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Application of Neural Networks in Perception System Management for an Indoor Mobile Robot

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Abstract*— In the mobile robotics field, localization and map building are very important tasks that a mobile robot must perform for a safe navigation. The present paper presents a multi-layer perceptron (MLP) neural classifier of obstacles with coded outputs. This means that the number of the network outputs is lower than the number of the recognizable patterns. In this way, the neural network is less cumbersome; this will make easier the network parametrizing and resizing to be applied to other type of environment. The developed classifier ensures the discrimination of all possible patterns using a little number of elements in the training set. Subsequently the problem of training slowness is avoided.

***Keywords*— Mobile robot, perception, neural network, pattern recognition, laser range sensor**

I. INTRODUCTION

The autonomy of a mobile robot reflects its ability to behave cleverly in an unexpected situation [1]. This can only be accomplished when the robot is fitted with means to gather the maximum of information about its current surrounding and a suitable tool to interpret them [2][3][4]. Even though a lot of work in this field has been done till now, the appearance of artificial intelligence has provided new tools which has persuaded the researchers to take back their work. The development of neural networks, which is one of the modern control methods, is essentially based on two objectives. The first objective is to develop computational methods that can perform reasoning and problem solving that require human skills. The second one is to explore an effective trade-off between precision and the cost in developing an approximate model of a complex system or function. One of several reasons of choosing modern method is their ability that allow a mobile robot to sense the environment in real-time and to act on the basis of the acquired data [3]-[6].

A mobile robot must be able to know its position in the environment in geometric coordinates [2]. This paper presents a simple method to design a pattern classifier with high performance. The interest of the developed system is that the robot can recognize the different situations encountered in an indoor environment such wall, passage, corner....

Neural networks are powerful tools to be used in pattern classification [7] and recognition [8] due to their:

- noise tolerance,
- training and generalization ability,
- real time processing.

The patterns recognition and classification system is illustrated in Fig. 1, it is built around a neural network.

A laser range telemeter is used as input device; its role is to provide measurements of the actual situation of the environment in order to create a relationship between perception and navigation [9]. In [8], a classical pattern classification approach is presented based on a MLP network where the number of the output neurons is equal to the number of recognizable patterns. It is to notice that the system is very complicated and the training data set is very important so the training time will be very large.

Our system (classifier) is based on the idea of coded outputs what allows him to avoid the problems reproaching much standard classifier neural network (MLP) such as the slowness of training [6][7]. Thus, our system is well adapted, has such problems what him a makes it possible to have good results compared to other approaches [2][4].

This paper is organized as follows: First we begin by explain the problem often met in robot mobile navigation, follows by simulation results and a general conclusion is given in the end

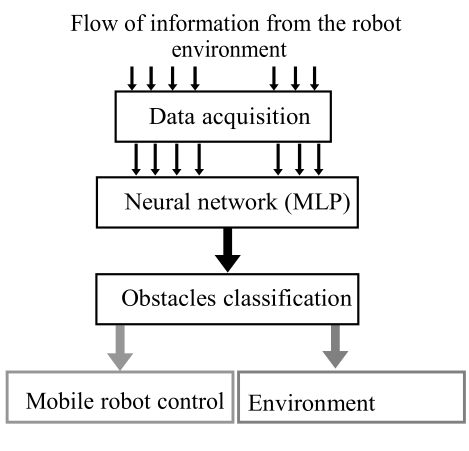

Fig. 1 Synoptic diagram of the designed system

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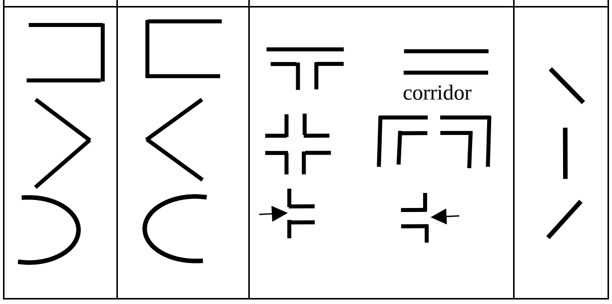
II. OBSTACLE CLASSIFICATION IN MOBILE ROBOTICS

A mobile robot can meet several situations in an environment, Table.1. In this environment the robot must answer "I am in front of such a quite precise situation" thus it must solve the problem of confusion and overlapping between the various situations in its mission.

TABLE I
VARIOUS CLASSES CONSTITUTING THE BASE OF TRAINING (ENVIRONMENT OF THE ROBOT)

Impasse	Corner	Passage	Wall



III. CODED PATTERNS APPROACH

One the disadvantages of the use of the conventional MLP neural networks in classification; their training slowness especially when an important number of patterns has to be discriminated [2], [10]-[12]. Another inconvenience is the cumbersome of the network architecture. In order to circumvent this problem, coded patterns approach is used. In this approach, patterns are coded in the way to get less outputs and a smaller training set. With n coded outputs, the MLP can discriminate 2^n patterns [2][11][13].

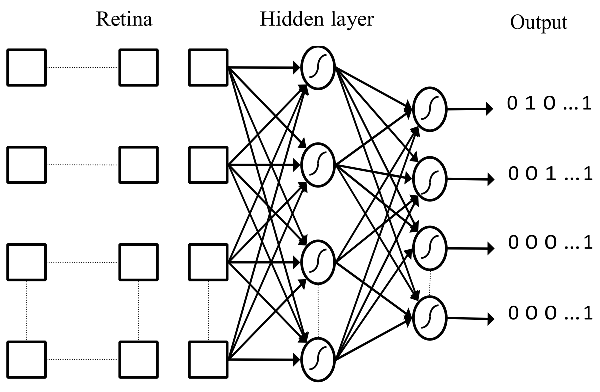


Fig. 2 Neural network Structure

In this paper, a multi-layer perceptron with a several layers of hidden nodes are used, apart from the output layer. We will look at feed forward architectures where no feedback connection is available, Fig. 2 shows a generic 3-layer network with N inputs, N_h hidden nodes and M output nodes.

Let's consider $x = (x_0, x_1, x_2, \dots, x_N)$, the input pattern with threshold, the values on the hidden nodes is:

$$h_j = \varphi_h(\tilde{h}_j) = \varphi_h\left(\sum_{k=0}^{N} w_{jk}\, x_k\right),\ \ j = 1 \dots N \qquad (1)$$

Where, φ_h is the activation function used in the hidden layer, and $h_0 = 1$ to introduce a threshold when calculating the output. The outputs $y_1, y_2, \dots, y_M$ are given by:

$$y_i = \varphi_0(\tilde{y}_i) \qquad (2)$$

$$y_i = \varphi_0\left[\sum_{j=1}^{N_h} w_{ij}\, \varphi_h\left(\sum_{k=0}^{N} w_{jk}\, x_k\right) + w_{i0}\right] \qquad (3)$$

Where φ_0 is the activation function for the output layer?

Learning Algorithm

The training algorithm chosen for this type of problem is the RPROP because of that it is characterized by its speed and its best convergence towards a minimum of the quadratic error and it requires especially a very little place in memory.

RPROP is a technique of training based on the value of the differential $\frac{\partial E}{\partial w_{ij}}$, and to take only of its sign changes, the weights update is given by the following formula:

$$\Delta w_{ij} = -sign\left(\frac{\partial E}{\partial w_{ij}}\right)\Delta_{ij} \qquad (4)$$

Δ_{ij}: update-value: value of modification of the weight, evolves acting changes of differentials sign of this same weight. The weights are changed only after each time (batch learning). During one step (iteration), differentials obtained after each presentation are added the element of the training set.

$$\Delta_{ij}^{(t)} = n^{+}\Delta_{ij}^{(t-1)}, \quad \text{if } \frac{\partial E^{(t-1)}}{\partial w_{ij}} * \frac{\partial E^{(t)}}{\partial w_{ij}} > 0$$

$$\Delta_{ij}^{(t)} = n^{-}\Delta_{ij}^{(t-1)}, \quad \text{if } \frac{\partial E^{(t-1)}}{\partial w_{ij}} * \frac{\partial E^{(t)}}{\partial w_{ij}} < 0$$

$$\Delta_{ij}^{(t)} = \Delta_{ij}^{(t-1)}, \qquad \text{else}$$

Where $0 < n^{-} < 1 < n^{+}$

$$\Delta w_{ij}^{(t)} = -sign\left(\frac{\partial E}{\partial w_{ij}}\right)\Delta_{ij} \qquad (5)$$

If the differential changed sign compared to (t-1): at this time, we passed above a local minimum, and we returned to the preceding weight (backtracking):

$$\Delta w_{ij}^{(t)} = -\Delta w_{ij}^{(t-1)}, \text{ if } \frac{\partial E^{(t-1)}}{\partial w_{ij}} * \frac{\partial E^{(t)}}{\partial w_{ij}} < 0$$

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IV. SIMULATION RESULTS

The data-gathering is performed by a simple perception system, which ensures this collection, built around a laser sensor. It is a turret placed in front of the mobile robot. Having a rotation of 180° to a prefixed step makes it possible to collect a well-defined whole of measurements, as shown in Fig.3. These measurements give a satisfactory idea on a zone of manoeuvrability whose swept surface depends on the mobile robot and its nature of movement. For more clearness an example was selected in order to show the values resulting from the laser rangefinder and their correspondent in mode reduced for various useful zones from detection.

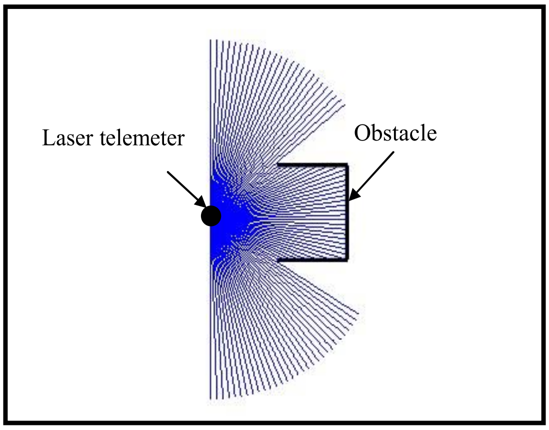

Fig. 3 Sweeping of a sensor has rangefinder laser

A. *Rate of Recognition*

Once the neural networks involved (after training), it is necessary to test it on a different data base from those used for training. This test at the same time makes it possible to appreciate the performances of the neural system and to detect the type of data which pose problem. In the case, we tried to test the degree of identification of elements within the same class, which led to the results of Table 1. limited at the number of 5 patterns for the training and 5 others for generalization.

TABLE 2

RATE OF THE SITUATIONS RECOGNITION

	Passage	T-crossing	Crossing
Training	5	5	5
Generalization	5	4	3
	Piece	Right angle	Left angle
Training	5	5	5
Generalization	3	3	3
	input	output	
Training	5	5	
Generalization	4	4	

B. *Resolution of Indecisions*

What will the network answer in indecisions situations? A solution insists to include these situations of indecision in one of the classes between which the network hesitates [1]. If one wants to solve the majority of the conflicts the aspect passage is most common in the indicated in the conflict event.

C. *Tests of Invariance by Deformation, Translation and Homothety*

The network allows recognizing forms independently of transformations such as translation, homothety and deformation. For geometrical forms this invariance is checked rather well.

1) *Deformation*

In this test, the performance of the network is obtained by a deformation of the forms which constitute the bases of training (disturbed forms) and thus the network can recognize the object of Fig. 5 to belong to the same class as the object of Fig. 4.

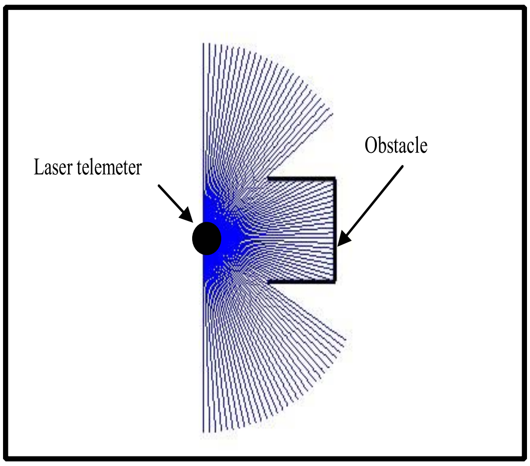

Fig. 4 U shaped Impasse (during the training)

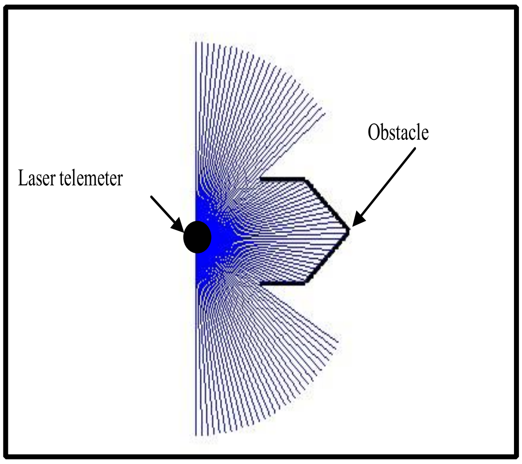

Fig. 5 Form recognized like impasse (during the validation)

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2) Translation

In this case, the performance of the network is checked by testing the recognition during displacement of the sensor (mobile robot) with respect to the obstacle. Thus, the network can recognize the object of Fig. 7 to belong to the same class as the object of Fig. 6 for various distances separating the robot from the obstacle. It is to be noticed here that the obstacle always remains inside the critical zone of pattern recognition.

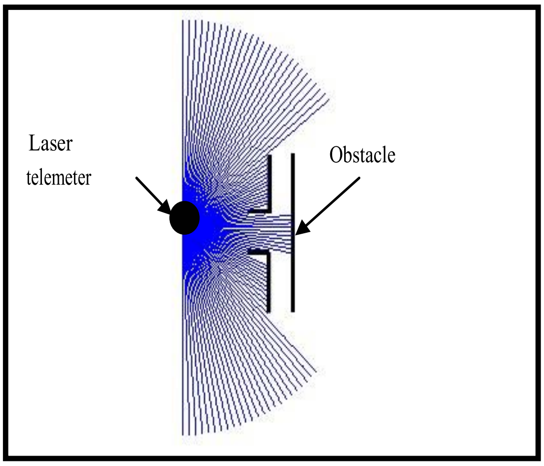

Fig. 6 T-crossing Form (during the training)

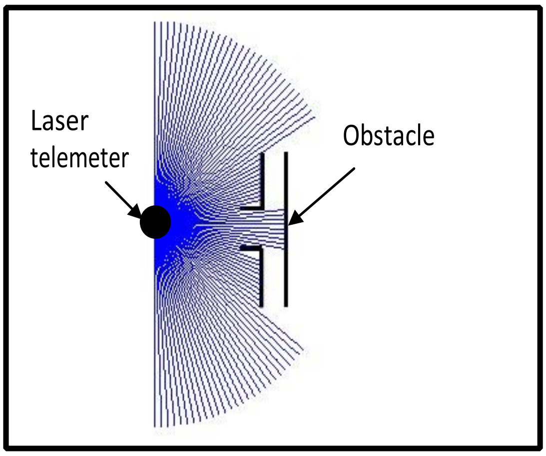

Fig. 7 T-crossing Recognition after sensor translation

3) Homothety

The performance of the network is tested by the multiplication of obstacles dimensions by factors called homothety factors. The factors retained for the tests are: 0.8, 0.9, 1.1 and 1.2 corresponding respectively to a contracting and an enlargement of the obstacles. Table 3 shows the rate of recognition of various forms for 5 values of homothety factor. Five values for the factor of homothety were selected to show the different cases of enlargement and contracting of the obstacles.

The results in Table 3 show very interesting rates of recognition. It is noticed that the developed neural network, reacts well during the multiplication by homothety factors which simulates changes in obstacle dimensions.

TABLE 3

RATE OF RECOGNITION OF THE SAME SHAPE OF OBSTACLE FOR VARIOUS DIMENSIONS

factor of homothety	passage	wall	Impasse
0.8	5	5	5
0.9	5	5	5
1	5	5	5
1.1	5	5	5
1.2	5	5	5
factor of homothety	corner	crossing	T-crossing
0.8	5	5	5
0.9	5	5	5
1	5	5	5
1.1	5	5	5
1.2	5	5	5
factor of homothety	piece	Right Angle	Left Angle
0.8	5	4	4
0.9	5	5	5
1	5	5	5
1.1	5	5	5
1.2	5	4	3
factor of homothety	input	output	
0.8	5	5	
0.9	5	5	
1	5	5	
1.1	5	5	
1.2	5	5	

D. *Confusion Matrix*

In the confusion matrix, different situation of conflict and overlapping are shown.

TABLE 4

CONFUSION MATRIX

	passage	Impasse	Input	Piece	Crossing	T- Crossing	Wall
Passage	100%	0%	0%	0%	0%	0%	0%
Impasse	6.66%	93.34%	0%	0%	0%	0%	0%
Input	0%	0%	93.34	0%	0%	6.66%	0%
Piece	0%	0%	0%	100%	0%	0%	0%
Crossing	0%	0%	0%	0%	86.67%	13.33%	0%
T- Crossing	0%	0%	0%	0%	6.66%	93.34%	0%
Wall	0%	0%	0%	0%	0%	6.66%	93.34

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V. Conclusion

This study enters within the general framework of classification. We chose to implement a neural network classifier with coded outputs because that it is well adapted with this type of problem, of which gives good results, for the classification operation, we tried to maintain the suggested structure the simplest as possible. Indeed, instead of reserving by each class an exit of the network what increases considerably the number of neurons in the output layer we limited to this level the number of neurons with 4 which can decode 16 possible forms. Thus, the conceived network could discriminate a significant number of forms all while maintaining a structure simple. The results obtained show, that with a restricted number of the shapes of obstacles at the time of the training, a good classification during tests of generalization. However, the principal function of a mobile robot is to achieve its goal, it is thus necessary to integrate this module in a control to make it possible to generate the adequate order for the skirting of the obstacle following its form. We estimate that this work is used to look further into the general information of the neuronal approach in the applications of classification.

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