Easing of Fuzzy Multiplexing in Complex Robot Arbitration by FBSP Grouping

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Summary
In Behavior-Based System (BBS), the control strategy is distributed among a set of specialized behaviors. Each behavior with particular intention runs completely independently to send commands to control the mobile robot. However, behavior with different intentions may generate conflicting command. Therefore, behavior coordination is an important issue. An intelligent behavior fusion is implemented to solve this problem. Each behavior has a certain degree of possible effects, with degree zero is the least desired action and degree one is the most desired action. The behaviors send certain degree as a possibility for each action set to achieve the objectives of the behaviors. The main controller then performs command fusion and selects the most favored action for the exploration. This will solve the action selection problem and improve the probability to succeed but when numbers of behavior crosses certain extent, fuzzy multiplexing or fuzzy fusion process leads to complex task. This existing technique of fuzzy multiplexing has been implemented by adapting FBSP (Fuzzy Based Sensor Perception) grouping. In this technique the number of behavior, which comes under same group, shares the common sensor by varying fuzzy range values. Experimental results are conducted for easy localization with low cost sensors and successful navigation using IR range sensors.

***Keywords*:**
Behavior coordination, Behavior fusion, Multi agents, Fuzzy Based sensor perception (FBSP).

1. Introduction

Autonomous robots are vehicles type devices capable of moving in an environment with a certain levels of autonomy. Autonomous navigation is associated with the external sensors that capture information from the environment through visual images, or through distance or proximity measurements. The most common sensors are distance sensors (infrared, ultrasonic, laser, etc.) capable of detecting obstacles, walls, pits, targets and other features by measuring their distances. When advanced autonomous robots navigate within indoor environments (building, industries, offices), they have to be empowered with the ability to move through corridors, to follow walls, to avoid obstacles, to turn corners and to reach the target within building.

In efforts to articulate approaches that can handle real world uncertainty, researchers are often faced with the necessity of considering compromise between developing intelligent systems that are difficult to control, or adopting a many number of assumptions that reduces the models design which are not enough to represent the actual system or the real world. The latter option control laws are typically valid only for systems where we can impose some assumptions. The option that involves complex real systems has been less rife due to the lack of analytical methods. Many approaches have been employed in navigation of mobile robots using mathematical model. Adaptive navigation is a method using differential equations to reach a pre-defined goal while avoiding obstacles but this analytical method is troublesome for complex behavior and environment.

Current research and application adopts non-mathematical model methods of computing such as fuzzy logic, genetic algorithm, and neural networks have showed the utility and ease of these paradigms for cognitive control of complex systems. In particular, fuzzy logic has proven to be a handy tool for handling real world uncertainty in case of robot exploration. Fuzzy logic does not need the mathematical description how the output functionality depends on the input. It is comparatively easy to adapt a system that deals with many situations without defining an analytical model of environment, by representing relations between inputs and outputs in an if-then rule. Fuzzy logic controllers provide a means of transforming

Linguistic control strategy based on expert knowledge into an automatic control strategy. It appears to be very useful for handling problems that are too complex to be analyzed by conventional quantitative techniques or when the available sources of information provide qualitative, approximate, or uncertain data. Fuzzy logic is suitable for multi-sensor fusion and integration.

2. Literature review

Behavior-based approaches have been established as a main alternative to conventional robot control in recent year’s [1].

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These approaches can be implemented and tested independently. The system architecture of behavior based approaches contains three levels i.e. high level, intermediate level and low level. A number of methods [2, 3, 4, 5, 6] based on Behavior Control has emerged since Brooks introduced the approach. There are two main issues in employing Behavior Control method: Behavior module construction and Behavior Fusion. A Behavior module is usually designed to be a Reactive System [2,3], which maps a sensed situation to an action. Fuzzy Logic Control was introduced to construct the Behaviors by many researchers [7, 8] as FLC requires no mathematical description and is able to represent human type knowledge on a control plant.

Behavior arbitration scheme introduced by Saffiotti et al., [9] uses FLC, which allows one behavior at a time. This has a limitation of working in clustered environment where the robot has to face more than one behavior at a time. There are various schemes developed for behavior integration, some of them are, e.g., [11], based on Brooks sub-assumption architecture [12] using a switching type of behavior arbitration. This method employs a priority scheme wherein the recommendation of only one behavior with the highest level is selected, while the other behaviors with lower priorities are ignored always. This type of approach leads to undesired performance in the following situation. Robot faces an obstacle situated directly in front of it. So the controller is decided to avoid obstacle behavior. The robot has two option either to turn right or left, when controller executes top level behavior it takes turn either left or right, but there may be a situation that the target may exist opposite to the selected turn its decision hampers the progress of the seek-goal behavior. Another technique [13] focuses on adding the inputs of each behavior using predetermined weighting factors. This leads to direct dispute in execution when multiple behaviors give adverse commands. To deal with these limitations, other strategies have employed fusion methodologies in which each behavior is allowed to provide the final output based on the situational context [9], [14] and [15]. Saffiotti [9] uses context-dependent blending, in which the current situation is used to decide between behaviors using fuzzy logic. Tunstel et al. [14] is similar to [9], in that, adaptive hierarchies of multiple fuzzy behaviors are combined using the concept of degree of applicability in particular context. In this approach, certain behaviors are allowed to influence the overall behavior as required by the current situation and goal.

The behavior fusion method employed by S parasuraman [12] implemented the approaches used by Saffiotti [9] and Tunstel et al. [14]. The differences in improved method are the Behavior arbitration process. In [9] he uses fuzzy logic's, which allows one behavior at a time to be active. In [10] method, independent behaviors are executed in a concurrent fashion, and depending on the situational context, outputs are blended together. Each behavior is assigned a weighting factor, and these factors are adjusted dynamically according the weight rules. The weighting factors determine the degree of influence of each behavior on the final motion command. In our method little contribution is added to the present state of knowledge, we adopted fuzzy based sensor perception grouping to make the fuzzy multiplexing simple when robot is added with more number of behavior features.

This paper is organized as follows: In Section 3, the experimental system design explained, Section 4, gives details of individual system behaviors, Section 5, Explains fuzzy based sensor grouping and multi behavior group, Section 6 gives Experimental test runs and results.

3. Experimental System Design

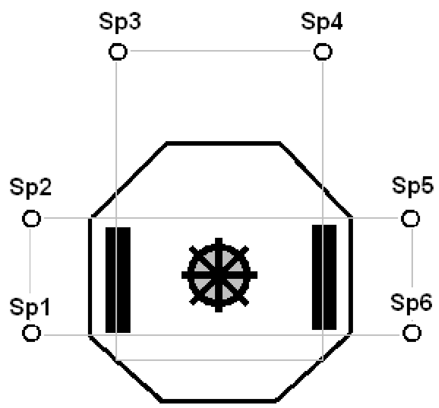


Fig: 1 Experimental vehicle Design 1

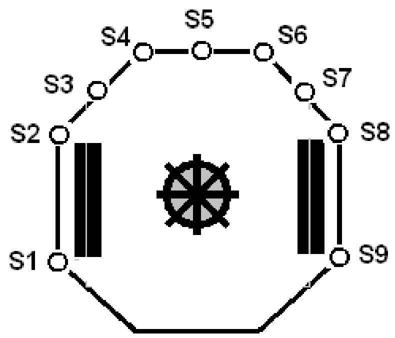
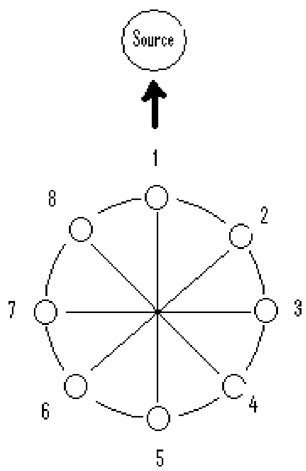


Fig: 2 Experimental vehicle Design 2

The vehicle has a custom-made octagonal acrylic polymer frame box, which is mounted with two independent driving wheels driven by two DC motors, respectively. It does not have any steering mechanism, but can change its navigation direction by differential drive mechanism. If the velocity of the right wheel is greater than the velocity of the left wheel, the robot will turn left. The speeds of the wheels are controlled by two separate PWM signals. DC battery is used to provide power to the motors and the control system. The vehicle is equipped with a IR sensors and LDR sensors. Arrays of IR sensors are used to obtain information from the dynamic environment, which the vehicle travels through. The sensors are mounted so that they can detect obstacles, Pits, wall, surface terrain slope etc that are in the left, front and right side of the vehicle. Figure 1 shows the locations of the sensors on the vehicle for pit and surface detection and Fig2 shows the location of sensors on the vehicle for rest. Mobile localization and way point steering is carried out using sets of LDR sensors which are mounted at the center of robot with certain height. An Atmega 16 microcontroller is used as the controller to implement the fuzzy logic controller, to communicate with the IR sensors, LDR sensors and to provide PWM signals to control the motors.

4. Individual Behavior Design

4.1 Localization Behavior: Initial positioning of mobile robot is done with low cost LDR sensors. Eight LDR sensors are positioned at an angle of 45^0, depending on the sensor which detects the light intensity, robot takes the turn.



Detecting Sensor	Desired Turn
1	0^0(ST)
2	-45^0(CCW)
3	-90^0(CCW)
4	-135^0(CCW)
5	180^0(CW)
6	135^0(CW)
7	90^0(CW)
8	45^0(CW)

Fig: 3 Sensor position and Desired turn for Localization

Fuzzy Input from the sensors
LDR1, LDR2, LDR3, …, LDR8= [Detected(D), NotDetected (ND)]
Fuzzy output
DesiredTurn=[TurnLeftReverse,TurnLeftShortReverse, TurnLeftHigh,TurnLeftLow,TurnZero,TurnRightLow, TurnRightHigh, TurnRightShortReverse]
O_1= [TLR, TLSR, TLH, TLL, TZ, TRL, TRH, TRSR]

Fuzzy rules for the localization behavior
Example:
IF <LDR1 is D> THEN <Desired Turn is TZ>
IF<LDR2 is D> THEN <Desired Turn is TRL>
;
;
;
IF<LDR 3 is D> THEN <Desired Turn is TLL>

4.2 Obstacle Avoidance Behavior: The vehicle is equipped with 9 Infrared range sensors to avoid obstacle (shown in Fig: 1), these sensors identify the obstacle, which is present in right, left and front. When the IR sensors detect that there are obstacles appearing around the robot, the controller has to slow down the speed of the robot and start to avoid the obstacles. To make the robot to avoid obstacles, all required fuzzy rules should be installed in the controller
Inputs from sensor to microcontroller
S1, S2, S5, S6,S7,S8,S9 = [NO ,MO, FO]
NO-Near distance to Obstacle, MO- Medium Distance to Obstacle, FO-Far Distance to Obstacle
Outputs to differential drive motors
Desired Angle = [LEFT (L), LOW LEFT (LL), STRIGHT (ST), LOW RIGHT (LR), RIGHT (R)]
Desired Speed = [SLOW (S), MEDIUM (M), FAST (F)]
Fuzzy rules for the Obstacle avoidance behavior
Example:
IF<S1and S2 is Near> and <S3and S6 is Medium>and <S8 and S9 is Medium> and < Way Point is Right> THEN < Turn Right>

4.3 Pit Avoidance Behavior: The vehicle is equipped with four IR sensors for pit detection and avoidance. This sensor identifies the surface and pit by finely tuned sensor values, Four IR sensors are used to obtain information from the dynamic environment that the vehicle travels through. The sensors are mounted so that they can detect pits, which are in the left, front and right side of the vehicle. Figure 1 shows the locations of the sensors on the vehicle.
Inputs from sensors:
SP1,SP2,SP3,SP4,SP5,SP6 = [SLR, PHR]
SLR-Surface Low Range, PHR-Pit High Range
Outputs:
Desired Angle = [LEFT (L), LOW LEFT (LL), STRIGHT (ST), LOW RIGHT (LR), RIGHT (R)]
Desired Speed = [Low, Medium, Fast]
Fuzzy rules for the Pit avoidance behavior
Example:
IF <SP1 and SP2 is SLR> and <SP3 is SLR> and <SP4 is SLR> and <SP5 and SP6 is SLR > THEN < Turn is Straight> and < Speed is High>
IF <SP1 and SP2 is SLR> and <SP3 is PHR> and <SP4 is PHR> and <SP5 and SP6 is PHR > THEN < Turn is Left> and < Speed is Low>

4.4 Wall or Edge following Behavior: This behavior gives the robot flexibility to follow the wall while maintaining its navigation. In this behavior there is a need for sensing along wall. The side sensors sense how for the wall is and also on which side, behavior action keeps the robot moving forward keeping a wall references. Left wall following behavior is sensed by sensors S1 and S2, where as the right wall is sensed by S8 and S9 sensors.
Inputs: S1, S2 = [Near (N), Far (F)]
Output: Turn [Left (L), Straight (S), Right (R)]

The fuzzy rule for wall following behavior is
Example:
IF<S1 and S2 is Far > and <S4 and S6 is Far> and <S8 andS9 is Near> and <target at Right>THEN <follow Right (R) wall>

IF<S1 and S2 is Near > and <S4 and S6 is Far> and <S8 andS9 is Far> and <target at Left>THEN <follow Left (L) wall>

4.5 Slope Riding Behavior: This behavior is Slope activated by using S5 sensor along with sensors S4 and S6. If the entire three sensors detect the obstacle then it treats as obstacle but in case if only the sensor S5 detects object at low range then it treats as slope and it moves over the slope road to reach the goal point.
Inputs: S4, S5, S6 = [Near (N), Far (F)]
Output: Turn [Left (L), Straight (S), Right (R)]
Fuzzy rules for the Slope Riding behavior
Example:
IF< S4 is Far> and <S5 is Near> and <S6 is Far> THEN <move Straight> (treats as slope)
IF< S4 is Near> and <S5 is Near> and <S6 is Far> THEN <move right> (treats as Obstacle)

4.6 Terrain Based Behavior: this behavior works out with four IR sensors (SP1,SP2,SP3,SP4,SP5 and Sp6) which is directed towards the ground (also for Pit avoidance behavior) as shown in fig: 1, depending on the range of values obtained from these sensor lead to the decision, if the sensors gives same range of values then speed is fast, if it gives various ranges of values then robot moves with low speed.
Inputs:
SP1,SP2,SP3,SP4,SP5,SP6 = [Smooth(S) , Hard(H)]
Output:
Desired Speed = [Low, Medium, Fast]
Fuzzy rules for the Terrain based behavior
Example:
IF <SP1 is H> and <SP2 is H >and <SP3 is S> and <SP4 is S> and <SP5 is H>and <SP6 is H > THEN < Speed is High>

IF <SP1 is H > and <SP2 is H >and <SP3 is S> and <SP4 is H> and <SP5 is S >and <SP6 is S > THEN < Speed is Low>

4.7 Waypoint and goal point behavior: The vehicle is equipped with LDR sensor this will sense the light of different intensity; here we used the different intensity lights for way point recognition. The inputs are received from LDR sensors, first it aligns towards the desired direction similar to localization and then it ahead towards the way point. Fuzzy Inputs, outputs and fuzzy rules for this behavior is same as localization behavior but here after detecting way point robot turns and moves ahead avoiding any obstacles if any.

We have not given Fuzzy inference system (FIS) in detail because membership function and rule formation is discussed in many of the papers, for all behaviors triangle and trapezoidal memberships were considered, fine tuning of the range value is done during experimental trials.

5. Fuzzy Based Sensor Perception Grouping

FBSP grouping is very help full for multiplexing more number of behaviors. Many research papers are published on fuzzy behavior fusion or multiplexing of output results, the methods adopted yield good result but the complexity of the method increases when more number of behaviors is required for the chosen environment.

In this paper we included method FBSP grouping to reduce the complexity of behavior fusion, here we considered 3 FBSP groups for total 7 Behaviors.

Fig: 4 shows three behavior groups GP-A, GP-B and GP-C, in each group there is more than one behavior which shares the common sensors, sharing of sensors is clearly based on fuzzy range values. The different behaviors under same group get activated one after the other sequentially based on the input readings. This avoids more number of output data's in fuzzy behavior fusion activity.

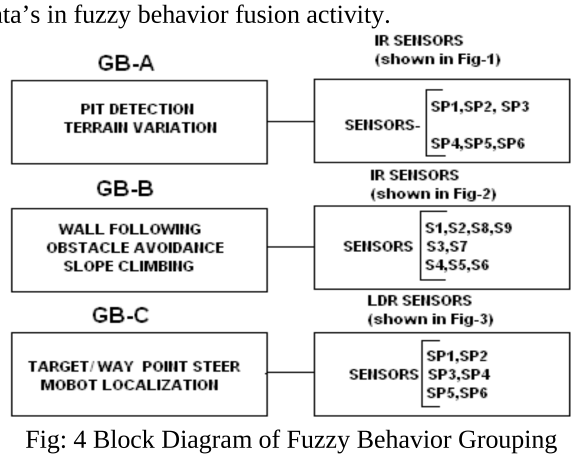


Fig: 4 Block Diagram of Fuzzy Behavior Grouping

5.1 Multi Group Behavior Fusion:

In this experimental robot setup, total three groups are considered Based on FBSP grouping technique. In each group, an array of sensor percept different range of fuzzy set values depending on the inputs required for particular behavior. The modification of linguistic variable and membership range is required for group behavior compared with individual behavior.

Group Behavior-A (GB-A)- [Surface reference range value, Surface variation value (for uneven surface), Pit range value]

Group Behavior-B (GB-B)- [Obstacle near distance range, Wall reference range, Obstacle far distance range (out of sensor range)]

GroupBehavior-C (GB-C)- [Light intensity for localization, Light intensity for waypoint]

Multi Group (A,B,C) Fusion based on situation context, The weight factor A_{w}, B_{w}, C_{w} is considered for behavior GB-A,GB-B and GB-C respectively, depending on the situation it takes degree of involvement.

The defuzzification process used here is the Center of Gravity (C.O.G) method, this simplifies and optimize the processing speed of controller.

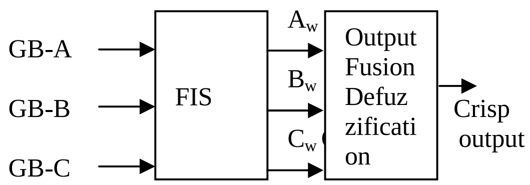
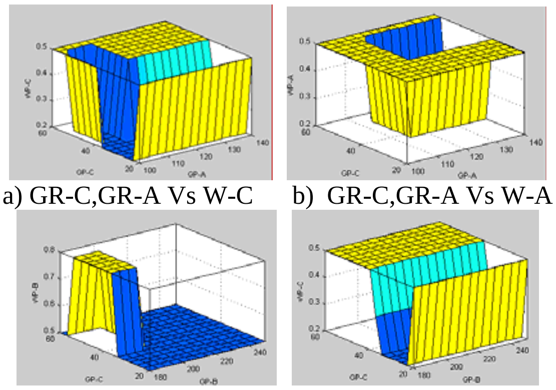


Fig: 5 Group behavior and Weight Factor

Logically, behavior group coordination problems can be solved considering two important facts 1) Judging which behavior should be activated in each context 2) methodology to combine the results from different behavior into single command. Group behavior coordination scheme takes preference based on many situation for Eg: if there is no obstacle or Pit on the way to the goal then GB-C takes higher priority rest shares partial weight factor. In case if there is obstacle infront of robot then GB-A takes higher weight factor.



a) GR-C,GR-A Vs W-C b) GR-C,GR-A Vs W-A

c) GR-C,GR-B Vs W-B d) GR-C,GR-B Vs W-C

Fig: 6 Surface viewer graphs for Group Behaviors

Figure: 6 show the surface viewer graph for different behavior input sets and fuzzy weight factor. The weight factor varies depending on the situation context.

6. Experimental Test Runs and Results

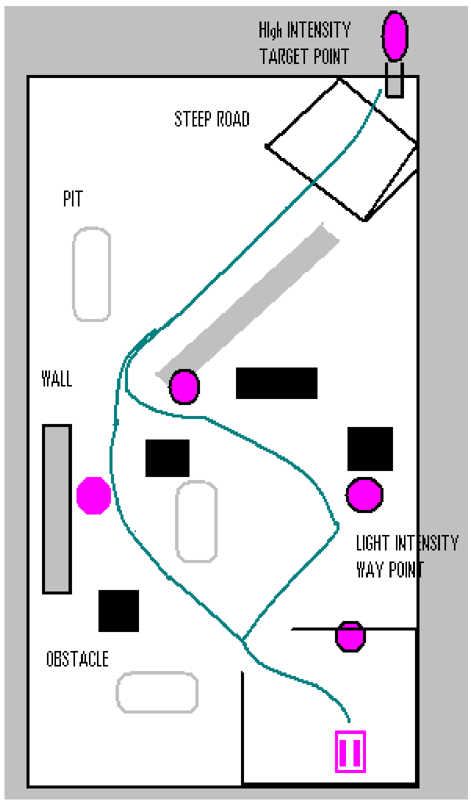


Fig: 7 TEST RUN - Robot Motion in Cluttered Environment

The mobile robot was placed on a pre-defined environment which we built considering all the behaviors and situations. We conducted many trial runs, above Figure shows one of the test run conducted for our robot in a cluttered environment. We chosen some obstacles and objects to create complex environment, all these obstacles and objects location on the way to target leads to certain kind of behavior. Initially we tried to position all the objects in different position so that the robot can come across each behavior; final results of two trials are shown. To steer the robot towards the goal way points are placed, way points are illuminated lights of different intensity. In order to incorporate these entire behaviors in our experiment, the mobile robot is mounted with 15 IR sensors and 8 LDR sensors. During our experimental test trials we noticed the variation of sensors inputs but we tried to tune for each run but this can be avoided by using sensor filtering or by using better sensors.

7. Conclusions

In this paper, we used context based multi perception grouping to overcome the difficulties occurs in fuzzy multiplexing when the robot has to explore through more number of behaviors. This method can effectively coordinate conflicts and competitions among multiple agents by weighting them and this coordination ability is nearly independent of a dynamic environment due to it robustness. The navigation algorithm developed has better functionality and real-time response since perception and decision units in the algorithm are integrated in one module and are directly oriented to a dynamic environment. The real time test results show that the proposed method for robot navigation using low cost IR and LDR sensors can automatically perform avoiding obstacles, Pit, Higher Steep, decelerating at undesirable terrain, following reference wall and moving to target and so on in complex and uncertain environments. This can be further improved by using high featured sensors like LIDAR, Camera Etc. here we assigned less number of perception for each sensors (Fuzzy Based sensor Perception Grouping) this can be extended to many by using proper fuzzy algorithms.

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