

USING FUZZY LOGIC FOR AUTONOMOUS NAVIGATION

Chris Kreucher, Michel Beauvais

Department of Electrical and Computer Engineering

University of Michigan – Dearborn, Dearborn, MI 48128-1491

ckreuche, michelab@umich.edu

ABSTRACT $\frac{3}{4}$ Successful navigation for unmanned autonomous vehicles (UAVs) depends on the ability of the navigation algorithm to fuse data from disparate sensor systems into a single direction command in real time, taking into account the various and sometimes contradictory goals of the UAV. In this paper, a fuzzy-based method of sensor data analysis, fusion, and navigation is investigated. The results of its implementation on the UAV *MOSFET*, an off-road testbed for testing on-road automotive navigation algorithms, are presented. Previous work in the field of intelligent navigation including obstacle detection, lane finding, and navigation is surveyed and compared to the current implementation.

Keywords $\frac{3}{4}$ Intelligent Transportation, Image Processing, Autonomous Navigation, Robotics.

I. INTRODUCTION

The Michigan Offroad Sensor Fusing Experimental Testbed (*MOSFET*) is an autonomous vehicle designed to navigate an unknown terrain which includes obstacles, lanes, and other traditional road-side obstructions.

In order to gather data about the world around it, *MOSFET* is equipped with several heterogeneous sensors. These sensors include one forward-looking camera used for obstacle detection and lane tracking, two side-looking cameras used for lane sensing, and a bank of 8 ultrasonic sensors used to detect physical obstacles (see Figure 1). Each of these sensors produces data that is most conveniently interpreted in a fuzzy framework.

The multiple sensor sets are necessary for two reasons: First, each of these three sets of sensors only provides information about a portion of the world around the vehicle. Second, each of the sensors is able to detect only some of the potential hazards in the scene. The fuzzy combination of these multiple modalities allows *MOSFET* to robustly find both lanes and obstacles in a large area around the vehicle.

This paper is organized as follows. In the following section, an overview of the autonomous navigation problem is given, followed by a summary of the solution provided by the proposed system. Section III provides a review of previous work in intelligent transportation using fuzzy logic techniques. Next, Section IV gives a complete

description of the sensors and algorithms that allow *MOSFET* to navigate autonomously. A detailed set of experimental results is given in Section V. Finally, section VI concludes with some relevant remarks.

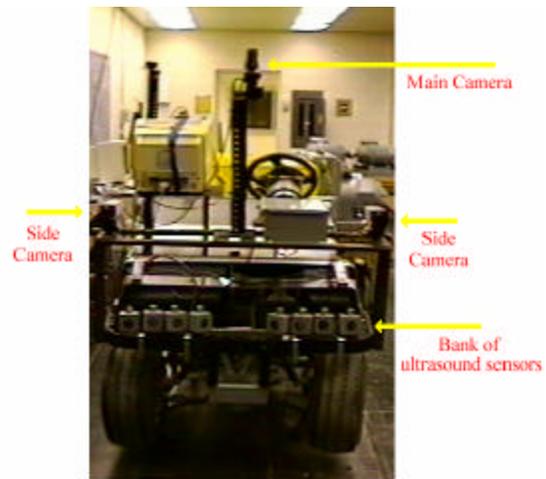


Figure 1: *MOSFET* and its Sensors

II. PROBLEM STATEMENT

In order to successfully develop an unmanned autonomous vehicle, it is necessary to design an algorithm able to take whatever information is known about the environment and fuse this into a set of data which can be used to navigate the vehicle.

There are several issues in the design of such an algorithm. First, it must be known what information will be available *a priori*, and what information will be available from the sensor systems. Second, the navigation criteria and goals must be defined.

In this paper, we consider the problem of outdoor autonomous navigation with no *a priori* knowledge about the particulars of the environment. The only knowledge of the terrain that will be assumed are those that exploit the existing infrastructure of the road: lane markings are typically yellow or white; obstacles are typically a different color from the background (e.g. red and orange traffic cones), or can be detected by their physical presence via ultrasonic sensors.

From this limited knowledge about the terrain, a set of navigation criteria can be developed, specifically that the

vehicle must avoid obstacles and follow lane markings simultaneously. Also, since the sensor data must be processed on line, the speed of the algorithm is important.

With the sensors employed here, it is clear that the problem at hand is particularly amenable to solution via fuzzy techniques:

- The side-looking cameras determine if lanes are “near” or “far” from the vehicle, and if they are oriented “towards” or “away from” the vehicle.
- The ultrasonic sensors can determine if obstacles are “near” or “far”, and an approximate direction.
- The main camera can determine which paths contain the most obstacles (lanes and physical obstacles) on a relative basis.

III. REVIEW OF RELATED WORK

There have been many investigations into autonomous navigation using fuzzy logic techniques. Ishikawa [1] presents an UAV designed to navigate a predefined path while simultaneously avoiding obstacles. Instead of the path being two lines as would be seen on a highway, it simply consists of one stripe that the vehicle follows (the vehicle is allowed to be on either side or on top of the line). A fuzzy controller is designed for each of the situations (path following and obstacle avoidance) and subsequently combined when both a path and an obstacle are present at once. Ishikawa’s system is different than *MOSFET* in that it follows a predefined, well-laid path instead of arbitrary paths on normal roadways. Furthermore, it uses a more limited set of sensors.

Another procedure for fuzzy lateral control is described by Blochl and Tsinas [2]. The goal of the work is similar to that set forth above and in [1], but the sensing equipment and logic decisions are different. First, instead of following a path, the test vehicle traverses a corridor. Using just a color CCD camera as a sensing device, Blochl and Tsinas are able to calculate the angular deviation (θ) from the wall. Subsequent processing allows them to generate $\Delta\theta$, the interframe difference in orientation (which gives knowledge of the rate of change of the angular deviation θ). In this scenario, ‘obstacles’ and ‘lanes’ are the same thing – the walls in the corridor.

Sng [3] presents a method of obstacle avoidance and wall following using two inputs and two outputs. The wall on the left is followed and obstacles in front of the vehicle are avoided. Sensors which determine the distance from the wall on the left to vehicle and the distance from an obstacle in front of the vehicle are used to generate two sets of input data. Using this data, commands are given to the two steering motors, one of which is on the left of the vehicle and one of which is on

the right. By giving different commands to the two motors, the vehicle is able to turn in a specified direction.

The fuzzy control for the platform MORIA is given in [4]. This platform differs from those mentioned above in two ways. First, it relies on ultrasonic sensors as inputs instead of cameras. Second, it is not interested in following a path or a wall, but only in avoiding collisions with physical obstacles that are identified with the sonar. MORIA’s control is based on a series of rules, that combine results of several homogenous sonar units.

Another system that relies on sonar as sensory input, called FLEXL, is examined in [5]. Once again, a set of rules are developed to provide the control of the vehicle. It is interesting, however, that the choice of variables is changed from some of the systems examined earlier even though the sensory equipment and the overall goals are identical. FLEXL uses distance to object (as was used in [2] and [3]), but augments this lone requirement with a consideration of velocity and a ‘collision corridor’. An obstacle detected by the sensor may or may not be in the vehicle’s collision corridor, which is determined by an analysis of the kinematics of the system. Essentially any obstacle that is not reachable by the vehicle in its present state is given significantly less weight because the chances of a collision are slim.

Garcia-Cerezo et al. [6] have designed a path following system (RAM-1) that attempts to follow a path made up of one lane. Two inputs are used, the distance from the center of the vehicle to the path and the orientation of the vehicle with respect to the lane. This second input is a subtle alteration of that used in [2], which calculates the orientation with respect to the direction of the lane in a less local sense. An additional feature of the paper is a consideration of the kinematics and dynamic constraints of the vehicle itself. The goal is to generate a steering angle to accomplish successful navigation.

Some other interesting applications of fuzzy in this include using a fuzzy supervisory system. The papers by Kachroo [7] and Ollero [8] describe fuzzy control systems that are integrated with other non-fuzzy controls, such as the PI and PID.

Yen and Pfluger [9] proposed a navigation algorithm which took advantage of heterogeneous sensor fusion using fuzzy techniques. In this navigation algorithm, all of the sonar sensors are fuzzified onto one set of disallowed directions. Next, the goal direction is fuzzified onto a set of all allowed directions. These fuzzy relations are then combined using the max operator, creating a fuzzy relation on the set of desired directions. The fuzzy navigation command is defuzzified using the centroid of largest area method, which is employed here as well.

The works surveyed here show that a robust control system can be implemented using fuzzy logic techniques. Furthermore, it is clear that a system that uses heterogeneous sensors to collect information about real world road situations and perform real-time control using fuzzy logic, such as *MOSFET*, is a novel extension of research previously done.

IV. SYSTEM DESCRIPTION

As mentioned previously, *MOSFET* employs three sets of sensors to analyze the surrounding area. All three of these sensors are processed independently to produce a fuzzy output, which represents the desirability or undesirability of all potential steering angles. Finally, the results of the three sets of sensors are fused and then defuzzified to produce a final steering decision.

A. Vision Sensors

MOSFET employs two sets of vision sensors: a main (forward-looking) camera that is used to detect obstacles whose color distinguishes them and lanes in front of the vehicle, and a set of side-looking (lane) cameras that find lanes near the vehicle.

1) Main Camera

MOSFET processes the main camera image using a novel color image segmentation algorithm [10] that is able to discriminate between backgrounds, lanes, and obstacles using color as is shown in the images below.

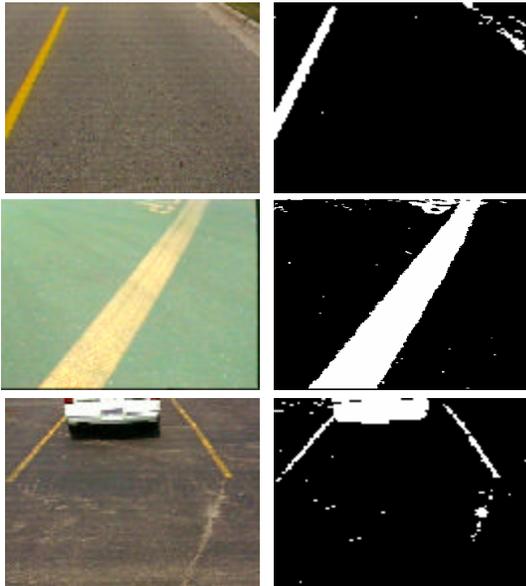


Figure 2: Examples of Main Camera Lane and Obstacle Detection.

Using the color segmented images and the standard inverse perspective transformation [10], a map of the

obstacles and lanes in front of the vehicle can be derived as shown below.



Figure 3: A Lane and Obstacle Map after Projection onto the Ground Plane.

The fuzzy set of prohibited directions is generated by an accumulation of the obstacle and lane pixels in front of the vehicle, weighted by the distance from the vehicle. The convention used here is that angles less than 90° are to the right of the vehicle, while angles greater than 90° are to the left of the vehicle. As is shown in Figure 4, there are two heavily prohibited directions for the images of Figure 3 – the obstacle and lanes to the left (approximately 100°) and the lane to the right (approximately 70°).

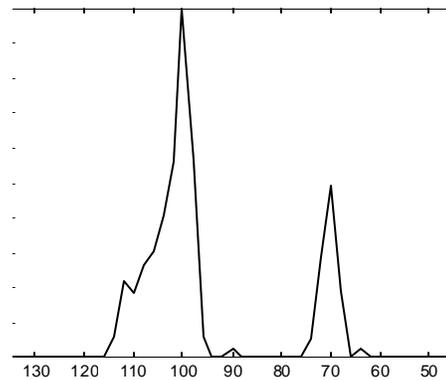


Figure 4: The relative 'obstacleness' of all angular paths from 45-135°.

2) Side-looking Cameras

MOSFET employs a modified version of the *STARLITE* [11] algorithm for side-looking camera lane detection. *STARLITE* utilizes a deformable template model to describe the shape of an ideal lane, and is able to robustly detect lane markings in presence of noise, shadowing, and occlusion. Shown in Figure 5 are a series of examples that demonstrate the efficacy of this lane finding procedure.

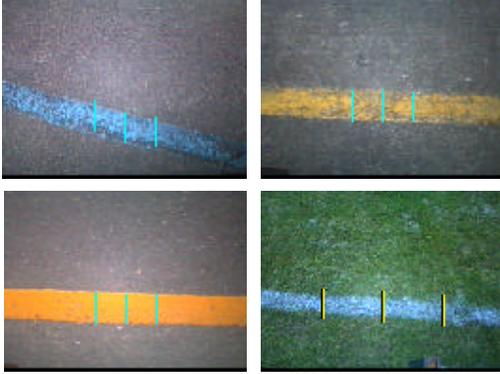


Figure 5: Lane finding using *STARLITE*. Lanes are found in three scanlines and are marked with a vertical bar to indicate their position

Use of *STARLITE* allows description of the lanes by two parameters – their distance from the vehicle (Dl and Dr , for the left and right lanes, respectively) and their orientation with respect to the vehicle (Ol and Or , for the left and right lanes, respectively). The distances, Dl and Dr , are in meters from the front center of the vehicle. A distance of approximately .7 meters indicates that the wheel is touching the lane. The orientations, Or and Ol , are positive for lanes oriented towards the right, and negative for lanes that are orientated towards the left.

The fuzzy steering command using the side-looking cameras is developed as follows. A set of fuzzy membership functions describe the proximity of the lane:

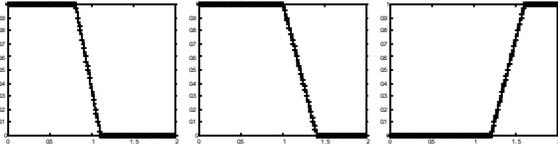


Figure 6: (Left to Right), The fuzzy membership functions for Very Near (VN), Near (N), and Far (F).

Similarly, a set of fuzzy membership functions are utilized to describe the orientation of the lane:

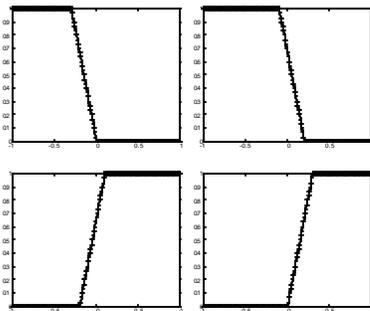


Figure 7: Membership Functions Very Negative (VN), Negative (N), Positive (P), and Very Positive (VP) orientations.

Finally, the output variable (steering angle) has the five fuzzy sets defined: Left (L), Right (R), Straight (S), Hard Left (HL) and Hard Right (HR).

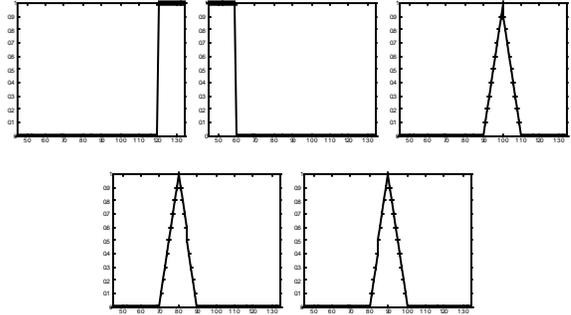


Figure 8: Membership functions for Hard Right, Hard Left, Right, Left, and Straight.

A set of fuzzy rules is used to perform the control actions required for the navigation. Fundamentally, the rules follow the following two premises:

1. The vehicle is to avoid being too near to the lane.
2. If the vehicle is a suitable distance from the lane, proceed straight.

Hence, the final list of 22 rules (11 for each lane) is:

```

R1: If (Dl= N) & (Ol= N/A) then (S= R)
R2: If (Dl=FAR) & (Ol= N/A) then (S= S)
R3: If (Dl= VN) & (Ol= *) then (S=HR)

R4: If (Dl=N) & (Ol= VNEG) then (S= S)
R5: If (Dl=N) & (Ol= NEG ) then (S= S)
R6: If (Dl=N) & (Ol= POS ) then (S= R)
R7: If (Dl=N) & (Ol= VPOS) then (S=HR)

R8: If (Dl=FAR) & (Ol= VNEG) then (S=L)
R9: If (Dl=FAR) & (Ol= NEG) then (S=S)
R10: If (Dl=FAR) & (Ol= POS) then (S=S)
R11: If (Dl=FAR) & (Ol= VPOS) then (S=R)

R13: If (Dr= N) & (Ol=N/A) then (S= L)
R13: If (Dr=FAR) & (Ol=N/A) then (S= S)
R14: If (Dr= VN) & (Ol= * ) then (S=HL)

R15: If (Dr=N) & (Ol= VNEG) then (S=HL)
R16: If (Dr=N) & (Ol= NEG ) then (S= L)
R17: If (Dr=N) & (Ol= POS ) then (S= L)
R18: If (Dr=N) & (Ol= VPOS) then (S= S)

R19: If (Dr=FAR) &(Ol= VNEG) then (S=L)
R20: If (Dr=FAR) &(Ol= NEG ) then (S=S)
R21: If (Dr=FAR) &(Ol= POS ) then (S=S)
R22: If (Dr=FAR) &(Ol= VPOS) then (S=R)

```

Figure 9: The rule base. Sometimes orientation data is unavailable (n/a) since the lane may be out of the cameras field of view or missed.

¹ In this case, any orientation will cause the reaction. Hence $Ol=*$ implies Ol can be anything.

The rule base may be more clearly illustrated by considering the following table.

| | VN | N | F |
|------|----|----|---|
| VNEG | HR | S | L |
| NEG | HR | S | S |
| POS | HR | R | S |
| VPOS | HR | HR | R |
| N/A | HR | R | S |

Table 1: Rules for the left lane. Labels across the top represent distance to the left lane (DI) and labels on the side represent lane orientations (OI). The rule base for the right lane is symmetric.

Use of these rules for both lanes generates a fuzzy set of *desired directions* from the lane camera sensor data.

B. Ultrasonic Sensors

The ultrasound sensors are then used to locate physical obstacles. Since the ultrasonic sensors return only the range of an object as information, the angular position of the obstacle is calculated using the trivial sonar model shown in Figure 10. In this model, the range information is used along with the known sonar detection cone to assume an obstacle's angular location as the center of the conic region swept out by the sonar.

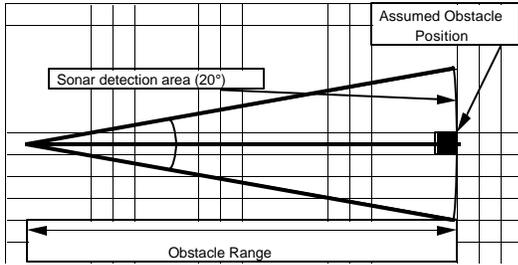


Figure 10: Trivial Sonar Model

The bank of 8 ultrasonic sensors is grouped into 4 groups of two. The sonar reading for each group is taken as the smallest valid measurement for the group. This has the benefit of reducing the number of fuzzy rules needed, with the cost of reducing the available information.

The set of *prohibited directions* is created by first fuzzifying the obstacle range reported by each of the 4 ultrasound sensor groups onto the set *prohibited directions* using only one fuzzy subset, NEAR, via the generic rule:

“If *sensor reading at x°* is NEAR, then *prohibited direction is y .*”

NEAR is defined on the universe of discourse of all possible detected obstacle ranges, from 0 meters to 10

meters. The membership function NEAR is defined as 1 for all distances less than 1.5 meters, and is linearly decreasing to zero at 2.5 meters (see Figure 11). The *prohibited direction* membership functions are wide enough so that the vehicle can avoid detected obstacles. Figure 11 shows membership values for an ultrasound sensor group one direction, which is typical.

Note that only four rules are necessary to obtain the fused obstacle information. The rules use max-min composition to produce the fuzzy output, which insures that close obstacles ‘override’ far obstacles.

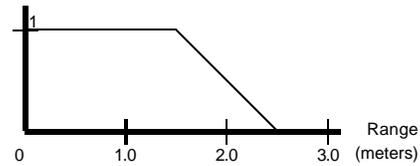


Figure 11: The near membership function

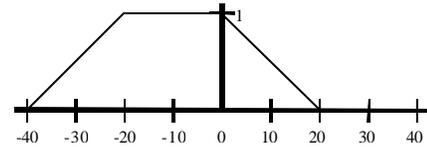


Figure 12: The prohibited directions for *around -10°*.

C. Sensor Fusion and Navigation

At this point, the algorithm fuses the *prohibited direction* sets generated by the main camera and ultrasonic sensors with the *desired direction* set from the lane cameras. This is done by taking *desired direction* and combining it with maximum of the *prohibited directions* to obtain the output *fused desired direction*. This is done using the fuzzy operation:

$$\mu_{\text{fused desired direction}} = \min[\mu_{\text{desired directions}}, 1 - \mu_{\text{prohibited directions}}] \quad (1)$$

where

$$\mu_{\text{prohibited directions}} = \max(\mu_{\text{main camera}}, \mu_{\text{ultrasonic sensors}}) \quad (2)$$

The final step is the defuzzification of *fused desired direction* into a crisp steering angle which can then be sent to the vehicle's steering controller. The manner of defuzzification chosen is the centroid of largest area (CLA) method [9].

The CLA method finds the set of angles in *fused desired direction* whose area is largest. A set of angles is determined by finding contiguous angles whose membership values are above a threshold. The threshold for this algorithm is determined dynamically, set at thirty

percent of the maximum value *actual direction*. Once the largest set of angles is determined, the algorithm finds the centroid of the area (see figure 8).

Using the CLA method has several advantages over the more commonly used center of area (COA) and mean of maximum (MOM) methods. In general, the CLA method tends to give a smoother response than the MOM method. In practical terms, this means that the steering angle oscillations with the CLA method will tend to be smaller than those with the MOM method.

The COA method gives a smooth response, but can cause the crisp steering angle output to be in an area where the value of *prohibited direction* is high. This can occur when *fused desired direction* is bimodal, which could mean that an obstacle is in front of the vehicle. Thus, the vehicle could potentially steer into an obstacle. The CLA avoids this pitfall by using only the largest area. For a bimodal distribution, the centroid of the largest mode would be found.

V. EXPERIMENTAL RESULTS

In this section, we present a complete result of the fuzzy navigation algorithm. First, the sensor data is acquired. Shown below are the original image obtained from the main camera, the distances and orientations of the left and right lanes found via the side cameras, and the 8 ultrasonic sensor returns. The ultrasonic sensors are identified by the direction in which they point.



$D_l = 1.2$ meters
 $D_r = 1$ meter
 $O_l = 0$ (straight)
 $O_r = 0$ (straight)

Figure 13: The Main Camera Data (left) and the Lane Camera Data (right)

| Sensor Direction | Dist. | Sensor Direction | Dist. |
|------------------|-------|------------------|-------|
| Left 1 | 0 | Right 1 | 0 |
| Left 2 | 0 | Right 2 | 0 |
| Center Left 1 | 3.8 m | Center Right 1 | 0 |
| Center Left 2 | 4.2 m | Center Right 2 | 0 |

Table 2: The Ultrasonic Sensor Data

First, the main camera image is processed in accordance with the algorithm outlined in section IV, resulting in the set of prohibited directions. The obstacle

on the left causes the large prohibition seen at approximately 105° , while the lanes on the right cause the prohibition seen at approximately 75° .

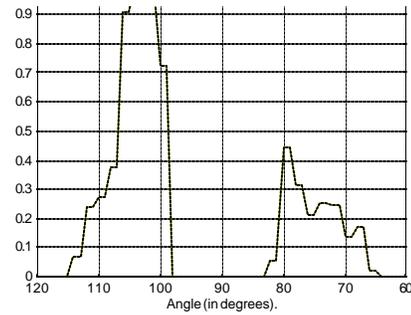


Figure 14: Main Camera Prohibited Angle Set.

Second, the ultrasonic sensor data is processed, resulting in the following set of prohibited angles. The two measurements recorded from the left-center ultrasonic sensors cause the prohibited angle set to heavily prohibit angles between 90° and 115° .

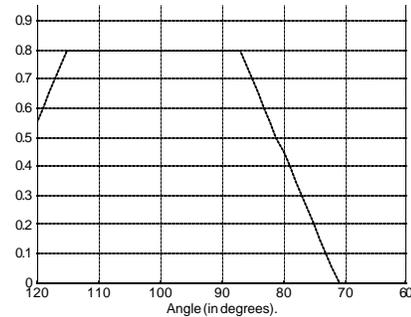


Figure 15: The Prohibited Angle Set Generated by the Ultrasonic Sensors.

Third, the lane camera data is processed, resulting in the following set of allowable angles. In this case, the left lane is further away than the right lane, so the desired steering direction from the lane cameras favors steering to the left.

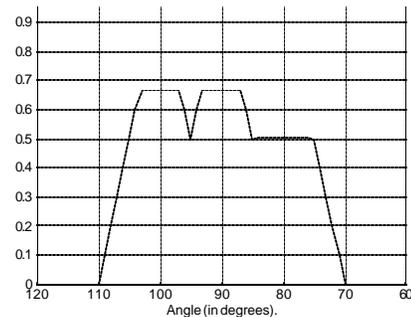


Figure 16: The Desirable Angle Set Generated by the Lane Cameras.

The three sets of sensor data are fused together to create one set of desired angles. In this case, there is conflicting information from the three sensors. The lane cameras indicate that steering left is more appropriate, as they can only image the lanes and not the obstacles. The main camera and ultrasonic sensors, however, record this obstacle and overcome the lane cameras left bias.

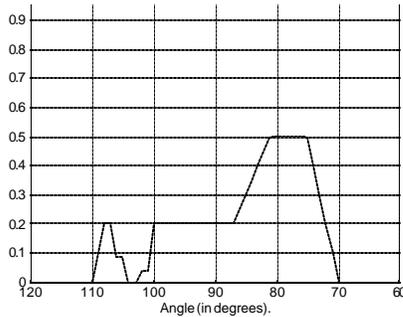


Figure 17: The Final Desirable Angle Set Found by Fusion of the 3 Sensor Suites.

Using the centroid of largest area method, the function in Figure 17 is defuzzified to a crisp steering angle of 84° , which represents a slight turn to the right. Clearly, the fusion of the three sensors provides more reliable steering information than any of the sensors alone. The fuzzy technique for sensor data analysis and fusion allows the disparate sensor modalities to be intelligently fused.

VI. CONCLUSIONS

The algorithm presented here shows how fuzzy logic can be applied to a problem involving intelligent transportation and image processing. It can robustly fuse heterogeneous sensor data to provide reliable navigation decisions.

The performance of the fuzzy algorithm is comparable to the performance of non-fuzzy algorithms implemented on the same vehicle, with the advantages of reduced computational complexity, and ease of modification that is inherent in with rule based systems.

VII. ACKNOWLEDGEMENTS

The authors are pleased to acknowledge the influence of the work of Dr. Sridhar Lakshmanan, Dr. Karl Kluge, and Mr. Randall DeFauw on this work.

References

[1] Ishikawa, S., "A Method of Autonomous Mobile Robot Navigation by using Fuzzy Control", *Advanced Robotics*, Vol 9, No 1, pp 29-52, 1995.

[2] Blochl, B. and Tsinas, L., "Automatic Road Following Using Fuzzy Control", *Control Engineering Practice*, Vol 2 No. 2, pp 305-311, 1994.

[3] Sng, H.L., "Fuzzy Logic Control of an Obstacle Avoidance Robot", *IEEE International Conference on Fuzzy Systems* Vol 1 pp 26-30, 1996.

[4] Surmann, H., Huser, J., and Peters, L., "A Fuzzy System for Indoor Mobile Robot Navigation", *IEEE International Conference on Fuzzy Systems* pp 84-88, 1995.

[5] Nijhuis, J., Neuber, S., Heller, J., Spohnemann, J. Evaluation of Fuzzy and Neural Vehicle Control, 1992.

[6] Garcia-Cerezo, A., Ollero, A., and Martinez, J.L., "Design of a robust high performance fuzzy path tracker for autonomous vehicles", *International Journal of Systems Science*, 1996, vol. 27, number 8, pp 799-806.

[7] Kachroo, P., Tomizuka, M., and Agogino, A., A "Comprehensive Strategy for Longitudinal Vehicle Control with Fuzzy Supervisory Expert System", *Proceedings of the IEEE International Conference on Systems, Man and Cybernetics* v 1 pp 765-770, 1995.

[8] Ollero, A., Garcia-Cerezo, A., Martinez, J.L., "Fuzzy Supervisory Path Tracking of Mobile Robots", *Control Engineering Practice* Vol.2 No. 2, pp 313-319, 1994.

[9] J. Yen and N. Pfluger. "A fuzzy logic based extension to Payton and Rosenblatt's command fusion method for mobile robot navigation." *IEEE Transactions on Systems, Man, and Cybernetics*, 25(6):971-978, 1995.

[10] M. Beauvais, C. Kreucher, and S. Lakshmanan. "Building World Models for Mobile Platforms Using Heterogeneous Sensor Fusion and Temporal Analysis." *Proceedings of the 1st IEEE Intelligent Transportation Systems Conference*, November, 1997.

[11] R. DeFauw, S. Lakshmanan, N. Narasimhamurthi, and M. Beauvais. "STARLITE: A Steering Autonomous Robot's Lane Investigation and Tracking Element." *Mobile Robots XI and Automated Vehicle Control Systems*, Proc. SPIE: 2903, 1996.