Cognitive tasks behavior of Intelligent Autonomous Mobile Robots

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***Abstract*—**In this paper we propose a neural network based navigation for intelligent autonomous mobile robots. The proposed neural networks algorithm deals with unknown static obstacles. Neural Networks deal with cognitive tasks such as learning, adaptation generalization and they are well appropriate when knowledge based systems are involved. To solve navigation problems, neural networks prove interesting to deal with the behaviour of autonomous mobile robots near the human being in reasoning. This paper deals with an algorithm for two dimensional (2D) path planning to a target for mobile robot in unknown environment. A complete path planning algorithm should guarantee that the robot can reach the target if possible, or prove that the target can not be reached. Just as human being, a neural network relies on previously solved examples to build a system of "neurons" that makes new decisions, classification and forecasts. Networks of neurons can achieve complex classification based on the elementary capability of each neuron to distinguish classes its activation function. In designing a Neural Networks navigation approach, the ability of learning must provide robots with capacities to successfully navigate in the environments like our proposed maze environment. The simulation results display the ability of the neural networks based approach providing autonomous mobile robots with capability to intelligently navigate in several environments.

***Keywords*—**Intelligent Autonomous Mobile Robots, Navigation, Learning, Neural Networks, Behavior.

I. INTRODUCTION

The objective of intelligent mobile robots is to improve engine autonomy. This improvement concerns three (03) essential aspects. First, robots must perform efficiently some tasks like recognition, decision-making, and action which constitute the principal obstacle avoidance problems. They must also reduce the operator load by using natural language and common sense knowledge in order to allow easier decision making. Finally, they must operate at a human level with adaptation and learning capacities.

Safe manoeuvring of Autonomous mobile robots in unstructured complex environments, densely cluttered with obstacles is still a major challenge in goal-directed robotic vehicle applications. The problem is particularly difficult because some of the navigational objectives may be in opposition to one another, to see the main composite of navigation system. It is important that algorithms for navigation control in cluttered environments not be too computationally expensive as this would result in a sluggish response.

It has been acknowledged that the traditional Plan-Sense-Model-Act approaches are not effective in such environments; instead, local navigation strategies that tightly couple the sensor information to the control actions must be used for the robot to successfully achieve its mission. The control complexity is overcome by decomposing the navigation control problem into more simple and well-defined sub-problems that can be controlled independently and in parallel.

These sub-problems and their controllers are known as reactive behaviours, and this approach is known as behaviour robotics. It has attracted the interests of many robotic applications and has even been used in industrial process control applications.

The robots are compelling not for reasons of mobility but because of their *autonomy*, and so their ability to maintain a sense of position and to navigate without human intervention is paramount. For example, AGV (autonomous guided vehicle) robots autonomously deliver parts between various assembly stations by following special electrical guide wires using a custom sensor.

Near the concept, the Helpmate service robot transports food and medication throughout hospitals by tracking the position of ceiling lights, which are manually specified to the robot beforehand. Several companies have developed autonomous cleaning robots, mainly for large buildings. One such cleaning robot is in use at the Paris Metro. Other specialized cleaning robots take advantage of the regular geometric pattern of aisles in supermarkets to facilitate the localization and navigation tasks.

We take into consideration that the Robots are distributed systems; multiple sensory, reasoning, and motor control processes run in parallel, often on separate processor hate rate only loosely coupled with one another. Each of these procure necessarily maintains its own separate, limited representation of the world and task; requiring them to constantly synchronize with the central knowledge base is probably unrealistic. Automated reasoning systems are typically built on a transaction-oriented model of computation. Knowledge of the world is stored in a database of assertion in some logical language, indexed perhaps by predicate name.

The motion of mobile robots in an environment where there are stationary obstacles, and other moving objects, requires the existence of algorithms that are able to solve the path and motion planning problem of these robots so that collisions are avoided. On the other hand, a suitable control law has to be designed, in order for the mobile robot to execute the desired motion. The problem becomes more difficult when the parameters that describe the model and/or the workspace of the robot are not exactly known.

Autonomous robots which work without human operators are required in robotic fields. In order to achieve the necessary tasks, autonomous robots to be intelligent and should decide on their own action. When the autonomous robots decide its action, it is necessary to plan optimally depending on their asked missions. In the case of a mobile robot, it is necessary to plan a collision-free path minimizing a cost such a time and distance.

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Although mobile robots have a broad set of applications and markets as summarized above, there is one fact that is true of virtually every successful mobile robot: its design involves the integration of many different bodies of knowledge. No mean feat, this makes mobile robotics as interdisciplinary a field as there can be. To solve locomotion problems, the mobile roboticist must understand mechanism and kinematics; dynamics and control theory. To create robust perceptual systems, the mobile roboticist must leverage the fields of signal analysis and specialized bodies of knowledge such as computer vision to properly employ a multitude of sensor technologies. Localization and navigation demand knowledge of computer algorithms, information theory.

Path planning plays an important role in various fields of application and research, among which are CAD-design, computer games and virtual environments, molecular biology, and robotics. However, the environment complexity is a specific problem to solve since this environment can be imprecise, vast, dynamical and partially or not structured. Robots must then be able to understand the structure of this environment. To reach the goal without collisions, these robots must be endowed with perception, data processing, recognition, learning, reasoning, interpreting, decision-making, and actions capacities.

For a specified period, autonomous mobile robots can operate autonomously, one very limited resource for underwater and space applications are energy. So, robots usually carry a rechargeable energy system, appropriately sized batteries on-board. For a specified period, intelligent autonomous robots can operate autonomously, one very limited resource for underwater and space applications are energy.

Additionally, Intelligent Autonomous Vehicles (IAV) are becoming more and more interesting for underwater, terrestrial, and space applications. These mechanical systems are constructed to respond any traditional working as in construction and agriculture. Previously, certain industrial operations required human skills may be tedious and exceptionally hardly ever. Above all, repetitive operations can result in reductions in quality control, as in visual inspections tasks. Also, these repetitive actions may be hazardous health risks as exposure to unsafe materials like radioactive and high pressure in underwater applications. So, the presence of human workers in these environments may be perilous which need the necessity to be replaced by intelligent systems, these systems can move, react, and carry out tasks in various environments by themselves like human [1,2,3,4].

To take the best decision and to react intelligibly, neural networks are the wishes to understand principles leading in some manner to the comprehension of the human brain functions and to build machines that are able to perform complex tasks requiring massively parallel computation.

Neural Networks deal with cognitive tasks such as learning, adaptation generalization and they are well appropriate when knowledge based systems are involved. In general Neural Networks deal with cognitive tasks such as learning, adaptation generalization and they are well appropriate when knowledge based systems are involved.

To solve navigation problems, neural networks prove interesting to deal with the behaviour of autonomous mobile robots near the human being in reasoning. This paper deals with an algorithm for two dimensional (2D) path planning to a target for mobile robot in unknown environment. The objective is to find a collision free path from an unknown initial position to an unknown target point. A complete path planning algorithm should guarantee that the robot can reach the target if possible, or prove that the target can not be reached. A few path planning algorithms are described here followed by the aim work of research in detail.

Our autonomous mobile robot is able to achieve these tasks: avoiding obstacles, taking a suitable decision, and attending the target which are the main factors to be realized of autonomy requirements. The algorithm returns the best response of any entering map parameters.

The simulation results illustrate the generalization and adaptation capabilities of neural networks. An interesting alternative for future work is the generalization of this approach by increasing the number of possible robot directions. In this paper we discuss clearly the proposed neural networks navigation for autonomous mobile robots.

The simulation part is an approach to the real expected result; this part is done using neural networks. The algorithm is implemented in several static environments; whereby the environment is studied in a two dimensional coordinate system. The algorithm permits the robot to move from the initial position to the desired position following an estimated trajectory

II. THE PROPOSED NAVIGATION BASED ON THE NEURAL NETWORKS

A .The principle of navigation

Navigation is one of the most challenging competences required of a mobile robot. Success in navigation requires success at the four building blocks of navigation: *perception,* the robot must interpret its sensors to extract meaningful data; *localization,* the robot must determine its position in the environment ; *cognition,* the robot must decide how to act to achieve its goals; and *motion control*(see the figure 1), the robot must modulate its motor outputs to achieve the desired trajectory. Of these four components, localization has received the greatest research attention in the past decade and, as a result, significant advances have been made on this front (see the figure 2).

If one could attach an accurate GPS (Global Positioning System) sensor to a mobile robot, much of the localization problem would be obviated. The GPS would inform the robot of its exact position, indoors and outdoors, so that the answer to the question, “Where am I?” would always be immediately available. Unfortunately, such a sensor is not currently practical.

The existing GPS network provides accuracy to within several meters, which is unacceptable for localizing human-scale mobile robots as well as miniature mobile robots such as desk robots and the body-navigating nanorobots of the future. Furthermore, GPS technologies cannot function indoors or in obstructed areas and are thus limited in their workspace.

But, looking beyond the limitations of GPS, localization implies more than knowing one’s absolute position in the Earth’s reference frame. Consider a robot that is interacting with humans. This robot may need to identify its absolute position, but its relative position. with respect to target humans is equally important. Its localization task can include identifying humans using its sensor array, then computing its relative position to the humans.

Furthermore, during the *cognition* step a robot will select a strategy for achieving its goals. If it intends to reach a particular location, then localization may not be enough. The robot may need to acquire or build an environmental model, a *map* that aids it in planning a path to the goal. Once again, localization means more than simply determining an absolute pose in space; it means building a map, then identifying the robot’s position relative to that map.

Moreover, when a robot moves in a specific space, it is necessary to select a most reasonable path so as to avoid collisions with obstacles. Several approaches for path planning exist for mobile robots, whose suitability depends on a particular problem in an application. For example, behavior-based reactive methods are good choice for robust collision avoidance. Path planning in spatial representation often requires the integration of several approaches. This can provide efficient, accurate, and consistent navigation of a mobile robot [9,10,11,12,13].

The major task for path-planning for single mobile robot is to search a collision –free path. The work in path planning has led into issues of map representation for a real world. Therefore, this problem considered as one of challenges in the field of mobile robots because of its direct effect for having a simple and computationally efficient path planning strategy.

The planner’s approximation of the configuration space is a direct function of the configuration space samples that the planner observes. Consequently, sampling is the search for the set of samples that provide enough information to construct a sufficient approximation of configuration space connectivity. For every configuration space, there are an optimal number of samples that must be selected to construct a sufficient approximation of configuration space connectivity.

Local planners impose an artificial potential field function on top of the configuration space. This potential field function is sloped so that its minimum is at the goal configuration. The artificial potential field is also influenced by configuration space obstacles. Configuration space obstacles have high artificial potentials that decline gradually with distance from the obstacle. At any instance, the robot calculates the derivative of the potential function and descends the maximal downward gradient in an effort to reach the minimum at the goal position. This calculation quickly determines the motion to take next.

For path planning areas, it is sufficient for the robot to use a topological map that represents only the different areas without details such as office rooms. The possibility to use topological maps with different abstraction levels helps to save processing time. The static aspect of topological maps enables rather the creation of paths without information that is relevant at runtime. The created schedule, which is based on a topological map, holds nothing about objects which occupy the path. In that case it is not possible to perform the schedule. To get further actual information, the schedule should be enriched by the use of more up-to date plans like egocentric maps [14,15, 16,17,18] .

Topological path planning is useful for the creation of long – distance paths, which support the navigation for solving a task. Therefore, those nodes representing for example, free region space are extracted from a topological map, which connect a start point with a target point. The start point is mostly the actual position of the robot.

The use of map to structure our environment has often been more efficient than previous technique. The difficulty in building a map of the environment lies in the cognition representation. For same types of navigation, it is more advantageous to use an implicit one. In the intelligent robot behaviour, this environment model map has an important role to play. So, building a map of the sensory input space is more interesting especially we give this subdivision by the following points: geometrical level, topological level and semantic level. For the first one the aim work is focused on the “cartographer work” where the flat earth model viewable area is an ideal planner surface S defined by the points of contact of the objects projected into the ground. The second illustrates the features map; it consists of the decomposition on free and occupied space, and gives a relationship between the free spaces [5,6,7,8].

Topological maps can be used to solve abstract tasks, for example, to go and retrieve objects whose positions are not exactly known because the locations of the objects are often changed. Topological maps are graphs whose nodes represent static objects like rooms, and doors for example. The edges between the nodes are part's relationships between the objects.

To generate the path, several sophisticated and classical algorithms exist that are based on graph theory like the algorithm; of the shortest path. To give best support for the path planning it could be helpful to use different abstraction levels for topological maps. For example, if the robot enters a particular room; of an employee for postal delivery, the robot must use a topological map that contains the doors of an office building and the room numbers.

Many researchers have addressed this problem. Many authors have considered a model with complete information, where the robot has perfect knowledge about the obstacles. The drawback of these approaches is that under many practical circumstances robot does not have access to complete information about the environment.

The intelligent mobile robots have many possible applications in a large variety of domains, from spatial exploration to handling material, and from military tasks to the handicapped help.

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The multi-level structure of path planning and execution propounded in provides a basic framework for dealing with problems in the control of autonomous vehicles. There are three basic levels of path planning and execution:

In global path planning, prior knowledge of the workspace is available which means that the robot navigates in known environment. Local path planning methods use ultrasonic sensors, laser range finders, and on-board vision systems to perceive the environment to perform on-line planning in this case a prior knowledge of the environment is not necessary and the robot navigate in an unknown environment.

The robot has to find a collision-free trajectory between the starting configuration and the goal configuration in a static or dynamic environment containing some obstacles. To this end, the robot needs the capability to build a map of the environment, which is essentially a repetitive process of moving to a new position, sensing the environment, updating the map, and planning subsequent motion.

Most of the difficulties in this process originate in the nature of the real world: unstructured environments and inherent large uncertainties. First, any prior knowledge about the environment is, in general, incomplete, uncertain, and approximate. For example, maps typically omit some details and temporary features; also, spatial relations between objects may have changed since the map was built. Second, perceptually acquired information is usually unreliable. Third, a real-world environment typically has complex and unpredictable dynamics: objects can move, other agents can modify the environment, and apparently stable features may change with time. Finally, the effects of control actions are not completely reliable, e.g. the wheels of a mobile robot may slip, resulting in accumulated zoometric errors

B The proposed neural network navigation approach

For the navigation approach problem, the environment complexity is a specific problem to solve since this environment can be imprecise, vast, dynamical and partially or not structured. Robots must then be able to understand the structure of this environment.

To reach the goal without collisions, these robots must be endowed with perception, data processing, recognition, learning, reasoning, interpreting, decision-making, and actions capacities. These faculties are the main source to be endowed an treated at the same time for autonomous mobile robot during the execution of mission. . More, these factors are the key of certain kind of intelligence. Reproduce this kind of intelligence is, up to now, a human ambition in the construction and development of intelligent machines, and particurly autonomous mobile robots [11,12].

To solve navigation problems, neural networks prove interesting to deal with the behaviour of autonomous mobile robots near the human being in reasoning.

Neural Networks are the wish to understand principles leading in some manner to the comprehension of the human brain functions and to build machines that are able to perform complex tasks requiring massively parallel computation.

In general Neural Networks deal with cognitive tasks such as learning, adaptation generalization and they are well appropriate when knowledge based systems are involved.

Thus, several approaches based on neural networks for autonomous mobile robots are oriented to design and achieve robots which simulate the human decision-making in similar way of acquiring some keys of intelligence. The key of intelligence is focused on the manner of: thinking, perceiving, and acting.

Networks of neurons can achieve complex classification based on the elementary capability of each neuron to distinguish classes its activation function.

The adaptation is largely related to the learning capacity since the network is able to take into account and respond to new constraints and data related to the external environments. Just as human being, a neural network relies on previously solved examples to build a system of "neurons" that makes new decisions, classification and forecasts.

The system of neural networks involves massively parallel computing: interconnected units process data at the same time. Activation map of neurons gives the "memory core". Several entities of memory are posed and connected to lead the circulation of information.

Learning capacity is the ability to achieve complex tasks like human brain. Learning can be supervised or unsupervised. The former deals with the classified pattern information, while the unsupervised learning does not and uses instead minimal information. The unsupervised learning algorithms offer the advantage of less computational procedure than supervised learning.

Several research approaches have pointed on the use backpropagation and reinforcement algorithms. These algorithms depend on learning, generalization, connection neurons, and patterns capability to select and treat models and elementary informations trough its activation. Afterwards, to be able to make a new decision and classification each time that information enters or deals with the system of “neurons”. The disadvantage of backpropagation algorithm is the learning speed and generalization which depend strongly on the selected learning patterns. On the other hand, the performances of the backpropagation learning algorithm are better than the reinforcement learning.

Historically, interest in Neural Networks stems from the wish to understand principles leading in some manner to the comprehension of the human brain functions and to build machines that are able to perform tasks requiring massively parallel computation. Essentially, Neural Networks deal with cognitive tasks such as learning, adaptation, generalization and optimization [5].

Networks of neurons can achieve complex classification based on the elementary capability of each neuron to distinguish classes through its activation function. NN must provide Robot with capacities to successfully navigate during the navigation.

The proposed navigation approach is based on the supervised gradient-back-propagation learning. The target localization is based on a neural networks recognition based by learning from data obtained by capturing distance and orientation.

During the navigation, the robot must localise its target and recognize the environment, build a map (i.e, obstacles and free spaces) from sensors. The identification of the “antecedent” and “conclusion” of the cognition system is based on the neural network approach. In addition the adaptively task is the strong interest of using Neural Networks. The Neural Networks could express the knowledge implicitly in the weights.

The robot must learn to build a map (i.e. target, obstacles, and free spaces from sensors). The robot must learn to decide the angle avoidance formulation using Neural Networks of human expert knowledge. This Neural Networks approach is trained to capture the human expert behavior in the decision-making operation .

In designing a Neural Networks navigation approach, the ability of learning must provide robots with capacities to successfully navigate in the environments like our proposed maze environment. Also, robots must learn during the navigation process, build a map representing the knowledge from sensors, update this one and use it for intelligently planning and controlling the navigation.

The general structure of the proposed Neural Networks navigation is presented in the figure3. From this structure we clarify the following levels:

Knowledge mapping: the model of the external environment plays an important role in the intelligent robot behavior. The human brain is able to create -simple maps of the external environment by compressing the huge amount of received sensory data, while preserving the relationships between important facts.

Action: the different map sensory informations are classified in several vectors where each component responds to a particular situation. These situations must be associated with the appropriate action taking advantage of the topology-preserving property of the network.

Reinforcement learning: reinforcement learning allows associations between detected sensory situations and appropriate actions trough “ trial and error” learning. This one uses only a priori knowledge such as “asked response” is executed. These associations are formed in unsupervised manner, i.e., with no “ supervisor or teacher” required.

The proposed approach offers features and advantages as expressing cognition at once explicitly and implicitly, processing inaccurate data in real-time, learning, generalization, and approaching human-like reasoning.

During the navigation, the robot must localize its target and recognize the environment. The movement of the robot are supposed possible only in four (04) direction and consequently four actions $A=[A_F, A_L, A_R, A_B]$ are defined as action to move Front, action to turn to the Left, action to turn to Right , and action to turn Back (see the figure 4). The situations of the static target localization are defined by $T=[T_F\ T_L, T_R, T_B]$ while the static obstacle avoidance situations are defined by $O=[O_1,O_2,O_3,\ldots,O_i]$.

Three layers constitute the proposed Neural Network structure as shown in the figure 5.

Layer 1: this layer represents the input layer with four (04) input nodes receiving the components of the vector $T=[T_F, T_L, T_R, T_B]$. This layer transmits the inputs to all nodes of the next layer.

Layer 2: this layer represents the hidden layer with i^{eme} nodes. The output of each node is obtained as follows:

$$\gamma_k = f\left(\sum_i X_i W_{1ki}\right) \qquad (1)$$

Where f is the output sigmoid function, W_1 : the weights of the output layer and

$$W_1(t+1) = W_1(t) + \Delta W_1 \qquad (2)$$

With $\Delta W_1 = \eta\delta\, y$ Whereas learning rate is : $0<\eta<1$ and Y : hidden output.

Layer 3: this layer represents the output layer with output nodes which are obtained by :

$$T_j = f(\sum_k \gamma_k W2_{jk}) \tag{3}$$

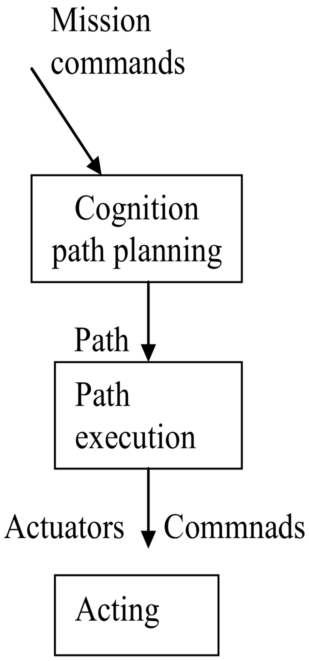


Fig. 1 Motion Control

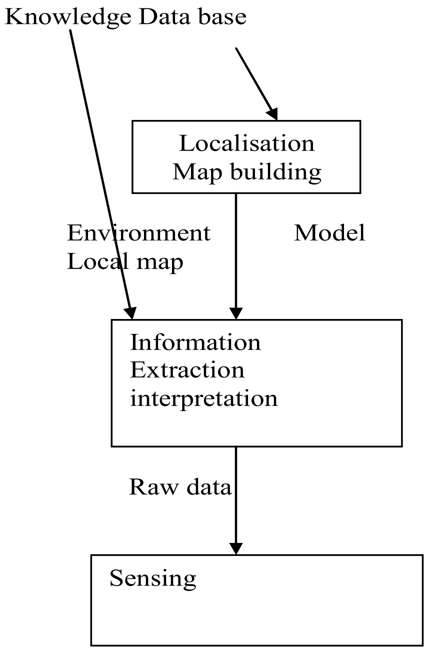
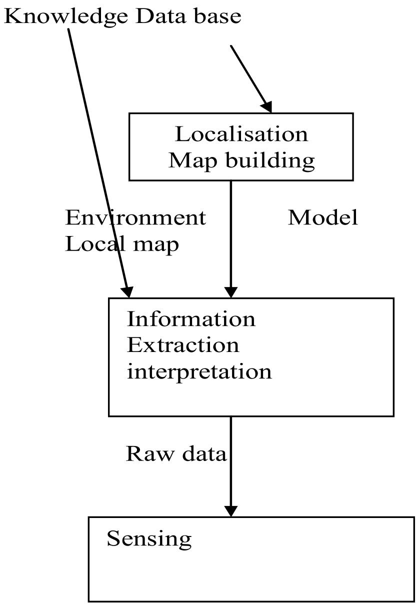


Fig. 2 Perception general view



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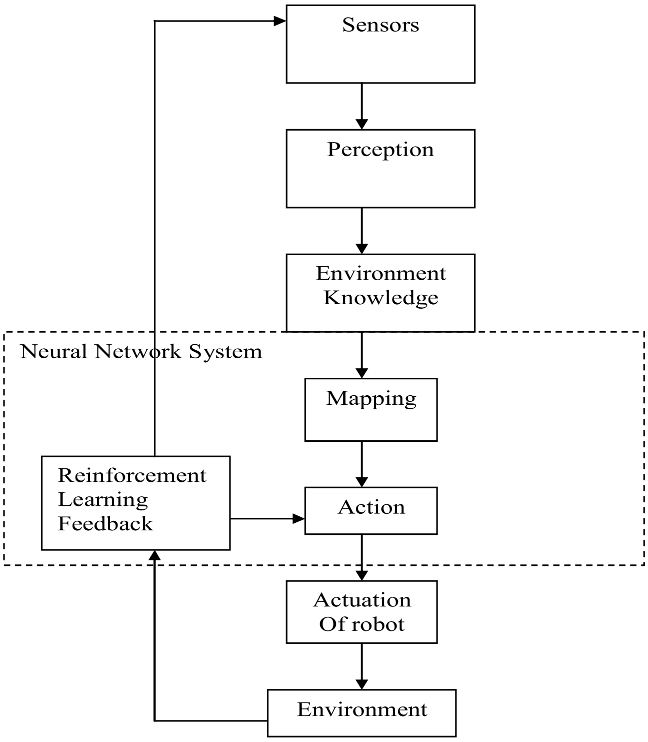

Fig. 3 General Structure of Neural Network navigation

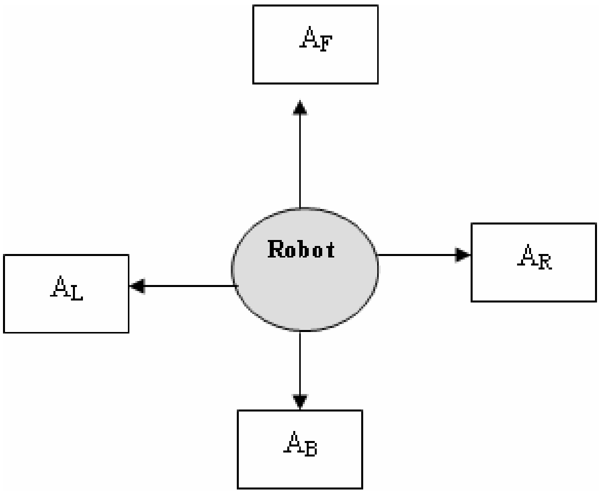

Fig. 4 robot and the four actions

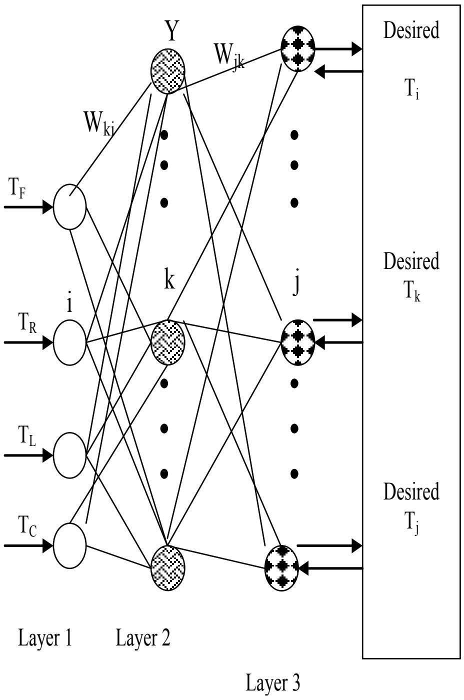

Fig. 5 Target Localization Neural Network

In the proposed approach, the Neural Network is trained to capture the behaviour of a human expert while controlling the obstacle avoidance operation. The network must mimic the input/output mapping of this human expert.

Both situations of T and O are associated by *Trial* and *Error* learning mechanism with the appropriate actions separately. Afterwards, the coordination of the two associated levels cited above allows the decision-making of the appropriate action.

This learning is guided only a feedback process, given by a factor *F* provided by the environment. This factor is estimated in order to give a reinforcement of the association between a given situation and an action if this latter leads to a favourable consequence to the robot ; if not , the factor F provokes a dissociation. Each neuron Ai s connected to all neurons Ti and Oj through connections weighted by the coefficients given by:

$$w_{ij} = -\Psi\left(\frac{A_i \ situation \ j}{\eta} t\right) + (\Psi - F) \tag{4}$$

Target localisation : *Situation$_j$*=Ti and F= $\begin{cases} F_1 \ if & H = 0 \\ 0 \ if & H = 1 \end{cases}$ (5)

Each situation Ti=, H is determined with regard to each action

Here we mean that situation of H_F, H_L, H_R, and H_C.

Obstacle avoidance : Situation j=Oj, and

$$F=\begin{cases} F_2 \text{ if} & \text{collision} \\ 0 \text{ if} & \text{not} \end{cases} \qquad (6)$$

With F1 > Ψ and $F_1>F_2$ 0< $\Psi<F_2$ if free obstacle environment (O=0,zero) .

III. Simulation Results

In order to evaluate, the average performance of our approach over various environments, we observed simulation of the neural networks navigation for great number of environments. We can change the position of obstacles so we get other different environments. These environments were randomly generated .To find a feasible and correct path after insertion of deletion of an obstacle, we simulate the behavior of our autonomous mobile robot by learning and applying the neural network principle.

The robot is simulated in different environments. To reflect the robot behavior acquired by learning in the explored environment and in new unvisited environments. The robot reacts in efficient and a satisfactory manner in these environments. As we can see the generalization and adaptation abilities of the system are achieved. The configuration of the environments changes by adding other shapes of static obstacles, in each situation the robot can navigate successfully.

For non intelligent react environments (environments contain on or two obstacles no more), the robot navigates and attends its target without collisions. In the case of complex environments, the robot reacts intelligently avoiding the obstacles and reaching the appropriate target. The system structure is able to achieve its task without collisions for every developed or proposed environment. Indeed, the networks grow to represent the problem as it sees fit. After learning, the target location situation is trained in the learning environments. From data obtained by computing distance and orientation of the robot-target, the robot is able to react, understand and achieve its mission perfectly.

The robot distinguishes the four direction driving the robot requires only very basic sensing and actuation capabilities. To maintain the idea; we have created several environments which contain many obstacles. The search area (environment) is divided into square grids. Each item in the array represents one of the squares on the grid, and its status is recorded as walkable or unwalkable area (obstacle). The robot starts from any position then using neural learning must move and attends its target.

The proposed approach can deal a wide number of environments and gives to our robot the autonomous decision of how to avoid obstacles and how to attend the target. More, the path planning procedure covers the environments structure and the propagate distances through free space from the source position. The results are very satisfactory to see the complexity of the principle and the extension versions of generation maps.

The simulation is done in different environments where the robot succeeds each time to reach its target without collisions. destination for source to the target without collision in free area. Sensing, deciding, thinking and reacting; the robot across perfectly the connection between the source S and the target T searching its target.

The figure 6 clarifies more the principle and show how the robot succeeds to reach the goal without collisions according to the configuration of the selected environments. Taking a suitable action and reacting at the appropriate way, the robot finds its safe way without collisions in efficient manner. If the algorithm does not converge, an error is returned as it is shown in the figure7.

To carry out tasks in various environments like in space applications, the robot succeeds to reach its target without collisions. The environment of navigation can be changed by user demand, that means that the robot can move in another environments where a given shape is designed by the user : a square and rectangle. The Robot come only move to free positions –/free area without obstacles/ and must stay within the environment searching its way from the starting position to the target position (a solution path) until it finds one or until it exhausts all possibilities /no possible paths see the figure 7.

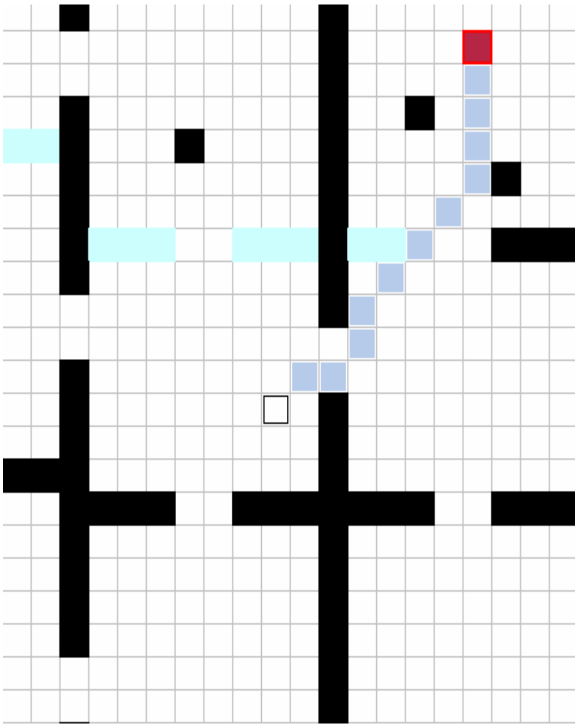

Fig. 6 Neural based navigation set-up1

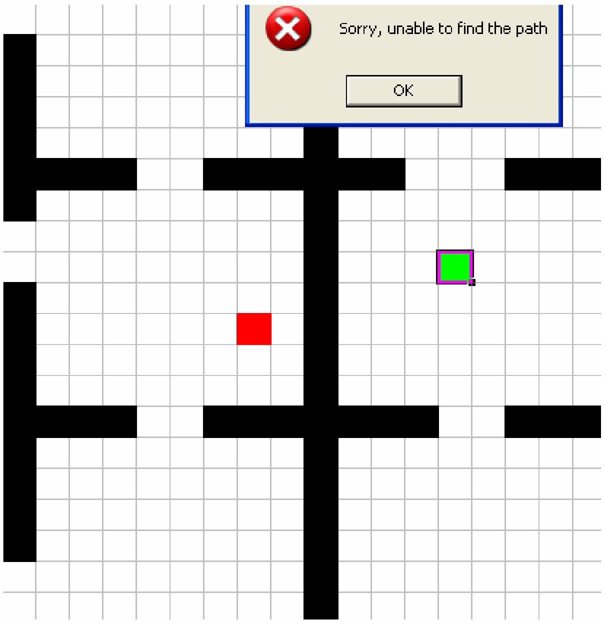
Sorry, unable to find the path

Fig. 7 Neural based navigation set-up2

IV. Conclusion

In this paper we presented an approach for mobile robot positioning and navigation which is based on the principle of the neural networks. Starting out from a start location and orientation in the grid, the mobile robot can autonomously head for destination Cells. On the way it determines its location in the grid using the principle of the neural networks.

We demonstrated how we implemented the underlying algorithm in software. Target location situations are associated with favorable actions in an obstacle-free environment explained in detail in this paper.

We have run our simulation in several environments where the robot succeeds to reach its target in each situation and avoids the obstacles capturing the behaviour of intelligent expert system. The proposed approach can deal a wide number of environments. This navigation approach has an advantage of adaptivity such that the intelligent autonomous mobile robot approach works perfectly even if an environment is unknown.

This proposed approach has made the robot able to achieve these tasks: avoid obstacles, deciding, perception, and recognition and to attend the target which are the main factors to be realized of autonomy requirements. Hence; the results are promising for next future work of this domain. Besides, the proposed approach can deal a wide number of environments. This system constitutes the knowledge bases of our *approach* allowing recognizing situation of the target localization and obstacle avoidance, respectively. Also, the aim work has demonstrated the basic features of navigation of an autonomous mobile robot simulation. The intelligent behaviour necessary to the navigation, acquired by learning enable the robot to be more autonomous and intelligent

The simulation results illustrate the generalization and adaptation capabilities of neural networks. An interesting alternative for future work is the generalization of this approach by increasing the number of possible robot directions.

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