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THE IMPLEMENTATION OF AN EFFICIENT TARGET FOLLOWING AGENT FOR AN AUTONOMOUS MOBILE ROBOT

Abstract: *In this paper we present an implementation of an efficient agent which allows to an autonomous mobile robot to follow a target. The agent is based on a neural network for the target position identification. The behaviour of the robot was tested in an open space environment using the simulation programme SMASIM.*

1. INTRODUCTION

The 'Laboratoire d'Electricité, Signaux et Robotique' (L.E.Si.R.), of 'l'Ecole Normale Supérieure de Cachan', France, develops a mobile robot (figure 1) called AMARA (AMARA is the French acronym for Multi-Agent Architecture for an Autonomous Robot).

In this paper, we present AMARA's perception system and we develop a target following agent based on neural network. Experimental results were made with SMASIM, a program developed at L.E.Si.R., which allows the simulation of navigation of one or more mobile robots.

2. PERCEPTION SYSTEM OF THE MOBILE ROBOT

The robot uses 5 home-made ultrasonic sensors (figure 2). These sensors use the common flying time measurement method to get the distance between the obstacle and the robot.

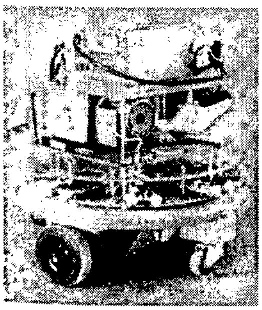

Fig. 1. AMARA robot

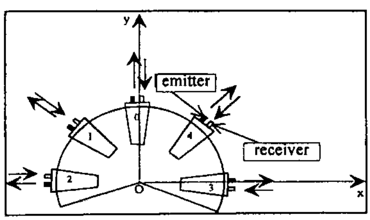

Fig. 2. Perception system of the AMARA robot

The sensors are placed on the robot such as the angle between their main axis is 45°. The emitters are allowed to emit sequentially. For each enabled emitter, the output data of all receivers are read.

We can notice that, to know the position of the target, it is enough to analyse the information of distance provided by the receiver corresponding to the transmitter (the response r_{ij}, $i=j$).

Thanks to the experimental results (illustrated in figure 3) we built the schematic representation shown in figure 4 [1]. We considered as useful data only the distances closer to the real robot-target distance (d<50 cm).

On the schematic representation in figure 4, the first circumference indicates the real distance measured by the receiver associated to the current transmitter.

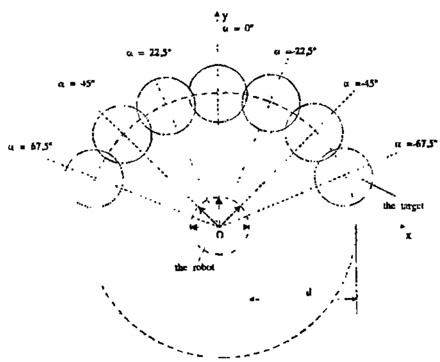

Fig. 3. Measure of location of a cylindrical target with the diameter ϕ=35 cm.

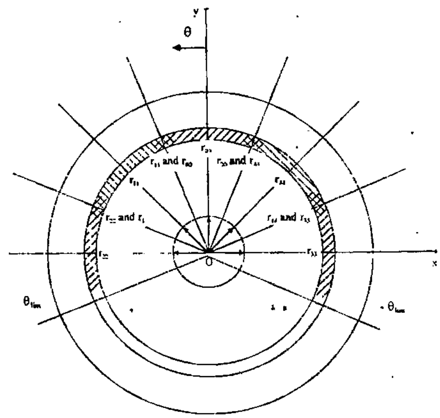

Fig. 4. Useful responses for identifying the position of a target situated on a circumference around the robot.

3. FOLLOWING AGENT

3.1. Neural network for the target detection

The neural networks techniques are generally used in the mobile robots domain for environment recognition [2] or to achieve the reactive navigation [3], [4], [5]. In this paper, the authors propose the using of a neural network for the determination of the target position to improve the algorithmic method presented in [6].

The neural network used has a perceptron structure with one hidden layer. The input and the output layers have 5 neurones and 1 neurone, respectively. For testing the performance of the neural network we used different number of neurones (10, 15 or 20) in the hidden layer.

The inputs of the neural network are the distances which are measured by each US module. The output of the neural network is the mobile robot movement order (m_O). To obtain a high precision of the target following we defined 3 basic movement orders:

- *straight* – for the straight ahead movement, coded by 0,
- *left* – for the rotation to left with $\theta>0$ coded with a positive number in the range (0, 1] (coded by 1 for $\theta=\theta_{lim}$),
- *right* - for the rotation to right with $\theta<0$ coded with a negative number in the range [-1, 0) (coded by -1 for $\theta=-\theta_{lim}$),

where θ_{lim} is the maximal angle θ (see figure 4) up to which the target is detected. For the used US we obtained by simulation $\theta_{lim}\approx 2\pi/3$ rad.

The dependence between the angle θ and the m_O is the following:

$$m\_O = \frac{\theta}{\theta_{lim}}, \text{ if } |\theta| \leq \theta_{lim} \tag{1}$$

If the receivers do not acquire any position information (i.e. for every US module the measured distances are grater or equal with *max_dist*=50+*r* [cm], where *r* is the robot radius) the movement order is *straight.*

Thus the neural network output varies between [-1, 1] depending on the relative position between the target and the robot. So, we shall use the nonlinear hyperbolic tangent (tanh) activating function.

For the neural network training, we used experimental and also simulated data obtained with the package program US_SIM [7]. Each time we chose a fixed epochs number (100) and we applied the Levenberg-Marquard algorithm [8]. For the neural network learning process we used the package program Neural Networks Toolbox from Matlab.

We tested the generalisation capacity of the neural network in function of the neurones number of the hidden layer and also of the data base dimension used in the learning process. The data base dimension used in the learning process was varied between 141 and 469 sample patterns.

3.2. Motors control

The motors of robot AMARA are engines step by step. The program establishes frequency f_C of the signal, which controls the engines in accordance with the relation [9]:

$$f_c = \frac{N}{50 \cdot 10^{-3}} = 20 \cdot N \text{ [Hz]} \tag{2}$$

where N is a number, ranging between 0 and 15, which comes from the discretization of the speed range.

After the position of the target has been found, it is necessary to calculate the speed module of the robot as well as the angle of rotation.

For establishing the speed module, we have used the following relation:

$$N = \begin{cases} \dfrac{d-18}{1.5} & \text{if} \quad d \geq 18 \\ \dfrac{d-18}{2.25} & \text{if} \quad d < 18 \end{cases} \tag{3}$$

with: N - number for speed command and d - distance between the robot and the target.

To obtain a rotational movement of the robot, it is necessary to control the motors with different speeds. The rotation angle is a function of the difference between the 2 motors speeds. The relationship between the angular position of the target and the difference between the speeds of the motors is established by table 1.

Angular position θ	Speed Difference $(v_r - v_l)$	Action
[- 11,25°, 11,25°]	0	straight
[11,25°, 33,75°]	2	rotate left +
[33,75°, 56,25°]	3	rotate left ++
[- 33,75°, - 11,25°]	- 2	rotate right +
[- 56,25°, - 33,75°]	- 3	rotate right ++

Table 1.

In the simulation programme we can command the motors with a step of the discrete speed as smaller as we want. Remind that, the output θ of the neural network establishes the target angular position. So, in this case we chose to command the difference between the speeds of the motors with the relationship:

$$v_r - v_l = MAX\_SPEED \cdot (-m\_O) \tag{4}$$

and the speed module with the following relation:

$$N = MAX\_SPEED \cdot (1 - |m\_O|) \tag{5}$$

where *MAX_SPEED* is a modifiable parameter in the programme.

4. EXPERIMENTAL RESULTS

We tested by simulation the efficiency of the propose agent for a various positions of the target placed around the AMARA robot. We used the facilities offered by SMASIM program [10]. The program permits the local navigation for one or more mobile robots. For each robot we can establish one or more navigation agents.

We studied different neural networks for the implementation of the target following agent. For example, in figure 5.a. it is presented the robot behaviour when the neural network has 10 neurones in the hidden layer and it was used a data base for the learning process with 235 sample patterns. In figure 5.b. we placed the robot and the target in the same initial position. In this case, the neural network hidden layer has 15 neurones and the data base for the learning process has 235 sample patterns. In figure 5.a. the robot follows the target with oscillations and between his trajectory and the target trajectory is a relative significant error. In figure 5.b. the robot follows very well the target but the entry on the target trajectory (i.e.

the reaction speed) is not very fast. This low reaction speed is illustrated by the loop of the robot trajectory.

An optimal robot behaviour is obtained if we use a neural network with 15 neurones in the hidden layer and if the learning process data base has 469 sample patterns. We tested the following agent based on this neural network and the results are presented in figure 6. In figure 6.a. we considered, for comparison, the same initial conditions for the robot and the target like in figure 5. It can be observed that we obtained a high accuracy of target following and a fast reaction speed. In figure 6.b. is presented a case in which we have chosen a great distance between the robot and the target.

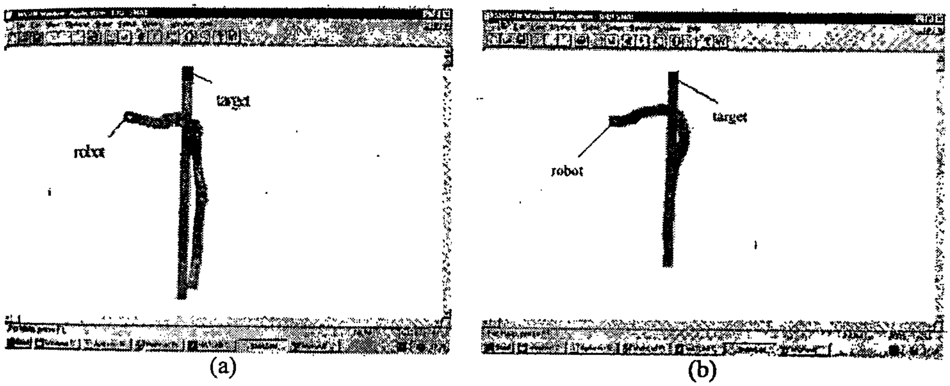

Fig. 5. The robot behaviour with different hidden layer neurones number.
(a) 10 neurones (b) 15 neurones

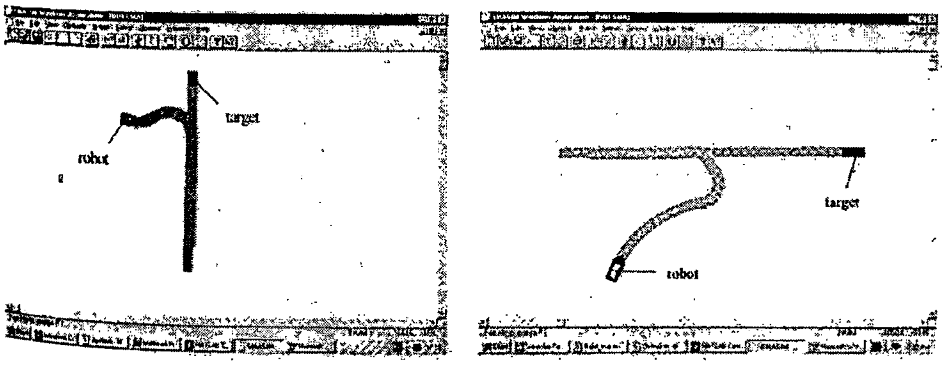

Fig. 6. The optimal robot behaviour in different cases for different distances between the robot and the target:
(a) small distance (b) great distance

The efficiency of the target following agent is characterised by the performance parameters: the distances between the trajectory of the mobile robot and the target and the oscillation degree of the robot trajectory. Based on the experimental results we can conclude that we obtain an efficient target following agent in an "open space" environment.

5. CONCLUSION

An interesting application for an autonomous mobile robots is to develop an agent which allows a target following.

The paper presents an efficient target following agent based on neural network, which allows the navigation of the robot in indoor environments of type "open space".

Based on the ultrasonic sensors measurements we locate the target position with a neural network. Than, we calculate the speed module and the rotation angle of the robot. The experimental results were done in the simulation program SMASIM. It can be noted an accurate follow-up of the target and a high reaction speed of the robot.

This method can be applied for the target following in the case of the robot navigation in different types of indoor environments. A finding in this domain is currently on work and will be presented in a next paper.

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