

Obstacle Avoidance of a wheeled mobile robot: A Genetic-neuro-fuzzy approach

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Abstract

Navigation and obstacle avoidance are very important issues for the successful use of an autonomous mobile robot. To allow the robot to move between its current and final configurations without any collision within the surrounding environment, motion planning needs much treatment. Thus to generate collision free path it should have proper motion planning as well as obstacle avoidance scheme. this work mainly deals with the obstacle avoidance of a wheeled mobile robot in structured environment by using genetic-neuro-fuzzy approach. Here five layer neural network with learning algorithm-genetic is used to determine the optimal collision-free path.

Keywords: Collision-free, Genetic-neuro-fuzzy and mobile robot.

Introduction

Current research in robotics aims to build an autonomous and intelligent robot, which can plan its motion in a dynamic environment. A successful use of an autonomous mobile robot depends on its controller. Controlling of a car-like robot is difficult as they are subjected to non-holonomic (nonintegrable) kinematic constraints involving the time derivatives of configuration variables [2, 3, 4, 5, 6] and dynamic constraints. The path of the robot is also constrained by the partially-unknown movement of the moving obstacles [7], known as uncluttered environment. Thus, to generate collision-free path of a car-like robot during its navigation among several moving obstacles, it should have proper motion planning as well as obstacle avoidance schemes. Both analytical like potential field method as well as graph-based techniques have been used to solve the navigation problems of robots involving static obstacles. But, all such methods may not be suitable for on-line implementations due to their inherent computational complexity and limitations. Soft computing includes fuzzy logic, genetic algorithm, neural network and their different combinations and it can solve such complex real-world problems within a reasonable accuracy. Since artificial neural networks (ANN) have the ability to learn the situations, many investigators have successfully applied the feed-forward neural network to develop the model re-

lated to the navigation problem of a car-like robot. In the present work, navigation problem of a mobile robot is tackled by using Genetic-neuro-fuzzy approach.

Mathematical formulation of the problem

A mobile robot has to move from an initial position to a final position by avoiding collisions with a set of obstacles in optimal path. To generate a collision-free path, the robot may have to move along a straight path or take a turn depending on the situations. The assumptions are

- 1) All the obstacles are represented by their respective bounding rectangles.
- 2) At a time, only one obstacle is considered and no two obstacles are allowed to overlap.
- 3) The wheels of the robot are subjected to pure rolling action only.

Fig. 1 shows a typical problem scenario, in which mobile robot is moving among obstacles, in the same workspace. The robot has to find its optimal collision-free path.

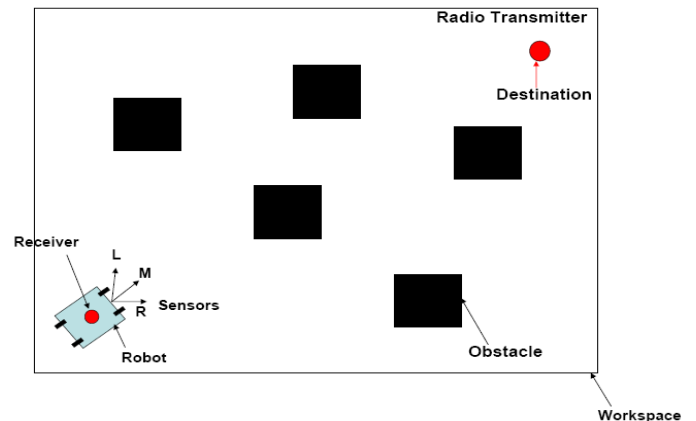


Figure 1: Robot motion among obstacle

The robot has to reach the destination. In front of the robot three ultrasonic sensors are placed at an angle of 30 degrees, these sensors will give the distance information of the obstacles. To locate the destination, a radio transmitter is placed at destination and a receiver is mounted on the robot so that the robot always receives radio signal from the transmitter. From the signal strength received by the robot it is possible to calculate the distance between the robot and destination using inverse law.

Developed algorithm

Navigation problem of the wheeled mobile robot has been solved by using Genetic-neuro-fuzzy approach.

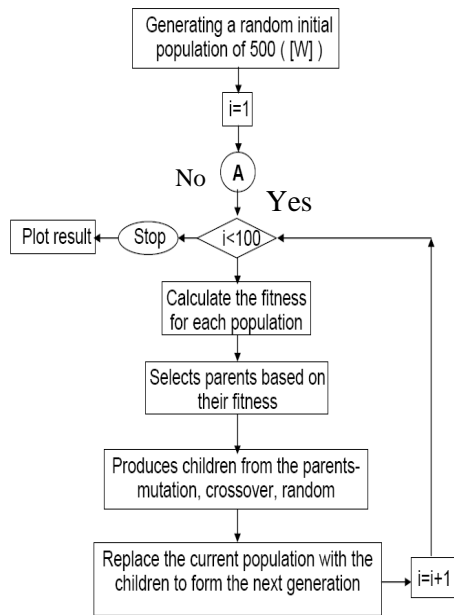


Figure 2: Flowchart showing genetic algorithm

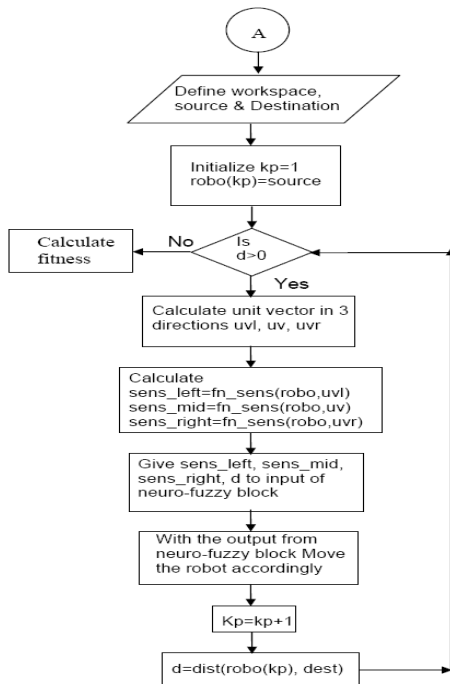


Figure 3: A schematic diagram showing flowchart of the motion planning scheme

Genetic-neuro-fuzzy approach

A possible solution of the problem is by using Genetic-neuro-fuzzy approach. By using Takagi and Sugeno Approach the condition variables-*distance from three sensors and distance between robot and destination* of the FLC are expressed in terms of membership function distributions.

Fig. 4 shows the author-defined membership function distributions of the input variables. For simplicity, the shape of the membership function is assumed to be triangular in nature. Two grades of *distance from three sensors* are considered: near (N), and far (F). The membership function distributions of *distance between robot and destination* are assumed to be similar and their total range is divided into three terms: very near (VN), near (N), and far (F).

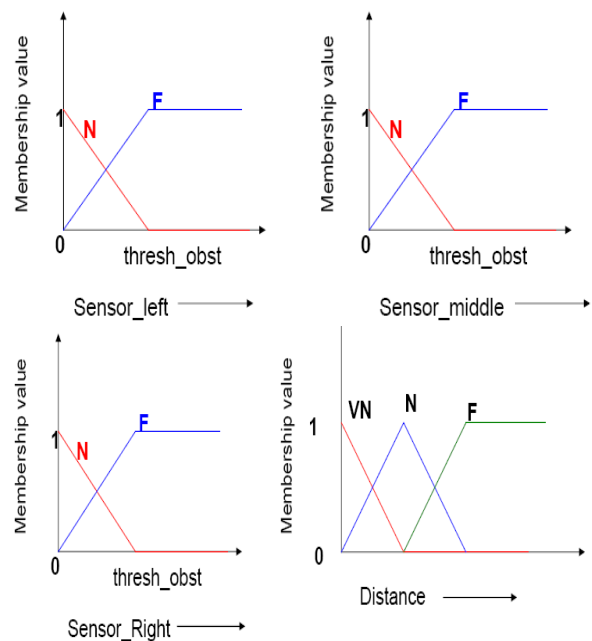


Figure 4: Membership function distributions for input variables of the FLC.

Neural Network

A five layer network with one hidden layer is used in this approach. The formulation of the developed neuro-fuzzy system is explained layer-by-layer as shown in Fig.5.

Layer 1. Four variables, namely distance from the three sensors and distance between robot and destination are fed as inputs to the network. The output will be the same as the input, as a linear transfer function has been considered in this layer.

Layer 2. The inputs of this layer are taken to be equal to the outputs of the first layer. Thereafter, these crisp values of the inputs are converted into the fuzzy membership function values, with the help of membership function distributions. For all the inputs, the membership function distributions are taken to be triangular, for simplicity.

Layer 3. This layer performs the task of logical AND operation. Each neuron lying in this layer is connected to

four neurons of the previous layer, as shown in Fig.5. Membership function values calculated in the previous layer are considered as the inputs of a particular neuron (say n th) lying in this layer.

Layer 4. This layer is the fuzzy inference layer. Each neuron lying in this layer is connected to all neurons of the previous layer and the connecting weights.

Layer 5. As the fuzzified output is not suitable for implementation as a control action, a crisp value corresponding to this fuzzified output is calculated. This process is known as de-fuzzification. Here de-fuzzification is done by multiplying layer 4 neurons with corresponding weights.

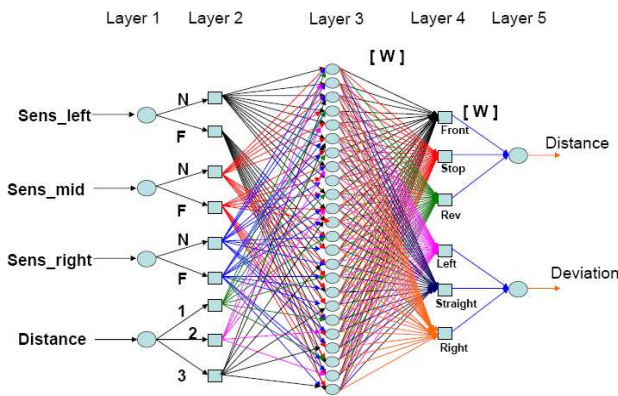


Figure 5: A schematic diagram of the neuro-fuzzy approach.

Genetic algorithm

Genetic algorithm is applied to find the optimal collision free path for the mobile robot. The robot will take different paths corresponding to different weights between layer3 and layer4. The weights to be optimized are,

$$[W] = \left[\{thresh_obs\}, \{thresh_pot\}, W_{front}, W_{rev}, W_{left}, W_{right} \right]_{1 \times 100}$$

Initially 500 random weight matrix populations are generated and tested on the robot to get 500 different paths. Among the 500 paths best 200 paths are determined using the fitness value. Here fitness value is the inverse of the total distance the robot has traveled. For the next generation 300 new population are generated by using Elite and Mutation. With the best 200 weights and 300 new weights the robot is tested. In this way the algorithm continues till the optimum path is obtained.

Results and Discussion

In the developed neuro-fuzzy approaches, training is done off-line with the help of Genetic algorithm. The computer simulation is carried out by considering different number of obstacles. A field of 20 m * 20 m is considered in computer simulation.

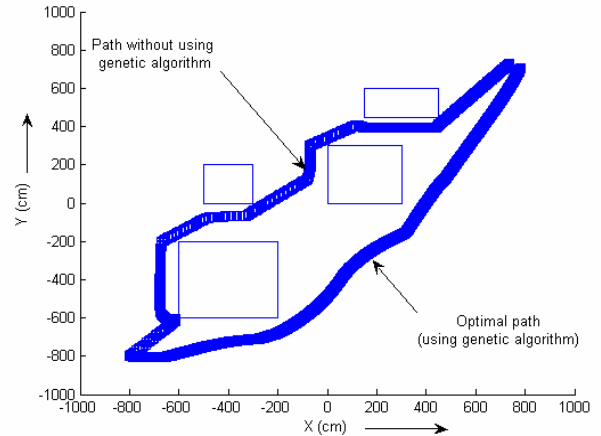


Figure 6: Robot motion among single obstacle

Conclusions

In this paper, a genetic-neuro-fuzzy strategy has been proposed to drive a mobile robot. This approach is able to extract automatically the fuzzy rules and the membership functions in order to guide a wheeled mobile robot. The proposed neuro-fuzzy strategy consists of a five-layer neural network along with an evolutionary (genetic) learning algorithm. This system has been implemented in simulation obtaining satisfactory results.

References

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