We are IntechOpen, the world's leading publisher of Open Access books Built by scientists, for scientists

6,900
Open access books available

185,000
International authors and editors

200M
Downloads

Our authors are among the

154
Countries delivered to

TOP 1%
most cited scientists

12.2%
Contributors from top 500 universities



WEB OF SCIENCE™

Selection of our books indexed in the Book Citation Index in Web of Science™ Core Collection (BKCI)

Interested in publishing with us?
Contact book.department@intechopen.com

Numbers displayed above are based on latest data collected.
For more information visit www.intechopen.com



3

Neural-Based Navigation Approach for a Bi-Steerable Mobile Robot

Azouaoui Ouahiba, Ouadah Noureddine,
Aouana Salem and Chabi Djeffer
Centre de Développement des technologies Avancées (CDTA)
Algeria

1. Introduction

Recent developments in robotics have revealed a strong demand for autonomous out-door vehicles capable of some degree of self-sufficiency. These vehicles have many applications in a large variety of domains, from spatial exploration to handling material, and from military tasks to people transportation (Azouaoui &Chohra, 1998; Hong et al., 2002; Kujawski, 1995; Labakhua et al., 2006; Niegel, 1995; Schafer, 2005; Schilling & Jungius, 1995; Wagner, 2006). Most mobile robot missions include autonomous navigation. Thus, vehicle designers search to create dynamic systems able to navigate and achieve intelligent behaviors like human in real dynamic environments where conditions are laborious.

In this context, these last few years small automated and non-pollutant vehicles are developed to perform a public urban transportation task. These vehicles must use advanced control techniques for navigation in dynamic environments especially urban ones. Indeed, several research works have recently emerged to treat this transportation task problem. For instance, the work developed in (Gu & Hu, 2002) presents a path-tracking scheme based on wavelet neural predictive control to model non-linear kinematics of the robot to adapt it to a large operating range. In (Mendes et al., 2003), a path-tracking controller with an anti-collision behavior of a car-like robot is presented. It is based on navigation and anti-collision systems. The first system uses a Fuzzy Logic (FL) to implement the path-tracking while the second system consists of estimating the trajectories and behavior of surrounding objects. Another work developed in (Bento & Nunes, 2004) treats also the path following problem of a cybernetic car. The developed controller with magnetic markers guidance is based on FL and integrates an anti-collision behavior applied to a bi-steerable vehicle. Other works use a visual control to achieve a desired task such as the work proposed in (Avina Cervantes, 2005). It consists to develop a visual-based navigation method for mobile robots using an on-board color camera. The objective is the use of vehicles in agriculture to navigate automatically on a network of roads (to go from a farm to a given field for example).

Although several investigations on the robot navigation problem have been developed (Avina Cervantes, 2005; Azouaoui & Chohra, 2002; Chohra et al., 1998; Gu & Hu, 2002; Kujawski, 1995; Labakhua et al., 2006; Mendes et al., 2003; Niegel, 1995; Schilling & Jungius, 1995; Sorouchyari, 1989), to date further efforts must be made to apprehend and understand

Open Access Database www.intehweb.com

Source: New Approaches in Automation and Robotics, Book edited by: Harald Aschemann, ISBN 978-3-902613-26-4, pp. 392, May 2008, I-Tech Education and Publishing, Vienna, Austria

the navigation behavior of a vehicle evolving in partially structured and partially known environments such as urban ones.
In this paper, an interesting neural-based navigation approach suggested in (Azouaoui & Chohra, 2002; Chohra et al., 1998) is applied with some modifications to a bi-steerable mobile robot Robucar. Indeed, this approach is based on basic behaviors which are fused under a neural paradigm using Gradient Back-Propagation (GBP) learning algorithm. This navigation is then implemented within a behavioral architecture because of its excellent real-time execution properties (Murphy, 2001).
The aim of this work is to implement a neural-based navigation approach able to provide the Robucar with more autonomy, intelligence, and real-time processing capabilities. In fact, the vehicle relies on its interaction with its environment to extract useful information. In this paper, the used neural navigation approach essentially based on pattern classification (or recognition) (Welstead, 1994) of target localization and obstacle avoidance behaviors is presented. This approach has been developed in (Chohra et al., 1998) for five (05) possible movements of vehicles, while in this paper this number is reduced to three (03) possible movements due to the Robucar structure. Second, simulation results of the neural-based navigation are presented. Finally, an implementation of the neural-based navigation on a real bi-steerable robot Robucar is given leading to a learning vehicle able to behave intelligently faced to unexpected situations.

2. Neural-based navigation approach applied to a bi-steerable mobile robot Robucar in partially structured environnments

To navigate in partially structured environments, the Robucar must reach its target without collisions with possibly encountered obstacles. In other terms, it must have the capability to achieve the target localization, obstacle avoidance, and decision-making and action behaviors. These behaviors are acquired using multilayer feedforward Neural Networks (NN).
This neural navigation is built of three (03) phases as shown in Figure 1. During the phase 1, from the temperature field vector X_T, the robot learns to recognize target location situations T_{j1} (j1 = 1, ..., 5) classifier while it learns to recognize obstacle avoidance situations O_{j2} (j2 = 1, ..., 6) classifier from the distance vector X_O during the phase 2. The phase 3 decides an action A_i (i = 1, ..., 3) from two (02) association stages and their coordination carried out by reinforcement Trial and Error learning.

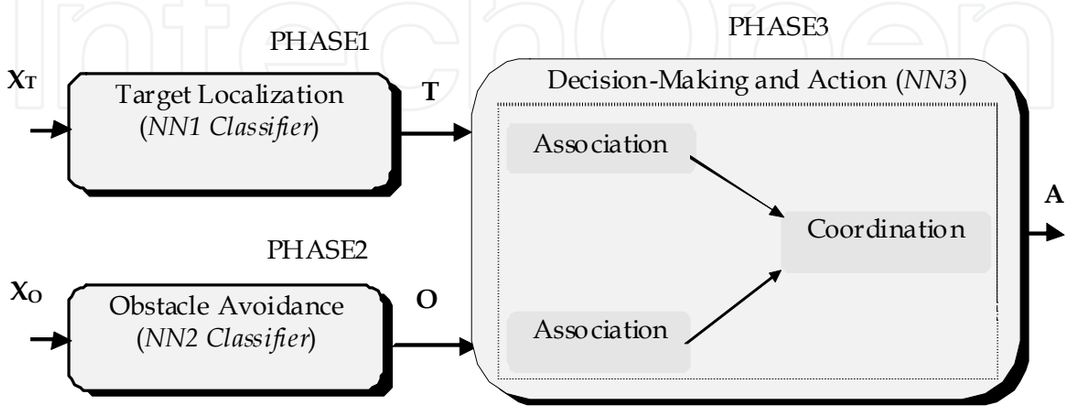


Fig. 1. Neural navigation system synopsis.

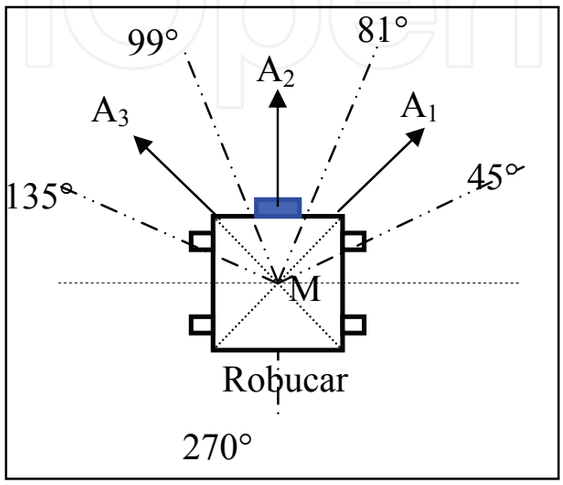
2.1 Vehicule and sensor

a) Vehicle.

The Robucar is a non-holonomic robot characterized by its bounded steering angle (-18°≤ ϕ≤ +18°) and velocity (0m/s ≤v ≤5m/s) (Figure 2(a)). Three movements of the Robucar are defined to ensure safety displacement in the environment. The possible movements are then in three (03) directions consequently three (03) possible actions are defined as action to move left (towards 18°), action to move forward (towards 0°), and action to move right (towards -18°) as shown in Figure 2(b). They are expressed by the action vector A = [A_1, A_2, A_3].



(a) Robucar.



(b) Robot model.

Fig. 2. Robucar and its sensor.

b) Sensor.

The perception system is essentially based on a laser-range finder LMS200 (SICK, 2001). It provides either 100° or 180° coverage with 0.25°, 0.5°, or 1.0° angular resolution. In this paper, the overall coverage area is divided into three sub-areas corresponding to the three possible actions as shown in Figure 2. Thus, to detect possibly encountered obstacles, three (03) areas are defined to get distances (vehicle-obstacle) from 45° to 81°, from 81° to 99°, and from 99° to 135° (see Figure 2). These areas are deduced from the Robucar dimensions to ensure its security.

2.2 Neural-based navigation system

During the navigation, the vehicle must build an implicit internal map (i.e., target, obstacles, and free spaces) allowing recognition of both target location and obstacle avoidance situations. Then, it decides the appropriate action from two association stages and their coordination (Chohra et al., 1998; Sorouchyari, 1989). To achieve this, the neural-based navigation system is used where the only known data are initial and final (i.e., target) positions of the vehicle.

a) Phase 1.

Target Localization (NN1 Classifier). The target localization behavior is based on NN1 classifier trained by the GBP algorithm which must recognize five (05) target location situations, after learning, from data obtained by computing distance and orientation of

robot-target using a temperature field method (Sorouchyari, 1989). This method leads to model the vehicle environment in five (05) areas corresponding to all target locations as shown in Figure 3. These situations are defined with five (05) Classes T_1, ..., T_{j1}, ..., T_5 where (j1 = 1, ..., 5):

$$\begin{aligned} &\text{If } 45° \le \gamma < 81° \text{ (Class } T_1\text{)},\\ &\text{If } 81° \le \gamma < 99° \text{ (Class } T_2\text{)},\\ &\text{If } 99° \le \gamma < 135° \text{ (Class } T_3\text{)},\\ &\text{If } 135° \le \gamma < 270° \text{ (Class } T_4\text{)},\\ &\text{If } 270° \le \gamma < 405° \text{ (Class } T_5\text{)}. \end{aligned} \quad (1)$$

where γ is the angle of the target direction.

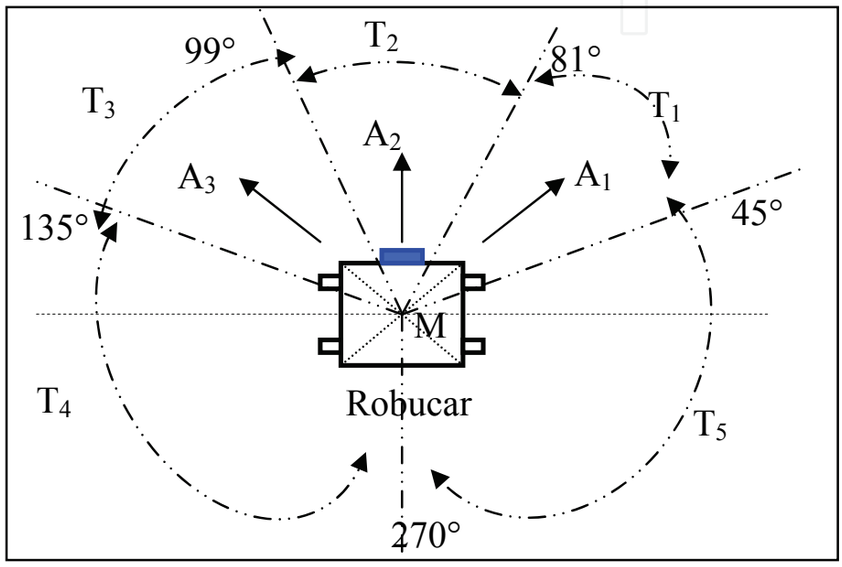


Fig. 3. Target location situations.

Temperatures in the neighborhood of the vehicle are defined by: t_L in direction 18°, t_F in direction 0°, and t_R in direction -18°. These temperatures are computed using sine and cosine functions as follows:

$$\begin{aligned} &\text{If } 45°< \gamma \le 80° \text{ (Class } T_1\text{)},\\ &\quad \text{Then } T_R = 12\sin(\gamma),\ T_F = 6\cos(\gamma),\ T_L = 6\cos(\gamma),\\ &\text{If } 80°< \gamma \le 99° \text{ (Class } T_2\text{)},\\ &\quad \text{Then } T_R = 6\,|\cos(\gamma)|,\ T_F = 12\sin(\gamma),\ T_L = 6\,|\cos(\gamma)|,\\ &\text{If } 99°< \gamma \le 135° \text{ (Class } T_3\text{)},\\ &\quad \text{Then } T_R = 6\,|\cos(\gamma)|,\ T_F = 6\,|\sin(\gamma)|,\ T_L = 12\sin(\gamma),\\ &\text{If } 135°< \gamma \le 270° \text{ (Class } T_4\text{)},\\ &\quad \text{Then } T_R = 12\,|\sin(\gamma)|,\ T_F = 6\,|\sin(\gamma)|,\ T_L = 12\,|\sin(\gamma)|,\\ &\text{If } 270°< \gamma \le 315° \text{ (Class } T_5\text{)},\\ &\quad \text{Then } T_R = 12\,|\sin(\gamma)|,\ T_F = 6\,|\sin(\gamma)|,\ T_L = 6\cos(\gamma),\\ &\text{If } 315°< \gamma \le 360° \text{ (Class } T_5\text{)},\\ &\quad \text{Then } T_R = 12\cos(\gamma),\ T_F = 6\cos(\gamma),\ T_L = 6\,|\sin(\gamma)|,\\ &\text{If } 360°< \gamma \le 405° \text{ (Class } T_5\text{)},\\ &\quad \text{Then } T_R = 12\cos(\gamma),\ T_F = 6\cos(\gamma),\ T_L = 6\sin(\gamma). \end{aligned} \quad (2)$$

These components are pre-processed to constitute the input vector X_T of NN1 (Azouaoui & Chohra, 2003; Azouaoui & Chohra, 2002; Chohra et al., 1998) built of input layer, hidden layer, and output layer as shown in Figure 4: architecture of NN1 where $X_i = X_{Ti}$ (i = 1, ..., 3), Y_k (k = 1, ..., 5), $C_j = T_{j1}$ (j = j1 = 1, ..., 5).

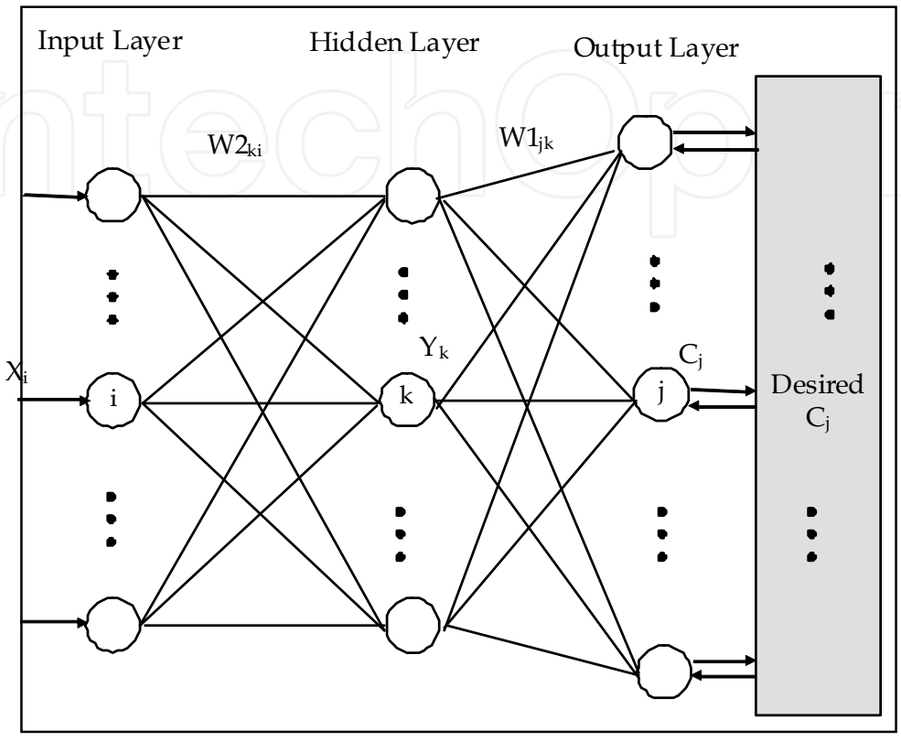


Fig. 4. Architecture of both NN1 and NN2.

After learning, for each input vector X_T, NN1 provides the vehicle with capability to decide its target localization, recognizing target location situation expressed by the highly activated output T_{j1}.

b) Phase 2.

Obstacle Avoidance (NN2 Classifier). The obstacle avoidance behavior is based on NN2 classifier trained by GBP which must recognize obstacle avoidance situations, after learning, from laser sensor data giving robot-obstacle distances. These obstacle avoidance situations are modeled as the human perceives them, that is, as topological situations: corridors, rooms, right turns, etc. (Anderson, 1995; Azouaoui & Chohra, 2003).

The possible movements of the Robucar lead us to structure possibly encountered obstacles in six (06) topological situations as shown in Figure 5. These situations are defined with six (06) Classes O_1, ..., O_{j2}, ..., O_6 where (j2 = 1, ..., 6).

The robot-obstacle minimal distances are defined in the vehicle neighborhood by: d_L in direction 18°, d_F in direction 0°, and d_R in direction -18° as shown in Figure 6. These components are pre-processed to constitute the input vector X_O of NN2 built of input layer, hidden layer, and output layer as shown in Figure 4: architecture of NN2 where $X_i = X_{Oi}$ (i = 1, ..., 3), Y_k (k = 1, ..., 6), $C_j = O_{j2}$ (j = j2 = 1, ..., 6).

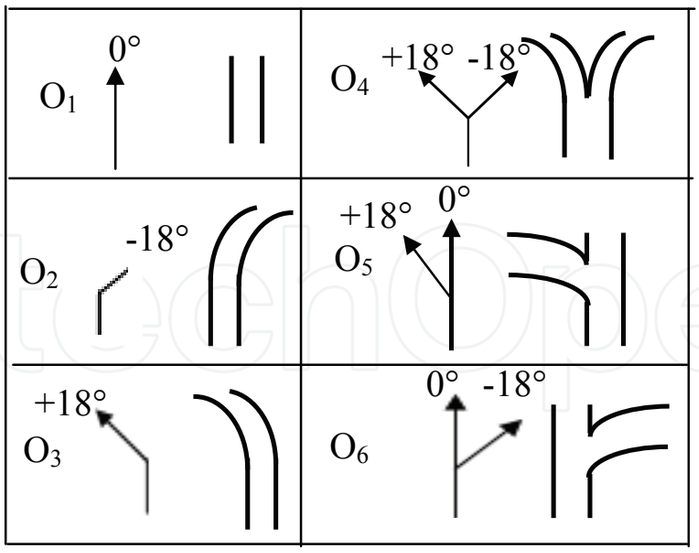


Fig. 5. Obstacle avoidance situations.

After learning, for each input vector X_O, NN2 provides the vehicle with capability to decide its obstacle avoidance, recognizing obstacle avoidance situation expressed by the highly activated output O_{j2}.

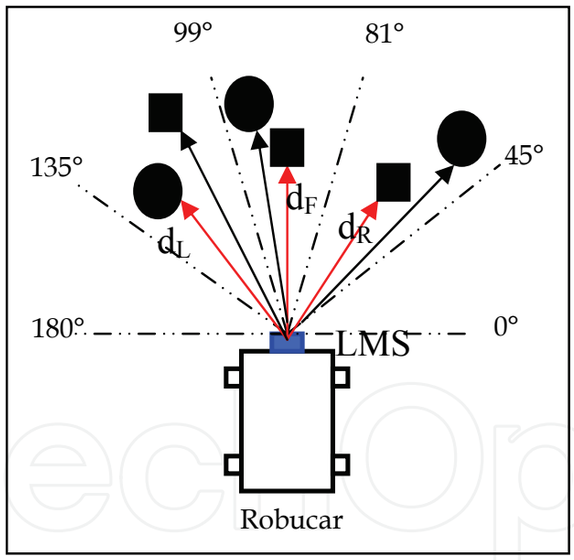


Fig. 6. Laser range areas for obstacle detection.

c) Phase 3.

Decision-Making and Action (NN3). Two (02) association stages between each behavior (target localization and obstacle avoidance) and the favorable actions (among possible actions), and the coordination of these association stages are carried out by NN3. Thus, both situations T_{j1} and O_{j2} are associated by the reinforcement trial and error learning with the favorable actions separately as suggested in (Sorouchyari, 1989). Afterwards, the coordination of the two (02) associated stages allows the decision-making of the appropriate action.

NN3 is built of two layers (input layer and output layer) illustrated in Figure 7.

1) Input Layer.
This layer is the input layer with eleven (11) input nodes receiving the components of T_{j1} and O_{j2} vectors. This layer transmits these inputs to all nodes of the next layer. Each node T_{j1} is connected to all nodes A_i with the connection weights U_{ij1} and each node O_{j2} is connected to all nodes A_i with the connection weights V_{ij2} as shown in Figure 7.
2) Output Layer.
This layer is the output layer with three (03) output nodes which are obtained by adding the contribution of each behavior. The Robucar learns through trial and error interactions with the environment. It learns a given behavior by being told how well or how badly it is performing as it acts in each given situation. As feedback, it receives a single information item from the environment. The feedback is interpreted as positive or negative scalar reinforcement. The goal of the learning system is to maximize positive reinforcement (reward) and/or minimize negative reinforcement (punishment) over time (Sorouchyari, 1989; Sutton & Barto, 1998). By successive trials and/or errors, the Robucar determines a mapping function (see figure 8) which is used for its navigation. The two association stages are obtained as developed in (Chohra et al., 1998).
After learning, NN3 provides the vehicle with capability to decide the appropriate action expressed by the highly activated output A_i.

3. Simulation results

In this section, at first the training processes of NN1, NN2, and NN3 are described. Second, the simulated neural-based navigation is described and simulation results are presented.

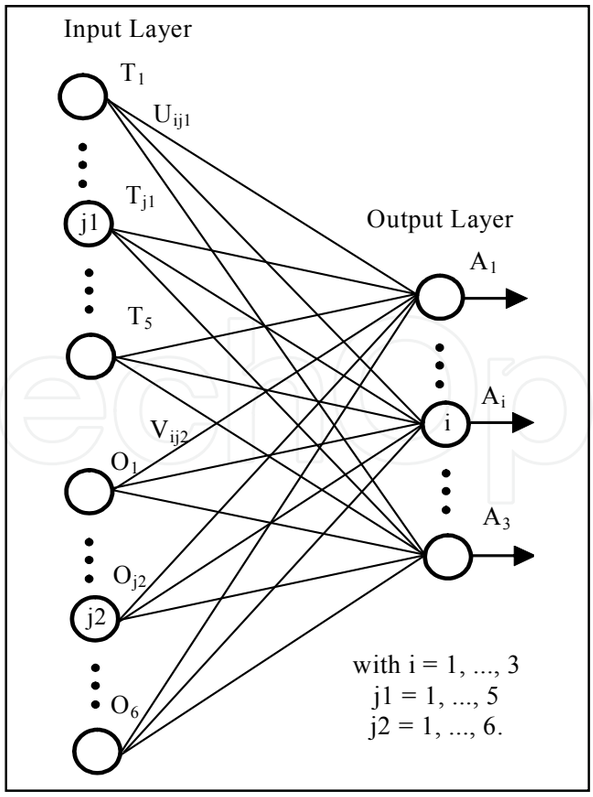


Fig. 7. Architecture of NN3.

3.1 Training of NN1, NN2, and NN3

a) Training of NN1. The used training set is composed of one hundred and nine (109) patterns corresponding to the five (05) target location situations. NN1 classifier yields convergence to the tolerance $Ea_1 = 0.06$ in well with the learning rate $\eta_1 = 0.1$.
b) Training of NN2. The used training set is composed of one hundred and fourteen (115) patterns corresponding to the six (06) obstacle avoidance situations. NN2 classifier yields convergence to the tolerance $Ea_2 = 0.16$ in well with the learning rate $\eta_2 = 0.4$.
c) Training of NN3. This training is achieved with the training of two association stages and their coordination.
1) Association.
In this stage, the training to obtain the weights U_{ij1} and V_{ij2}, constituting the training of NN3, is achieved respectively in an obstacle-free environment (i.e., O = 0) for the target localization behavior and without considering the temperature field (i.e., T = 0) for the obstacle avoidance behavior.
The training results are illustrated in Figure 8 where the weights U_{ij1} and V_{ij2} are adjusted to obtain the reinforced actions among favorable actions. Matrices of the two behaviors are

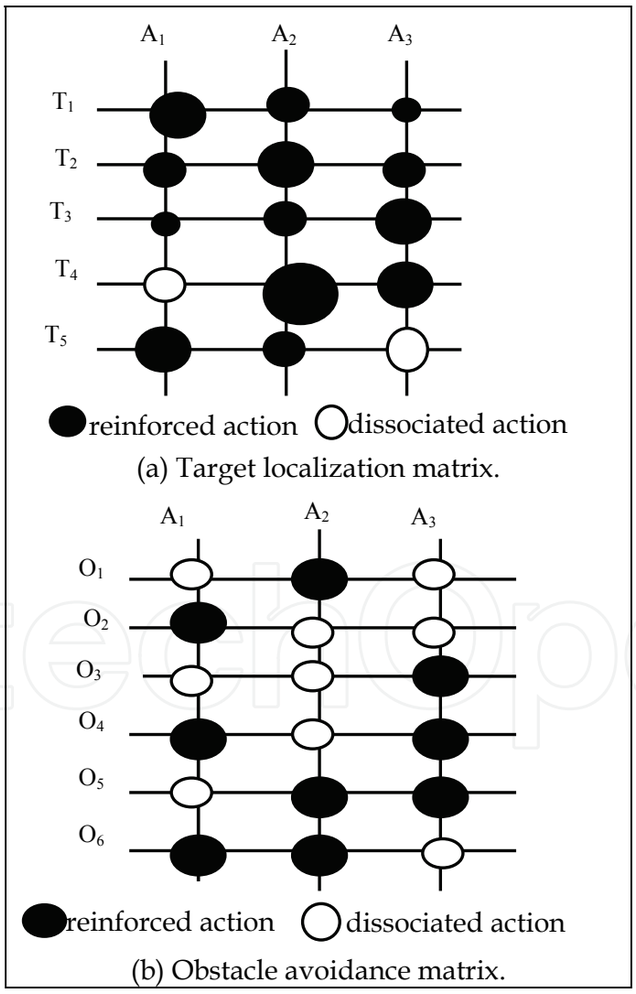


Fig. 8. Association matrices.

represented in this figure: solid circles correspond to positive weights which represent favorable actions, indicating reinforced association, where values are proportional to the area of circles and the most reinforced action is the one having the great positive weight. Hollow circles correspond to negative weights which represent dissociated actions.
The choice of the most reinforced action is guided by the principle that the vehicle must avoid obstacles just to avoid collisions for the obstacle avoidance behavior and it must take the straighter action towards its target for the target localization behavior.
2) Coordination.
The coordination of the two association stages is conducted by the fact that actions generated by obstacle avoidance have precedence over those generated by target localization. In fact, the detection of the maximum temperature is interpreted as the goal of the vehicle while the generated actions by the presence of obstacles are interpreted as the reflex of the vehicle.

3.2 Simulation of the neural-based navigation on the Robucar

To reflect the vehicle behaviors acquired by learning, the Robucar navigation is simulated in different static and dynamic partially structured environments. The simulated vehicle has only two known data: its initial and final (target) positions. From these data, it must reach its target while avoiding possibly encountered obstacles using the neural-based navigation approach.
Tested in the environment of Figure 9 corresponding to a corridor of our centre CDTA (Centre de Développement des Technologies Avancées), the vehicle succeeds to avoid walls and obstacles by choosing the appropriate action by steering right or left according to the given situation as shown in Figure 10 where the evolution of v and ϕ is given. At point A, it stops because it finds itself in a blocked situation (walls at both sides and obstacle in front).

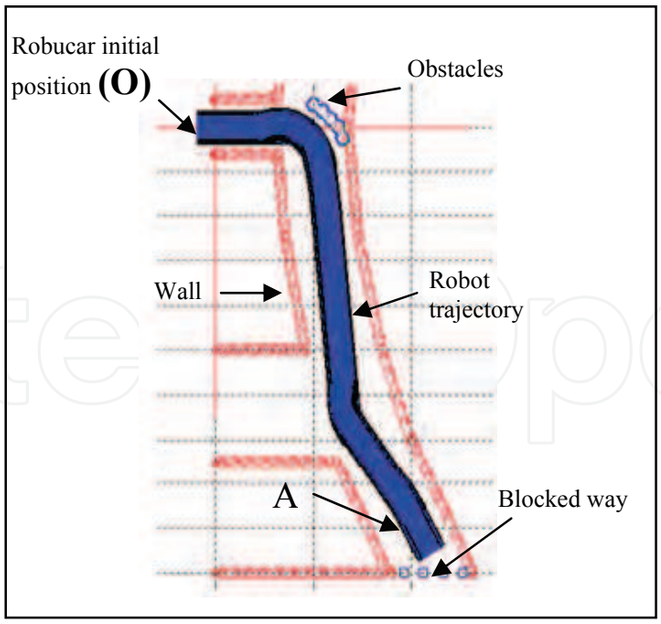
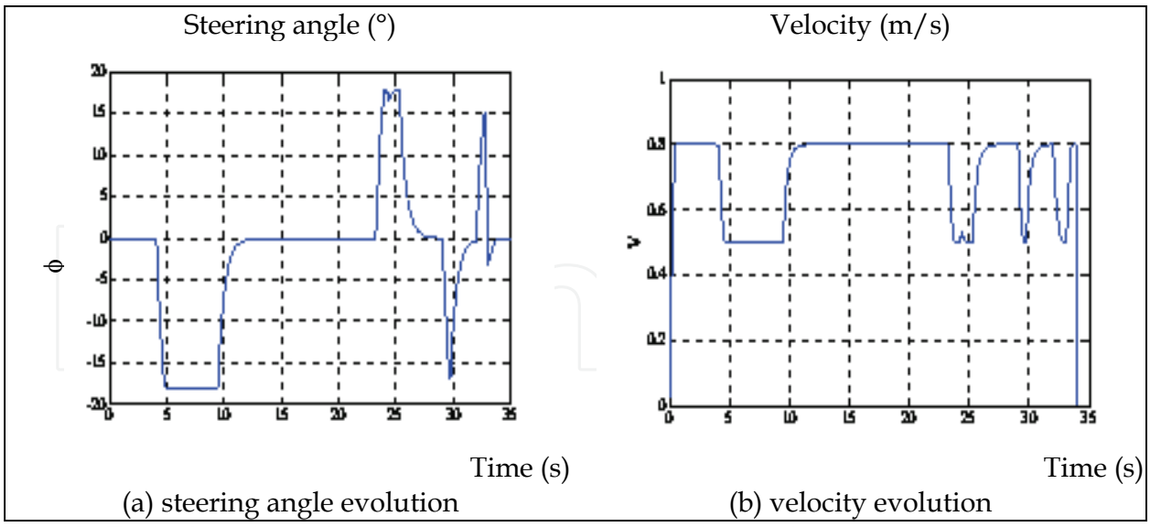


Fig. 9. Corridor environment1 with a blocked way.

The robot at point O in Figure 11 could not reach its target directly because of the wall at its right, so it goes strait until it finds a way to turn right (Figure 11 at point A and Figure 12 at time 1s). Afterwards, it goes strait ahead until point B where it steers to reach its target.



(a) steering angle evolution (b) velocity evolution

Fig. 10. Evolution of steering angle and velocity of corridor environment1.

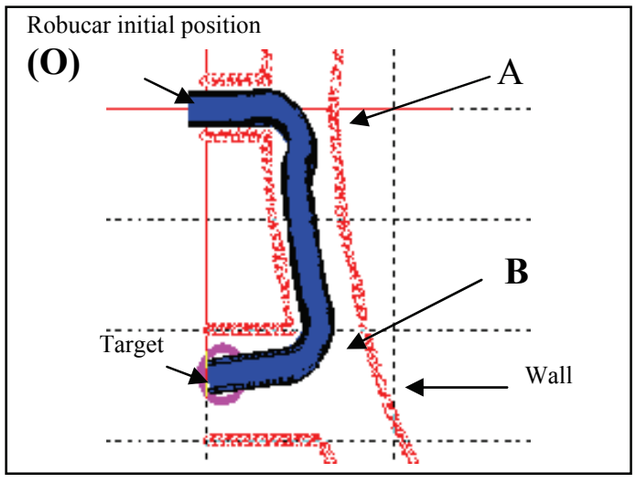
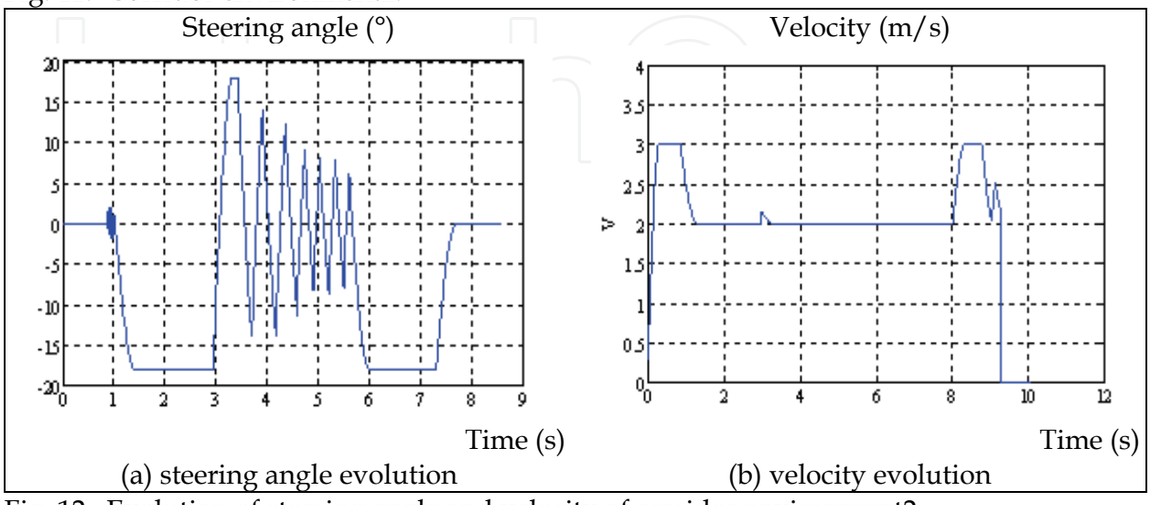


Fig. 11. Corridor environment2.



(a) steering angle evolution (b) velocity evolution

Fig. 12. Evolution of steering angle and velocity of corridor environment2.

The oscillations in Figure 12(a) are due to the fact that the robot tries to point to its target each time it doesn't detect obstacles but the wall pushes it away until point B.

4. Experiments of the neural-based navigation on the Robucar

In this section, experimental results are given for different environments.
Figure 13 corresponds to the confined corridor of CDTA. Obstacle A is put to force the robot to steer right and obstacle B to block a way.
The experiments show that the Robucar behaves intelligently since it moves avoiding collisions with walls (wall1 and wall2) and obstacle A. At this point, it turns right and goes forwards until it detects obstacle B and stops because it finds itself in a dead zone. Note that the same behavior has been observed in the simulation of Figure 9.
Figure 14 (a) gives the trajectory of the Robucar which corresponds to the corridor configuration. The evolution of the steering angle and velocity is illustrated in Figure 14 (b) and (c).
The example of Figure 15 shows a Robucar moving in a dynamic partially structured environment. It avoids the obstacles and reaches its target as shown in Figure 16. At point (c), suddenly an obstacle is put in the robot's trajectory to cause a dead zone and moved after a while (see Figure 16(c) where the velocity between 14s and 19s is equal to zero). The robot stops when it detects the obstacle and restarts when the obstacle is taken out and reaches its target at location (5m, -5m).

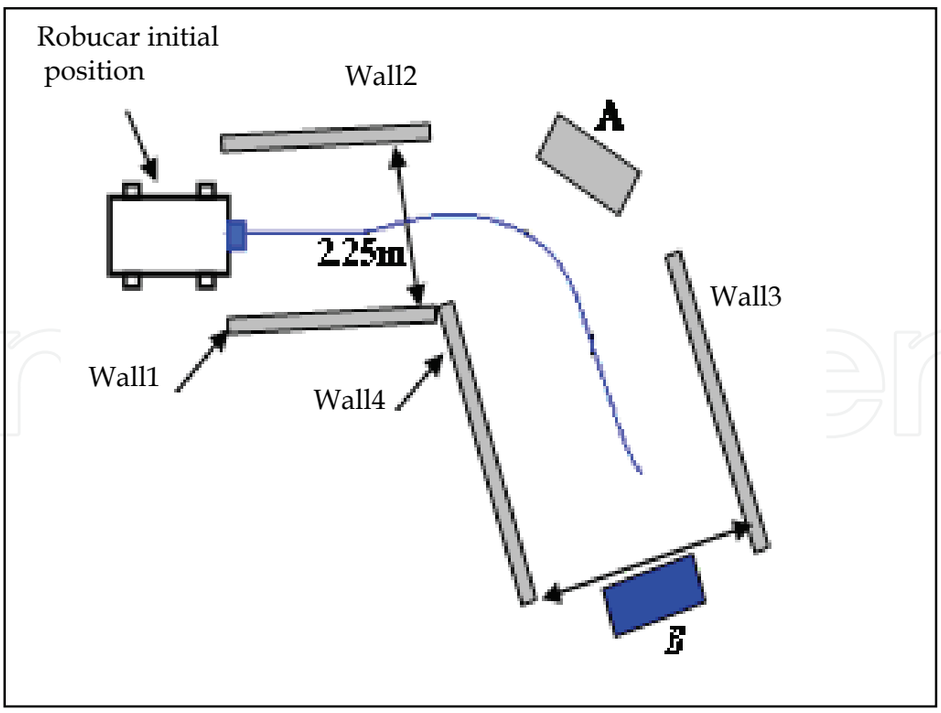


Fig. 13. Internal environment.

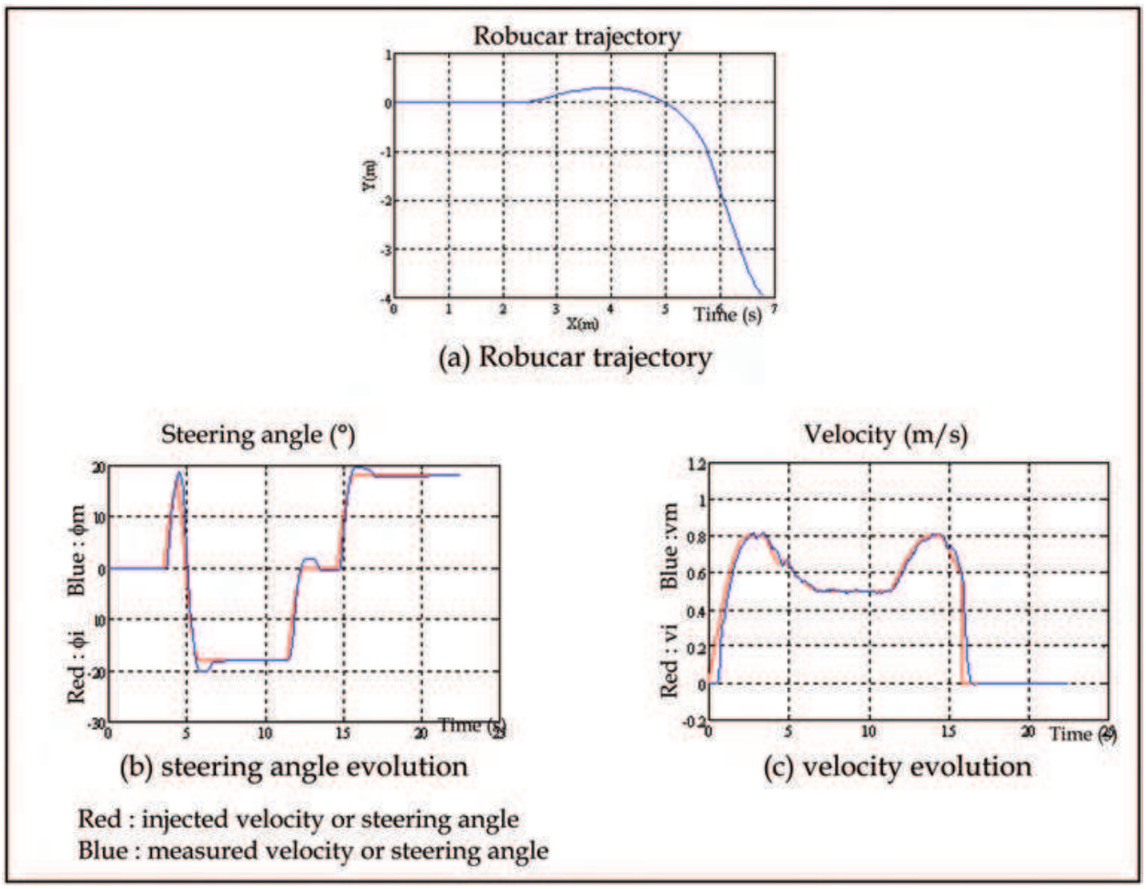


Fig. 14. Robucar trajectory and evolution of steering angle and velocity (internal environment).

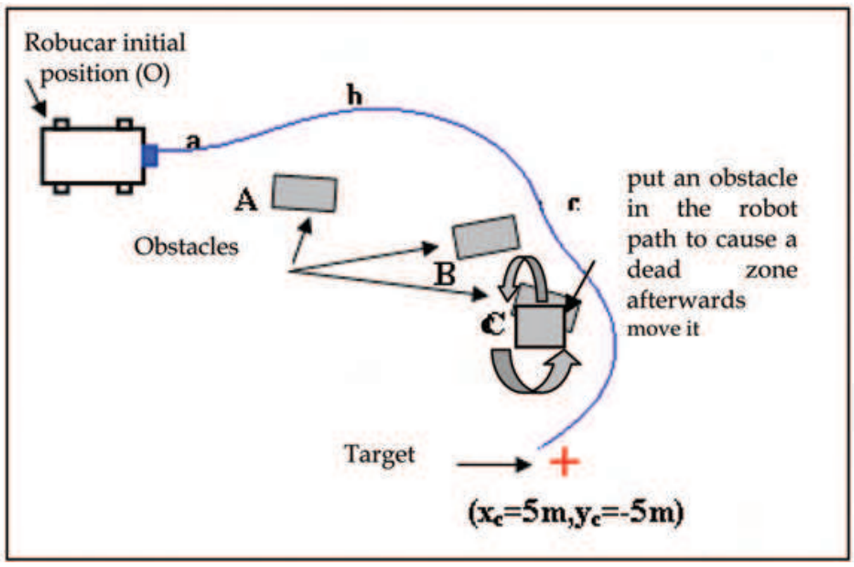


Fig. 15. External environment.

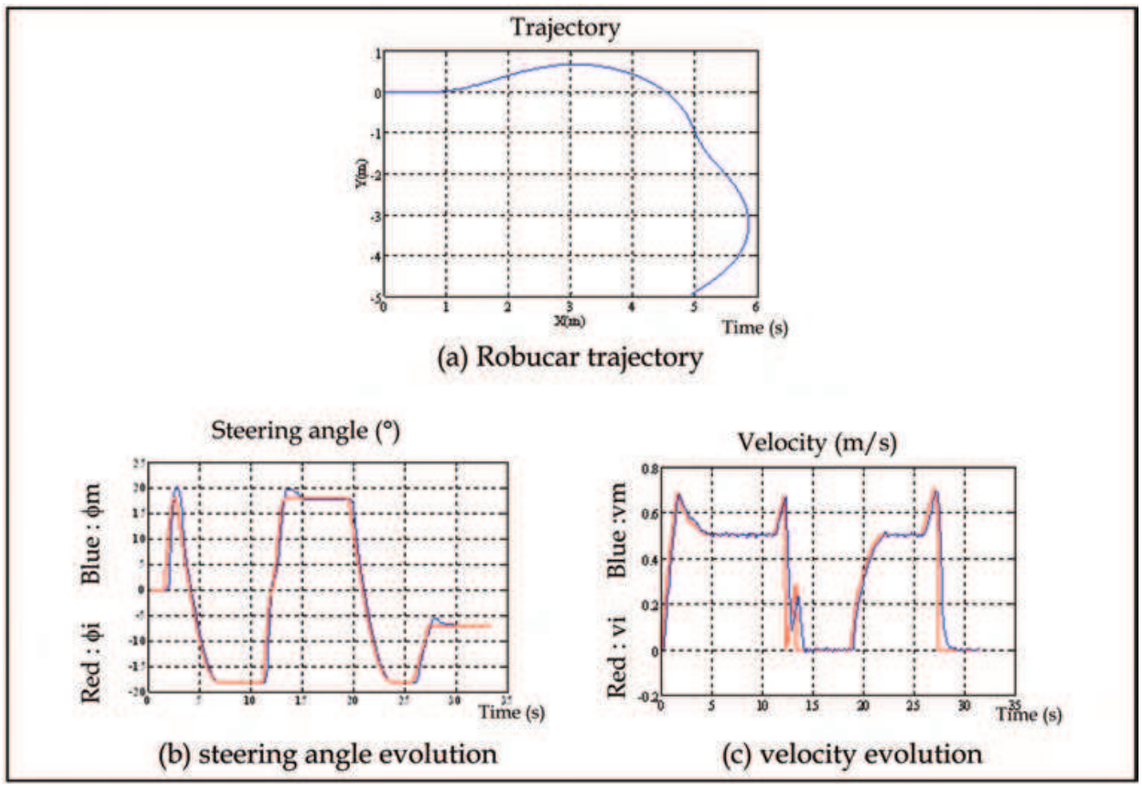


Fig. 16. Robucar trajectory and evolution of steering angle and velocity (external environment).

5. Conclusion

In the implemented neural-based navigation, the two intelligent behaviors necessary to the navigation, are acquired by learning using GBP algorithm. They enable Robucar to be more autonomous and intelligent in partially structured environments. Nevertheless, there are a number of issues that need to be further investigated. At first, the Robucar must be endowed with one or several actions to come back to eliminate a stop in a dead zone situation. Another interesting alternative is the use of a better localization not only based on odometry but by fusing data of other sensors such as laser scanner.

6. References

Anderson, A. (1995). *An Introduction to Neural Networks*. The MIT Press, ISBN: 0262011441, Cambridge, Massachusetts, London, England.

Avina Cervantes, J.G. (2005). *Navigation visuelle d'un robot mobile dans un environnement d'extérieur semi-structuré*, PhD thesis, France.

Azouaoui, O. & Chohra, A. (2003). Pattern classifiers based on soft computing and their FPGA integration for intelligent behavior control of mobile robots, *Proc. IEEE 11th Int. Conf. on Advanced Robotics ICAR'2003*, pp. 148-154, ISBN: 972-96889-9-0, Portugal, June 2003, Universidade de Coimbra Publisher, Coimbra.

Azouaoui, O. & Chohra, A. (2002). Soft computing based pattern classifiers for the obstacle avoidance behavior of Intelligent Autonomous Vehicles (IAV), *Applied Intelligence: The International Journal of Artificial Intelligence, Neural Networks, and Complex*

Problem-Solving Technologies, Vol. 16, N° 3, May/June 2002, pp. 249-271, ISSN: 1573-7497 (online).

Azouaoui, O. & Chohra, A. (1998). Evolution, behavior, and intelligence of *A*utonomous *R*obotic *S*ystems (*ARS*), *Proceedings of 3rd Int. IFAC Conf. Intelligent Autonomous Vehicles*, pp. 139-145, Spain, March 1998, Miguel Angel SALICHS and Aarne HALME editors, Madrid.

Bento, L.C. & Nunes, U. (2004). Autonomous navigation control with magnetic markers guidance of a cybernetic car using fuzzy logic, *Machine intelligence and robotic control*, Vol. 6, No.1, March 2004, pp. 1-10, ISSN: 1345-269X.

Chohra, A.; Farah A. & Benmehrez, C. (1998). Neural navigation approach for *I*ntelligent *A*utonomous *V*ehicles (*IAV*) in Partially structured Environments, *International Journal of Applied Intelligence: Artificial Intelligence, Neural Networks, and Complex Problem-Solving Technologies*, Vol. 8, No. 3, May 1998, pp. 219- 233, ISSN: 1573-7497 (online).

Gu, D. & Hu, H. (2002). Neural predictive control for a car-like mobile robot, *International Journal of Robotics and Autonomous Systems*, Vol. 39, No. 2-3, May 2002, pp. 73-86, ISSN: 0921-8890.

Hong, T.; Rasmussen, C.; Chang, T. & Shneier, M. (2002). Fusing ladar and color image information for mobile robot feature detection and tracking, Proceedings of *7th International Conference on Intelligent Autonomous Systems*, pp. 124-131, ISBN: 1-58603-239-9, CA, March 2002, IOS Press, Marina del Rey.

Kujawski, C. (1995). Deciding the behaviour of an autonomous mobile road vehicle, *Proceedings of 2nd International IFAC Conference on Intelligent Autonomous Vehicles*, pp. 404-409, Finland, June 1995, Halme and K. Koskinen editors, Helsinki.

Labakhua, L. ; Nunes, U. ; Rodrigues, R. & Leite, F. S. (2006). Smooth trajectory planning for fully automated passengers vehicles, International Conference on Informatics in Control, Automation and Robotics, pp. 89-96, ISBN: 972-8865-60-0, Portugal, August 2006, INSTICC Press, Setubal.

Mendes, A. ; Bento, L.C. & Nunes, U. (2003). Path-tracking controller with an anti-collision behavior of a bi-steerable cybernetic car, *9th IEEE Int. Conference on Emerging Technologies and Factory Automation (ETFA 2003)*, pp. 613-619, ISBN: 0-7803-7937-3, Portugal, September 2003, UNINOVA-CRI and Universidade Nova de Lisboa-FCT-DEE publisher, Lisboa.

Murphy, R. R. (2000). Fuzzy logic for fusion of tactical influences on vehicle speed control, *In: Fuzzy logic techniques for autonomous vehicle navigation,* Dimiter Driankov and Alessandro Saffiotti editors, pp 73-98, Physica-Verlag, ISBN: 978-3-7908-1341-8, New York.

Niegel, W. (1995). Methodical structuring of knowledge used in an intelligent driving system, *Proceedings of 2nd International IFAC Conference on Intelligent Autonomous Vehicles*, pp. 398-403, Finland, June 1995, Halme and K. Koskinen editors, Helsinki.

Schafer, B.H. (2005). Detection of negative obstacles in outdoor terrain, *Technical report*, Kaiserlautern university of technology, 2005.

Schilling, K. & Jungius, C. (1996). Mobile robots for planetary exploration, *PControl Engineering Practice,* Vol. 4, N° 4, April 1996, pp. 513-524, ISSN: 0967-0661.

SICK. (2001). Hardware setup and measurement mode configuration, *Quick manual for LMS communication setup, SICK AG*, Germany, June 2001.

Sorouchyari, E. (1989). Mobile robot navigation: a neural network approach, *In Annales du Groupe CARNAC1 no. S,* pp. 13-24.

Sutton, R.S. & Barto, A. (1998). *Reinforcement Learning : an Introduction.* MA: MIT Press, ISBN-10: 0-262-19398-1, Cambridge.

Wagner, B. (2006). ELROB 2006, *Technical paper*, University of Hannover, May 2006.

Welstead, S. T. (1994). *Neural Network and Fuzzy Logic Applications C/C++*. John Wiley & Sons Inc., ISBN-10: 0471309745, Toronto.



New Approaches in Automation and Robotics

Edited by Harald Aschemann

ISBN 978-3-902613-26-4

Hard cover, 392 pages

Publisher I-Tech Education and Publishing

Published online 01, May, 2008

Published in print edition May, 2008

The book New Approaches in Automation and Robotics offers in 22 chapters a collection of recent developments in automation, robotics as well as control theory. It is dedicated to researchers in science and industry, students, and practicing engineers, who wish to update and enhance their knowledge on modern methods and innovative applications. The authors and editor of this book wish to motivate people, especially under-graduate students, to get involved with the interesting field of robotics and mechatronics. We hope that the ideas and concepts presented in this book are useful for your own work and could contribute to problem solving in similar applications as well. It is clear, however, that the wide area of automation and robotics can only be highlighted at several spots but not completely covered by a single book.

How to reference

In order to correctly reference this scholarly work, feel free to copy and paste the following:

Azouaoui Ouahiba, Ouadah Noureddine, Aouana Salem and Chabi Djeffer (2008). Neural-Based Navigation Approach for a Bi-Steerable Mobile Robot, New Approaches in Automation and Robotics, Harald Aschemann (Ed.), ISBN: 978-3-902613-26-4, InTech, Available from: http://www.intechopen.com/books/new_approaches_in_automation_and_robotics/neural-based_navigation_approach_for_a_bi-steerable_mobile_robot

INTECH
open science | open minds

InTech Europe

University Campus STeP Ri
Slavka Krautzeka 83/A
51000 Rijeka, Croatia
Phone: +385 (51) 770 447
Fax: +385 (51) 686 166
www.intechopen.com

InTech China

Unit 405, Office Block, Hotel Equatorial Shanghai
No.65, Yan An Road (West), Shanghai, 200040, China
中国上海市延安西路65号上海国际贵都大饭店办公楼405单元
Phone: +86-21-62489820
Fax: +86-21-62489821

© 2008 The Author(s). Licensee IntechOpen. This chapter is distributed under the terms of the Creative Commons Attribution-NonCommercial-ShareAlike-3.0 License, which permits use, distribution and reproduction for non-commercial purposes, provided the original is properly cited and derivative works building on this content are distributed under the same license.

IntechOpen

IntechOpen