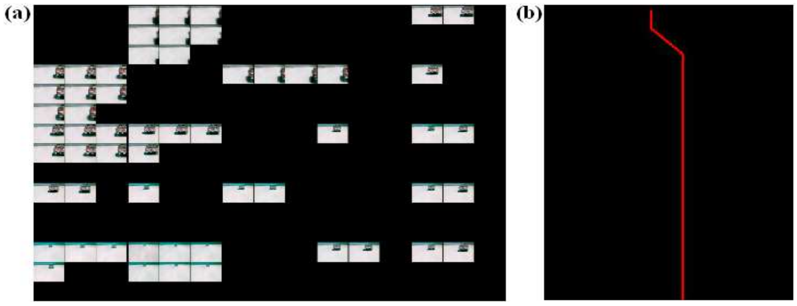

Figure 15 – (a) Exploration/training Stage; (b) Task Completion - optimal case.

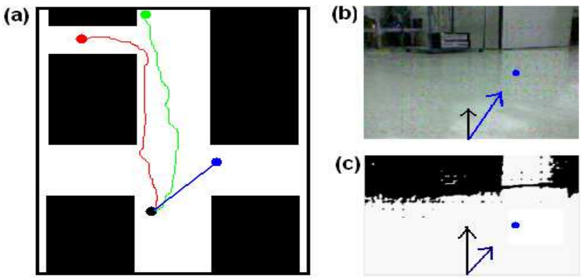

Figure 16 - (a) Actual environment; (b) Image generated by the camera of the robot & Calculated Center of Mass; (c) *TH Finder* Result & Calculated Center of Mass; (a. Red) Route during the Exploration/Training Stage; (a. Green) Route during the task completion; (a. Blue) shows the preferential route of the monocular vision system without the neural network.

6. CONCLUSION

As seen in this paper, an autonomous or (semi)-autonomous system have its level of autonomy. The robotic platform selected and the monocular vision system characterizes the system with a low level of autonomy. However, the self-organizing maps have been applied to the navigation systems. The experiments conducted here have shown that the use of neural network may provide a more robust navigation system based on the monocular vision to task completion. Some initial experiments were performed so that the robot, shown in figure 7, runs tasks autonomously, after the exploration/training stage. These results were not included in this paper due to the absence of a kinematics model of the robot, which did not allow the movements to be ideally performed (controlled), hindering the collection of results.

However, the experiments simulated with a set of images demonstrated that the method considered here may be promising for the learning of the navigation area, during the performance of the robot movements. For further study, the figure 14 (g) shows a model of continued learning. This learning would allow the neural network to continue learning during the task performance, since the study for dynamic environments is of paramount importance to autonomous or semi-autonomously navigation.

Another important point is to simulate the exploration/training stage, with different parameters to the self-organizing map, as herein it was decided to let them to be fixed. Some changes were made, but there was no improvement in the results.

Finally, in the experiments of autonomous navigation, whether for the exploration/training stage, or for the task completion, a robot replacement is suggested.

7. ACKNOWLEDGEMENTS

The authors wish to thank Prof. Dr. Romis Ribeiro de Faissol Attux for their kind attention to our work and for the useful discussions, and also Mr. Paulo Victor de Oliveira Miguel for his support in the simulation tests.

This work was supported in part by CNPq.

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5. RESPONSIBILITY NOTICE