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Sensors Fusion Technique for Mobile Robot Navigation using Fuzzy Logic Control System

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1. Introduction

The mobile robot navigation with complex environment needs more input space to match the environmental data into robot outputs in order to perform a realistic task. At the same time, the number of rules at the rule base needs to be optimized to reduce the computing time and to provide the possibilities for real time operation. In this paper, the optimization of fuzzy rules using a Modified Fuzzy Associative Memory (MFAM) is designed and implemented. MFAM provides good flexibility to use multiple input space and reduction of rule base for robot navigation. This paper presents the MFAM model to generate the rule base for robot navigation. The behavior rules obtained from MFAM model are tested using simulation and real world experiments, and the results are discussed in the paper and compared with the existing methods.

In most of the researches in the area of fuzzy logic based mobile robot systems, use only few inputs to simplify the navigation process in order to test the hypothesis. In order to perform realistic tasks with a mobile robot in complex surroundings, the number of inputs should not be so limited. This raises some important questions to be explored. They are: How can the fuzzy control system be scaling up without throwing out useful data or decreasing the input space by non-fuzzy means? How can a reactive fuzzy system respond to a complex environment? The schemes used by Sugeno's car [M. Sugeno, Murofushi, T. Mori, T.Tatematasu, J. Tanaka (1989)] the extraction of specific state variables from sensor data before the fuzzy control stage. Thus, the sensor data have been matched to a world model. The resulting effect is to reduce the size of the input space to the rule set. The disadvantages in the robot described by Pin, et al. [F. G. Pin H. Watanabe, J.R. Symon, and R.S. Pattay (1992)] features 15 ultrasonic rangefinders, without matching data to a world model. However, the sonar data is bunched together into three inputs, each being the minimum of a neighborhood of five, before being sent to the controller. Another disadvantage of their system is the need for special computer hardware for real-time operation. Papers cited in [(M. Balzarotti and G. Ulivi(1996), A. Ollero, A. Garcia-Cerezo et al (1997), J. Pereira and J.B Bowles (1994), E. Tunstel, et al (1994) and C. Voudouris et.al,1995)] are mainly focused on some kind of environmental features like walls, road edges, white lines on the floor, avoid obstacles etc. In the research article cited in [P. Althauas et.al, 2001], sonar sensors are used to map the structured indoor environment to navigate the robot with simple behaviors

called obstacle avoiding and corridor following. The input space is restricted only for these behaviors and not to the entire mapping of the environments.

In the past, several works relating to FAM have been done for control applications. Kosko's FAM [B. Kosko (1992)] is one of the earliest attempts to integrate the fuzzy sets, and neural network is used to learn the mapping of the inputs to output. Kosko's FAM is restricted to limited rule based applications. The FAM models have been successfully applied to problems like backing up a truck-and-trailer [S.G Kong and B. Kosko, (1992)], target tracking [Hirohide Ushida (1999)] and voice-cell control in ATM networks [T. D. Ndousse (1994)], where distinctive features like modularity, robustness, and adaptability have been demonstrated. Despite of aforementioned feature, FAM does not provide acceptable solution when there are a large number of fuzzy inputs. In the proposed approach, an improved FAM is established and the number of rule bases is optimized without throwing away any useful inputs.

Based on the MFAM, the most influential navigation rules of the fuzzy system inputs are arranged in the first level. The outputs of the first level together with the next most important variables are arranged in the second level and so on. In each level, the fuzzy system output is modified according to the degree of importance of the corresponding input. Finally, the control rule is activated, when the measurement of the obstacle distance exactly matches the rule condition part ('if' part of the rule). The final decision made is based on the corresponding action part ('then' part of the rule) of the matched rule and not based on the aggregated output of the entire rules. Thus, the computational complexity to estimate the control output is minimized in each control cycle using the proposed MFAM. The rules obtained from FAM model are experimented using Active Media Pioneer Robot. The input and output data of the robot control system are observed and investigated and the results are provided in this paper.

2. Theoretical work

2.1 MFAM model

The fuzzy relation formed by the collection of rules is represented as the fuzzy set and denoted as R. In a fuzzy control system, the control rules in the collection R are first matched with the available data (context), then a matched rule is fired, thereby providing a control action. Usually the context would be the measured outputs of the process, and these are crisp quantities, and the control action that drives the process is also a crisp quantity. However, for general considerations, the context data are denoted by a fuzzy set D and the control action is denoted by a fuzzy set C. The compositional rule of inference states that [S. Parasuraman, V.Ganapathy, Bijan Shirinzadeh (2005)]:

$$C = D \circ R = \bigvee_{x \in X} \wedge \left\{ \mu_D(x), \mu_R(x_1, x_2, ... x_n) \right\} \tag{1}$$

Based on the equation (1), the fuzzy relation formed by the collection of rules is represented as the fuzzy set and denoted as R as given below.

$$R = \left\{ R_1, R_2 R_3 .... R_i, ... R_k \right\} \tag{2}$$

where R_k is the total number of rule inference and Ri is the ith rule of the FIS and is expressed in equation (2) as

$$IF X_1 \text{ is } A_{1i} \text{ and } X_2 \text{ is } A_{2i} \text{ and.......and } X_n \text{ is } A_{ni} \text{ Then Z is } C_i \tag{3}$$

where $X_1, X_2, \ldots X_n$ are the input variables (sensor data), $A_{1i}, A_{2i} \ldots A_{mn}$ are the input fuzzy linguistic variables, C_i is the output linguistic variable of the model, Z is the output, n is the dimension of the input vector and m is the fuzzy set. The following fuzzy relation is used to implement the ith rule Ri.

$$R_i(X_1, X_2, \ldots, X_n, Z) = \left[A_{1i}(X_1) \wedge A_{2i}(X_2) \wedge \ldots \wedge A_{mn}(X_n) \right] \rightarrow C_i(z) \tag{4}$$

By applying compositional rule of inference as defined in the equation (1), an n dimensional fuzzy input vector $\overline{X}$, with $(\overline{X}_{10}, \overline{X}_{20}, \ldots \overline{X}_{i0}, \ldots \overline{X}_{n0})$, is generated. During the process of compositional rule of inference the context inputs need to compose the input vector $\overline{X}$ with the fuzzy relation Ri to produce the output $C_i^{'}$ and is given by

$$C_i^{'} = \left(\overline{X}_{10}, \overline{X}_{20}, \ldots \ldots \overline{X_{i0,}} \ldots \overline{X}_{mn} \right) \circ R_i \tag{5}$$

where $\overline{X}_{i0}$ is the fuzzified crisp value of X_{i0} and $C_i^{'}$ is the defuzzified output of the ith rule and defined as follows.

$$C_1^{'}(Z) = \left[A_{1i}(X_{10}) \wedge A_{2i}(X_{20}) \wedge \ldots \ldots \wedge A_{mi}(X_{m0}) \right] \rightarrow C_i(Z) \tag{6}$$

The overall system output is obtained by using min and max aggregation operators based on the equation (6) as follows:

$$C = \overset{k}{\underset{i=1}{U}} C_1^{'} = \overset{k}{\underset{i=1}{U}} \left(\left[A_{1i}(X_{10}) \wedge A_{2i}(X_{20}) \wedge \ldots \ldots \wedge A_{mi}(X_{m0}) \right] \rightarrow C_i(Z) \right) \tag{7}$$

where k is the number of rules in the system. In order to relate the mth fuzzy set of the ith fuzzy rule, the fuzzy implication model by Mamdani's min operator is used to interpret the logical rules. [C. T. Lin and C.S.G.Lee (1991), J. S. R Jang (1993), H. Ushida, T.Yamaguchi, and T. Takagi (1995), F. G. Pin and Y.Watanabe (1993)] Combining the equations (4) and (7), it can be rewritten as follows:

$$\mu_{R_i}(X_{1i,} X_{2i}, \ldots \ldots X_{mi}) = \overset{k}{\underset{i=1}{\min}} [\mu_{A_{mn}}(X_{mn}) \tag{8}$$

The final output membership function is

$$\mu_C(Z) \text{ is } y_c(z) = \overset{k}{\underset{i=1}{\max}} [\min[\mu_{A_{mn}}(x_{mn}), \mu_{R_i}(X_{1i,} X_{2i}, \ldots \ldots X_{mi}]] \tag{9}$$

In equation (9), $\mu_{R_i}(X_{1i}, X_{2i}, \ldots \ldots X_{mi})$ is the membership function of ith rule and the value of i = 1 to k, and k is the total number of rules. The total number of rules in the rule base depends on the input variables ($X_{1i}, X_{2i}, \ldots \ldots X_{mi}, \ldots X_{mn}$). Here the input variables are the linguistic fuzzy sets of sensor values.

2.2 Modified Fuzzy Associative Memory

If the number of fuzzy inputs and linguistic variables of each fuzzy set increases, the number of fuzzy rules grow exponentially. As an example, a model with Active Media

Pioneer Robot uses eight input and two output fuzzy sets. If each input fuzzy set is represented by three fuzzy linguistic variables and each output fuzzy set is represented by seven fuzzy linguistic variables, then a single layer of inference will lead to determining $3^8 = 6,561$ rules that would be difficult to evaluate, time consuming and making real time operation difficult. In order to reduce the number of rules, without reducing any of the fuzzy inputs, the new methodology is proposed, which uses compositional rule of inference as described by equations (1) and (9). The following section describes the proposed methodology MFAM to integrate the multiple sensors. The FIS is generated based on the MFAM rules. MFAM is a process of encoding and mapping the input fuzzy sets to output fuzzy sets. The relationships between the fuzzy sets and rules are shown as a Modified Fuzzy Associative Memory. A fuzzy-logic rule as per the equation (10) is given below.

$$R1: (Ai, Bi) \rightarrow Ci \tag{10}$$

This is called a "fuzzy association." A Fuzzy Associative Memory (FAM) is formed by partitioning the universe of discourse of each condition variable (i.e., Ai and Bi in the above example) according to the level of fuzzy resolution chosen for these antecedents, thereby generating a grid of FAM elements [Bo Hyeun Wang, George Vachtsevanos, 1990]. The entry at each grid element of the FAM corresponds to the fuzzy action (Ci in the above example). The equation (10) is good enough to get the FAM rules if only two input fuzzy sets and one output fuzzy set are present in the process. If the number of input fuzzy sets and linguistic variables of each fuzzy set is more than two then the proposed Modified Fuzzy Associative Memory (MFAM) is suitable to optimize the number of rules and integrate the entire input variables to the process effectively. The proposed MFAM is defined based on the following FAM rule reduction theorem.

2.3 MFAM rule reduction theorem

MFAM rule reduction theorem is defined as follows: Let a fuzzy implicative rule for a two input system is defined of the form, "if X_{1i} and X_{2i} then Z_i", then the fuzzy implicative rules for more than two input system is defined using compositional rule of inference and is given below.

$$(X_{1i+1}, X_{2i+1}) \circ (X_{1i} \text{ and } X_{2i} \rightarrow Z_i) = Z_i'$$

Based on the law of compositional rule of inference and associativity [19] the output Z_i' is expressed as follows:

$$Z_i' = [(X_{1i+1}) \circ (X_{1i} \rightarrow Z_i)] \wedge [(X_{1i+1}) \circ (X_{1i} \text{ and } X_{2i} \rightarrow Z_i)] \wedge [(X_{2i+1}) \circ (X_{2i} \rightarrow Z_i)]$$
$$\wedge [(X_{2i+1}) \circ (X_{1i} \text{ and } X_{2i} \rightarrow Z_i)] \tag{11}$$

where X_{1i}, X_{2i}, X_{1i+1}, X_{2i+1} are the fuzzy inputs ($i = 0, 1,2, …,n$) with fuzzy sets m (m=1,2,3). The final control output is obtained by combining equations (11) and (9) and is as given below.

$$\mu_C(z) = \max_{\substack{i=1 \\ x \in U}}^{k} [[(X_{1i+1}) \circ (X_{1i} \rightarrow Z_i)] \wedge [(X_{1i+1}) \circ (X_{1i} \text{ and } X_{2i} \rightarrow Z_i)] \wedge [(X_{2i+1}) \circ (X_{2i} \rightarrow Z_i)]$$
$$\wedge [(X_{2i+1}) \circ (X_{1i} \text{ and } X_{2i} \rightarrow Z_i)]] \tag{12}$$

Applying min and max compositional inferences, the equation (12) is written as

$$\mu_{c}(z) = \max_{\substack{i=1 \\ x \in U}}^{k} [\min [(X_{1i+1}) \circ (X_{1i} \rightarrow Z_i)], [(X_{1i+1}) \circ (X_{1i} \text{ and } X_{2i} \rightarrow Z_i)], [(X_{2i+1}) \circ (X_{2i} \rightarrow Z_i)],$$

$$[(X_{2i+1}) \circ (X_{1i} \text{ and } X_{2i} \rightarrow Z_i)]] \qquad (13)$$

The MFAM matrix is established based on the above output membership function as stated in the equation (13).

2.4 Establishment of FIS using MFAM Rule

The Establishment of MFAM matrix tables involves the following assumptions:

- The variables (X_{11}, X_{21}, X_{31}), (X_{12}, X_{22}, X_{32})…(X_{16}, X_{26}, X_{36}) are the crisp values of the distance measurement obtained from the sensors (S1 to S6) of the mobile robot.

- Similarly, the variables $(Z_1, Z_2, Z_3$ and $Z_4)$ are the crisp values of turn angles obtained after defuzzification, which are used by the mobile robot.

- The Mamdani-Style inference [C. W. de Silva, (1995)] system is used to perform the fuzzification, rule evaluation and defuzzification process.

- During the rule evaluation, the composition inference is performed to obtain the behavior rules in such a way that the rule combinations will have a tendency to select the direction of the robot that is closest to the front direction, so that the robot does not make unnecessary rotations.

- Rule combinations are obtained based on the human expertise and experience

- The rule evaluation is performed in two steps. (a) when there are two fuzzy variables; the equation (10) is perfectly applied and (b) when there are more than two inputs, then the compositional rule inference equation (13) is applied.

During the design of behaviour rules, the MFAM uses the fuzzy sets and their corresponding linguistic variables as indices to a lookup table. The MFAM rule structure has been proposed using the following steps:

- The most influential navigation rules of the fuzzy system inputs are from the front sensors, which are located in the front direction of the robot. These rules are arranged in the first level based on the Equation (10) and referred to as Preferred Front sector rules (PF).

- The outputs of the first level together with the next most important variables are arranged in the second level and the navigation rules are formulated. The composition of the rules are based on the MFAM theorem and the rules are referred to as Preferred Right (PR) and Preferred Left (PL) and

- In each level, the fuzzy system output is modified according to the degree of importance of the corresponding inputs. Finally, as per the compositional rule of inference as defined by the Equation (13), MFAM has applied the steps (a) and (b), and the resultant rules are tabulated as shown in the Table 1.

The FIS uses the MFAM rule matrix, which involves the processes of fuzzification, rule evaluation and defuzzification procedures.
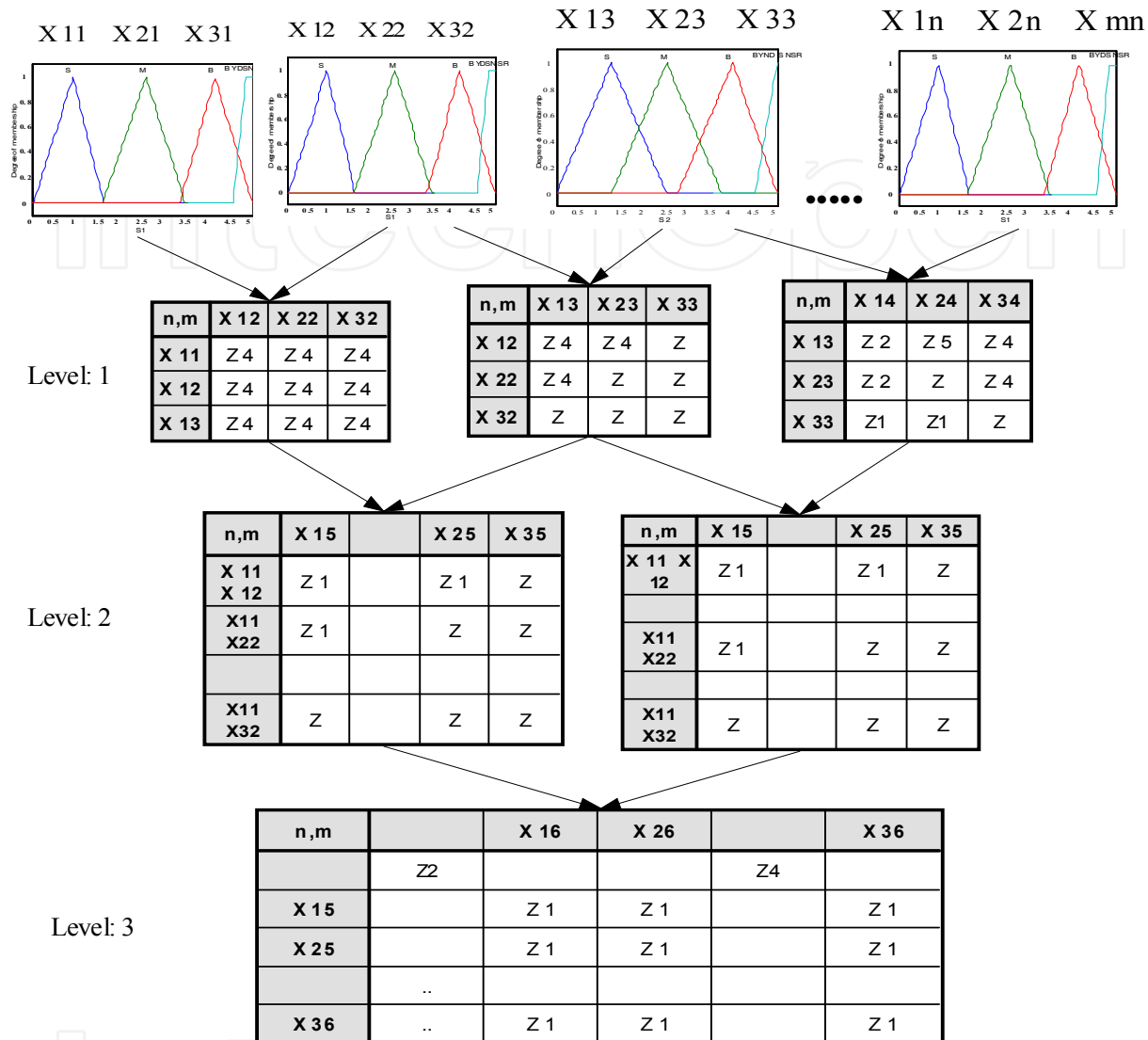

n,m	X 12	X 22	X 32
X 11	Z 4	Z 4	Z 4
X 12	Z 4	Z 4	Z 4
X 13	Z 4	Z 4	Z 4

n,m	X 13	X 23	X 33
X 12	Z 4	Z 4	Z
X 22	Z 4	Z	Z
X 32	Z	Z	Z

n,m	X 14	X 24	X 34
X 13	Z 2	Z 5	Z 4
X 23	Z 2	Z	Z 4
X 33	Z1	Z1	Z

Level: 1

n,m	X 15		X 25	X 35
X 11 X 12	Z 1		Z 1	Z
X11 X22	Z 1		Z	Z
X11 X32	Z		Z	Z

n,m	X 15		X 25	X 35
X 11 X 12	Z 1		Z 1	Z
X11 X22	Z 1		Z	Z
X11 X32	Z		Z	Z

Level: 2

n,m		X 16	X 26		X 36
	Z2			Z4	
X 15		Z 1	Z 1		Z 1
X 25		Z 1	Z 1		Z 1
	..				
X 36	..	Z 1	Z 1		Z 1

Level: 3

Table 1. MFAM Matrix Table

3. Experimental works

The proposed MFAM methodology for mobile robot navigation is validated using the simulation study. The simulation environment consists of simulated obstacles such as walls, blocks, lines, circles, and partitions that are drawn in an unstructured manner as shown in Figure 1. In the simulation environment, sensor locations of the robot are defined circumferentially and the sensors S3, S4, S5, S6, S7, S8, S9, and S10 are set as the front direction sensors. The input and output parameter settings and their corresponding linguistic terms are defined based on the real world data of the Active Media Pioneer Robot considered for this simulation study. These parameters are then encoded using the proposed MFAM based FIS
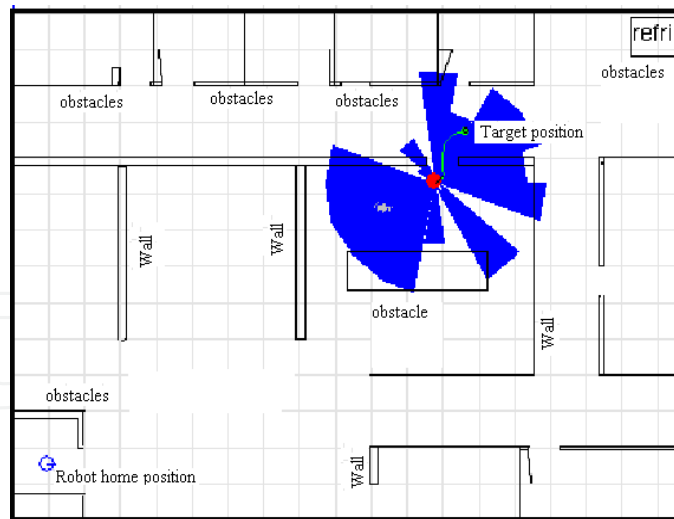
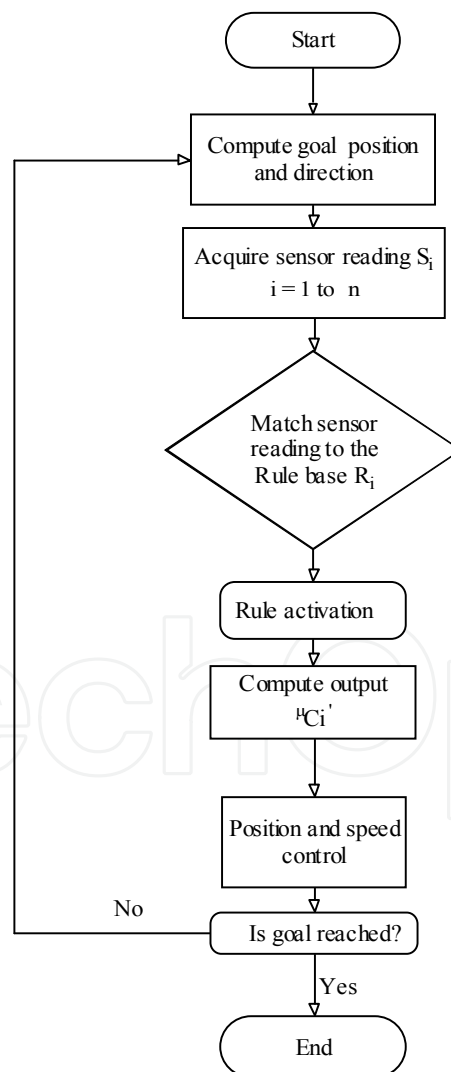Fig. 1. Simulation environment for robot navigation.

Fig. 2. Implementation of MFAM for obstacle avoidance behavior while the robot reaching the goal position.

A procedure is established for robot navigation and it is shown using the flowchart given in Figure 2. The obstacle positions in the environment are obtained using sensors S1 to S10. The final defuzzified output is fed to the controller to navigate the robot towards the target position. Figures 3 (a to h) show the various situations with multiple obstacles that a robot encounters during navigation. Based on these observations, the effectiveness of the use of multiple inputs and their roles during behaviour rule design are discussed below.
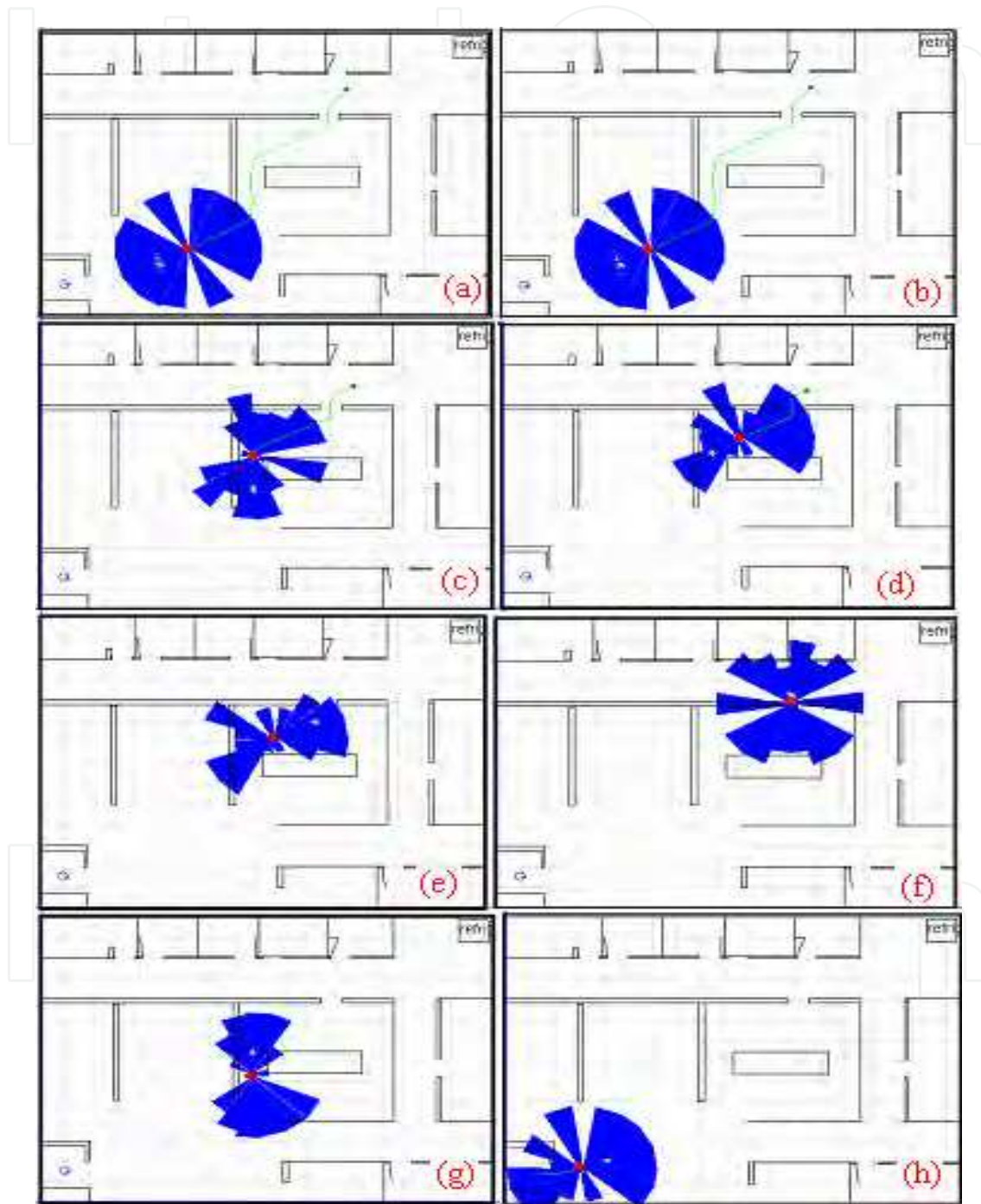
Fig. 3. (a)-(h) Simulation environment with obstacle avoidance behavior while reaching to the goal position.

The results of the simulation consist of inputs (sensor readings from sensor 0 to 14) and outputs (turn angle and speed), which are further analyzed to measure the effectiveness of MFAM. The example of the turn rule activation at a particular situation is illustrated in Figure 4. The surface view illustrates the turn rule activation based on the sensors S8 and S9.
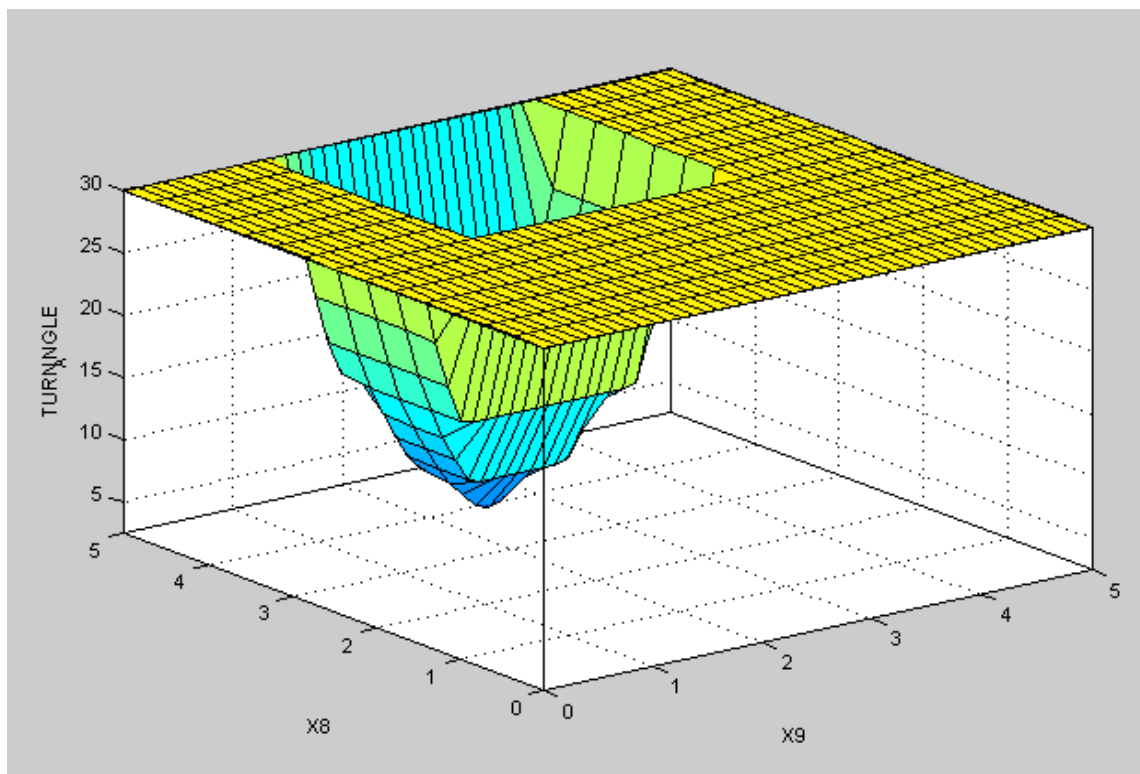
Fig. 4. Example of the rule activation, based on the sensor values received by sensors S8 (X8) and S9 (X9).

3.1 Results and Discussions of the Simulation Studies

The MFAM rules are applied and simulations are carried out for various starting and end positions with different target locations. The simulation results are recorded in all cases, when the robot encounters obstacles while moving from the initial position to the goal position. Based on these observations, the effectiveness of the use of multiple inputs and their roles during behaviour rule design are discussed below.

Figure 5 shows the sensors' responses of the environment in terms of the robot controller cycle time plotted against obstacle distances measured by sensors S3 to S10 and the steering angle in degrees. This plot illustrates various obstacle distances from the robot, which are perceived by the sensors S3 to S10 while the robot is in navigation. These multiple input data are then fuzzified using the compositional rule of inference as described in the proposed MFAM. In order to describe the role of each sensor, some critical environment in the plot shown in Figure 5 is enlarged and obstacle distances perceived by various sensors are shown in Figure 6 between the cycle time 200 x 20 ms to 300 x 20 ms. This plot clearly shows the multiple obstacle distances as perceived by sensors S4, S5, S6, S7 S9 and S8 and the robot steering angle during 240 x 20 ms to 295 x 20 ms time period. This implies that the environment consists of obstacles, which are detected in the respective sensor directions. In

these situations the robot is required to turn and avoid obstacles. The corresponding turn angle is computed using the proposed MFAM based FIS and the computed value is then applied to the control system.
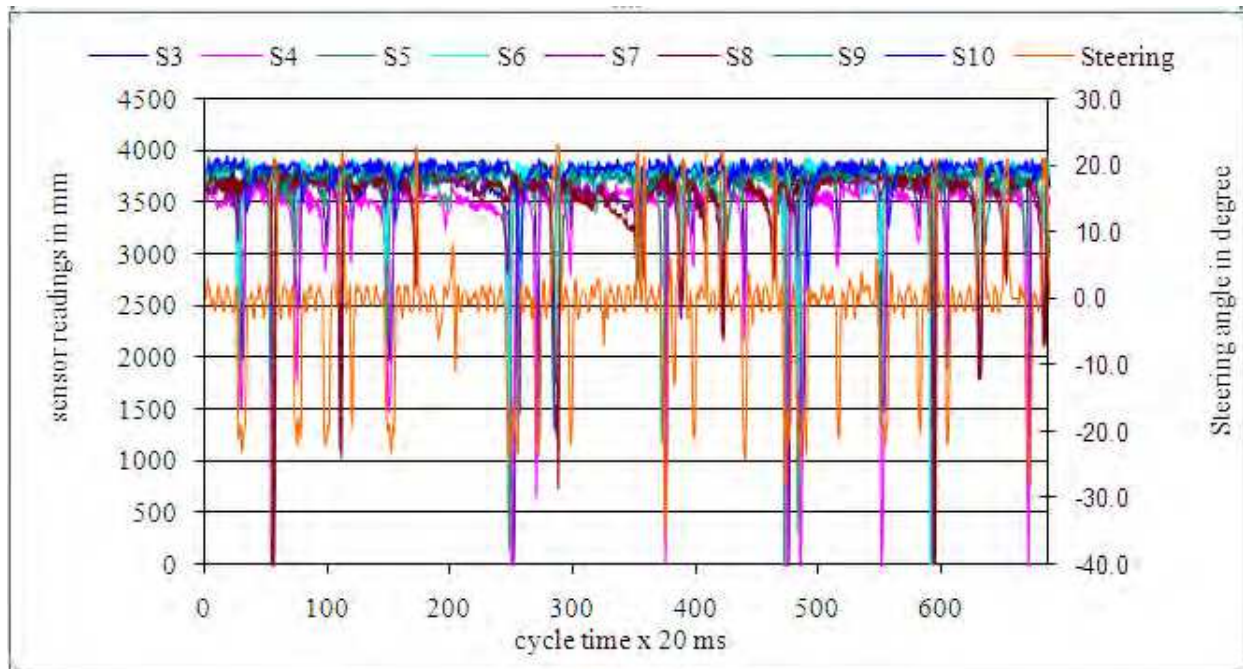

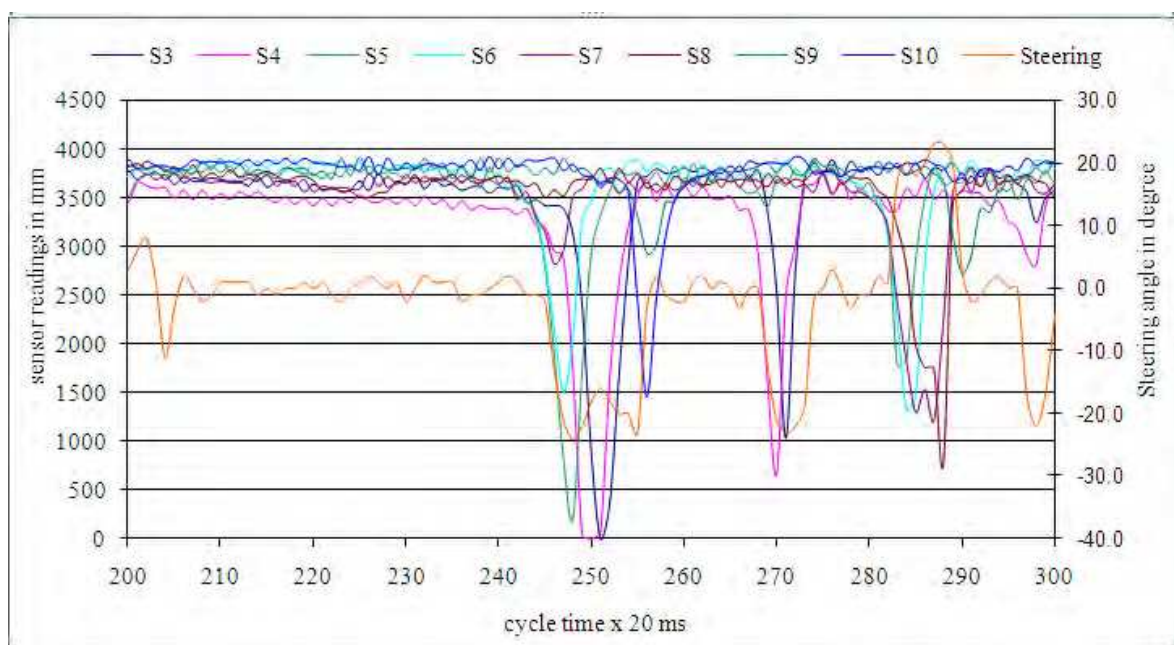Fig. 5. Cycle time drawn against obstacle distances (sensor readings) from robot and turn angle of the robot.

Fig. 6. Enlarged region of Figure 5 between the cycle time 200 x 20 to 300 x 20 ms plotted against obstacle distances from robot and the steering angle of the robot

Sensor	Obstacle details obtained from sensors		Robot output		
	Obstacle distances in mm	Direction of obstacle location from robot in degrees	Right wheel	Left wheel	Steering angle
S3	28	67			
S4	40	45			
S5	108	22	-18 deg	7 deg	-25 deg
S6	1500	0			
S7	2800	-45			

Table 2. Results provide the obstacle distances as perceived by multiple sensors and the corresponding turn angle between the cycle time 240 x 20 ms and 260x 20 ms.

Table 2 provides the number of sensors involved to perceive the obstacle environment in a particular situation and the corresponding steering angle of the robot. The tabulated data are obtained from the plot shown in Figure 4.12 between the cycle times 240 x 20 ms to 260 x 20 ms for the selected critical situations. In these situations the multiple sensor fusion using the proposed MFAM and the corresponding rule activation is illustrated as follows:
"IF X13 and X14 and X15 and X26 then Z4".

where   X13 is Sensor 3 and fuzzy distance measure is small (1) fuzzy set,

X14 is Sensor 4 and the fuzzy distance measure is small (1) fuzzy set,

X15 is Sensor 5 and the fuzzy distance measure is small (1) fuzzy set,

X26 is Sensor 6 and the fuzzy distance measure is medium (2) fuzzy set and

Z4 is Robot output and the fuzzy measure is Small Positive (MP)

The illustrated situation is shown in Figure 3 (e). From the simulation studies and the observed results, it has been found that the behaviour rules obtained from linguistic variables of multiple sensors can be effectively integrated using the proposed MFAM and used for robot navigation.

4. Experimental Studies and Investigations of MFAM using Active Media Pioneer Robot

The behavior rules obtained using the proposed MFAM methodology is demonstrated and investigated using Active Media Pioneer Robot. In the previous section, simulation study uses the front sensor data S3 to S10 to guide the robot for navigation. Similarly, in real world experiment, the same sensor configurations are used and these sensors are sensors S0, S1, S2, S3, S4, S5, S6, and S7. The experimental environment consists of real obstacles such as walls, doors, and obstacles that are situated in an unstructured manner as shown in Figures 8. The experimental studies are performed using various combinations among sensors (S1, S2, S3, S4, S5 and S6) without changing the environment and with the same starting and goal

positions. In order to illustrate the importance and significance of multiple sensor fusion using the proposed MFAM for mobile robot navigation, experiments are carried out with the selected combination of sensors as S3-S4, S2-S3-S4-S5, and S1-S2-S3-S4-S5-S6. These combinations are chosen randomly from the robot as shown in Figure 7.
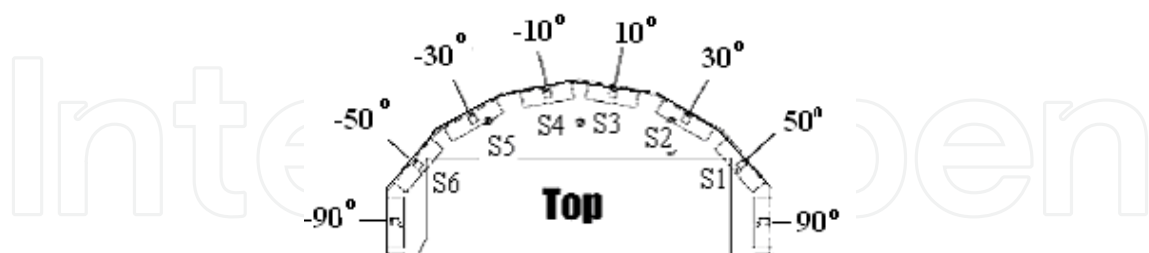

Fig. 7. Location of sensors in Active Media Pioneer Robot.

In each of the experiments, the obstacle distances perceived by each sensor and the direction of robot movements (output activation values) are obtained. These results are investigated using the graph showing the control cycle time plotted against various sensors perception data and the robot steering angles.

4.1 Experimental Studies using Sensors S3 and S4
The most influential navigation rules of the robot navigation system comes from the front sensors S3 and S4, which are located in the front direction of the robot. In this experiment, only front sensors S3 and S4 are taken into account to perceive the environment and build the navigation rules. These navigation rules are applied to the robot control system and the experiments are performed. The experimental environments are shown in Figures 8 (a) - (d) while the robot is in navigation.

Fig. 8. Real world experiments using only sensor S3 and S4.

Figure 8 (a) is the initial position of the robot. As the robot is starting to navigate (Figure 8 (b)), sensor S3 detects obstacle, and based on this encountered obstacle, robot deviates and navigates towards the target position. Again, the robot is detecting another obstacle from the direction facing the sensor S4 as shown in the Figure 8 (c). After deviating from the encountered obstacle in the sensor direction S4, the robot is encountering a large obstacle, which is perceived by sensors other than S3 and S4. Since in this study, sensors S3 and S4 are only considered into account to build the navigation rules, further navigation of the robot to avoid the encountered obstacles is not viable. The experimental results of the above situations are obtained, and the performance of the proposed methodology is investigated and the results are discussed. The experiments are repeated several times with the same environment and with the same starting and goal positions.
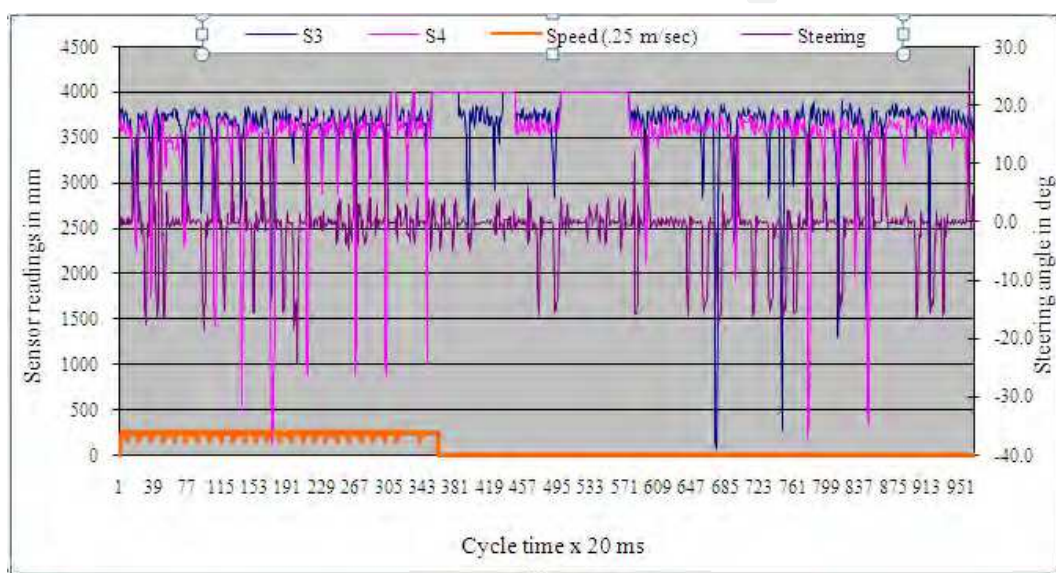
Fig. 9. Cycle time plotted against the responses of sensors S3 and S4 in terms of obstacle distances from robot, steering angle, and speed of the robot.

Fig. 10. Enlarged portion of Figure 9 between cycle times 280 X 20 to 440 x 20 ms plotted against obstacle distances from robot, steering angle and speed of the robot.

The plot shown in Figure 10 is the cycle time drawn against the obstacle distances measured by the sensors, speed of the robot and robot steering angles. For ease of visualization and explanations, a section of the results plotted in the Figure 9 are shown enlarged in Figure 10. It is found from the plot that the robot navigates autonomously with a constant speed of 250 mm/sec and it avoids obstacles, and navigates autonomously up to 1.785 meter of the span. The mobile robot stops after traveling 1.785 meter due to the obstacles in front of robot facing other sensors as shown in Figure 8 (d). During this period, (between 358 x 20 ms to 448 x 20ms) there are no obstacles in the proximity of the front of sensors S3 and S4. Whereas the other sensors on the right hand side of the robot as shown in Figure 8 (d) detect obstacles. From the observations of the navigation results, it is found that the insufficient knowledge of the environment causes the robot to stop. Similar experiments have been carried out for the following combinations of selected sensors.

4.2 Experimental Studies using Sensors S2, S3, S4, and S5.

In this experimental study, front sensors S2, S3, S4, and S5 are taken into account to acquire the environment details and build the navigation rules. The experiment is repeated several times with the same environment and with the same starting and goal positions. The environment shown in Figures 11 (a) - (d) illustrates the robot navigation while the robot encounters obstacles. In Figure 11 (d), the robot encounters obstacle from the direction of sensors S1 and S2 (right hand side of the robot), and as a result, the robot stops. This is due to the sensors S1's input, which is not considered into account to build the navigation rule. In the following section, the experimental results are discussed and illustrated to show the autonomous performance of mobile robot while the mobile robot uses the front sensors S2, S3, S4, and S5.

Fig. 11. Real world experiments using sensors S2, S3, S4 and S5

The Figure 12 is the cycle time plotted against the obstacle distances measured by sensors, speed of the robot, and robot steering angle. Since the number of sensors involved in the Figure 12 (S2, S3, S4 and S5) is more, it is difficult to visualize the graph. Hence, a particular portion of the graph (which shows the critical situation during navigation) is enlarged and shown in Figure 13. It is found from the plot that the robot navigates autonomously with the constant speed of 250 mm/sec and avoids encountered obstacles upto 3.005 meters of the span. The mobile robot stops after traversing 3.005 m, due to the obstacles in front of robot facing the other sensor (sensor S1) as shown in Figure 11 (d). During the non-acting time of the robot controller, (between 601 x 20 ms and 648 x 20ms) there are no obstacles near the sensors S2, S3, S4, and S5. Whereas the other sensor on the right hand side of the robot (S1) as shown in Figure 11 (d) detects obstacles. From the observations of the navigation results and investigations, it is found that there are insufficient sensor perceptions again and because of this reason, the robot stops.

Fig. 12. Cycle time drawn against the responses of sensors S2, S3, S4, and S5 in terms of obstacle distances from robot, steering angle, and speed.
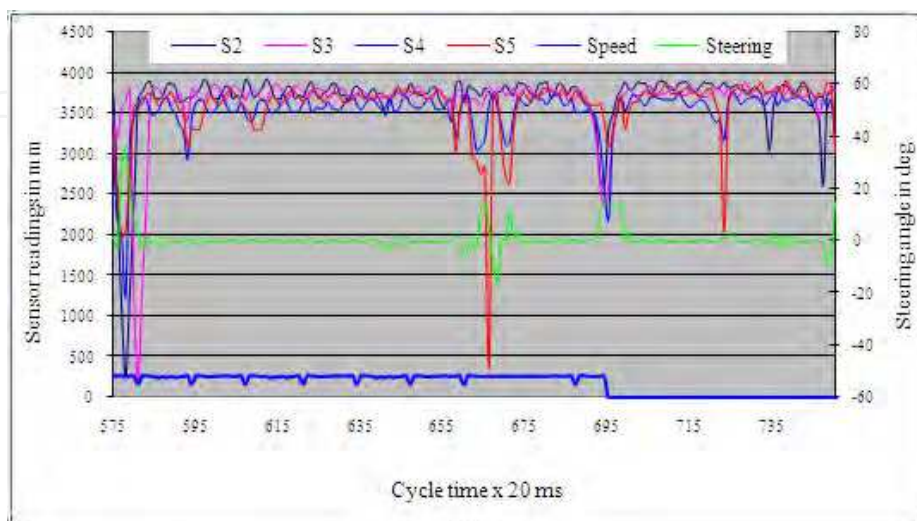

Fig. 13. Enlarged region of Figure 12 between cycle time 550 X 20 and 700 x 20 ms drawn against obstacle distances from robot, steering angle, and speed of the robot.

4.3 Experimental Studies using Sensors S1, S2, S3, S4, S5 and S6

In this experiment, front sensors S1, S2, S3, S4, S5, and S6 are taken into account to obtain the environment details and establish the navigation rules. The experiment is repeated several times with the same environment and with the same starting and goal positions. Figures 14 (a) - (e) illustrate the robot navigation through obstacles. In this experiment, the robot encounters many obstacles and in all the situations, the robot navigates successfully without any collisions and reaches the goal position. The experimental results are analysed and the autonomous performance of mobile robot is evaluated while the mobile robot uses the front sensors S1, S2, S3, S4, S5, S6, and the results are given in the following section.

Fig. 14. Experimental studies in Active Media Pioneer Robot using sensors S1, S2, S3, S4, S5 and S6
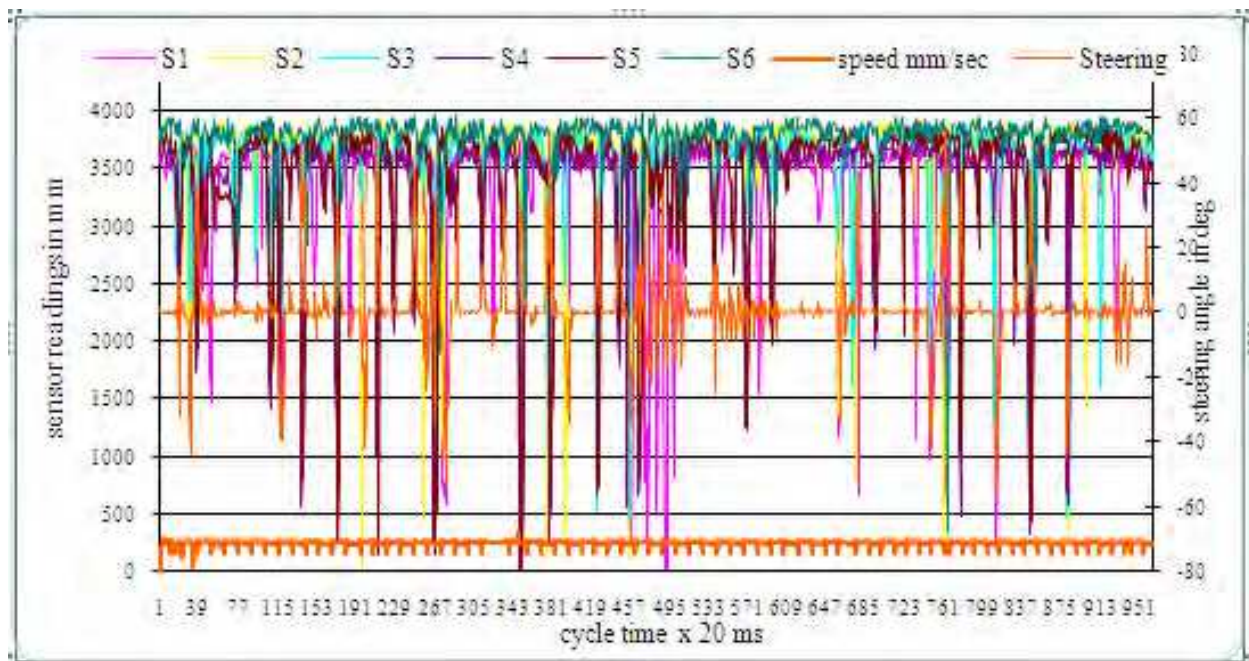
Fig. 15. Cycle time drawn against the responses of sensors S1, S2, S3, S4, S5, and S6 from robot, steering angle, and speed.
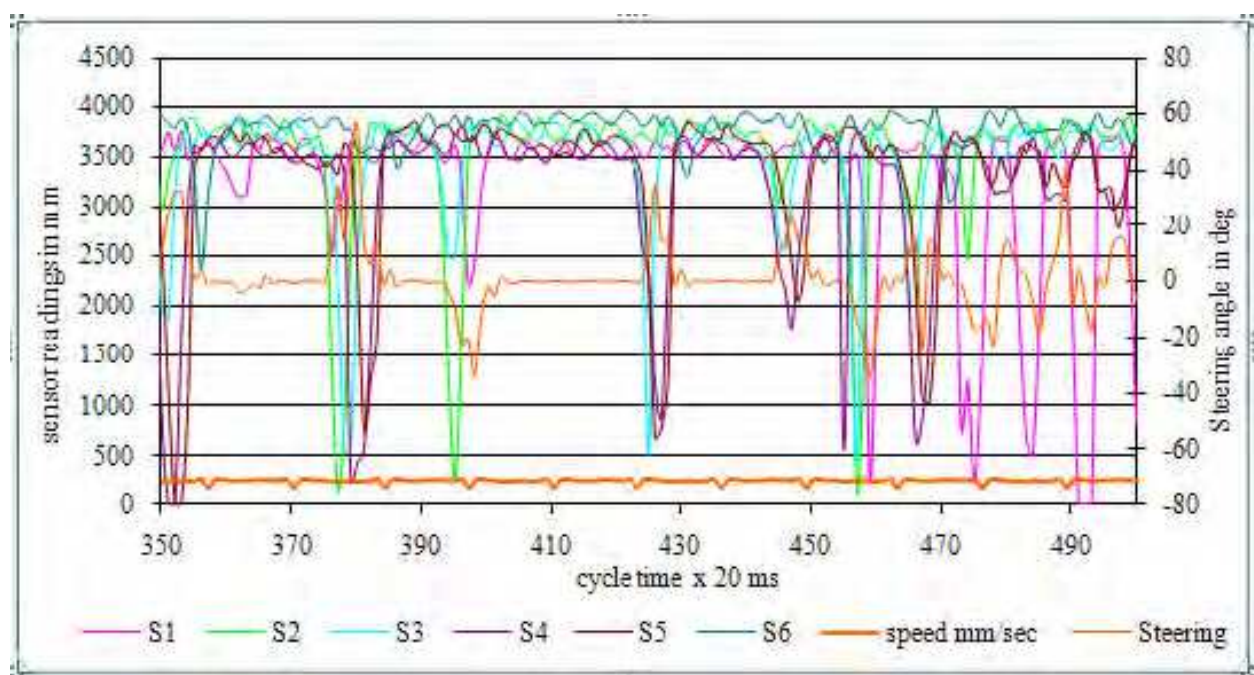

Fig. 16. Enlarged region of Figure 15 between cycle time 350 x 20 and 500 x 20 ms plotted against obstacle distances from robot, steering angle and speed of the robot.

The graph shown in Figure 15 is the cycle time plotted against the obstacle distances measured by sensors, speed of the robot and robot steering angle. Since the number of sensors used for navigation is greater than the previous experiments, the sensor results shown in Figure 15 cannot be seen clearly. Therefore, the selected critical portion of the graph is enlarged and shown in Figure 16. It is observed from the enlarged graph that the robot navigates autonomously with a constant speed of 250 mm/sec and avoids the encountered obstacles up to the target position (4.83 meters from the starting position). This plot shows the continuous responses of sensors S1 to S6 while navigating from start to the goal position. For example, when the robot traverses a distance of 1.9 meters (380 x 20 ms), it encountered many obstacles, which are in the close vicinity of the robot (350 to 550 mm from robot reference point) in the directions of 50°, 30°, and 10° and -10°. This implies that the environment consists of obstacles, which are identified in the respective sensor directions. In these situations the robot is required to turn and avoid those obstacles. The required defuzzified output (turn angle) is obtained from MFAM based FIS and is provided to the robot control system. The turn angle deviations are obtained from control system outputs in terms of X-Pos (right wheel's encoder data) and Y-Pos (Left wheel encoder data).

Sensors	Output results of robot navigation in various selected situations as illustrated in the Figure 4.22					
	Time 370x20 to 390x20 ms		Time 420 x 20 to 430 x 20 ms		Time 450 x 20 to 470 x 20 ms	
	Obstacle distances	Turn angle	Obstacle distances	Turn angle	Obstacle distances	Turn angle
S1	2528		3532		459	
S2	124		521		108	
S3	554		----		457	
S4	384	56 deg	897	36 deg	564	-35 deg
S5	789		678		3834	
S6	3767		3908		3783	

Table 3. Output results of multiple sensors and the corresponding turn angle in various situations while using all the sensors for the robot navigation (reference Figure 16)

Table 3 provides the result of the selected situations during robot navigation using the proposed MFAM rules. The Table 3 shows the number of sensors involved to perceive the obstacle environment of the selected situations and the corresponding steering angle of the robot. The tabulated data are obtained from the experimental investigation using the sensors S1, S2, S3, S4, S5 and S6. Example of navigation rule activation as per the MFAM matrix for the selected situation is as follows:

"IF X13 and X14 and X15 and X26 then Z4".

Where, X13 is Sensor 3 and fuzzy distance measure is small (1) fuzzy set,

X14 is Sensor 4 and the fuzzy distance measure is small (1) fuzzy set,

X15 is Sensor 5 and the fuzzy distance measure is small (1) fuzzy set,

X26 is Sensor 6 and the fuzzy distance measure is medium (2) fuzzy set and

Z4 is Robot output and the fuzzy measure is Small Positive (MP)

It is observed that the robot speed from starting to goal position is constant and the robot does not collide with any of the obstacles. From the present experimental studies, it is found that more sensor data are required to ensure full robot autonomy that is achieved while using all the sensors in the sensor space, which are considered for navigation during mobile robot navigation.

5. Results and Discussions

The experimental investigations as studied above are summarised and shown in the chart of Figure 17. The experimental studies are performed using the navigation rules, which include the various combinations among the available sensor inputs (S1, S2, S3, S4, S5 and S6). In all the experiments, the environment is kept unchanged with the same starting and goal positions.
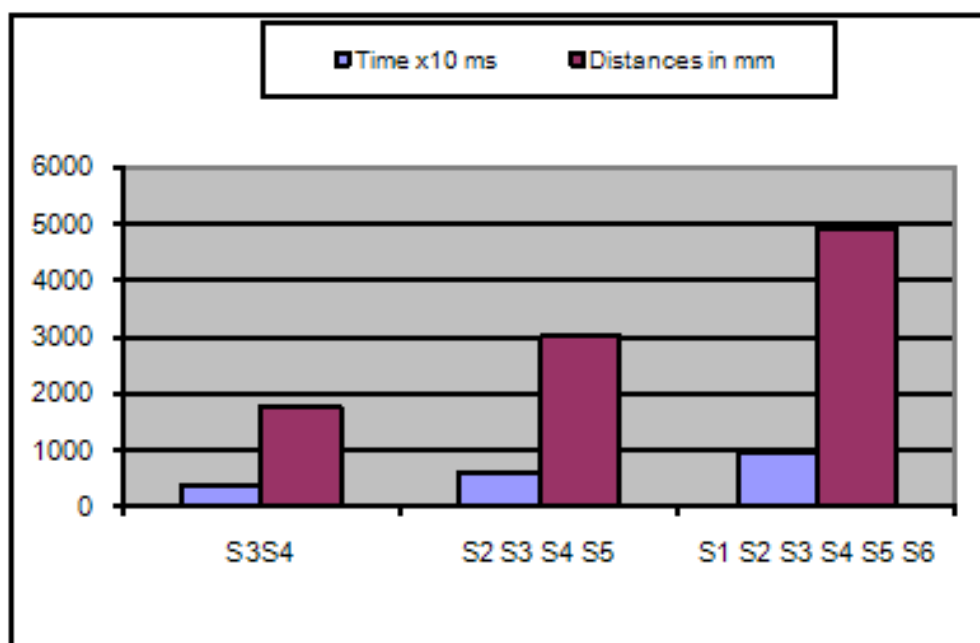
Fig. 17. Effectiveness of sensors and their fusion during robot navigation.

The effectiveness of MFAM is demonstrated by evaluating the autonomous performance of the mobile robot using the experimental results as illustrated in the chart shown in Figure 8. The chart shows the various combinations of sensors considered into account for robot navigation plotted against the distance travelled and the time of robot traversal. As seen from the Figure 8, it is found that that when all the sensors S0 to S6 are used for robot navigation, the complete autonomous performance is achieved, whereas the use of less data with less number of sensors for robot navigation results in an incomplete autonomous performance during navigation. Since the proposed MFAM rules effectively uses all sensor data to find the navigation path, the performance of navigation is improved considerably.

6. Conclusion

In this paper the optimization of fuzzy rules using modified Fuzzy Associative memory (FAM) is designed and implemented. The behavior rules obtained from FAM is tested in a simulation environment and validated by conducting real world experiments on a popular robot. The experimental results clearly indicate the mapping of multiple inputs to outputs with optimum path in every control cycle of the robot navigation. This approach involves the natural way of dealing with the environments using simple linguistic logic rules without using any mathematical model. The knowledge base of each behavior rule is easy to comprehend, because it captures the behavior rules in a linguistic form. The strength of the proposed methodology is the mapping of the inputs to the output through compositional association of multiple input variables, thus reducing the number of rules without elimination of any of the sensor's input. The robot navigation used in this research is purely perception based and perceived data are optimized and fully used for building navigation rules. Utilization of the proposed FAM methodology for other applications requires minimum modifications during setting of input and output linguistic variables.

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Mobile Robots Navigation

Edited by Alejandra Barrera

Mobile robots navigation includes different interrelated activities: (i) perception, as obtaining and interpreting sensory information; (ii) exploration, as the strategy that guides the robot to select the next direction to go; (iii) mapping, involving the construction of a spatial representation by using the sensory information perceived; (iv) localization, as the strategy to estimate the robot position within the spatial map; (v) path planning, as the strategy to find a path towards a goal location being optimal or not; and (vi) path execution, where motor actions are determined and adapted to environmental changes. The book addresses those activities by integrating results from the research work of several authors all over the world. Research cases are documented in 32 chapters organized within 7 categories next described.

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