A Fuzzy Logic Hierarchical Intelligent Control System Paradigm for an In-Line-Of-Sight Leader-Following Robotic HMMWV

Paper submitted to the

Journal of Robotic Systems
Special Issue on
Neuro-Fuzzy Intelligent Robotic Systems

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March 5, 1999

Abstract

A hierarchical intelligent control system paradigm for a vision-based autonomous driving scheme is presented for a leader-lollowing HMMWV. The paper shows how fuzzy logic is employed to represent knowledge at the organizational level, resolve conflicting perceived information and plan the best path for the vehicle. After introducing the methodology, simulation and experimental aspects for realizing and testing the scheme are discussed.

Keywords : Artificial Intelligence, Fuzzy-Logic, Leader-Follower, Simulation, Unmanned Robotics.

1 Introduction

The US Army has been investigating the concept of a leader-follower (LF) robotic ground vehicle convoy for potential military applications. The idea is to have a lead vehicle (leader) followed by one or more autonomous or semi-autonomous robotic vehicles (followers) in a caravan over on-road and off-road environments. The leader vehicle is either manually driven or driven through tele-operation from a fixed base station on a mobile station located in one of the convoys. The follower vehicles use their onboard sensing, decision and actuation capabilities, without human intervention, to follow the path of the leader as they move through static and/or dynamic environments. The type of convoying vehicles may vary in (light to heavyweight) size and (wheel or track) traction specifications. Soldiers can employ the robotic capability of a follower vehicle to relieve fatigue drivers during long and nonstop journeys, reduce operator work load in times of busy engagement, reduce the crew size needed in a mission, and enhance driving safety.

The US Army Tank-Automotive Armaments Command (TACOM) in Warren, Michigan has conducted R&D studies in the concept of a LF convoy for the High Mobility Multipurpose Wheeled Vehicles (HMMWV's). Successful individual experiments of non-line-of-sight (NLOS) and in-line-of-sight (ILOS) leader-following convoy schemes have been demonstrated at a TACOM test track and recorded on video tapes. ILOS leader-following refers to vision-based path planning and autonomous driving with the leader vehicle in the view of the follower vehicle. NLOS leader-following can have a larger trailing distance where the leader vehicle may not be in the view of the follower. In this case, the planning and driving will be aided by GPS and time-delay techniques. This is explained in more detail in Section 2.2. Figure 1 shows an experiment in which an autonomous follower HMMWV trails a leader CUCV (Commercial Utility Cargo Vehicle).

Continuing effort is being carried out by TACOM and Oakland University to fuse the multiple strategies into robust and intelligent convoy schemes. The thrust in this L/F HMMWV effort is to investigate the essence of an 'expert' driver's knowledge for driving a follower vehicle to follow a leader vehicle on on-road and off-road routes. The objective is to develop an intelligent system that utilizes available NLOS and ILOS sensing/actuation hardware and knowledge base computers on-board both the leader and follower vehicles to perform the anthropomorphic task for convoying formation.

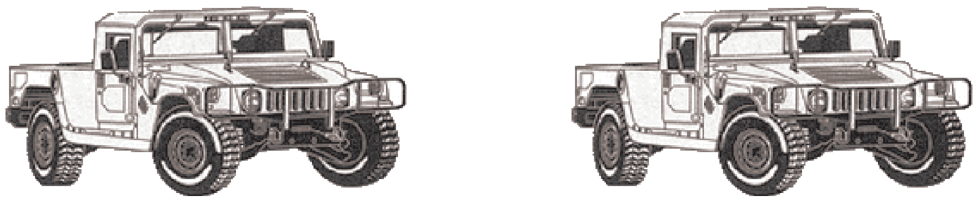
Figure 1: Autonomous follower HMMWV with a CUCV leader

Several systems for autonomous vision-based convoy driving have been developed. The system by Kehtarnavaz at.al [9] was tested over short distances (approximately a mile), over a limited variety of roads and a maximum speed of 33 km/h. The system developed by Schwarzinger et.al. [22] and Zielke et.al. [25] was tested with the follower vehicle driven manually. In one test, it was reported that during a 5-min drive on the autobahn, the pursued vehicle was correctly located 94.7% of the time in a total of 1594 images. The system by Kories et.al. [10] was only tested on video taped image sequences. The method developed by Dickmanns et.al. [3] and Dickmanns et.al. [4] was tested in a limited fashion whereby convoy driving was reported at speeds of approximately 5 m/s and over short distances and short durations (approximately 90s). In the broader context of visual target tracking, many methods have been developed and implemented (Aloimonos and Tsakiris [1], Dickmanns and Graffe [6] [5], Gennery [7], Lowe [11], Papanikolopoulos et.al. [13], Pomerleau [15] [16]). The ALVINN system for road following ([15] [16]) can be said to be the most succesful sustained visual tracking in outdoors environment.

In this paper, we will only present an **ILOS fuzzy logic vision based autonomous driving strategy** for a follower to trail a leader over roadways. The follower must drive safely as it pursues the leader by resolving conflicting vision information and control behaviour. We show how different types of fuzzy inference systems can be used to realize a hierarchical intelligent control paradigm that imitates, in some sense, the way a person would drive a follower vehicle.

The meaning of “Intelligence” in this paper will be interpreted in the sense of a fixed descriptive knowledge base. Intelligent Control (IC) in its simplest form can be viewed as a knowledge processing scheme: The inputs consist of data and goals, while the output consists of some control action [23]. IC also uses human/animal/biologically motivated techniques and procedures (representation and/or decision making) to develop and implement a controller for a system [14]. The ILOS LF scheme in this paper employs the hierarchical intelligent control system paradigm of [12] [18] with the help of fuzzy logic.

The task of Leader-Following is posed imprecisely, the number of functions to be performed by



<u>Equipment Onboard **Follower**</u>
VX-Works Computer System
Global Positioning System
Inertial Measurement Unit
Telemetry Tx/Rx
IR Receiver
Computer Vision
Night Vision
Laser Radar, Sonars
Robotized Driving Mechanisms

<u>Equipment Onboard **Leader**</u>
VX-Works Computer System
Global Positioning System
Inertial Measurement Unit
Telemetry Tx/Rx
Beacons/IR Tx
Night Vision
Laser Radar, Sonars
Head-Up Display

Figure 2: Equipment onboard the leader and follower HMMWV

the controller is often incomplete, and the situations of the operation are given in an approximate way. Control engineering started in the belief that control process design is a trade-off with the parameters of the system. Later it became clear, that a trade-off with the model as well as the structure of the system is needed for control design. At this time when the negotiation of imprecise tasks, functions and situations has become a part of the design, it becomes clear that the trade-off must also include the process of task formulation. The above factors lead to the hierarchical structure of an intelligent control paradigm where the controller is to emerge from understanding of 1) control methodologies, 2) imprecise and incomplete system models, 3) incomplete knowledge of the environment and 4) task negotiation as a part of control system as well as control process.
The hierarchical intelligent contol system paradigm helps to classify tasks, structure knowledge, and attack the problem appropriately at the different levels.

2 System Hardware and Overall Convoy objective

To analyze, design and engineer the leader-follower system, it is advantageous to consider the system engineering requirements from a top down approach. An understanding of the scope, applicable engineering principles, hardware specifications, simulation, rapid prototyping, systems integration, testing, personnel resourse, scheduling and most importantly available funding for the project is crucial. Hence, an overview of the system hardware and overall objective for the project is described in this section.

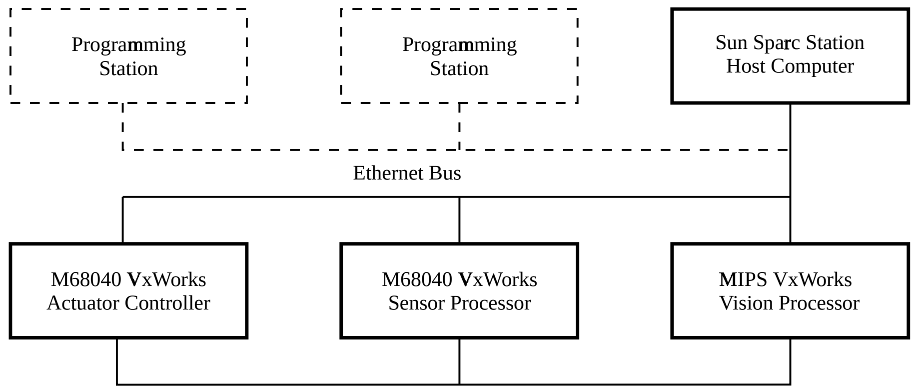


Figure 3: Network of real-time control computer hardware for leader and follower HMMWV's

2.1 System Hardware Configuration

Figure 2 lists the main equipment onboard the follower and leader HMMWV's that have been installed for conducting LF convoying operations. Note that different sets of hardware can be selected and integrated through software to perform either ILOS or NLOS or combined ILOS/NLOS LF experiments. Most of the equipment was installed and configured by RedZone Robotics, Inc [17].

Figure 3 shows the computer hardware for the communication network and real-time controller capabilities on-board the follower and the leader HMMWV. A Sun SparcStation is the host computer that serves the subsystems over the Ethernet; it has a C-compiler and libraries for programming the subsystems and implementing the L/F schemes. The MIPS and the two M68040 boards are VxWorks-based processors for performing L/F schemes in real time. The MIPS processes the digitized images received from the video camera/board; the first M68040 handles inputs from the multi-sensors, while the second M68040 controls the throttle, brake and steering actuators. Users can develop programs from the Sun workstation and other remote programming stations.

2.2 Overall LF Objectives

The robotic LF HMMWV convoy concept developed at TACOM is implemented in a two-vehicle scenario. The leader vehicle is manually driven, whereas the follower vehicle is computer driven to autonomously trail the leader. The approach taken to realize this effort is a hybrid integration of three sensing methods: 1) The common global reference frame, 2) a local reference frame and 3) direct sensing of leader vehicle motion. The common global reference frame is achieved by using a NavStar GPS system, developed and deployed by the DoD. The local reference frame is achieved by using vision systems developed for road following. The vehicles motions are sensed by utilizing dead-reckoning and inertial measurements. The idea of the hybrid system provides for very graceful failure modes. If any one of the sensing techniques does not function due to actual failure or unfavorable environmental conditions, the other two in combination are sufficient to continue the convoying. The strategy for convoying therefore is a combination of in-line-of-sight and non-line-of-sight leader-following schemes.

Close convoying reduces the probability of other traffic/persons getting in between convoy vehicles. When convoying at close distance, the ILOS-following scheme will be applied. Vision sensing is used to map the position of the lead vehicle in the local reference frame of the follower vehicle. Both environmental and leader information together with the information of the vehicle motion sensors, will provide a closed solution for the path planning algorithm. *Single*-objective convoying where only the leader vehicle has to be followed, was conducted earlier by Schneiderman, et. al. [21], [20].

In military operation, non-close-following vehicles (± 100 yards spacing) address the tactical requirements for providing sufficient spacing between vehicles to insure that an air-attack does not make it easy to hit multiple targets. Also, if dangerous loads are involved, hitting one vehicle does not necessarily mean a chain reaction of explosions. NLOS leader-following applies in this situation. When convoying at larger distances, the common global reference frame is applied for positioning. A path is recorded by the lead vehicle and transmitted to the following vehicle. The following vehicles use their global and local positioning sensors to track the path and drive safely through the environment.

At the present time, the three (global reference, local reference and direct sensing) schemes have been seperately tested and proven feasible as individual stand-alone systems. The ultimate objetive is to combine these schemes using a dominance mechanism that decides the run-time role of each scheme for executing combined ILOS and NLOS LF scheme.

3 Problem Description (Scope of the Paper)

The scope of this paper is concerned only with the design, simulation and experiments of a fuzzy logic vision-based autonomous ILOS LF driving scheme. The proposed scheme is built on the paradigm of a Hierarchical Intelligent Control System (HICS) as shown in Figure 4. The idea is to develop an intelligent autonomous vision-based robotic follower for trailing the leader vehicle at a safe separation distance, stay on the road and avoid obstacles, simultaneously. For the objective of the Leader-Following scheme in this paper, the goal of the follower vehicle is to stay on the road and avoid cutting corners or curves in the process of following the leader. The goal also calls for the scheme to be robust in that the leader vehicle may momentarily be outside the view of, or becomes unrecognizable by the follower, as it follows the road.

The essential equipment onboard the follower HMMWV for this ILOS LF objective is a computer vision system and robotized driving mechanisms for the steering wheel, throttle pedal, brake pedal and gear shift, controlled by a UNIX computer with VXWorks-based parallel processors. The camera on the follower is used to view the leader and the lane markers/edges of the road. Note that other sensors will not be used for this particular ILOS LF operations.

The scope of this paper focuses on the theoretical and practical aspects of designing a fuzzy logic based hierarchical intelligent control strategy for performing the task of autonomous ILOS LF driving. The following issues will be addressed:

1) Vision (Feature extraction from processed computer images)

2) Perception (Perceived leader maneuvers and road information)

3) Planning (Fusion of perceived visual cues for path planning)

4) Actuation (Driving skills for performing LF tasks)

5) Computer Study (simulation and visualization)

6) Experiments (Actual experimental testing)

4 Hierarchical Intelligent Control Structure

A Hierarchical Intelligent Control System (HICS) Paradigm has been formulated as a multi-level hierarchical structure obeying the Principle of Increasing Precision with Decreasing Intelligence [12], [18]. In these papers, probabilistic models were used to express the uncertainty of reasoning, planning decision making at the organizational level, the assignment of tasks at the coordination level, and the control activities at the execution level. Entropies were used as measures of the execution of various commands by the Intelligent Machine and for the optimal decision making. In what follows, we adopt the philosophy of this paradigm in the LF-based ILOS scheme using fuzzy logic.

4.1 Hierarchical Intelligent Control System Paradigm

The HICS paradigm for a general autonomous mobile robot is shown in Figure 4. Figure 5 shows the more specific adoption of this paradigm for the vision-based ILOS LF scheme. The hierarchical structure for the scheme can be divided into the following levels.

Organizational level . This highest level in the hierarchy deals with the knowledge base for intelligent decisions. In the ILOS LF scheme, the knowledge is represented by fuzzy logic rule base (linguistic logic statements) and data base (membership functions) for road following and lead vehicle tracking. The knowledge base also contains the dominance rules for fusing various information, defusing conflicts and optimizing decisions.

Coordinational level . This level deals with run-time perception and planning decision. For the present purpose, the perception involves feature extraction of road, lane and obstacle models, and leader position and motion, and determination of confidence levels or uncertainties in these perceptive information. The planning stage evaluates the perceived information and plans the

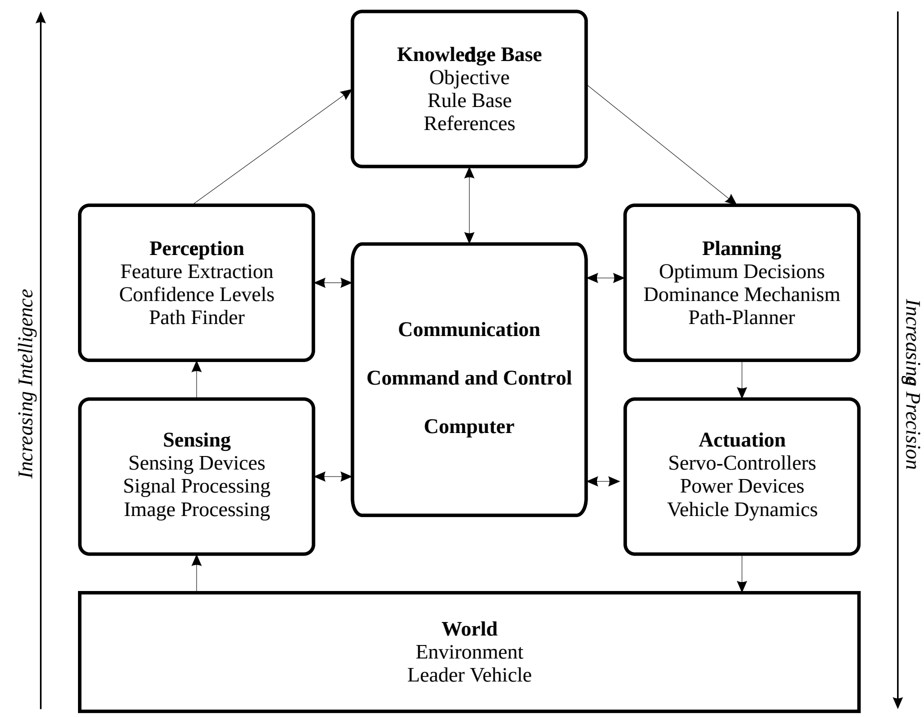


Figure 4: A Hierarchical Intelligent Control System (HICS) ([12] and [18]) for Leader-following.

best path for the follower vehicle, based on the interpretation of the knowledge base defined in the organizational level.

Execution level . The lowest level in the hierarchy executes numerically precise functions for the sensors and controllers. In the present case, the vision system acquires information on road edges and obstacles, and the position of the leader vehicle inputs. The controller drives the vehicle according to the path that was planned by the organizational and coordinational level.

These three basic hierarchical levels for the HICS paradigm are to be implemented using the real-time computers outlined in Section 2.1. More specifically, the knowledge base (see Figure 4) for the ILOS LF scheme (see Figure 5) consists of:

1. Pathfinder Logic for three types of driving behaviours or skills, namely, Leader Position Pathfinder, Right Edge Pathfinder and Left Edge Pathfinder,

2. Confidence Logic for evaluating reliability of perceived computer vision information,

3. Dominance Logic for resolving conflicts in driving behaviours,

4. Driving Logic for handling vehicle speed and steering dynamics.

It turns out that various methods of fuzzy inference mechanisms can be appropriately employed: The Pathfinder and Confidence Logic, for example, utilizes a Mamdani-style inference technique, the Dominance Logic employs Sugeno-style inference and the Driving Logic uses a ANFIS mechanism.

5 Vision based Autonomous Follower Driving Scheme

Figure 5 shows the hierarchical control structure for implementing the fuzzy logic vision-based autonomous driving scheme for the follower HMMWV. At this implementation schematic level, the structure can be sectioned into the following subsystems: Computer Vision, Perception (Perceived Visual Cues / Pathfinder / Reconnoiterer), Planning (Fused Visual Information / Navigator), Actuation (Controller) and Vehicle Dynamics.

5.1 Computer Vision System

The computer vision onboard the follower provides vital information of the lane markers and leader position/motion for the ILOS LF scheme. The vision pattern recognition processes the digitized images and computes the following information:

- *Identified dimension and RGB color composition of the leader vehicle.*
- *Trailing distances and heading angle between the leader and follower; and*
- *Lane marker model for representing the offset, heading and curvature of the right and left road edges.*

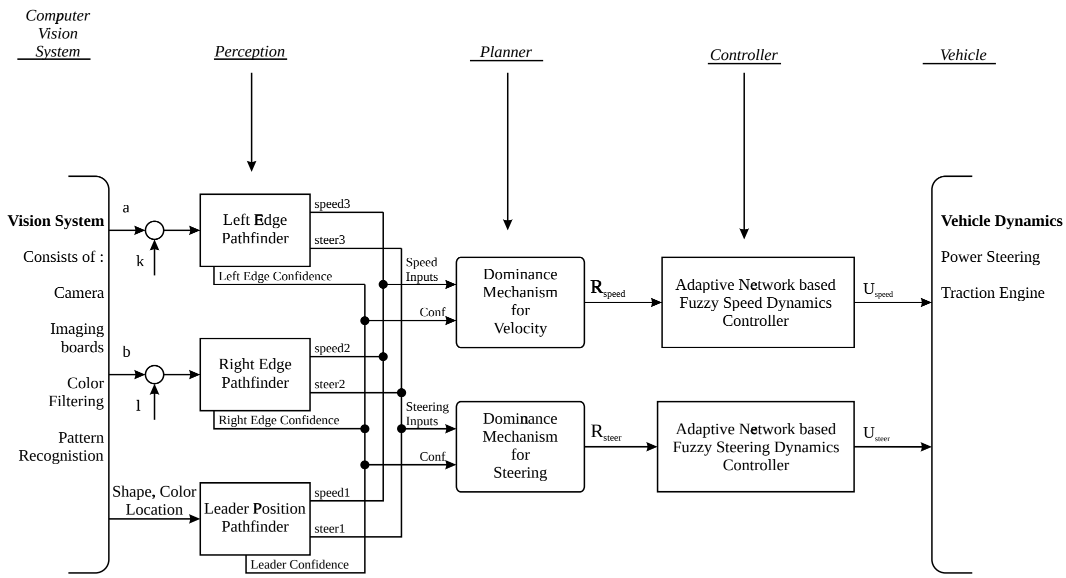


Figure 5: Vision-based hierarchical intelligent control strategy for ILOS LF HMMWV.

5.1.1 Acquisition of leader Position and Motion

Refering to Figures 6 and 7, X_L and X_F denote the lateral positions, and Y_L and Y_F the longitudinal positions of leader and follower HMMWVs, respectively. The relative displacements E_x and E_y between the two vehicles produces the separation or trailing distance R. Similarly, θ_L and θ_F denote the heading positions of leader and follower, respectively, and ϕ denotes the heading difference between the two. R and ϕ are used to define the relative position of the leader with respect to the follower. This information is extracted from the camera view, shown in Figure 11. The distance R is deduced from the size of the rectangular rear gate of the leader vehicle, and the angle ϕ from the lateral displacement of the leader in the image. At the same time, fuzzy logic is used to compute the confidence or reliability level in the visual acquisition and recognition of the leader based on the identified dimensions and color of the leader vehicle from the visual information.

5.1.2 Acquitsition of Road and Obstacle Information

Lane/Edge Marker Model. The vision system detects the edges or lane markers of a road using the so-called lane marker model. The image processing and detection algorithms for the model are described in detail in reference [19]. From the processed images of road scenes, the right edge of the road can be approximated by a lane marker model as a polynomial function $x_R = a_0 + a_1 y + a_2 y^2$, where x and y are lateral and longitudinal coordinates in the camera view. (see Figure 11). The parameters, a_0, a_1 and a_2 are estimates of offset, heading and curvature of the road. A sample of the

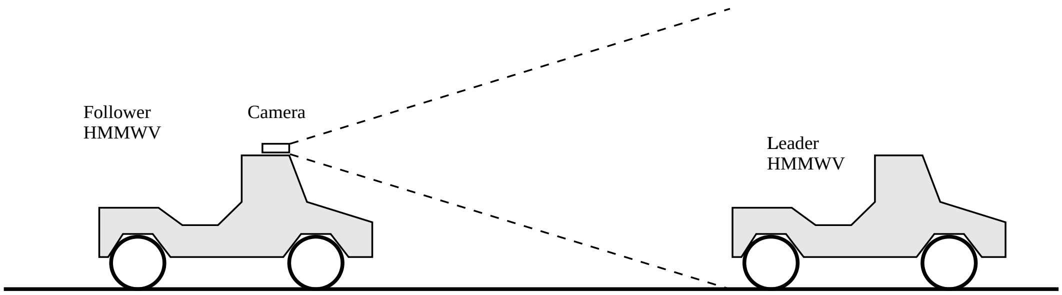


Figure 6: In-Line-Of-Sight (ILOS) leader/follower concept.

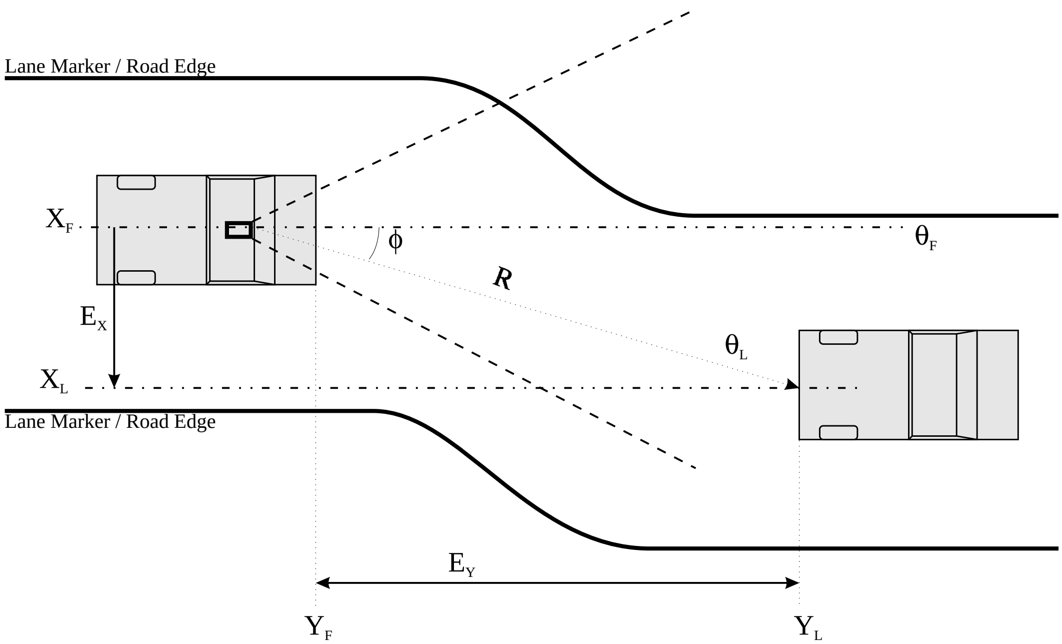


Figure 7: Top view of leader-follower formation.

lanes that can be represent by the marker model is shown in Figure 8, where a_0, a_1 and a_2 take on the values from a combination of the sets $a_0 = \{-1, 0, 1\}$, $a_1 = \{-1, 0, 1\}$ and $a_2 = \{-1, 0, 1\}$.

Similarly, the left edge of the road can be approximated by lane marker model $x_L = b_0 + b_1 y + b_2 y^2$. To utilize the marker model parameters in steering logic, we define the right and left edges of **straight roadways** as $x_{RS} = k_0 + k_1 y + k_2 y^2$ and $x_{LS} = l_0 + l_1 y + l_2 y^2$. The straight roadway models represent the neutral reference direction for steering the vehicle. The *error lane marker models* can then be defined as

$$x_R - x_{RS} = (a_0 - k_0) + (a_1 - k_1)y + (a_2 - k_2)y^2 \tag{1}$$

$$x_L - x_{LS} = (b_0 - l_0) + (b_1 - l_1)y + (b_2 - l_2)y^2 \tag{2}$$

It turns out that these error offsets, heading and curvatures can be used to differentiate curve or cross road edges from simple straightways. Steering commands can be based on the errors in coefficients $(a_i - k_i)$ and $(b_i - l_i)$ with i = 0, 1, and 2.

Obstacle Models. Using appropriate image processing techniques, an obstacle on a road can be picked up as part of the edge of the road, and hence detected as sharp changes in heading and curvature in the error lane marker model. These changes can be flagged as potential obstacles being detected. Differentiation of simple road edges from obstacles can be analysed by using fuzzy logic decisions.

5.2 Perception - Perceived Visual Cues Hierarchy

5.2.1 Rule Base for Direct Tracking of Leader Vehicle (Leader logic)

Driving commands for the follower to directly track the leader are based on the trailing distance R and direction ϕ. The Mamdani-style fuzzy logic rule base for tracking the leader vehicle is as follows (**Leader** logic).

```
1. If (distance is close) and (direction is left) then (steer3 is left)(speed3 is slow) (1)
2. If (distance is close) and (direction is straight) then (steer3 is straight)(speed3 is slow) (1)
3. If (distance is close) and (direction is right) then (steer3 is right)(speed3 is slow) (1)
4. If (distance is ok) and (direction is left) then (steer3 is left)(speed3 is normal) (1)
5. If (distance is ok) and (direction is straight) then (steer3 is straight)(speed3 is normal) (1)
6. If (distance is ok) and (direction is right) then (steer3 is right)(speed3 is normal) (1)
7. If (distance is far) and (direction is left) then (steer3 is left)(speed3 is normal) (1)
8. If (distance is far) and (direction is straight) then (steer3 is straight)(speed3 is fast) (1)
9. If (distance is far) and (direction is right) then (steer3 is right)(speed3 is normal) (1)
```

5.2.2 Rule Base for Confidence in Acquired Leader Position (Confidence logic 1)

Two tests can be performed on the image from the camera, to check the confidence of the aquired leader position. The image processing algorithm locates a rectangle which represents the marker on the back of the leader vehicle. See Figure 11. The two features extracted are the geometry width/height (W/H) ratio and color (R,G,B) of the rectangle. The first indicator for geometry

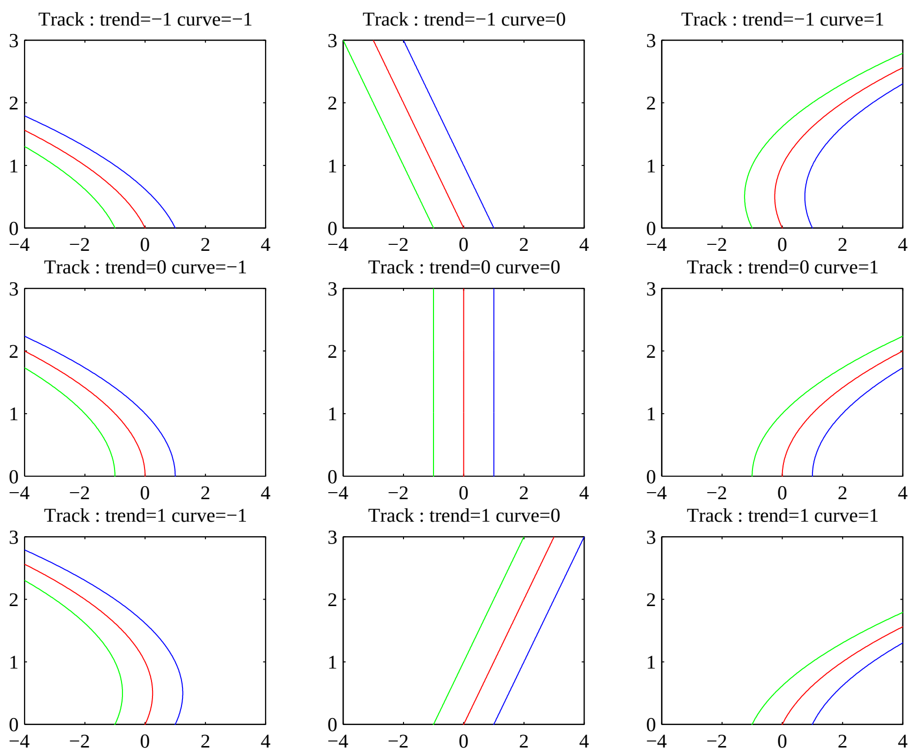


Figure 8: Samples of lane marker polynomial model $x_R = a_0 + a_1 y + a_2 y^2$ with $a_0 = \{-1, 0, 1\}$, $a_1 = \{-1, 0, 1\}$ and $a_2 = \{-1, 0, 1\}$.

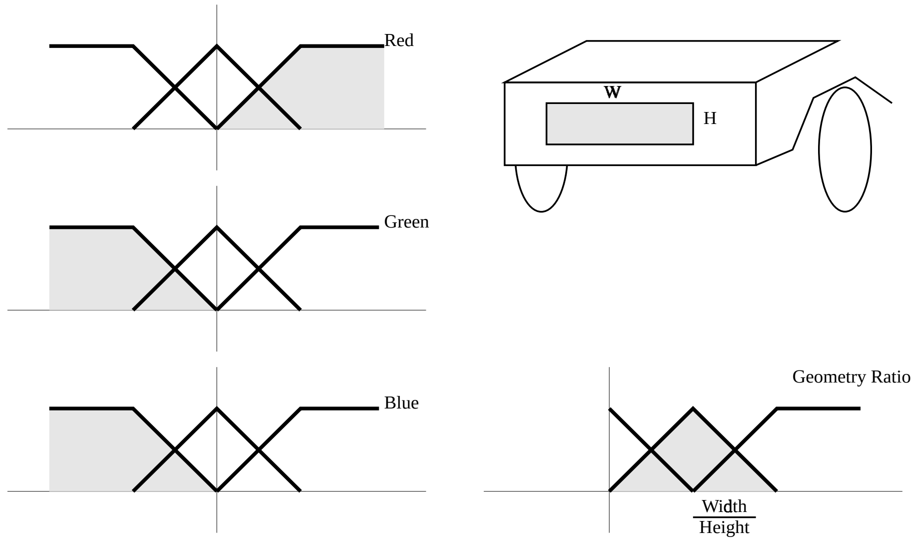


Figure 9: Fuzzy membership functions for confidence factors for the leader vehicle

confidence `cgeometry` is a simple fuzzy logic conclusion based on the membership function of W/H, as illustrated in Figure 9.

The second indicator `ccolor` is a fuzzy logic that checks the composition of the RGB-components of the rectangle. Since a red rectangular beacon is used, the desired memberships are as shown in Figure 9; high values for red, and low values for green and blue. The identified dimensions and color of the leader vehicle from visual information therefore yields a set of fuzzy confidence factors for the visual aquisition and recognition of the leader.The identified dimensions and color of the leader vehicle from visual information therefore yields a set of fuzzy confidence factors for the visual aquisition and recognition of the leader. The combined fuzzy confidence factor in acquisition or recognition of the leader vehicle can be computed as

$$\texttt{cdirect} = \texttt{ccolor} \wedge \texttt{cgeometry} \tag{3}$$

5.2.3 Rule Base for Confidence in Acquired Lane Model (Behaviourist logic 2 and 3)

Driving commands for road following are based on the error lane marker models. The applied Mamdani-style fuzzy logic rule base for following the right edge of the road is shown below (**RMarker** logic).

```
1. If (a0-k0 is neg) and (a1-k1 is neg) and (a2-k2 is neg) then (steer2 is left)(speed2 is slow) (1)
2. If (a0-k0 is neg) and (a1-k1 is neg) and (a2-k2 is small) then (steer2 is left)(speed2 is slow) (1)
3. If (a0-k0 is neg) and (a1-k1 is neg) and (a2-k2 is pos) then (steer2 is left)(speed2 is normal) (1)
4. If (a0-k0 is neg) and (a1-k1 is small) and (a2-k2 is neg) then (steer2 is left)(speed2 is normal) (1)
```

```
 5. If (a0-k0 is neg) and (a1-k1 is small) and (a2-k2 is small) then (steer2 is left)(speed2 is normal) (1)
 6. If (a0-k0 is neg) and (a1-k1 is small) and (a2-k2 is pos) then (steer2 is right)(speed2 is normal) (1)
 7. If (a0-k0 is neg) and (a1-k1 is pos) and (a2-k2 is neg) then (steer2 is left)(speed2 is normal) (1)
 8. If (a0-k0 is neg) and (a1-k1 is pos) and (a2-k2 is small) then (steer2 is right)(speed2 is normal) (1)
 9. If (a0-k0 is neg) and (a1-k1 is pos) and (a2-k2 is pos) then (steer2 is right)(speed2 is slow) (1)
10. If (a0-k0 is small) and (a1-k1 is neg) and (a2-k2 is neg) then (steer2 is left)(speed2 is slow) (1)
11. If (a0-k0 is small) and (a1-k1 is neg) and (a2-k2 is small) then (steer2 is left)(speed2 is normal) (1)
12. If (a0-k0 is small) and (a1-k1 is neg) and (a2-k2 is pos) then (steer2 is straight)(speed2 is normal) (1)
13. If (a0-k0 is small) and (a1-k1 is small) and (a2-k2 is neg) then (steer2 is left)(speed2 is normal) (1)
14. If (a0-k0 is small) and (a1-k1 is small) and (a2-k2 is small)then(steer2 is straight)(speed2 is fast) (1)
15. If (a0-k0 is small) and (a1-k1 is small) and (a2-k2 is pos) then (steer2 is right)(speed2 is normal) (1)
16. If (a0-k0 is small) and (a1-k1 is pos) and (a2-k2 is neg) then (steer2 is straight)(speed2 is normal) (1)
17. If (a0-k0 is small) and (a1-k1 is pos) and (a2-k2 is small) then (steer2 is right)(speed2 is normal) (1)
18. If (a0-k0 is small) and (a1-k1 is pos) and (a2-k2 is pos) then (steer2 is right)(speed2 is slow) (1)
19. If (a0-k0 is pos) and (a1-k1 is neg) and (a2-k2 is neg) then (steer2 is left)(speed2 is slow) (1)
20. If (a0-k0 is pos) and (a1-k1 is neg) and (a2-k2 is small) then (steer2 is left)(speed2 is normal) (1)
21. If (a0-k0 is pos) and (a1-k1 is neg) and (a2-k2 is pos) then (steer2 is right)(speed2 is normal) (1)
22. If (a0-k0 is pos) and (a1-k1 is small) and (a2-k2 is neg) then (steer2 is left)(speed2 is normal) (1)
23. If (a0-k0 is pos) and (a1-k1 is small) and (a2-k2 is small) then (steer2 is right)(speed2 is normal) (1)
24. If (a0-k0 is pos) and (a1-k1 is small) and (a2-k2 is pos) then (steer2 is right)(speed2 is normal) (1)
25. If (a0-k0 is pos) and (a1-k1 is pos) and (a2-k2 is neg) then (steer2 is right)(speed2 is normal) (1)
26. If (a0-k0 is pos) and (a1-k1 is pos) and (a2-k2 is small) then (steer2 is right)(speed2 is slow) (1)
27. If (a0-k0 is pos) and (a1-k1 is pos) and (a2-k2 is pos) then (steer2 is right)(speed2 is slow) (1)
```

Similar rules are used for issuing commands to follow the left road edge (**LMarker** logic).

5.2.4 Rule Base for Confidence in Acquired Lane Model (Confidence logic 2 and 3)

One of the properties of the Lane Marker model is that the coefficients of the edge polynomials take on small values even for the sharpest turns on a normal roadway under normal driving condition. Hence, the coefficients take on numerical values in a small region around 0. If there is no good fit for the edge polynomials, coefficients will be outside this region. A fuzzy logic for confidence level, `cleft` and `cright`, in aquisition and recognition of the left and right roadedges was setup based on the idea depicted in Figure 10.

5.3 Planning - Resolved Path from Dominant Visual Cues

Thus far, we have three sets of behaviourist fuzzy logic rules for driving the follower vehicle based on visual cues; they are the Leader, RMarker LMarker logic described in Section 5.2. In addition we also associated fuzzy confidence factors with each of these behaviourist rules, namely `cdirect`, `cright` and `cleft` confidence. From these inputs, the planning hierarchy has to generate the overall command signals for the vehicle speed and steering. The command signals, denoted by R_{speed} and R_{steer}, will be determined as outputs of Sugeno-style fuzzy inference system.

5.3.1 Rule Base for Dominance Mechanism

Dominance Mechanism for Steering. The Sugeno-style fuzzy logic rule base for generating the overall R_{steer} is shown below. The objective is to use the different informations *wisely* to achieve

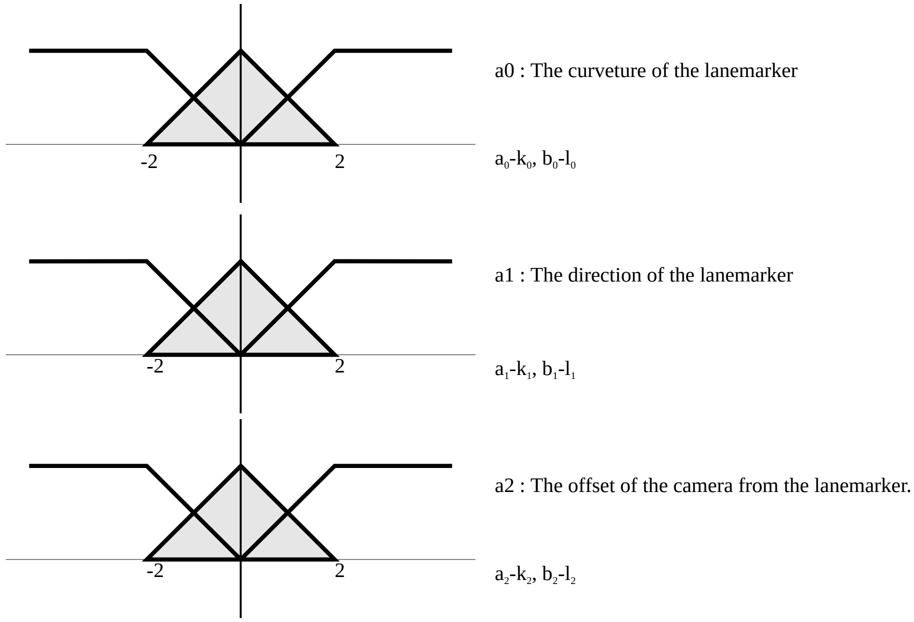


Figure 10: Fuzzy membership functions for confidence factors for roadedges

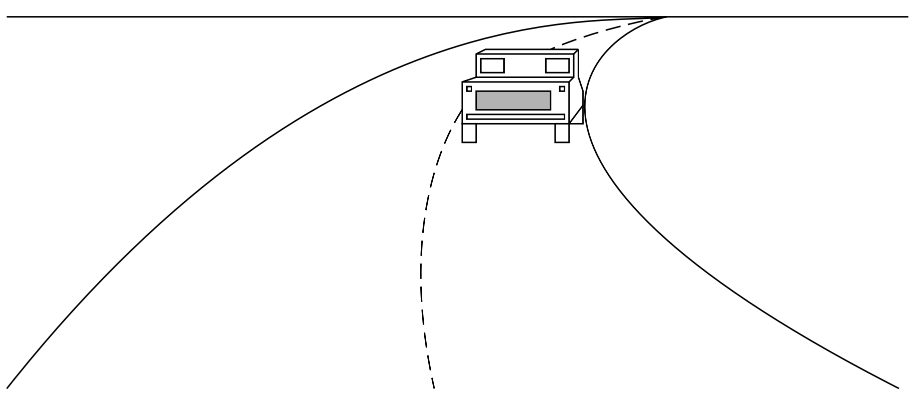


Figure 11: View of the leader vehicle, from follower's perspective.

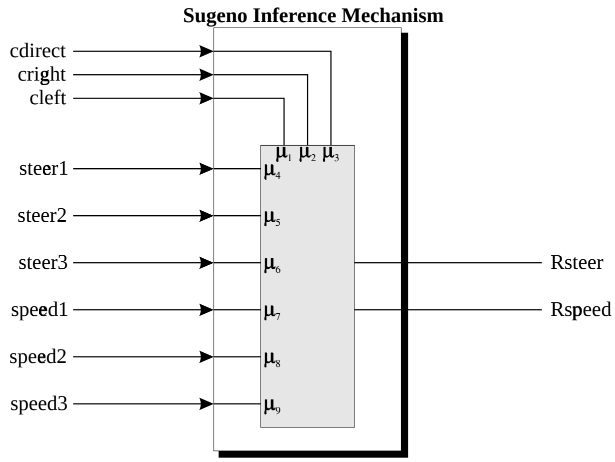


Figure 12: Sugeno style inferencing mechanism with inputs and outputs as used in this model.

the ILOS LF objective as was explained in Section 3. The word *wisely* refers to the knowledge that is conserved in the following dominance rule-base. The dominance mechanism will try to keep up with the lead vehicle but stay within its lane.

```
 1. If (cleft is good) and (cright is good) then (Rsteer is lmarker and rmarker) (1)
 2. If (cleft is good) and (cright is bad) and (cdirect is bad) then (Rsteer is lmarker) (1)
 3. If (cleft is good) and (cright is bad) and (cdirect is good) and (steer1 is left) and (steer2 is left) then (Rsteer is lmarker) (1)
 4. If (cleft is good) and (cright is bad) and (cdirect is good) and (steer1 is left) and (steer3 is left) then (Rsteer is lmarker) (1)
 5. If (cleft is good) and (cright is bad) and (cdirect is good) and (steer1 is left) and (steer2 is right) and (steer3 is right)
  then (Rsteer is rmarker) (1)
 6. If (cleft is good) and (cright is bad) and (cdirect is good) and (steer1 is right) and (steer2 is left) then (Rsteer is lmarker) (1)
 7. If (cleft is good) and (cright is bad) and (cdirect is good) and (steer1 is right) and (steer3 is left) then (Rsteer is lmarker) (1)
 8. If (cleft is good) and (cright is bad) and (cdirect is good) and (steer1 is right) and (steer2 is right) and (steer3 is right)
  then (Rsteer is lmarker and leader) (1)
 9. If (cleft is bad) and (cright is good) and (cdirect is bad) then (Rsteer is rmarker) (1)
 10. If (cleft is bad) and (cright is good) and (cdirect is good) and (steer1 is right) and (steer2 is right) then (Rsteer is rmarker) (1)
 11. If (cleft is bad) and (cright is good) and (cdirect is good) and (steer2 is right) and (steer3 is right) then (Rsteer is rmarker) (1)
 12. If (cleft is bad) and (cright is good) and (cdirect is good) and (steer1 is left) and (steer2 is right) and (steer3 is left)
then (Rsteer is lmarker) (1)
 13. If (cleft is bad) and (cright is good) and (cdirect is good) and (steer1 is right) and (steer2 is left) then (Rsteer is rmarker) (1)
 14. If (cleft is bad) and (cright is good) and (cdirect is good) and (steer2 is left) and (steer3 is right) then (Rsteer is rmarker) (1)
 15. If (cleft is bad) and (cright is good) and (cdirect is good) and (steer1 is left) and (steer2 is left) and (steer3 is left)
then (Rsteer is rmarker and leader) (1)
 16. If (cleft is bad) and (cright is bad) then (Rsteer is leader) (1)
```

The output of the dominance mechanism `Rsteer` will be the output of either one of the pathfinders, or a weighted combination of two pathfinders. For instance, in rule 8, the steering output will be the combination of the steering command of the left lane pathfinder and the leader pathfinder.

In words, the rule base says that if the left and right lane markers have good confidence levels, the combination of their steering commands is used to drive the follower vehicle (rule 1). If the confidence of one of the lane markers is poor and the confidence of the lead vehicle is also poor, then only the reliable lane marker information is used (rules 2 and 9). The need for fuzzy decision becomes more critical if one of the lane markers information and the lead vehicle information both have high confidence levels. Suppose both the confidence levels for the right lane pathfinder and the

function	consequent	`cleft`	`cright`	`cdirect`	`steer1`	`steer2`	`steer3`
f_1	`lmarker and rmarker`	0	0	0	0.5	0.5	0
f_2	`lmarker`	0	0	0	1	0	0
f_3	`rmarker`	0	0	0	0	1	0
f_4	`lmarker and leader`	0	0	0	0.5	0	0.5
f_5	`rmarker and leader`	0	0	0	0	0.5	0.5
f_6	`leader`	0	0	0	0	0	1

Table 1: The six different output functions representing the consequence of the Sugeno-style fuzzy logic dominance mechanism. The coefficients for the linear combination of inputs shown, were used for evaluating the consequence.

leader pathfinder are good. The right lane marker pathfinder commands the follower vehicle to turn left, whereas the clue from the lead vehicle information is to turn right. We resolve this situation by steering according to the right lane marker steering command. This example is the explanation of rule 14. When the confidences of both lane markers are poor, this means that we do not have clues about the road, or may be off-road. In this case we track only the leader vehicle (rule 16). The other rules are interpreted similarly.

The consequence part of a Sugeno-style inference mechanism consists of functions which are represented as a linear combination of the inputs. This technique is implemented by the Sugeno style fuzzy inference system (FIS) block that is provided in the MATLAB fuzzy logic toolbox [24]. Table 1 shows the functions and parameters for the consequence.

The Sugeno inference mechanism is graphically represented in Figure 12. During the simulation, all the rules are evaluated for each sample time step. Each condition in the antecedent part of the rules has a membership μ_n, where the index n indicates the index of the condition. For the rule-base, the membership of `cleft` will be denoted by μ_1, the membership of `cright` by μ_2, the membership of `cdirect` by μ_3, the membership of `steer1` by μ_4 and so on, see Figure 12. Each rule is evaluated and the corresponding output function is weighted with the product of the membership functions in the antecedant. The outputs are summed and divided by the total weight of the membership functions, which concludes with the final output for the steering command R_{steer}. In equation form this can be written as:

$$R_{steer} = \frac{\mu_1^1\mu_2^1 f_1 + \mu_1^2\mu_2^2\mu_3^2 f_2 + \mu_1^3\mu_2^3\mu_3^3\mu_4^3\mu_5^3 f_2 + \cdots}{\mu_1^1\mu_2^1 + \mu_1^2\mu_2^2\mu_3^2 + \mu_1^3\mu_2^3\mu_3^3\mu_4^3\mu_5^3 + \cdots} \tag{4}$$

where from Table 1 it can be derived that $f_1 = 0.5(\texttt{steer1} + \texttt{steer2})$, and $f_2 = \texttt{steer1}$. The superscripts 1, 2, 3 in Equation 4 denoted that the μ_i's were evaluated using rules 1, 2, 3, etc.

Dominance Mechanism for Speed. The structure of the fuzzy logic dominance mechanism for R_{speed} is similar to that of the steering logic described above. The Sugeno-style FIS is as represented in Figure 12, although the rules were set to describe speed and trailing distance.

5.4 Vehicle Actuation Systems

The vehicle actuation systems receive two commands, one for speed (R_{speed}) and one for steering (R_{steer}) from the planning stage, discussed in the previous section. The actuators are responsible for executing the planned commands or path. However, since driving a vehicle is a highly non-linear task, a simple compensator such as PID-controller would not be able to satisfactorily drive the follower along its planned path. It was decided that an Artificial Network-based Inference System (ANFIS) [8] could be applied to actuate the driving mechanism of the following vehicle according to the issued speed and steering commands.

Actuation patterns of the human driver were measured and recorded together with the commands from the pathplanner and used as training sets for the ANFIS. When the ANFIS has been trained, it was programmed to take over the vehicle from the human driver and perform driving manouvers with the same skills under similar situations.

6 Simulation

A two-vehicle convoy simulation was developed using Matlab/Simulink to analyze the proposed fuzzy logic vision based autonomous leader following scheme, described in the previous section. The main simulation diagram, Figure 13, shows the two vehicles, the scenery animation, and holds all the simulation algorithms for the vision. The fuzzy Perception and Planner block implements the autonomous driving scheme of the follower Vehicle. We briefly explain the implementation of the scheme for the simulation.

Knowledge Base. Referring to the HICS paradigm of Section 4, the top-level in the hierarchy is the most intelligent but most imprecise one. In the simulation, the intelligence for the ILOS LF scheme was represented by knowledge base fuzzy rules, described in Section 5.

Simulation of the frame grabbing vision. From the environment the vision system will sense the leader location, the road edges and obstacles by means of a simulated visual frame grabbing system. The vision system is simulated by projecting a fixed prerecorded trackset of road edges, together with a wire frame model of the leader vehicle in a perspective onto a 2D-plane, as if it was a view from a true camera. See Figure 14. It suffices to mention that standard graphical transformation techniques were used in the simulation, since detailed description of the software is not the emphasis of this paper. The signal processing and feature extraction part of the simulation yields the information on the leader vehicle and road edges:

$$\text{leader vehicle}: \ R \text{ and } \phi \tag{5}$$

$$\text{Right roadedge}: \ a_0 y^2 + a_1 y + a_2 \tag{6}$$

$$\text{Left roadedge}: \ b_0 y^2 + b_1 y + b_2 \tag{7}$$

Perception. The three blocks (Left Edge Navigator, Right Edge Navigator and leader Navigator) in the middle of Figure 15 represent a Mamdani-style fuzzy logic realization of the perception, using

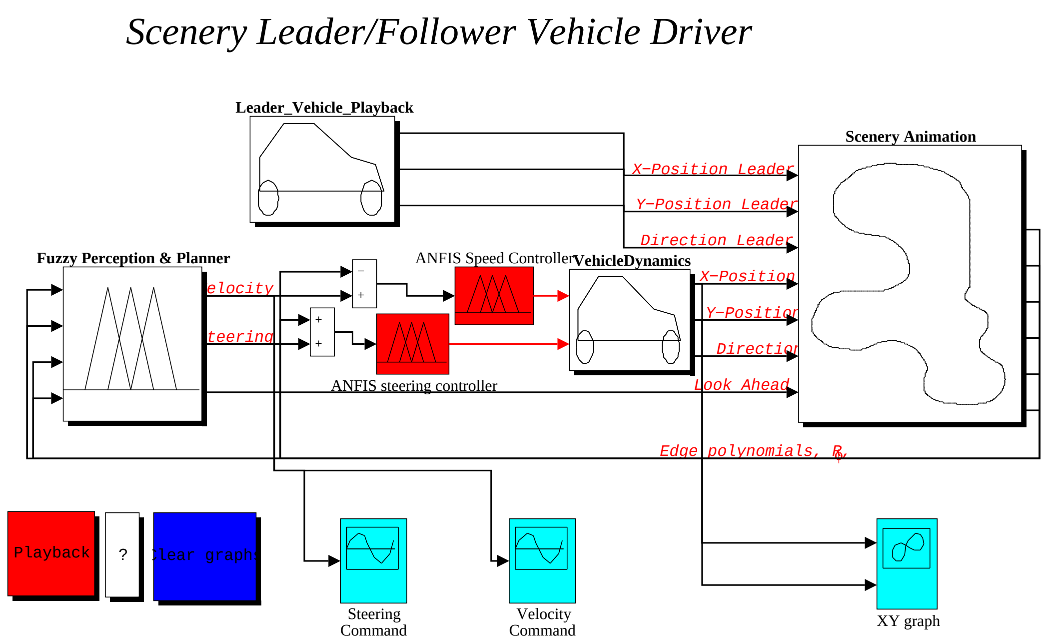


Figure 13: Main SIMULINK schematic for the leader-follower simulation

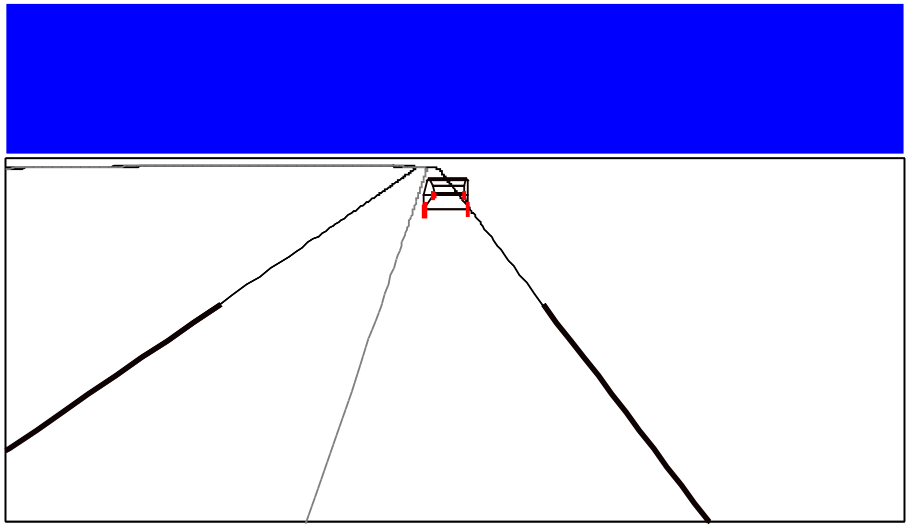


Figure 14: Visual output of the vision simulation algorithm. Estimates for the lane markers are drawn as bold type on the road edges.

the rule bases described in Section 5.2. The leader navigator produces the candidate speed and steering commands for leader tracking while the left and right edge navigators produce candidate commands for road following. Confidence factors for each navigator are similarly implemented in the simulation as an uncertainty measure (explained in Section 5.2). If the information of a navigator is not to be trusted, then the response of the navigator has bad reliability (in fuzzy terms).

Planning. Sugeno-style fuzzy logic based inference systems are used to evaluate and combine the various information from the navigators. Confidence factors are used as antecidents to weight the outputs of the navigators, the fuzzy logic is effectively a dominance mechanism for issuing speed and steering commands.

Actuation. The aim is to drive the follower according to the issued commands. Due to the nonlinear and unknown characteristics in the steering and speed dynamics, we choose to use a "black box" type controller that imitates the way a human controls the speed and steering actuators. For our approach we use an Adaptive Network-based Fuzzy Inference System (ANFIS) [8] to learn and tune itself to control the vehicle. The in-out pattern for the controller was aquired through human-in-the-loop simulation of the vehicle actuation and motion dynamics. The ANFIS controller is shown as the steering and speed controller blocks in Figure 13. Figure 16 shows the dynamics from the speed and steering commands to the x and y position and heading of the follower vehicle.

Simulation Results. Figure 17 shows the trajectories of a typical leader-follower simulation with the proposed fuzzy logic autonomous ILOS LF scheme. In the simulation run, the dominance mechanism keeps the follower on the road as it trails the leader. The right side of Figure 17 shows

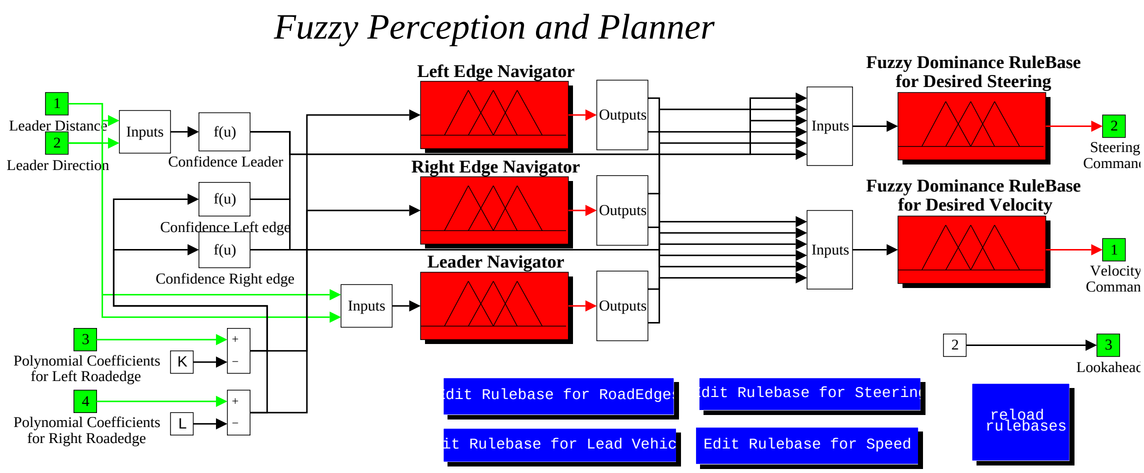


Figure 15: fuzzy Navigator and Dominance Mechanism

that the follower stays on the roadways even though the leader crosses the roadedges (see legends). Animation of the simulation results shows that the follower vehicle speeds up and slows down to stay on the road as it tries to keep up with the leader vehicle. Note that it is difficult to demonstrate this animation on paper.

7 Experiments

Experimental tests of the ILOS LF driving scheme were succesfully conducted and recorded on video at the test track facility at the US Army TACOM, Warren, Michigan. A typical test run is shown in Figure 1. This work was done under the US Army Summer Faculty Research Engineering Program [2]. For the test at the time, however leader-follower convoy speed was limited to 10 mph for safety precautions. A video tape of the experiment was shown at the SAE Congress held in Detroit last February. Further preparations are being made to conduct more elaborate experiments to evaluate the leader-following performance and observe the characteristics of the programmed intelligent autonomous driving scheme.

8 Conclusions

In conlusion, the leader-follower convoy is an excellent platform for testing the fuzzy logic based hierarchical intelligent control system paradigm. The fuzzy logic knowledge base was used to plan vehicle driving strategy by resolving conflicting perception. Computer simulation provides a

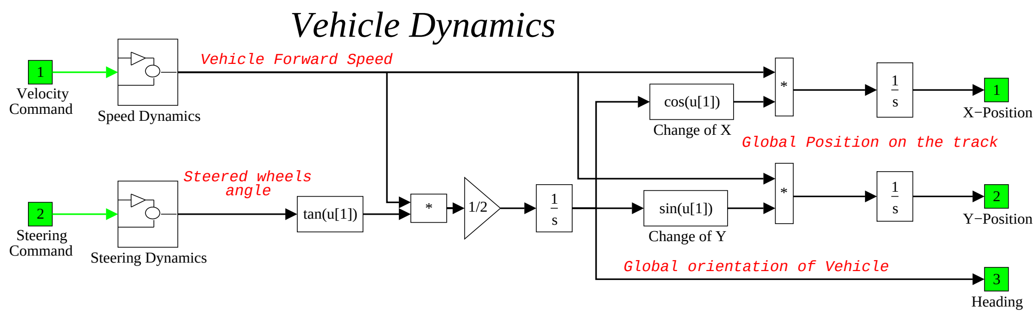


Figure 16: Simulink Sub-schematic where the vehicle is modeled. The two DC-motors are modeled as first order systems.

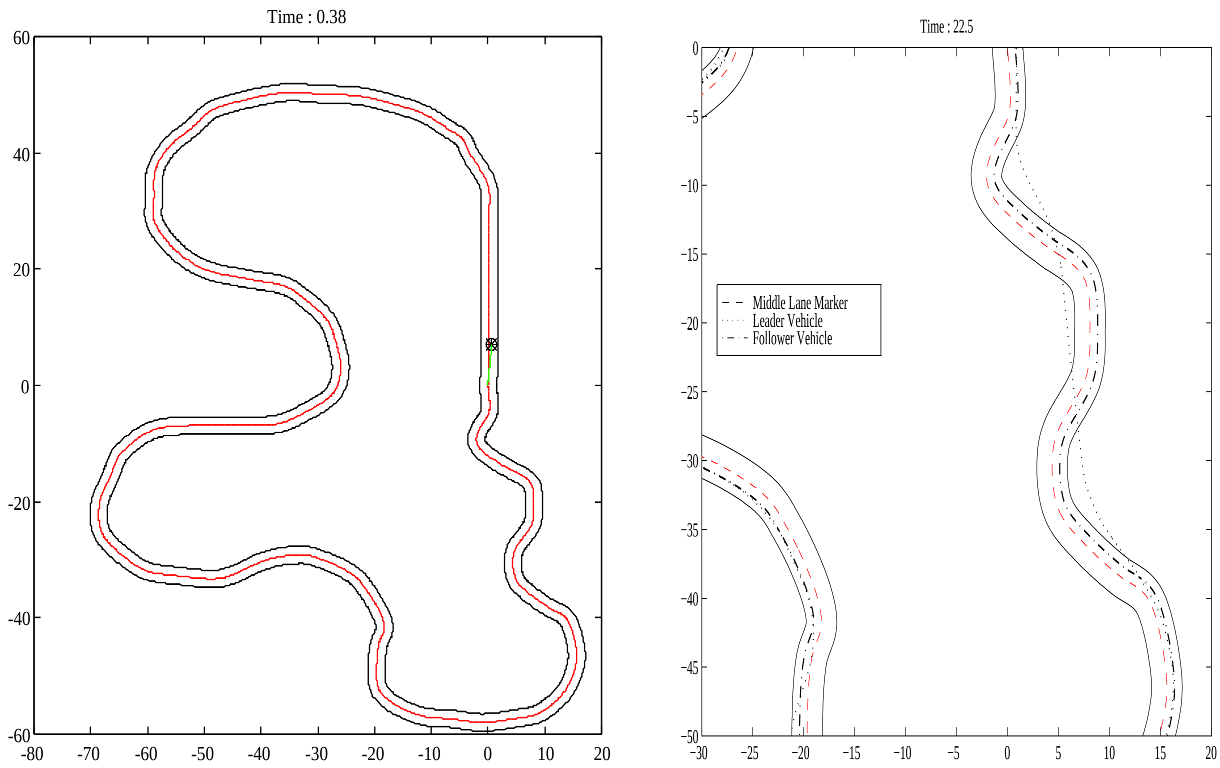


Figure 17: The topview of the overall track is shown on the left-hand side. On the right a part of the course is zoomed in to show the simulation result of the ILOS LF scheme.

means to analyze, design, and tune the proposed driving scheme. Actual experiments with specially equipped HMMWV's demonstrate encouraging success. Further refinements of the project are currently being worked on. The on-board ILOS LF scheme is beneficial for an autonomous and semi-autonomous military vehicle and can be extended to commercial application.

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