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Neuro-Fuzzy Based Autonomous Mobile Robot Navigation System

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***Abstract*—Neuro-fuzzy systems have been used in past years for robot navigation applications because of their ability to learn human expertise and to utilize this knowledge to develop autonomous navigation strategies. In this paper, neuro-fuzzy based systems are developed for behavior based control of a mobile robot for reactive navigation. The proposed systems transform sensors' input to yield wheel velocities. Novel algorithms are proposed for a) to find the range of the mobile robots from nearby obstacles and b) to generate training pairs for neural network, optimally. With a view to ascertain the efficacy of proposed system; developed neuro-fuzzy system's performance is compared to neural and fuzzy based approaches. Simulation results show effectiveness of proposed system in all kind of obstacle environments.**

Keywords—Mobile robot; Reactive navigation;Neural Network,Fuzzy system; Behavior control; Fuzzy membership functions

I. INTRODUCTION

Autonomous robot navigation [1] means the ability of a robot to move purposefully and without human intervention in environments that have not been specifically engineered for it. Autonomous navigation requires a number of heterogeneous capabilities like ability to reach a given location; to reach in real time to unexpected events, to determine the robot's position; and to adapt to changes in the environment.

For a mobile robot to navigate automatically and rapidly, an important factor is to identify and classify mobile robots' perceptual environment [1]. The general theory for mobile robotics navigation is based on a following idea: the robot must *Sense* the known world, be able to *Plan* its operations and then *Act* based on the model.

Various approaches are found in literature for mobile robot navigation including neural and fuzzy based systems. The approach [2] considered neuro-fuzzy system architecture for behavior-based control of a mobile robot in unknown environments. Another approach [3] has described a reactive obstacle avoidance that enables robot to move in an unknown environment in which resultant velocity command to each wheel motion controller is generated through Fuzzy Kohonen Clustering Network (FKCN) instead of by conventional fuzzy inference. Several other methods exploiting fuzzy control schemes ([5]-[13]), have been proposed for avoiding unexpected obstacles. Humans have a remarkable capability to perform a wide variety of physical and mental task without any explicit measurements or computations. Fuzzy logic provides a formal methodology for representing and implementing the human expert's heuristic knowledge and perception based actions. Our proposed system's conceptualization is analogous to that indicated in general terms by [2]; while our actual detailed system is new. The rest of this paper is organized as follows: In Section II, we introduce proposed algorithm for the development of the neuro-fuzzy based reactive navigation algorithm. Relevant simulation results are presented in Section III. We conclude the paper in Section IV.

II. PROPOSED ALGORITHM FOR ROBOT NAVIGATION

We propose, an algorithm for mobile robot's reactive navigation in presence of static as well as dynamic obstacles using neuro-fuzzy based system. Proposed algorithm overcomes the shortcoming of current approaches in terms of learning mechanism used. The problem formulation for the basic motion planning problem, in general terms is as follows[4]: Let *A* be the single rigid object –the robot – moving in a euclidian space *W*, called workspace, represented as R^N, with N= 2 or 3. Let B_1, B_2...B_q be the fixed rigid objects distributed in *W*. The B_i's are called obstacles. Assume that both geometry of *A*, B_1, B_2...B_q and the locations of B_i's in W are accurately known. With assumptions that no kinematics constraints limit the motion of *A*. given an initial position and orientation; a goal position and orientation of *A* in *W*, generate a path *T* specifying a sequence of positions and orientations of *A* avoiding contact with B_i's, starting at the initial position and orientation; and terminating at the goal position and orientation..

A. Mobile Robot Configuration

We consider two dimensional workspace for mobile robot as shown in Fig.1. Mobile robot is having initial coordinates as x-coordinate (x_o) and y-coordinate (y_o). Similarly, target position coordinates are denoted as x_t and y_t respectively. Mobile robot's current position (calculated and updated at each step) can be denoted as x_{curr} and y_{curr}, angle between target with respect to positive y axis is θ_{tr}. Robot's pose (head) with respect to positive y axis is considered as θ_{hr}, θ_{head} is the heading angle between target and robot current position, *Span* (S) is the distance between left and right wheel, V_l and V_r are mobile robots left wheel and right wheel velocities, respectively.

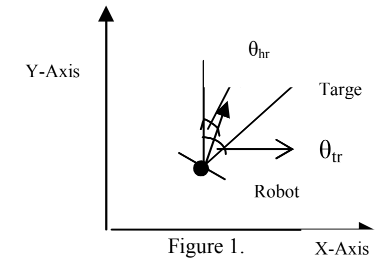

Fig. 1 Mobile Robot Configuration

The mobile robot has two independently driven co-axial wheels. We consider a mobile robot with differential drive wheel. Initial and final positions are known to the robot at any time. At each step, current location and orientation are computed. No history of past sensor readings are retained and thus robot is having pure reactive navigation. Obstacles may be stationary or may be mobile.

B. Proposed Algorithm for Range Calculation of a Mobile Robot from given Obstacles

Acquisition of precise range information of a mobile robot from each nearby obstacle is one of the most important tasks for robot navigation. Mobile robot needs to effectively sense surrounding environment. In this paper, we propose, a new frame work to find range information for robot navigation in presence of moving obstacles. The important point is that because of presence of moving obstacles, prior geometry information may not help. But, our model acquires geometry information from sensed signals of different sensors. This makes our approach very general and can be used for any scenario. Following steps summarize our algorithm to find out range of obstacle from robot A to Obstacle B:

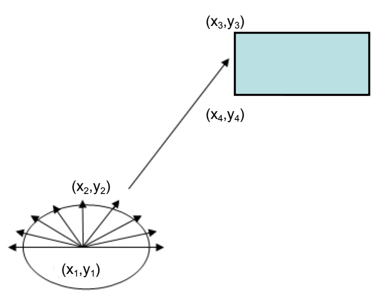

Fig: 2 Range Calculation of a Mobile Robot from given Obstacles

1. As shown in Fig.2, on the robot side; let total N ultrasonic sensors be placed to sense the surrounding environment. Consider signal of k^{th} sensor (N_k).

2. Let, (x_1, y_1) and (x_2, y_2) are two points on robot to represent k^{th} sensor. The ray emerging from mobile robot can be considered in terms of parametric form of straight line as:

$$x = x_1 + (x_2 - x_1) D_k, \qquad (1)$$

$$y = y_1 + (y_2 - y_1) D_k, \qquad (2)$$

Where, D_k real value - denotes the distance of a mobile robot from obstacle. In order to ensure that robot looks only in forward direction and the maximum range of ultrasonic sensor D_{max},

$$0 < D_k < D_{max} \qquad (3)$$

3. For the obstacle side; consider (x_3, y_3) and (x_4, y_4) be two points representing one line segment on the i^{th} obstacle. In terms of parametric form of straight line as:

$$x = x_3 + (x_4 - x_3) S_{ij} \qquad (4)$$

$$y = y_3 + (y_4 - y_3) S_{ij} \qquad (5)$$

Where, S_{ij} - a real value presenting line segment of i^{th} obstacle's j^{th} side. To ensure that a particular ray emitted by robot hits the line segment (side of the obstacle);

$$0 <= S_{ij} <= 1 \qquad (6)$$

4. Solution of simultaneous equations will give us distance D_K, i.e. distance between robot's k^{th} sensor to the i^{th} obstacle's j^{th} side:

$$D_K = \frac{((y_4 - y_3)*(x_1 - x_3) - (y_1 - y_3)*(x_4 - x_3))}{((y_2 - y_1)*(x_4 - x_3) - (y_4 - y_3)*(x_2 - x_1))} \qquad (7)$$

5. Computation of the value of D_K is to be carried out for each of total N sensors.

6. For example, rectangle shaped n obstacles will have 4*n edges. For total N sensors, there will N* (4* n) size matrix computed at each step.

C. Sensors Arrangement, Quantization of Sensor Values & Defining Heading angles

In our algorithm, we consider robot fitted with N ultrasonic sensors in the front. If the front (head) of the robot is at 0 degrees (w.r.t. +y axis), then the sensors are located between -90 to +90 degrees each being separated by θ_s degrees as shown in Fig. 3.

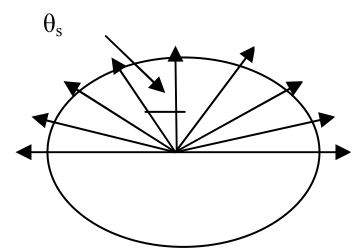

Fig. 3 Arrangement of ultrasonic sensors

Considering d(i)–ultrasonic data for i^{th} sensor; distances to the obstacles may defined as below:

Left_obs = min{d (i)} where, i= 1,2…x.
Front_obs = min{d (i)} where, i= x+1,x+2 …y.
Right_obs = min{d (i)} where, i= y+1, y+2,.. N

Grouping and Quantization of the Sensor values:

These sensor values are grouped and quantized before sending into the intelligent network. Sensors grouping will enable mobile robot for better environmental sensing by optimizing computational complexities to the speed of computation. Quantization formula for groups (X_i) where, i=1, 2...M (M<=N) is as follows:

$$X_i = \begin{cases} 1 & \text{for } 0 < d_i <= D_{min,} \\ 2 & \text{for } D_{min} < d_i <= D_{med}, \\ 3 & \text{for } d_i \; i > D_{med}, \end{cases}$$

Where, d_i is the minimum sensor value of the i^{th} group.

Defining Heading Angle

We define heading angle (θ_{head}) as follows:

- If $\theta_{head} < p$ then $\theta_{head} = \alpha$,
- If $p <= \theta_{head} <= q$ then $\theta_{hed} = \beta$,
- If $q <= \theta_{head}$ then $\theta_{head} = \gamma$.

Once surrounding environmental sense competed; set of information is available for planning. Next step is to train intelligent system with these set of information. As stated earlier, neuro-fuzzy systems have capabilities to learn and then perform intelligent task based on learning. Next subsections describe training neuro-fuzzy based system.

D. *Two stage Neuro-Fuzzy* System

Neural networks have got remarkable generalisation capabilities, once trained properly. Fuzzy systems have been used in robot navigation as they provide formal methodology to capitalize human expertise to make decisions; into machines. Hybrid systems have been used in many applications in order to take advantage of individual systems. We consider two stage neuro-fuzzy based hybrid architecture as shown in Fig.4. Our hybrid System's conceptualization is based on [2] however; overall design is entirely new based on optimal learning algorithm defined in next sub section. Our proposed framework contains optimum learning of neural networks that overcomes the problems faced by existing approaches. First stage neural network has four inputs. Out of four inputs, three inputs are the distance information from the left, front and right obstacles present in robot's perceptual environment. The fourth input is the heading angle. As output of neural network, we get *Reference Heading Angle* (RHA); an inferred angle than original head angle. In the second stage, fuzzy logic processes these bettered information and drives the output wheels of mobile robot.

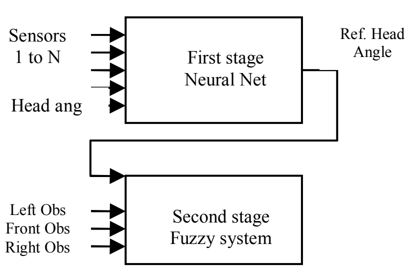

Fig.4 Two stage Neuro-Fuzzy System

Outputs to the system are Left and right wheel velocities. Input sensory information's cardinality for the Neural and Fuzzy networks can be shared same or can kept higher for neural network to take maximum advantage of neural networks learning capabilities.

Training using neural network:

Training of intelligent system is crucial for successful navigation of mobile vehicle. Training is difficult in the sense that input space may contain infinitely many possibilities mobile robot need to learn effectively. Many times mobile robot needs to execute operations in hazardous environments like fire or space missions where, online training is not feasible. Off line training is possible in such cases. Mobile robot needs to sense environment in real time and also to make precise decision based on learning. Few training approaches are found in literature i.e. a) generating training sequences by experimental set up and b) heuristic approach based on expert rules. In the first approach (training by experimental setups), learning is done by setting different environmental set ups. i.e. different start, end (target) positions, different obstacles positions etc. In this case, number of training pairs resulted for different input pairs may not be evenly distributed. Some of the input pairs may appear more number of times, while some may appear lesser or even not appear. Training may not be considered optimum as; for some inputs patterns are not learnt while some are over learnt. In case of second alternative (training by expert rules [3]), training is done by fewer number of input patterns. This type of training may save training time, may give good performance in some cases but, they may not perform well in all kind of environmental conditions. This is because of the fact that selection of training pairs is for particular task and they do not represent entire space uniformly. Hence, their output in unexplored space of input space is not guaranteed.

We propose, mobile robot's training based on uniform sampling that overcomes the problems with above mentioned methods. The proposed algorithms not only takes samples from entire sample space (to provide heterogeneity), also takes equal number of sample data from all possible input space (to provide homogeneity). In the proposed algorithm, actual sensor readings are considered to be quantized in to n linguistic values. Uniform sampling of these quantized values will enable us a) to consider entire space of input region and; b) will enable us to generate optimum number of training pairs required for training.

In the proposed approach, we train the network as follows:

1. First, let input cardinality (number of sensor inputs) of the neural networks equal to m. Also, assume that each input takes n linguistic values (e.g. near, medium, far). Then we can generate total n^m training pairs.
2. Second, output values of each of these input patterns are decided based on experimentation or by expert rules.
3. Neural network is trained accordingly to training pairs generated and performance of the network can be checked using proper evaluating function e.g. MSE (mean square error)
4. If any correction is required; make adjustment to step 2 and then repeat steps.

Fuzzy Inference System (FS)

As shown in Fig 4, for the second stage of fuzzy system; out of four inputs, three inputs are the distance information from the left, front and right obstacles present in robot's perceptual environment. The fourth input is the reference heading angle (RHA) which is the output of first stage. Their values can be selected as mentioned earlier. Each of input takes 3 linguistic values (near (1), medium (2), far (3)). Hence, total 81 training rules are generated.

Defining Fuzzy membership functions

Membership functions for input and output variables are defined as shown in Fig.5. Linguistic values near, med (medium) and far are chosen to fuzzify left_obs, front_obs and right_obs. Linguistic values slow, med (medium) and fast are defined to show output parameters left and right velocities. Mobile robot moves in a given environment from start position to the end position. In order to avoid obstacles in its path, reactive navigation is done in response to the sensor data perception. Various reactive behaviors like *obstacle avoidance*, *following edges* and *target steer* are defined as described by [5] using fuzzy logic rule base. Behavior based fuzzy reasoning performs better than inhibiting or surpassing strategy based on priorities setting. Hence, we have used behavior based fuzzy reasoning in our work. We have defined a set of fuzzy logic rules to describe various behaviour in our earlier work [13].

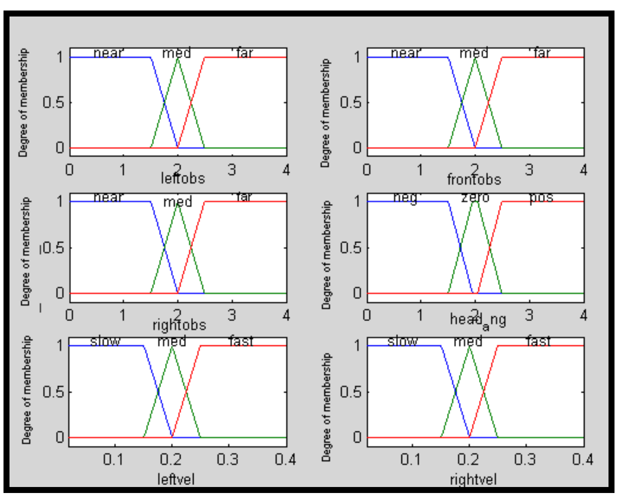

Fig.5 Membership functions regarding input output variables

These fuzzy rules show that the robot mainly adjusts its motion direction and quickly moves to the target if there are no obstacles around the robot. When the acquired information from the ultrasonic sensors shows that there are no obstacles to the left, front or right of robot, its main reactive behavior is target steer. When the acquired information from the ultrasonic sensors shows that there exist obstacles nearby robot; it must try to change its path in order to avoid those obstacles. When the robot is moving to a specified target inside a room or escaping from a U-shaped obstacle, it must reflect following edge behavior.

III. SIMULATION RESULTS

To demonstrate the effectiveness, robustness and comparison of various systems discussed in earlier, we present simulation results as follows. We have considered mobile robot having differential drive mechanism with wheels 50 cm apart diametrically (i.e. span of mobile robot). Total ultrasonic sensors (N_s) are equal to 9.These Sensors are equally separated by $\theta_s = \pi/8$ and detect the distance of obstacle along the radial direction up to *300 cm.* The wheels can have a maximum velocity up to *30 cm/s*. Input dimensions to the neural, fuzzy & neuro-fuzzy system are kept to four. Sensor values considered are D_{min}=100 cm and D_{med}=200cm. In order to define heading angle (θ_{head}), we have taken p, q, α, β, γ values as -π/8, +π/8, 1, 2, and 3 respectively. Fuzzy rules are generated taking 3 linguistic values and 4 inputs. Total 3 groups are made in order to give them as inputs to fuzzy system module. As the final value for each group, we take the minimum value among the corresponding sensors readings which are fed to system module. left, front and right obstacles are considered equally important and hence to find the effective inputs to the fuzzy systems. The membership function values are fine tuned by simulating the navigation in many different setups and correcting the errors over number of experiments. For fuzzy reasoning Min - Max (Min- for the implication and Max- for aggregation) is used. De-fuzzification is done using centroid method. By fuzzy reasoning necessary behaviors are weighted to determine final control variables i.e. left and right velocities.

Comparison of Robot Navigation with Neuro-Fuzzy System (NFS) to Neural and Fuzzy System

Fig. 6(a) shows the path comparison of a mobile robot between single stage neural [6] and fuzzy approaches [13] while; Fig.6 (b) shows the mobile robot path comparison between neural [6] and proposed neuro-fuzzy systems. These results suggest that, in the case of second stage (driving stage), fuzzy systems are preferred. This is because neural network's output in the unexplored regions of inputs is not predictable and error at each stage get accumulated and hence, do not give good, stable paths.

Fig. 7(a) illustrates robot navigation with fuzzy system [13] while; Fig. 7(b) shows robot navigation with proposed neuro-fuzzy system. Comparing the results, it found that in Fig.7 (a) robot eventually strikes the obstacles located to the left bottom corner while with the same scenario in the case of neuro fuzzy system successfully avoids the same obstacle. These is because in the case of single stage fuzzy systems that one of the inputs (i.e. heading angle) contradicts to the perception by the other inputs while; in the case of neuro-fuzzy system computing reference heading angle (RHA) suggest more practical input to the fuzzy system of the second stage. Neuro–Fuzzy system architecture uses neural network to the input side of Fuzzy system for understanding environment. This is because to understand higher dimensional complex environment; neural network having point to point mapping performs more efficiently than fuzzy systems that has set to set mapping. These simulation results highlight the fact that adding neural stage to the input side enhances environmental sensing capacity to the fuzzy system. The same fact is observed for multiple simulations done with various environmental conditions. Fig.8 (a-b) demonstrates robustness of neuro-fuzzy based mobile robot navigation system in complex environment conditions.

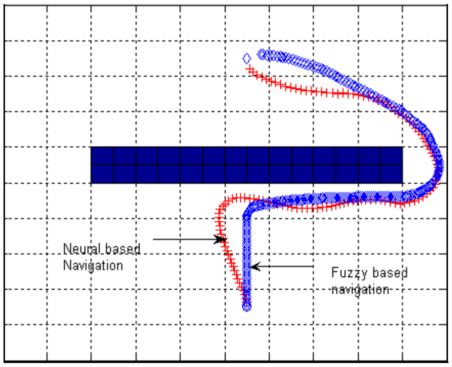

Fig. 6 (a) Comparison of Robot navigation: Neural & Fuzzy system

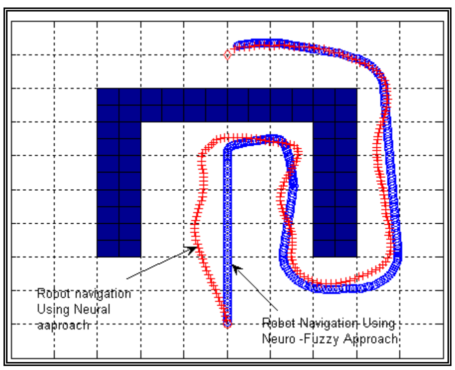

Fig. 6(b) Comparison of Robot navigation: Neural & Neuro- Fuzzy system

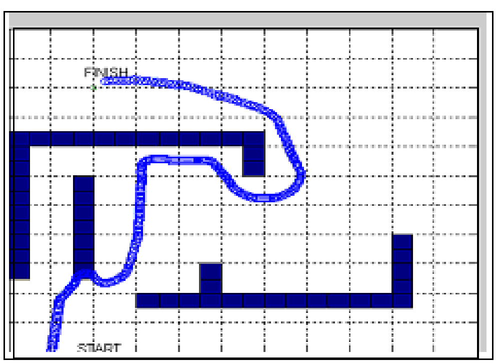

Fig. 7 (a) Robot navigation with single stage Fuzzy system

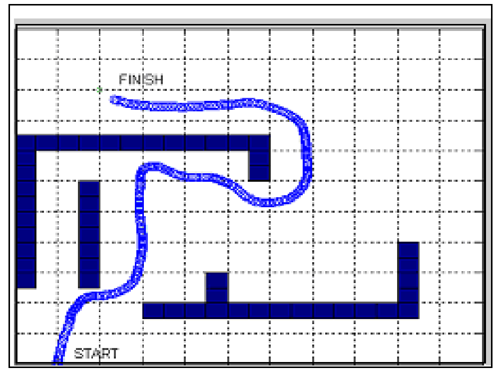

Fig. 7 (b) Robot navigation with Two stage Neuro- Fuzzy system

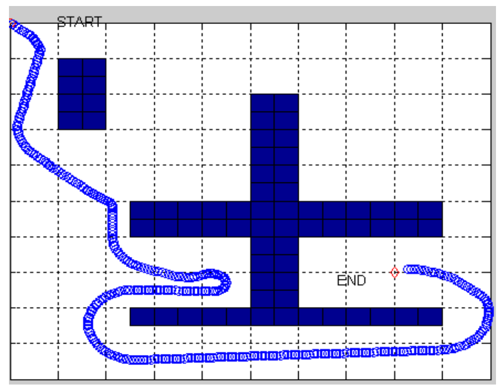

Fig.8a)

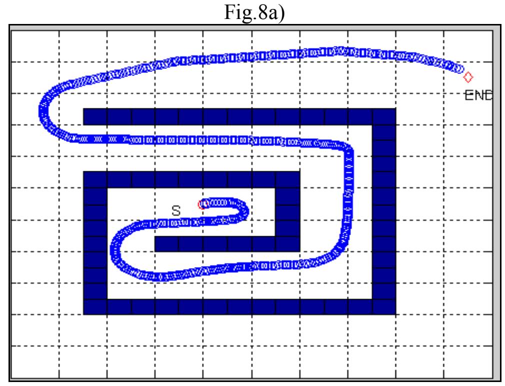

Fig.8 b)

Fig.8 (a-b) Robot navigation with neuro- fuzzy system in different complex conditions

IV. Conclusions

In this paper, a new approach for robot navigation algorithms neuro-fuzzy based systems is discussed. The mobile robot performs reactive navigation and suitable for real time, dynamic environment rather than looking for optimal path as performed by path planning techniques. Simulation results for mobile robot navigation with neuro-fuzzy based system demonstrate the good performance in complex and unknown environments navigated by the mobile robot. Simulation results suggest that, information on environment (Sense) should be obtained by neural networks while; more correct decisions (Act) should be made by the use of fuzzy systems. In future, algorithms may be developed for multiple robots cases and comparison can be done for more neuro fuzzy based approaches.

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