Abstract - This paper presents the issues associated with Mobile Robot Navigation and the establishment of a new technique to navigate the mobile robot in a real world environment. The issues discussed are (i) If multiple obstacles are appeared in the environment with equal distances as perceived from multiple sensors of robot, then the corresponding multiple obstacles are treated as a whole and the robot deviate from obstacles widely and avoid then reaching to the target. As a result of the wide deviation, the robot takes long time and long path to reach the target position. (ii) Behavior rule selection when multiple obstacles are appeared in the environment with equal distances from robot. The robot navigation with optimal path, time and rule selection are more important and critical task, whenever the mobile robots are engaged to search the lives in the event of natural disaster like earthquake etc. A new methodology is proposed and used for resolving the above issues and discussed in this paper. The mathematical aspect of resolving conflicts is presented the following section.

Keywords: Mobile robot Navigation, Fuzzy logic system, Behavior selection, Behavior Conflicts.

I. INTRODUCTION

Numerous behavior rule selection and/or behavior coordination mechanisms can be found in the literature. Safiotti [1] suggests dividing action selection mechanisms into two groups that he calls arbitration and command fusion which correspond to Mackenzie’s [2] state-based and continuous classes respectively. Arbitration or state-based mechanisms are suitable in situations where only a relevant subset of the robot’s behavior repertoire needs to be activated in a given state.

Behavior arbitration schemes [3] emphasized the testing of hypotheses of behavior rather than solving real-life tasks. Konolige, et al [4] used fuzzy control in conjunction with modeling and planning techniques to provide reactive guidance of their robot. Computer simulations [5] feature a mobile robot that navigates using a planned path and based on fuzzy logic. Song et.al [6] presented a scheme for independent control of two drive wheels on their simulated robot. When an obstacle is detected by one of the robot’s proximity sensors, the fuzzy controller increases the speed of the respective wheel to turn away from it. Another approach [7], more strongly motivated by the biological sciences, appeared on the heels of the subsumption architecture. Arkin [8] addressed the implications of schema theory for autonomous robotics [9]. A neural network [10], [11] relies on training to relate inputs to outputs. Although observing the weights gives us an idea about the input — output relations, the governing rules cannot be explicitly stated.

The shortcoming of the above approaches is as follows: (i) Optimal path to reach the target position. If multiple obstacles are appeared in the environment with equal distances as perceived from multiple sensors of robot, then the corresponding multiple obstacles are treated as a whole and the robot deviate from obstacles widely and avoid then reaching to the target. As a result of the wide deviation, the robot takes long time and long path to reach the target position. (ii) Behavior rule selection when multiple obstacles are appeared in the environment with equal distances from robot. The Alpha Level Fuzzy Logic System (ALFLS) is established and used for behavior rule selection without any behavior rule conflicts when more than one action of the same type is present during mobile robot navigation.

II. THEORETICAL WORK

The behavior rule conflict situation is illustrated in the Figure 1. In this illustration, the environment consist of several obstacles which are represented in a fuzzy scale called Small, Medium and Big with the measure of (0-2 meters), (2-3.5 meters) and (3.5 –5.0 meters) respectively. In the above environment, there are two obstacles appear in small fuzzy set (0 to 2 meters) at two different distance ranges as detected by front sensors S3 and S4. Similarly another two obstacles appear in the Medium fuzzy set. In these situations the active navigation rules are presented as below.

If S3 Small and S4 Medium Then Z SN (1)
If S3 Small and S4 Big Then Z SN (1)
If S3 Medium and S4 Medium Then Z Zero (1)
If S3 Small and S4 Small Then Z MP (1)

The activation strength of each rules appeared as '1' at a particular instant. In this situation, a particular rule needs to be activated. This type of situation is resolved by defining each of the input fuzzy set into alpha-interval and the limits are established. The corresponding output membership grade is estimated as a truth membership value and referred as alpha or truth-value.

Figure 1. Environment with multiple Obstacles showing the Conflict Situations.

When an alpha threshold is applied to the truth of a rule’s predicate, it determines whether or not the truth is sufficient to fire the rule. And as a result of single behavior rule activation in the above context, the navigation path must be optimized with minimum deviation from obstacles. When there are no behavior conflicts, the formulation established using fuzzy logic approach [5] is good enough to navigate in the complex environment. The following section presents the mathematical formulation of ALFLS. The output membership of the navigation system consists of output of normal and behavior conflicting environmental context. The control system chooses the output membership function between the above two contexts based on the maximization of the truth-values. Based on the Table 1, the possible rule activations of the present illustration as given in Figure 1 is expressed mathematically and given in the Table 2. In this table only two input X3 and input X4 (front sensor data (S3 and S4)) are considered, which are used to detect obstacles that appear in the front region of the robot as illustrated in Figure 1.

TABLE 1. DECISION TABLE: IF AND THEN RULES

| C | X1 | X2 | ... | Xj | 2 |
|---|----|----|-----|----|---|
| X1 | C1 | C2 | ... | Cj | 1 |
| X2 | C1 | C2 | ... | Cj | 1 |
| ... | ... | ... | ... | ... | ...

Considering the fuzzy set of the above two sensors, the possible behavior rule sets are shown in the Table 2. The behavior rules shown by the shaded cells are conflict rules as discussed in the illustration.

TABLE 2. IF AND THEN RULE

| INPUT X | INPUT X4 |
|---------|---------|
| Small (S) | Medium (M) | Big (B) |
| Small (S) | MP | SP | SP |
| Medium (M) | SN | Z | Z |
| Big (B) | SN | Z | Z |

MP: Output fuzzy set representing Medium Positive (steering angle 30 to 50 deg)
SP: Output fuzzy set representing Small Positive (steering angle 10 to 30 deg)
SN: Output fuzzy set representing Small Negative (steering angle -10 to -30 deg)
Z: Output fuzzy set representing Zero (steering angle is 0)

The measurement values of input parameters X3 and X4 obtained from the sensors S3 and S4 have to be translated to the corresponding linguistic variables. Normally any reading has a crisp value, which has to be matched against the appropriate membership function representing the linguistic variable. The matching is necessary because of the overlapping of terms as shown in Figures 2 (a) and (b), and this matching is called, coding the inputs or fuzzification.

Figure 2. Fuzzy input corresponding to x0 and y0

In Figure 2, the reading \( x_0 \in U_1 \), \( \alpha \leq x_0 \leq \alpha_{x_{0}} \), that corresponds to two values \( \mu X_1, i (x_0) \) and \( \mu X_1, i+1 (x_0) \) of the input X1. Where \( \alpha \) is the intervals of fuzzy set. They can be interpreted as the truth-values of \( x_0 \) related to fuzzy set \( X_i \) and \( X_{i+1} \), correspondingly. In the same way the fuzzy inputs are obtained corresponding to the reading \( y_0 \in U_2 \) and \( \alpha \leq y_0 \leq \alpha_{y_{0}} \). In both the Figures, only a few terms of the fuzzy sets X1 and X2 are presented. The straight line passing through \( x_0 \) parallel to \( \mu \in [0,1] \) intersect only the terms \( X_1i \) and \( X_1i+1 \) of X1 thus reducing the fuzzy terms to crisp values denoted as shown below.

\[ X_1, (x_0) = \{ \mu X_1, i (x_0), \mu X_1, i+1 (x_0) \} \]

Similarly the line passing through \( y_0 \) intersects only the terms \( X_2i \) and \( X_2i+1 \) of X2 giving the crisp values as shown below:

\[ X_2, (x_0) = \{ \mu X_2, i (x_0), \mu X_2, i+1 (x_0) \} \]

The active rules shown in the Table 2 are redefined and are shown in Table 4.3 as a generalized formulation to resolve the conflicting behavior rule selection. Four cells in Table 3 contain nonzero terms. These cells are called active cells. Table 3 shows only four rules that are active as illustrated in...
The conflict rules as illustrated in the example are presented mathematically as below.

**Rule 1**: If \( X_3 \) is \( X_{i1} \) (\( x_0 \)) and \( X_4 \) is \( X_{2,j} \) (\( y_0 \)) then \( Z \) is \( C_{ij} \),

**Rule 2**: If \( X_3 \) is \( X_{i,j} \) (\( x_0 \)) and \( X_4 \) is \( X_{2,j+1} \) (\( y_0 \)) then \( Z \) is \( C_{i,j+1} \),

**Rule 3**: If \( X_3 \) is \( X_{i1+1} \) (\( x_0 \)) and \( X_4 \) is \( X_{2,j} \) (\( y_0 \)) then \( Z \) is \( C_{i+1,j} \),

**Rule 4**: If \( X_3 \) is \( X_{i1+1} \) (\( x_0 \)) and \( X_4 \) is \( X_{2,j+1} \) (\( y_0 \)) then \( Z \) is \( C_{i+1,j+1} \).

In the equation (2), the then part of each rule is called the strength of the rule and the strength is denoted as \( \alpha \). The strengths \( \alpha_{ij} \) of the rules are obtained and given as below.

\[
\alpha_{ij} = \mu_{X_{i1}}(x_0) \land \mu_{X_{2,j}}(y_0) = \min (\mu_{X_{i1}}(x_0), \mu_{X_{2,j}}(y_0)),
\]

\[
a_{i,j+1} = \mu_{X_{i1}}(x_0) \land \mu_{X_{2,j+1}}(y_0) = \min (\mu_{X_{i1}}(x_0), \mu_{X_{2,j+1}}(y_0)),
\]

\[
a_{i+1,j} = \mu_{X_{i+1,1}}(x_0) \land \mu_{X_{2,j}}(y_0) = \min (\mu_{X_{i+1,1}}(x_0), \mu_{X_{2,j}}(y_0)),
\]

\[
a_{i+1,j+1} = \mu_{X_{i+1,1}}(x_0) \land \mu_{X_{2,j+1}}(y_0) = \min (\mu_{X_{i+1,1}}(x_0), \mu_{X_{2,j+1}}(y_0)),
\]

where the numbers \( \alpha \), \( \alpha_{i,j+1} \), \( \alpha_{i+1,j} \) and \( \alpha_{i+1,j+1} \) are called rule strengths, and are shown in Table 4. The Table 4 is similar to Table 3 with the difference that the active cells in Table 4 are occupied by the numbers expressing the strength of the rules while the same cells in Table 3 are occupied by fuzzy outputs.

**TABLE-3. DECISION TABLE WITH ACTIVE CELL.**

| INPUT X4 | INPUT X3 | \( \mu_{X_{i1}}(x_0) \) | \( \mu_{X_{2,j}}(y_0) \) | \( \mu_{C_{ij}}(z) \) |
|----------|----------|----------------|----------------|----------------|
| \( \alpha_{ij} \) | 0 | 0 | 0 |
| \( \alpha_{i,j+1} \) | 0 | \( \mu_{X_{i1}}(x_0) \land \mu_{X_{2,j+1}}(y_0) \) |
| \( \alpha_{i+1,j} \) | \( \mu_{X_{i+1,1}}(x_0) \land \mu_{X_{2,j}}(y_0) \) |
| \( \alpha_{i+1,j+1} \) | \( \mu_{X_{i+1,1}}(x_0) \land \mu_{X_{2,j+1}}(y_0) \) |

**TABLE-4. ACTIVE RULE.**

| INPUT X3 | INPUT X4 | \( \mu_{X_{i1}}(x_0) \) | \( \mu_{X_{2,j}}(y_0) \) | \( \mu_{C_{ij}}(z) \) |
|----------|----------|----------------|----------------|----------------|
| \( \alpha_{ij} \) | 0 | 0 | 0 |
| \( \alpha_{i,j+1} \) | 0 | \( \mu_{X_{i1}}(x_0) \land \mu_{X_{2,j+1}}(y_0) \) |
| \( \alpha_{i+1,j} \) | \( \mu_{X_{i+1,1}}(x_0) \land \mu_{X_{2,j}}(y_0) \) |
| \( \alpha_{i+1,j+1} \) | \( \mu_{X_{i+1,1}}(x_0) \land \mu_{X_{2,j+1}}(y_0) \) |

Control output (CO) of each rule is defined by operation conjunction applied, based on the strength of the rules (number expressing the strength) and the fuzzy output and given as above. This is equivalent to performing max operation on the corresponding elements in the active cells and are shown in the Table 5.

**TABLE-5. CONTROL OUTPUT RULES.**

| INPUT X3 | INPUT X4 | \( \mu_{X_{i1}}(x_0) \) | \( \mu_{X_{2,j}}(y_0) \) | \( \mu_{C_{ij}}(z) \) |
|----------|----------|----------------|----------------|----------------|
| \( \alpha_{ij} \) | 0 | 0 | 0 |
| \( \alpha_{i,j+1} \) | 0 | \( \mu_{X_{i1}}(x_0) \land \mu_{X_{2,j+1}}(y_0) \) |
| \( \alpha_{i+1,j} \) | \( \mu_{X_{i+1,1}}(x_0) \land \mu_{X_{2,j}}(y_0) \) |
| \( \alpha_{i+1,j+1} \) | \( \mu_{X_{i+1,1}}(x_0) \land \mu_{X_{2,j+1}}(y_0) \) |

\( \forall \) (max) operation is performed on a number and a membership function of a output fuzzy set. Number of linguistic fuzzy set on each fuzzy input \( i = j \). In this context, the real number \( \alpha \) and the output membership function \( \mu \) (Z) can be obtained as shown below. In this context, the real number \( \alpha \) and the output membership function \( \mu \) (Z) can be obtained as shown below.
\[ \mu_{Ci} \land \mu_{C}(Z) = \max \left( \mu_{\alpha i}(Z) \cdot \mu_{Ci}(Z) \right) \]  

where \( Z \) is the output variable. The \( i \)th output membership function \( \mu_{Ci}(Z) \) is expressed as

\[ \mu_{Ci}(Z) = \max(\mu_{\alpha i}(Z) \cdot \mu_{Ci}(Z)) \]  

where \( \mu_{\alpha i}(Z) = \{Z | Z \in U, \alpha_i \leq Z \leq \alpha_{i+1}\}, \alpha \in [0,1] \) and

\[ \mu_{Ci}(Z) = \max\{\min[\mu_{\alpha i+1}(Z) \circ (X_{1i} \rightarrow Z)], \mu_{\alpha i}(Z) \circ (X_{1i} \text{ and } X_{2i} \rightarrow Z), \mu_{\alpha i+1}(Z) \circ (X_{2i} \rightarrow Z)\} \]

The final output of the fired rule is obtained using equation (7). MFAM model.

### A. Implementation of ALFLS

The Figure 4 illustrates a typical fuzzy control system of a mobile robot navigation system for obstacle avoidance while goal seek behavior is performed. Its function is to compute the output states (final output membership function) of the system from sensor inputs using ALFLS based Fuzzy Inference System (FIS), compare them with desired state, compute the final outputs for position and speed and send the signal to the motors of the mobile robot. The robot sensors data are collected into a data pool called Local Perception Space (LPS). A set of fuzzy variables of each behavior rule based on normal environmental context [12] is rewritten as follows. \( \mu_{Ci}(Z) = \max\{\min[\mu_{X_{1i}+1}(Z) \circ (X_{1i} \rightarrow Z)], \mu_{\alpha i}(Z) \circ (X_{1i} \text{ and } X_{2i} \rightarrow Z), \mu_{\alpha i+1}(Z) \circ (X_{2i} \rightarrow Z)\} \)

The real world experiments are conducted using 3-alpha and 2-alpha intervals and the performance of the mobile robot using the proposed techniques are discussed in the following sections. The real world environment consists of real obstacles such as blocks, walls, and curved walls etc., which are situated in an unstructured manner as shown in Figure 5. The experiments were conducted several times in the same environment with the same starting and the target positions and for different alpha interval.

### III. EXPERIMENTAL INVESTIGATION

The 3-alpha Intervals: In order to illustrate the capability and performance of ALFLS techniques, the experimental studies are carried out as follows. Firstly, the obstacle distances of the environment from the robot represented by ‘small’ fuzzy set are well defined by dividing the corresponding distance ranges into three intervals and referred as 3-alpha intervals. The navigation rules are established using the three alpha intervals and experimental studies are carried out. Secondly, in order to demonstrate the variations of the performance of the ALFLS techniques, the experimental studies are repeated using two intervals of the ‘small’ fuzzy set and are referred as 2-alpha intervals.
Obstacles avoidance while Seeking Goal using 3-alpha Intervals: Figure 2 shows the robot navigation in a real world environment using the proposed ALFLS method with 3-alpha interval.

These distances are classed into three different alpha intervals as perceived by sensors S1 to S6. In this environmental situation, the 3-alpha navigation rule is chosen to avoid the encountered multiple obstacles and as a result, the robot deviates from the encountered obstacles with the turn angles deviations from +30 to –20 deg. This is illustrated in the enlarged portion of the graph in Figure 5. From the above experiment, it has been observed that due to the 3-alpha intervals used in establishing behaviour rules, the robot deviates from obstacles (as perceived by sensors) in close vicinity and navigate towards the target. The navigation path deviations are as close to as ±30 degrees. As a result of the close deviation, the time taken that the robot reaches the target is faster with optimum path when multiple obstacles are present close to the robot. The significant variations of the results of ALFLS methodology are illustrated by changing the alpha intervals to two ranges (2-alpha intervals) and are discussed and given in the following section.

A. Obstacles Avoidance while Seeking Goal using the 2-alpha level Intervals

These experiments have been conducted similar to the above method without changing the environment. The range of the input fuzzy set small is changed into two intervals and the navigations rules are established and tested with experiments. The navigation path in this experiment is shown by a series of Figures 8 from (a) to (f). The experimental results are discussed and shown in Figure 9 and the enlarged portion of Figure 8 is given in Figure 9. It can be seen from the graph shown in Figure 10, that the robot deviations due to the
encountered obstacles are more than the deviations illustrated in the 3-alpha intervals while the robot moved towards the target. The robot turn angle deviations are $\pm 70$ degrees for the similar obstacle environment as done in 3-alpha intervals. Due to the larger turn angle from encountered obstacles, the navigation path of the robot is too long to reach the target.

Due to the larger intervals, the robot turns over wider angle and avoided obstacles during navigation. Some times this also affects the behavior selection, when more than one obstacles are present at the same intervals with two different distances closer to the robot. In this situation the proposed ALFLS is more suitable to map the sensor’s inputs and behavior rule selection. The graph shown in Figure 12 shows significant improvements using ALFLS than the fuzzy logic approaches for mobile robot navigation.

IV. RESULTS AND DISCUSSIONS

The effectiveness of ALFLS is demonstrated using the real world experimental results of Khepera II and are given in the Figures 9 and 10. This plot is the robot controller cycle time plotted against the robot steering angle of Khepera –II using 3-alpha and 2 alpha level navigation rules. As observed from the graph, the navigation path deviations are as close to $\pm 30$ degrees while using 3 alpha intervals and $\pm 70$ degrees while using the 2-alpha intervals navigation rules. As a result of wider deviation using 2-alpha fuzzy set, the robot takes a longer path to reach the target.

It can be observed from the experiments that the robot reached the target with a optimum path using minimum deviation from obstacles while using navigation rules obtained from 3-alpha intervals as established in ALFLS. This is shown in the graph given in Figure 11. It is also found that the time taken for the robot to reach the target position is small while using 3-alpha intervals fuzzy sets, which is shown in Figure 11. The effectiveness of ALFLS is demonstrated and found that the navigation rules obtained from 3-alpha intervals have shown significant improvements during navigation.

Figure 9: Plot showing the cycle time drawn against the sensor readings in mm obtained

Figure 10: Plot showing the enlarged section of Figure 6.20 between cycle times 400 to 650 x 20 ms plotted against obstacle distances

Figure 11: Graph showing the cycle time plotted against robot steering angle for 3-alpha fuzzy outputs and 2-alpha fuzzy outputs

The existing Fuzzy logic approaches used larger interval of input, output fuzzy sets, and build the navigation rules. Due to the larger intervals, the robot turns over wider angle and avoided obstacles during navigation. Some times this also affects the behavior selection, when more than one obstacles are present at the same intervals with two different distances closer to the robot. In this situation the proposed ALFLS is more suitable to map the sensor’s inputs and behavior rule selection. The graph shown in Figure 12 shows significant improvements using ALFLS than the fuzzy logic approaches for mobile robot navigation.

Figure 12: Comparison of the proposed ALFLS based MFAM with the existing methodology Mathematical model, Fuzzy logic and Algorithm based approaches.

CONCLUSION

The experimental study is conducted to investigate the proposed ALFLS methodology for mobile robot navigation using Khepera II mobile robot. The Experimental investigations show that the proposed formulation reduces the complexity of building the navigation system in a complex environment. The proposed methodology demonstrated improved performance of mobile robot navigation in terms of the (i) smaller time taken of the robot to reach the target and (ii) the distance traveled to reach the target position, which is shorter compared to the other accepted methods.
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