

# A BEHAVIOUR BASED HIERARCHICAL FUZZY CONTROL ARCHITECTURE FOR AGRICULTURAL AUTONOMOUS MOBILE ROBOTS

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**Abstract.** This paper describes the design and implementation of a real-time autonomous mobile robot aimed at navigating in real farms with no operator intervention. The agricultural environment being targeted consists of an irregular terrain supporting crops or sparsely populated with objects which gives rise to complex problems of identification, monitoring and control.

In this paper we introduce a fuzzy hierarchical controller for such agricultural robots. The controller utilises co-operating behaviours (obstacle avoidance, edge following, goal seeking) to navigate in tight spaces and navigate towards its target (bales of hay, boxes of fruit/vegetables). It can also be used to follow crop edge (for purposes of crop cultivation, irrigation, etc.). The work advances the subject by providing a novel hierarchical architecture that simplifies fuzzy controller design and provides a control architecture with a fast response, robust performance, and the ability to deal with dynamic outdoor environments.

## 1. Introduction

The need for increased farm productivity set against a declining workforce is driving work on developing fully automated farm machinery, including the development of unmanned agricultural vehicles[2]. In a factory such automation is relatively simple but in an agricultural setting the inconsistency of the terrain, the irregularity of the product and the open nature of the working environment result in complex problems of identification, sensing and control. Problems can range from the effects of varying weather conditions on vehicle sensors and traction performance, through to the need to deal with the presence of unauthorised people and animals. All these problems provide good opportunities for fuzzy systems as they excel in dealing with imprecise and varying conditions which characterises such situations.

Producing fully autonomous farm vehicles is a difficult objective although there have been notable steps in this direction, such as the Aurora greenhouse robot[6], but the application and environment variation in the greenhouse is restricted with respect to the outdoor situations. Other research [5, 7] has investigated using vision in crop harvesting. Also Cho[3] has developed fuzzy control for unmanned operation of rice combine in simulation.

The agricultural robot must react to dynamic events in unstructured agricultural environments, using multiple sensors. For mobile robots, the size of the input space requires a complicated control function. This mapping can be made more manageable by breaking down the space for analysis by multiple agents, each of which responds to specific types of situations, and then

integrating the recommendations of these agents. Agents also called behaviours, pioneered by Brooks[1], and composed of many simple co-operating units, have produced very promising results when applied to the control of mobile robots.

There are many forms of behaviour co-ordination. Classical robot architectures such as the subsumption architecture[1] use an on-off switching schema: in each situation, one behaviour is selected and is given complete control of the effectors. This simple scheme may be inadequate in situations where several criteria should be taken into account. Also this rigid organisation contrasts with the requirement that an autonomous robot can be programmed to perform a variety of different tasks in a variety of environments[9]. Later proposals relied on dynamic arbitration policies, where the decision of which behaviour to activate depends on both the current (sub-goal), given by the planner and the environmental conditions. Both fixed and dynamic arbitration policies can be implemented using the mechanisms of fuzzy logic. The two main advantages in doing so are the ability to express partial and concurrent activation of behaviours and the smooth transition between behaviours.

In this paper we present a *Hierarchical Fuzzy System*. The example we shall present utilises four basic fuzzy behaviours which are left/right edge following, goal seeking, obstacle avoidance. We also use the concept of fuzzy context rules developed by [9] in order to have smooth transition between the behaviours in a reactive way. The proposed system provides a *simple design* procedure and achieves *smooth behaviour* transitions. The system was tested on an indoor mobile robot navigating an environment consisting of irregular geometrical objects and layout. The robot successfully escaped from mazes, followed edges, avoided obstacles, and reached its goals. The same control architecture was then moved to our outdoor robots (a large diesel powered agricultural vehicle, and an electrical vehicle) with newly developed sensors to deal with agricultural domain. The robot has been applied under different out-door conditions for large periods to test the repeatability and stability of the control architectures. The robot has shown a smooth and stable response, It had shown the ability to deal with various sorts of irregular and sparse crop edges ranging from weeds and hay to bush hedges. In the following sections we explain the system and the robots in more detail.

## 2. The Hierarchical Fuzzy Logic Controller (HFLC) Design

Lotfi A. Zadeh introduced the subject of fuzzy sets in 1965[11], where he proposed that one of the reasons humans are better at control than conventional controllers is that they are able to make effective decisions on the basis of imprecise linguistic information.

The work described in this paper suggests a solution based on using fuzzy logic to both implement individual behaviour elements and the necessary arbitration (allowing both fixed and dynamic arbitration policies to be implemented). We achieve this by implementing each behaviour as a fuzzy process and then using other fuzzy processes to co-ordinate them. The resultant architecture takes a hierarchical tree structure form and is shown in figure 2.

The benchmark tasks targeted by this work are *collecting field based objects* (e.g. hay bales, fruit boxes) and *cutting crops*. In this paper a hierarchical fuzzy controller was developed (consisting of numerous co-operating fuzzy processes) which aims at facilitating farm vehicles to safely navigate to target objects such as hay bales. The initial design and experimentation has taken place within our laboratory and have tested the crop following and object collection tasks successfully. Then the control architecture was transferred to our out-door robots, and the crop following task was successfully implemented. In the next stage, we will implement the object collection task, by adding a vision system developed by our group[10] for bales of hay location detection which supplies x-y co-ordinates of the bales location.

In the following design of each single behaviour we will use singleton fuzzifier, triangular membership functions, product inference, max-product composition, height defuzzification. The

selected techniques are chosen due to their computational simplicity. The equation that maps the system input to output is given by

$$\frac{\sum_{p=1}^M y_p \prod_{i=1}^G \alpha_{A_{ip}}}{\sum_{p=1}^M \prod_{i=1}^G \alpha_{A_{ip}}} \quad (1)$$

Where M is the total number of rules , y is the crisp output for each rule,  $\alpha_{A_{ip}}$  is the product of the membership functions of each rule inputs, G is the number of inputs. More information about fuzzy logic can be found in [4].

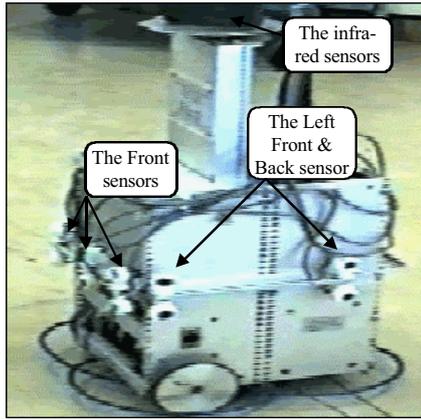


Figure 1: The indoor robot and its sensor configuration

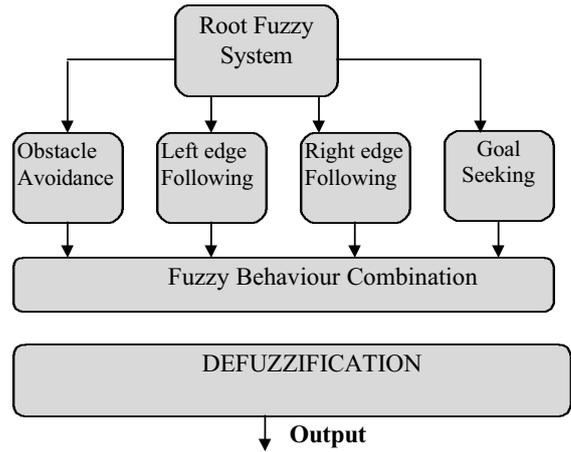


Figure 2: The behaviour co-ordinated system.

Ruspini [8] defines fuzzy command fusion as interpretation of each behaviour producing unit as an agent expressing preferences as to which command to apply. Degrees of preferences are represented by a possibility distribution (or fuzzy as in our case) over the command space. In our HFCL architecture a fuzzy operator to combine the preferences of different behaviours into a collective preference is used. According to this view, command fusion is decomposed into two steps: preference combination and decision. In figure 2 each behaviour is treated as an independent fuzzy controller and then using fuzzy behaviour combination we obtain a collective fuzzy output which is then defuzzified to obtain a final crisp output. The proposed system enables *more flexible arbitration* policies to be achieved by using fuzzy meta-rules or context rules. These have the form IF context THEN behaviour [9] which means that a behaviour should be activated with a strength determined by the context (i.e. a formula in fuzzy logic). When more than one behaviour is activated , their outputs will have to be fused and each behaviour output will be scaled by the strength of its context. In case of using fuzzy numbers for preferences, product-sum combination and height defuzzification. The final output equation is given by:

$$C = \frac{\sum_i (BW_i * C_i)}{\sum_i BW_i} \quad (2)$$

Where i represent the active behaviours activated by context rules which can be right/left edge following behaviour, obstacle avoidance, goal seeking.  $C_i$  is the behaviour command output (left and right velocity in our case). These vectors have to be fused in order to produce a single vector C to be applied to the mobile robot.  $Bw_i$  is the behaviour weight. The behaviour weights are calculated dynamically taking into account the situation of the mobile robot. For example, the obstacle avoidance behaviour weight increases as the obstacle comes closer this can be done by calculating the minimum distance of the front sensors  $d_1$  in figure 6 and then calculating the

weight of the obstacle avoidance behaviour using the membership functions in figure 6. Then using the context rules we can determine which behaviours are active and apply equation 2 to obtain the final output. By doing this we do not need any pre-plan as the system plans for its self depending on the current situation of the environment.

The behaviours implemented in this system are the minimum set of behaviours we need to demonstrate this architecture working in our target “farm object fetch” application and crop edge following.

### 3. The Proposed Architecture

As explained earlier, the underlying principle is that the robot controller will be built from a set of fuzzy processes each providing some basic machine behaviour. Thus the first task is to define a set of basic behaviours that will allow the robot to complete the challenge. This work uses 4 basic behaviours, namely goal seeking, obstacle avoidance, right/left edge-following .

The obstacle avoidance behaviour is used to avoid obstacles while navigating in a field. The three front sensors of the robot are used , which are the *Left Front Sensor* (LFS), the *Medium Front Sensor* (MFS), the *Right Front Sensor* (RFS), the configuration is shown in figure 1. We use here only three input *Membership Functions* (MF) for each input as shown in figure 3, the rule base was designed using human experience. The output MF is shown in figure 4 and they are for left and right wheel velocities of the robot which is the same for all behaviours.

The left and right edge following are used to follow an edge on the right or left side of the robot. The behaviours will be used to follow a crop when initially positioned near a crop and deactivating the other behaviours. The left or right wall behaviours will be activated to cause crop following. The right edge following behaviour uses two right side sensors RSF (right side front) and RSB (right side back) . The left edge following behaviour uses two left side sensors LSF (left side front) and LSB (left side back). The MF for each input as shown in figure 5. The fuzzy rule base of the right edge following is shown in table 1 and its complement is the rule base for the left edge following.

In goal seeking behaviour, we have one input from the infrared detector and the goals are in the form of infrared emitting beacons, the input is in the form of bearing of the robot from its goal sensed by the infrared scanner sensor, its MF is shown in figure 7, the rule base was designed using human experience. Note that the imprecision of the infrared detector is high which helps to simulate the problems in the open environment and give our controller a real challenge. In the outdoor robot, we will determine the bearing from our goal by using our machine vision technique for locating bales of hay[10]. Note that all the MF and the rule bases will remain the same when moving the control architecture to the outdoor robots except for the output MF because in the outdoor robots we have two independent motors for steering and speed, but we will still have 2 output variables each represented by 4 fuzzy set.

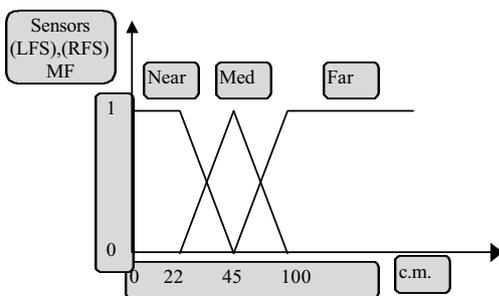


Figure 3: The input MF of the front sensors.

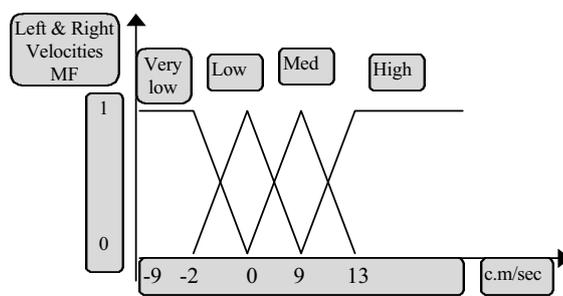


Figure 4: The output MF of the velocities of the robot.

In behaviour co-ordination there are some few parameters that must be calculated in the root fuzzy system. These parameters are the minimum distance of the front sensors which is represented by  $d1$ , the minimum distance of the left side sensors which is represented by  $d2$ , the minimum distance of the right side sensors is represented by  $d3$ . After calculating these values, each of them is matched to its MF which are shown in figure 6 and these fuzzy values are used as inputs to the context rules which are : *IF  $d1$  IS LOW THEN OBSTACLE AVOIDANCE. IF  $d2$  IS LOW THEN LEFT WALL FOLLOWING. IF  $d3$  IS LOW THEN RIGHT WALL FOLLOWING. IF  $d1$  IS HIGH AND  $d2$  IS HIGH AND  $d3$  IS HIGH THEN GOAL SEEKING.* These context rules determines which behaviour is fired and to what degree, then the final robot output is calculated using equation 2. The hierarchical architecture used in our system is shown in figure 2.

Table 1: The Fuzzy rule base of the right edge

RSF	RSB	LEFT VELOCITY	RIGHT VELOCITY
NEAR	NEAR	VERY LOW	HIGH
NEAR	MEDIUM	VERY LOW	HIGH
NEAR	FAR	VERY LOW	HIGH
MEDIUM	NEAR	HIGH	VERY LOW
MEDIUM	MEDIUM	MEDIUM	MEDIUM
MEDIUM	FAR	VERY LOW	HIGH
FAR	NEAR	VERY HIGH	VERY LOW
FAR	MEDIUM	VERY HIGH	VERY LOW
FAR	FAR	HIGH	MEDIUM

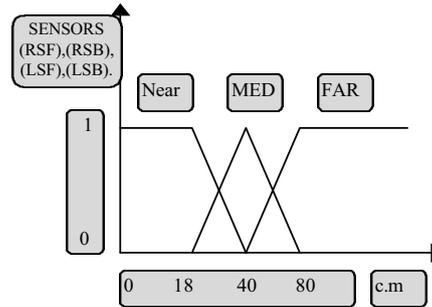


Figure 5: The MF of the side sensors

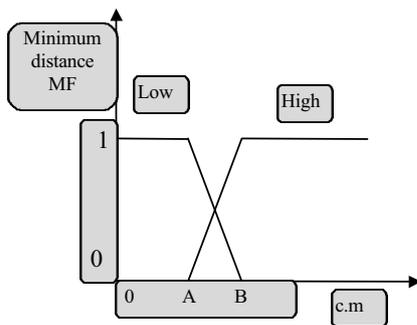


Figure 6: The MF of the minimum distances, for  $d1$   
 $A=40$  c.m.,  $B=100$  c.m. For  $d2, d3$   $A=40$  c.m.,  $B=80$  c.m.

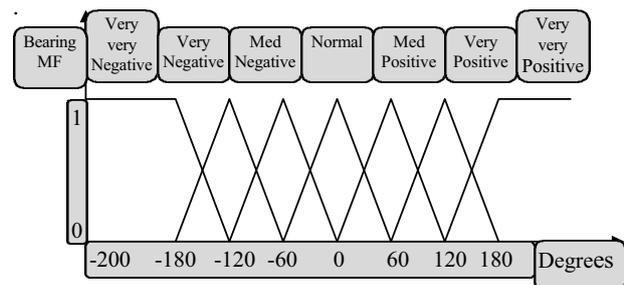
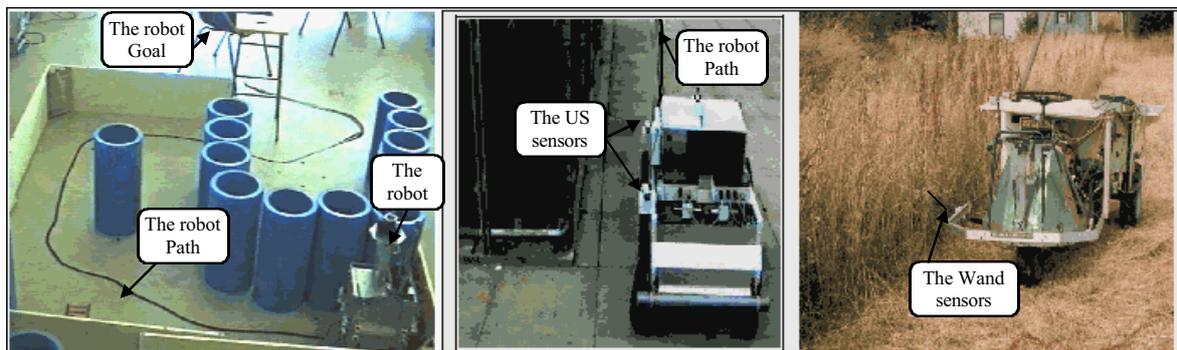


Figure 7: The goal seeking MF.



(a)

(b)

(c)

Figure 8: a) The indoor robot escapes a maze and achieves its goal. b) The electrical outdoor robot follows an irregular fence using its US sensors. c) The diesel outdoor robot follows a real crop edge with its wand sensors.

#### 4. Experimental Results

The performance of the architecture has been assessed in two main ways. Firstly we conducted practical experiments with the indoor robots to track the robot paths and reactions to the benchmark tasks (which are maze escaping, edge following and goal seeking), as well as trying the robot in mazes with irregular geometrical shapes as shown in figure 8-a. The same architecture was then transferred to the outdoor robots. We have used different outdoor sensors such as the mechanical wands and Ultra Sound (US) sensors which are especially designed to work in the outdoor environment. Figure 8-b shows the robot path of the electrical outdoor robot when tried in the university outdoor squares. In this experiment the robot had succeeded in following this irregular rectangular fence under different weather condition. In figure 8-c we tried the diesel robot with the mechanical wand sensors in a hay field which has irregular edge and corners. The robot had given stable, repeatable and robust response, and have tracked the crop edge successfully within a tolerance of 1 inch.

#### 5. Conclusion

In this paper we have introduced a new fuzzy hierarchical controller for mobile robots for application in agriculture. Its main advantages are that it provides a *simple design* procedure, good *real-time performance* and achieves *smooth behaviour transitions*.

In our experiments the indoor robot navigated successfully in tight corridors, avoided obstacles and escaped from mazes, dealt with all the irregular shapes that were presented to it. The robot demonstrated a robust and fast performance. The same control architecture was moved to the outdoor robots in which the robot gave a similar smooth and fast response and was able to track various crop edges under different environmental and ground conditions.

For the future work we will use our vision system to implement the object collection task in the real field which was implemented in the indoor robots. We are also investigating the integration of an on-line learning using genetic algorithms into the HFCLC in order to learn the fuzzy membership functions and the rule bases of the different behaviours and their co-ordination using real robots with no need for simulation, this system is aimed to adapt the robot under different conditions that the robot might encounter in the real field.

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