Soft Computing Techniques for the Path Following Behavior and Moving Target Pursing by a Mobile Robot

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Abstract-- **This paper presents a navigation method for an autonomous mobile robot. In order to equip the robot by capacity of autonomy and intelligence in its environment, the control system must perform much complex information and processing tasks in real time, and it is well suited to use the soft-computing techniques. The objective of this paper is to elaborate intelligent control systems for the path following behavior by a mobile robot using fuzzy and neuro-fuzzy controllers. The proposed controllers are used for pursing a moving target. Simulation results show the effectiveness of the designed controllers. The results are discussed and compared.**

Index Terms-- **mobile robot, path following, neuro-fuzzy controller, hybrid learning, moving target pursing.**

I. INTRODUCTION

Soft-computing paradigms have provided a powerful tool to deal with mobile robot navigation process, which exhibits incomplete and uncertain knowledge due to the inaccuracy and imprecision inherent from the sensory system. Fuzzy logic based decision-making and neural networks have been found to be the most attractive techniques that can be used for this purpose [1][2].

Fuzzy systems have the ability to make use of knowledge expressed in the form of linguistic rules. Fuzzy system is tolerant to noise and error in the information coming from the sensory system, and most importantly; it is a factual reflection of the behavior of human expertise. The knowledge of the operator would be presenting in the form of a set of fuzzy linguistic rules. They offer the possibility of implementing expert human knowledge and experience [3].

Ever since the fuzzy systems were applied in industrial applications, developers know that the construction of a well performing fuzzy system is not always easy. Their main drawback is the lack of a systematic methodology for their design [4]. Usually, tuning parameters of membership functions is a time consuming task. Neural network learning techniques can automate this process, significantly reducing development time, and resulting in better performance.

Techniques based on the use of Artificial Neural Networks (ANN) have a great interest in control and robotic domains [5]. The fastness of treatment and their capacity of approximating complex nonlinear functions motivate their use for mobile robot control. Learning allows autonomous robots to acquire knowledge by interacting with the environment [5][6].

The merger of neural networks and fuzzy logic led to the creation of neuro-fuzzy controllers which are currently one of the most popular research fields. Generally, neuro-fuzzy systems can be classified into two categories; adaptive neuro-fuzzy inference system (ANFIS) [7] and hybrid neuro-fuzzy systems [8]. The first category is the most widely used, and they are designed to combine the learning capabilities of neural networks and reasoning properties of fuzzy logic. The main function of neural network is to learn about the fuzzy inference system (FIS) behavior and uses this knowledge to adaptively modify its parameters. The adaptability of the fuzzy inference system can be achieved by either rule base modification and/or membership functions modifications. Rules can be generated, modified, and/or eliminated, while membership functions of the input variables can adjusted and tuned by scaling mechanism [7]. The basic idea behind the use of the second category is to replace all or parts of the basic modules that builds a FIS [8][9]. The only advantage that can be gained from such arrangements is the high processing speed, presuming that a hardware implementation of such neural networks exists.

In this paper an approach to design simple fuzzy and neuro-fuzzy controllers are described for the path following task. The control systems generate the appropriate action that will drive the mobile robot straight on the path to reach the final destination.

The present paper is organized as follows: section 2 gives a brief presentation of Fuzzy and ANFIS techniques. In section 3, we will describe the path following behavior. The proposed controllers are introduced and explained in section 4. Section 5 shows simulation results for examples of the path following task. In section 6, we present a moving target pursing by a mobile robot. Section 7 concludes this paper.

II. FUZZY AND NEURO-FUZZY SYSTEMS

A. Fuzzy Logic System

Fuzzy logic systems are inspired by the remarkable human capacity to reason with perception-based information. Rule based fuzzy logic provides a formal methodology for linguistic rules resulting from reasoning and decision making with uncertain and imprecise information. The block diagram of a fuzzy control system is shown in Fig. 1 [3][8].
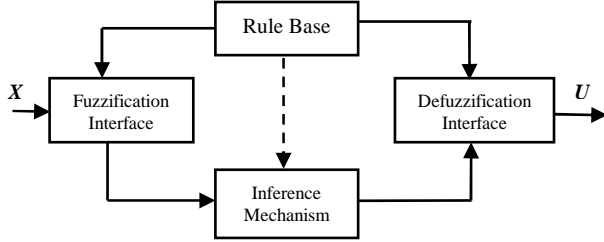

Fig.1. Fuzzy logic structure

The fuzzy Logic controller (FLC) is composed generally of the following elements [3]:

- *A fuzzification interface:* converts controller inputs into information that the inference mechanism can easily use to activate and apply rules.
- *A rule-base:* a set of *If-Then* rules which contains a fuzzy logic quantification of the expert's linguistic description of how to achieve good control.
- *An inference mechanism: (inference engine):* It emulates the expert's decision making in interpreting and applying knowledge about how best to control the process.
- *A defuzzification interface:* converts the conclusions of the inference mechanism into real control inputs for the process. There are two types of FLC; Mamdani model and that of Takagi-Sugeno [3].

B. Adaptive Neuro-Fuzzy Inference System

Inspired by the idea of basing the fuzzy inference procedure on a feed forward network structure, Jang [7] proposed a fuzzy neural network model (**A**daptive **N**eural-based **F**uzzy **I**nference **S**ystem). He reported that the ANFIS architecture can be employed to model nonlinear functions, identify nonlinear components on-line in a control system, and predict a chaotic time series. It is a hybrid neuro-fuzzy technique that brings learning capabilities of neural networks to fuzzy inference system. The learning algorithm tunes the membership functions of a sugeno-type fuzzy inference system using the training input-output data. ANFIS consists of five layers; the adaptive nodes of the neural network are the nodes in layers 1 and 4. If we assume that the rule base contains two fuzzy if-then rules of a Takagi and Sugeno's type [3]:

R_1 : If x is A_1 and y is B_1 Then $y = f_1(x, y) = p_1 x + q_1 y + r_1$

R_2 : If x is A_2 and y is B_2 Then $y = f_2(x, y) = p_2 x + q_2 y + r_2$

The output of the nodes in layer 1 is the membership values of the premise part:

$$O_i^1 = \mu_{A_i}(x) , i = 1,2 \tag{1}$$

Every node in layer 2 is a fixed node labeled *M*, which multiplies the incoming signals:

$$O_i^2 = w_i = \mu_{A_i}(x) \times \mu_{B_i}(y) , i = 1,2 \tag{2}$$

Every node in layer 3 is fixed node labeled *N* for normalization. it calculates the ration of the *i-th* rule's firing strength to the sum of all rules firing strengths:

$$O_i^3 = \overline{w}_i = \frac{w_i}{w_1 + w_2} , i = 1,2 \tag{3}$$

In layer 4, every node is an adaptive node while the function is:

$$O_i^4 = \overline{w}_i \times f_i = \overline{w}_i (p_i x + q_i y + r_i) . , i = 1,2 \tag{4}$$

Where $\overline{w}_i$ is the output of layer 3 and p_i, q_i, r_i are the parameters for the first order Sugeno rule.

The overall output of the network can be defined as:

$$O_i^5 = f = \sum_i \overline{w}_i \times f_i \tag{5}$$

C. Hybrid learning techniques

Using a given input-output data set, constructs a fuzzy inference system whose membership function parameters are tuned (adjusted) using either a back-propagation algorithm alone or in combination with a least squares method [7]. This adjustment allows the fuzzy systems to learn from the data they are modeling. If we suppose that the S_1 is the set of premise parameters and S_2 is consequent parameters set. Jang proposed that the learning task is done in two passes using a hybrid learning algorithm as shown at table 1. As depicted; in the forward pass the first set is fixed and S_2 is optimized by the least square estimate (*LSE*). In the backward pass S_1 is tuning by the back-propagation algorithm [7].

TABLE 1
TWO PASSES IN THE HYBRID LEARNING PROCEDURE FOR ANFIS

	Forward Pass	*Backward Pass*
Premise Parameters	Fixed	Back-propagation
Consequent Parameters	Least Squares Estimate	fixed

After a learning phase, the controller is able to generate the appropriate actions for the desiring task.

III. PATH FOLLOWING BEHABIOR

A. Mobile robot configuration

The mobile robot used in this work is a tricycle robot with non-holonomic property that restricts its mobility in the sideways direction and with limitation of angle. It has two rear driving wheels and a passive front wheel. The inputs of this kinematic system are the steering angle of the front wheel α and the linear velocity v_r. The outputs are the coordinates of the robot: (x_r, y_r, θ_r) (see Fig.2). In perfect adhesion conditions, this kinematic model can be described by the following equations [10]:

$$\dot{x}_r = v_r \cos(\theta_r)$$
$$\dot{y}_r = v_r \sin(\theta_r) \tag{6}$$
$$\dot{\theta}_r = \frac{v_r}{l} tg(\alpha)$$

Where Δt is the sample time and l the robot long.

B. Path following behavior

The path following is one of the basic missions of a mobile robot. It is a significant task that must have the robot, because it permits this machine to execute its path with a minimum error [10]. The path following behavior consists to direct the robot to follow a trajectory at the best possible precision and arrives to a final destination. Generally, the mobile robot executes its movement with a constant velocity and estimates the trajectory position with its own odometric sensors. The trajectory to follow is stored in the memory in the form of a three elements vector (x_p, y_p, θ_p). In the present work we can use a vector with two elements (x_p, y_p) generated by a module named (trajectory generation module). The third parameter will be calculated by the robot during movement. In its actual position, the robot (Fig.2) calculates the error angle θ_{er} using the desired orientation θ_d which allows it to go ahead to the desired point of path [6][10][11]. Which are given by equations 7 and 8 respectively:

$$\theta_d = arctg\left(\frac{y_p - y_r}{x_p - x_r}\right) \tag{7}$$
$$\theta_{er} = \theta_d - \theta_r \tag{8}$$

IV. PROPOSED CONTROLLERS

In this section, the developed controllers are explained. They are based on simple design methods using fuzzy logic controller and neuro-fuzzy controller for a path following behavior by a mobile robot.
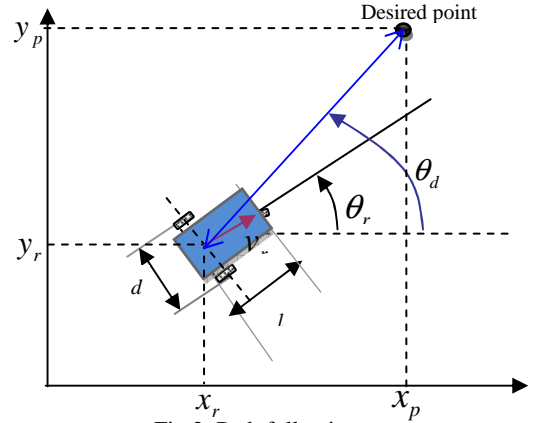

Fig.2. Path following strategy

A. Fuzzy logic controller

The bloc diagram of the robot controller is shown in Fig. 3. The calculation module compares the actual robot coordinates with the coordinates of the path and computes the angle noted θ_d. This value is compared with the orientation of the robot delivered by the odometry module in order to compute the angle error θ_{er} according the equations 7 and 8. The Takagi-Sugeno fuzzy controller uses this angle and its variation noted $d\theta$ to generate the appropriate action α. The fuzzy sets used for fuzzify the input-outputs variables are shown in figures 4, 5 and 6.
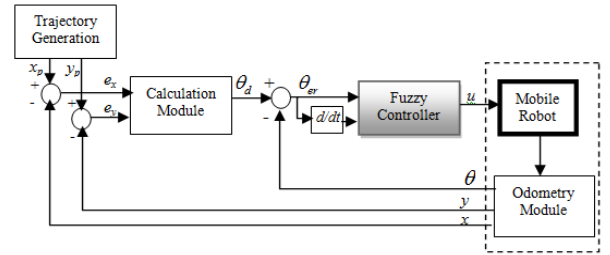

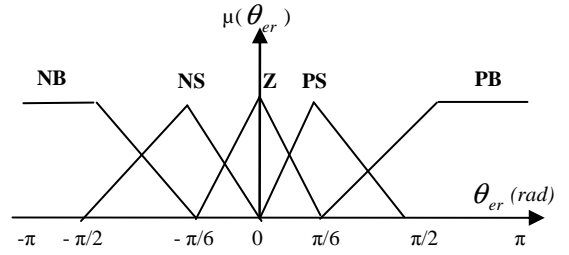Fig.3. Fuzzy controller

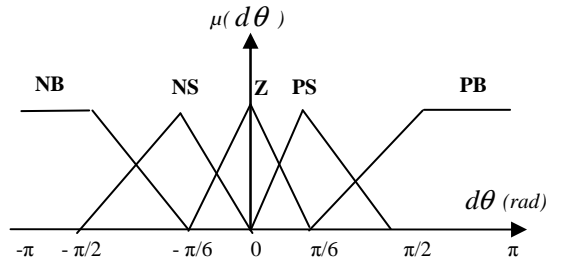Fig.4. The membership functions of θ_{er}

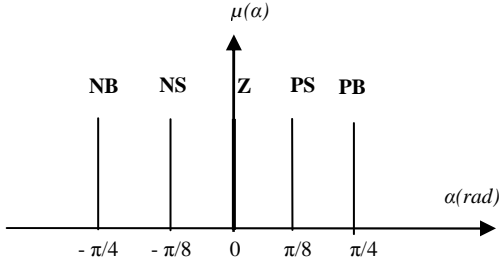Fig.5. The membership functions of $d\theta$

Fig.6. The fuzzy sets of the output control

The used linguistic values for all input-output variables are:
Z: Zero, **PS:** Positive Small**, PB:** Positive Big, **NB:** Negative Big, **NS:** Negative Small.

The proposed control strategy is expressed symbolically by the fuzzy rules presented at table 1. Figure.7 shows the surface control of the used fuzzy control system.

TABLE I
RULE BASE FOR THE PATH-FOLLOWING TASK

$d\theta$	θ_{er}				
	NB	NS	Z	PS	PB
NB	NB	NB	NB	NS	Z
NS	NB	NB	NS	Z	PS
Z	NB	NS	Z	PS	PB
PS	NS	Z	PS	PB	PB
PB	Z	PS	PB	PB	PB

The output control applied to the mobile robot is given by equation 9:

$$\alpha = \sum_{i=1}^{N} w_i \alpha_i \qquad (9)$$

Where w_i is the truth value rule i for a given input vector, N is the number of rules. The truth value is calculated by:

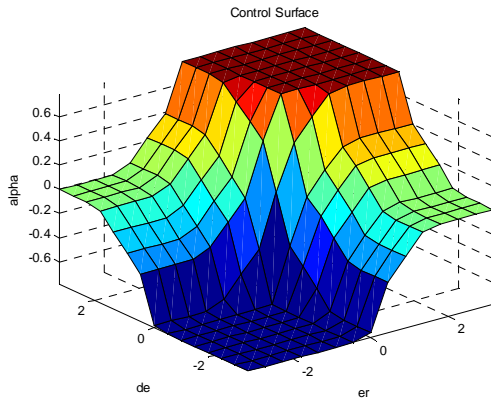$$w_i = \mu_{A_n}(\theta_{er}) \times \mu_{Bm}(d\theta) \qquad (10)$$

Fig.7 Control surface for the designed fuzzy controller

The principle input for the path following task is the angle error. In order to simplify the studied strategy, we can use only this value as an input for the neuro-fuzzy controller. With an assumption of that, the robot is firstly located on the path.

B. Neuro-Fuzzy controller

The robot controller is an ANFIS model. It is a one order Takagi-Sugeno model trained by a data-base for this task. At each sample, the movement represented by the angle error θ_{er} is given to the controller to let the robot to reach the next reference. Figure.8 presents the proposed neuro-fuzzy controller. The network structure is similar to that of a neural network, which maps inputs through output membership functions and associated parameters, and then through output membership functions, associated parameters to outputs; its structure can be used to interpret the input/output map.
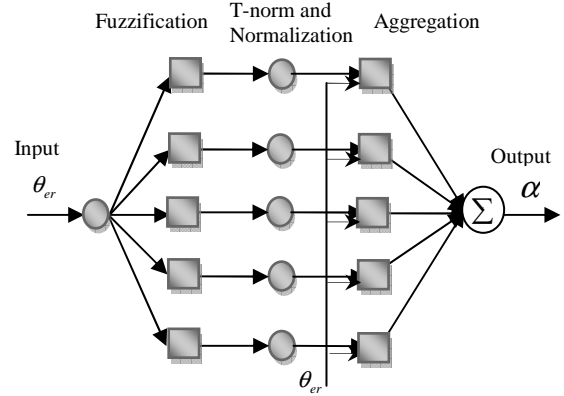

Fig.8. The proposed ANFIS structure

1. Learning phase

This phase consists to adjust the fuzzy controller parameters (premise part and conclusion part) using the training data for the path following task. This data-base contains two vectors of the angle error θ_{er} and its appropriate action α. The input variable of the neuro-fuzzy controller is fuzzified using the same labels used in the previous section but with a gaussian membership functions type. After the learning phase, these membership functions are modified and adjusted.

2. Control phase

The bloc diagram of this control system is shown in Fig.9. At each step, the calculation module computes the desired angle noted θ_d. This value is compared with the orientation of the robot to compute the angle error θ_{er}. The trained neuro-fuzzy controller uses this angle to generate the appropriate action conducting the robot to reach the next point of the path.
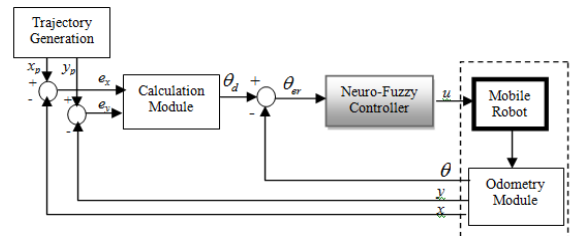

Fig.9. Neuro-Fuzzy controller

V. SIMULATION RESULTS

In order to test the designed controllers, different reference paths are chosen to provide several direction changes and types of curves. The paths are composed of segments (discontinuous curve which does not respect the kinematic constraints of the robot). These paths lead the robot to the final destination called goal.

For the ANFIS method, to compare the desired control output with the ANFIS one; Fig.10.a shows the two responses. A big similarity between them is observed. As depicted in Fig.10.b, the error is minimized to zero illustrating the best learning of the controller. The simulation results for a path with one segment are given in Fig.11 and Fig.12 using the fuzzy and neuro-fuzzy controllers respectively. The path following is good and satisfactory; the robot can follow the path with a minimum error. For different straight paths with different slopes following using the two controllers, the results are shown in Fig.13 and 14. In this case, the robot is initially at (10,10) point with a null orientation. As depicted, the proposed controllers can behave correctly in all cases and this task is realized efficiency. The robot tends to overlapping the trajectory by few errors at the first turning.
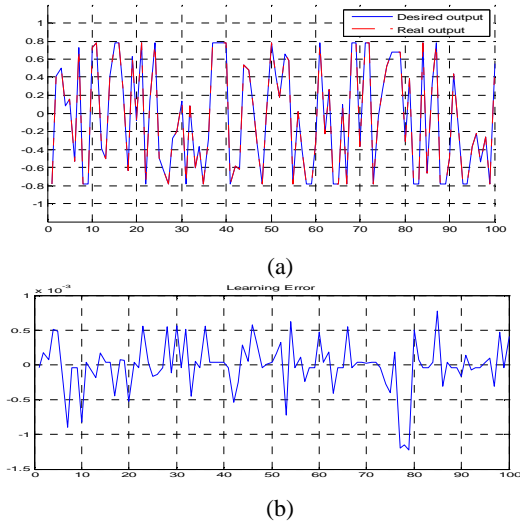

(a)

(b)

Fig.10 (a) the desired control with the ANFIS output
(b) the learning error.
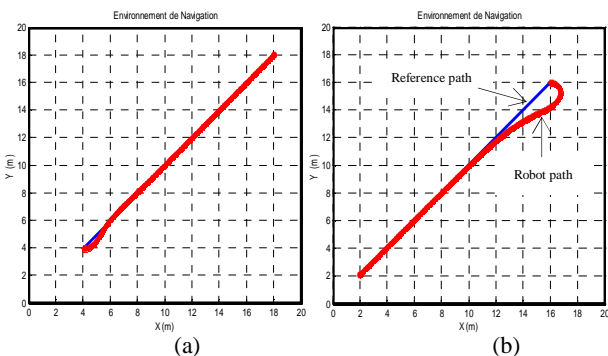

(a)   (b)

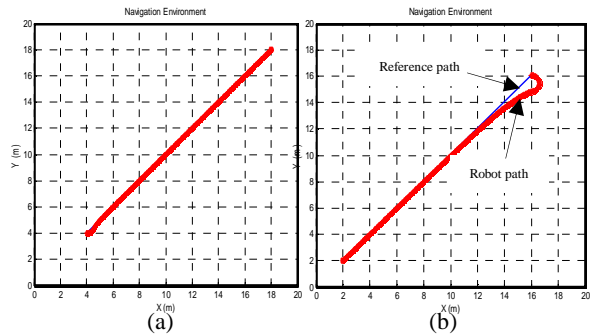Fig.11. Line following using fuzzy controller

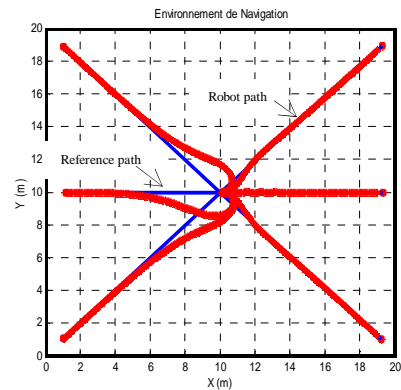Fig.12. Line following using Neuro-fuzzy controller

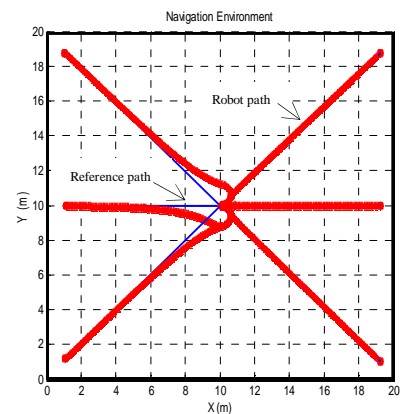Fig.13. Straight paths following using fuzzy controller

Fig.14. Straight paths following using ANFIS controller

The application of these controllers for a V form path composed of two segments and presenting attenuated angles (not respecting the kinematic constraints of the robot and steering limitation) leads to the robot trajectory depicted in Fig.15. The path following is good but a minimum error is observed. This error is smaller when using the neuro-fuzzy controller due to the data base used in training task. The tracking error exists at changed points of the trajectory due to the curvature discontinuity which leads to abrupt change of α at the turning steps, and is due especially to the limitation of the steering angle (control value).
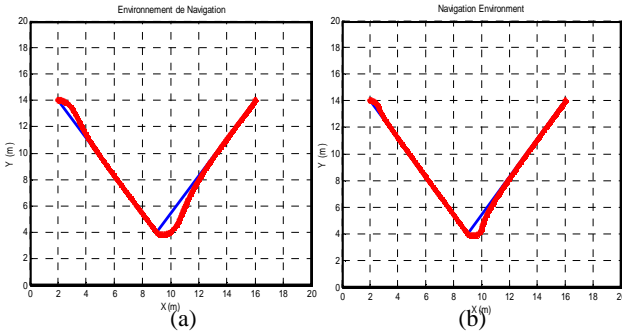
Fig.15. Robot trajectory for V shaped reference trajectory using fuzzy controller (a) and neuro-fuzzy controller (b).

VI. MOVING TARGET PURSING

If we consider a moving target in the robot environment, the task is to purse this target; while there coordinates are known at any time. The mobile robot purses the target by the calculation of the steering angle that conducts the robot ahead to the target. In the first example (Fig.16), the mobile robot is initially located at point (4,4) with a null orientation. The target is located at (4,12) and will start moving along a straight line parallel to the abscissa axis. While the target starts moving the mobile robot begins pursing it. The pursing will be halted when the robot catches the target. Another example is shown in Fig.17 which illustrates the efficiency of the robot controllers; when the target has a sinusoidal path. It is also shown that the proposed controllers can guide the robot toward the target and purse it effectively. The task is faster when we use the ANFIS controller than the fuzzy one.
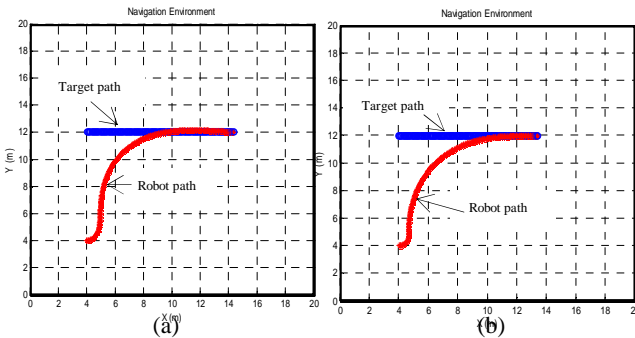

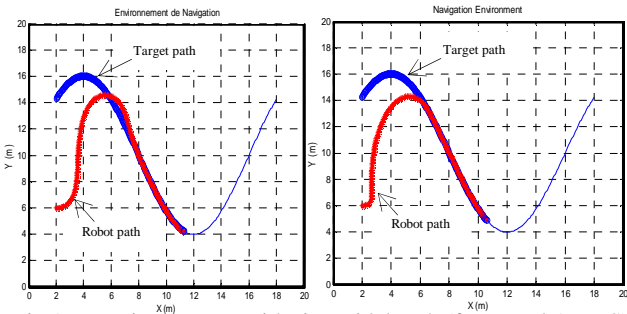Fig.16. Moving target pursing using fuzzy and ANFIS controller

Fig.17. Pursing a target with sinusoidal path (fuzzy and ANFIS)

VII. CONCLUSION

In this paper, we have presented a control systems based on intelligent techniques for the mobile robot navigation. The first technique is based on the fuzzy logic control and the second is an ANFIS controller. These controllers are used to realize the path following behavior and moving target pursing. Different reference trajectories with different curves are simulated. The simulation results show the efficiency of the two proposed controllers for the robot control and permitting to equip the mobile robot with a certain degree of intelligence. The results show a big similarity between the two approaches. The advantage of the proposed controllers is the simplicity and the efficiency for the robot control.

As prospects, it is interesting to improve the robot behavior and apply this strategy on a real mobile robot. The interest of this type of approach will be given to other optimization approaches for the fuzzy controllers.

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