

Intelligent Cruise Control

David Taylor (06423001 SS Mathematics)

Introduction

The topic we chose for our project was an autonomous cruise control system which uses fuzzy logic. Ours differed from standard cruise control systems as we added an automatic braking capability in the case of potential collisions.

We thought that fuzzy logic was well suited to cruise control as there are many linguistic variables. Our simulation returned very reasonable answers, and so we deemed it a success. It was extremely beneficial to use fuzzy logic for this system, as to figure out the power changes by a brute force calculation takes significantly longer.

Background

Cruise control is a system that automatically maintains the speed of the vehicle determined by the driver, it does this by applying the throttle to increase engine power. Adaptive cruise control (ACC) has the added benefit of detecting potential collisions and thus automatically applying the brakes. These adaptive systems use either lasers or radars mounted on the front of the vehicle to determine the vehicle in front's proximity and relative speed.

Fuzzy logic is well suited to adaptive cruise control as terms such as "close", "sharp incline" and "fast" are used extensively, particularly the application of fuzzy logic to the problem with fuel efficiency. That is when the driver is in full control they are more likely to "surge" (stop and start) resulting in more "jerky" motion. Fuzzy logic systems smooth out this "jerkiness".

Model

Ours is an intelligent cruise control system which maintains the vehicle's speed at 120km/h by applying changes in power via the engine (positive changes) or the brakes (negative changes). We included an automatic braking system to avoid collisions.

We have assumed that the vehicle is travelling on a motorway which can have varying gradients. To simplify our model we did not consider changes in friction between the tyres and road surface. We also assumed pleasant weather conditions, again for simplicity.

We chose to consider the Volkswagen Golf TSI 1.4 litre (2008) as our vehicle.

Inputs

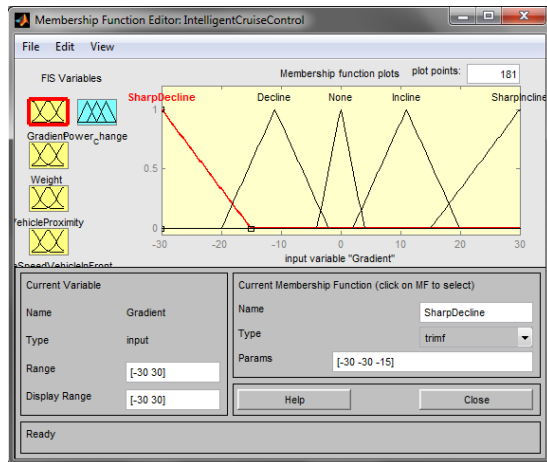
We decided on the following inputs:

- Gradient
- Weight
- Proximity of Vehicle in Front
- Relative Speed of Vehicle in Front

Gradient

As we are considering motion on a motorway, we decided to choose gradients ranging from a 30 degree decline (sharp decline) to a 30 degree incline (sharp incline).

We decided to have symmetric, triangular membership functions for the gradient.



Weight

Our changes in weight were based on passenger number. The weight of the vehicle with a 90% full tank of fuel and one person is 1344kg (light) and the weight of the vehicle with a 90% full tank of fuel and five persons is 1632kg (heavy). Here we assumed the average weight of a person to be 72kg.

We chose the membership functions to be symmetric and triangular.

Proximity of Vehicle in Front

Assuming that the road users are competent and cautious, we decided that the ranges for proximity to a vehicle in front should be 0m (close) to 30m (far). The membership functions for proximity were chosen to be triangular, but not symmetric. “Far” was given a much larger range than “close” as we considered a vehicle far away not to have a large impact on the power change.

Relative Speed of Vehicle in Front

Here we assumed that the relative speed of the vehicle in front is only important if it is moving toward us. That is, we don’t consider the situation when the vehicle in front is moving away from us.

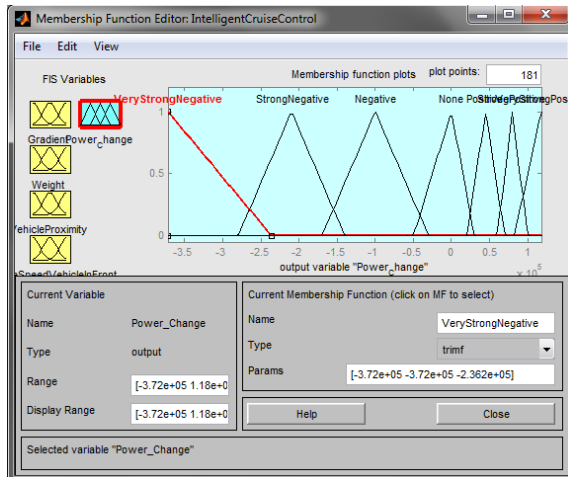
So our range of speed is from 0m/s (slow) to 15m/s (fast). Again, our membership functions were triangular and also not symmetric. We gave “fast” a larger range than “slow” as this was an important factor in terms of safety.

The table below summarizes our inputs:

Input Variable		Linguistic Variables			
Gradient	Sharp Decline	Decline	None	Incline	Sharp Incline
Weight		Light	Normal	Heavy	
Proximity of Vehicle in Front		Close	Normal	Far	
Relative Speed of Vehicle in Front		Slow	Average	Fast	

Output

We decided on the one output, namely the power change. Again with safety being the priority in our model, we gave much larger ranges to the negative power change (i.e. when the brakes should be applied) than to the positive power change (i.e. when the engine should increase power output). The ranges were determined by the specifications of the engine and some simple mechanics equations (see appendix). The upper limit for positive power change is 118kW (very strong positive). The lower limit for negative power change is -372kW (very strong negative). The membership functions were biased towards the negative power change, again for safety reasons.



The table below summarizes our output:

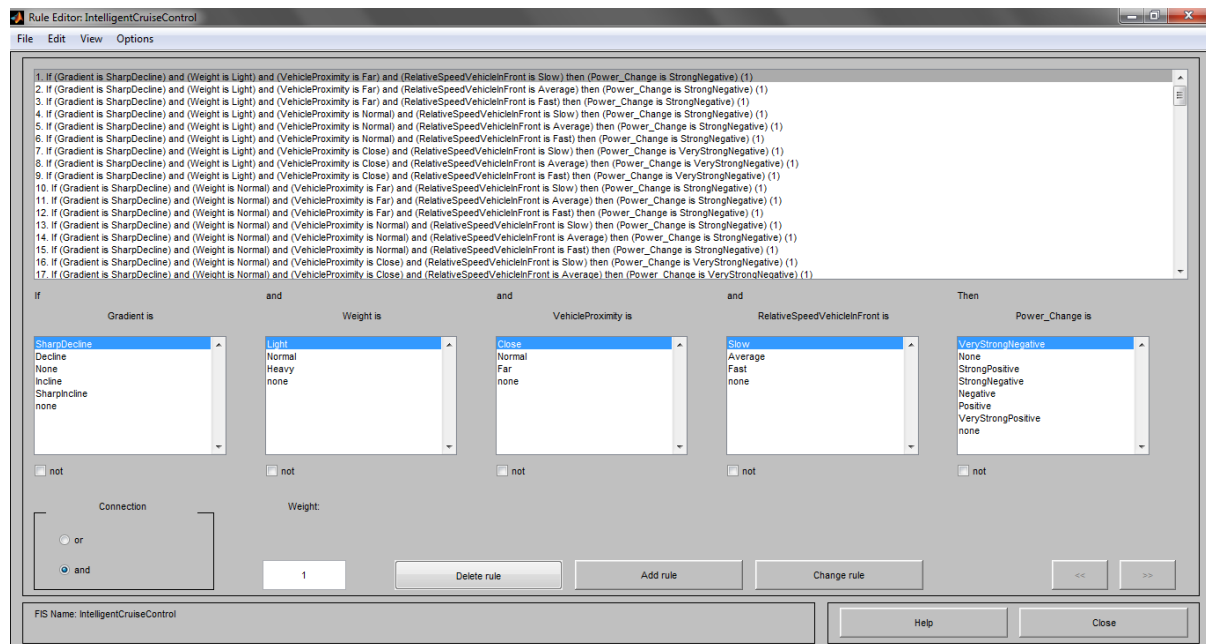
Output Variable	Linguistic Variables						
Power Change	Very Strong Negative	Strong Negative	Negative	None	Positive	Strong Positive	Very Strong Positive

Rules

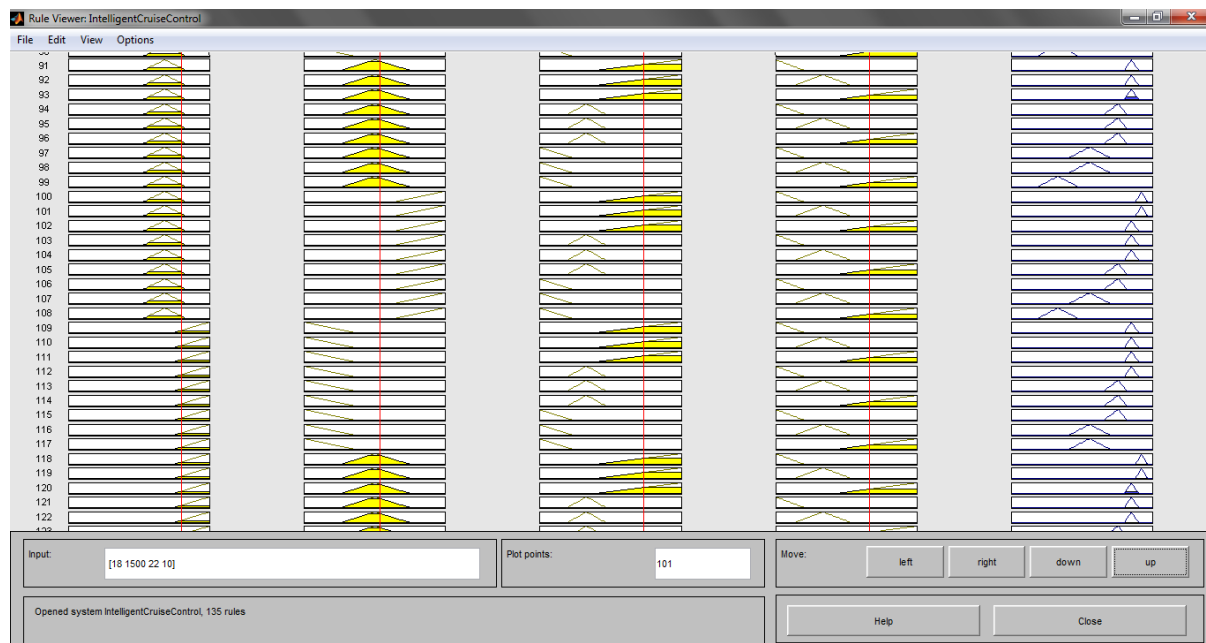
Our rules numbered $5 \times 3 \times 3 \times 3 = 135$. For each combination of linguistic variables, we laboriously determined each output. Once we were happy with the appropriate values of the power change we entered the rules into MatLab. Here is a typical example of our rules:

“If (Gradient Is SharpDecline) and (Weight is Light) and (VehicleProximity is Far) and (RelativeSpeedVehicleInFront is Slow) then (Power_Change is StrongNegative)”

Below is a screenshot of some of our rules:



This is a screenshot of some rules with the red lines indicating the “alpha-level cuts” and (although difficult to see) the blue trapezoids on the right indicating the rules that were fired:



Defuzzification

Moving from a fuzzy variable to a crisp output is called “defuzzification”. We decided to choose the Mamdani approach for its simplicity, speed and efficiency. This approach uses the centroid method to defuzzify the aggregate, giving the crisp output.

The centroid method uses the “centre of gravity” of the membership function to calculate the crisp value of the output variable.

This was automatically computed by the Fuzzy Toolkit in MatLab.

Simulation

The final stage of this project was to check that our model gave reasonable results. We did this by inserting various values into the rules and analysing the outputs.

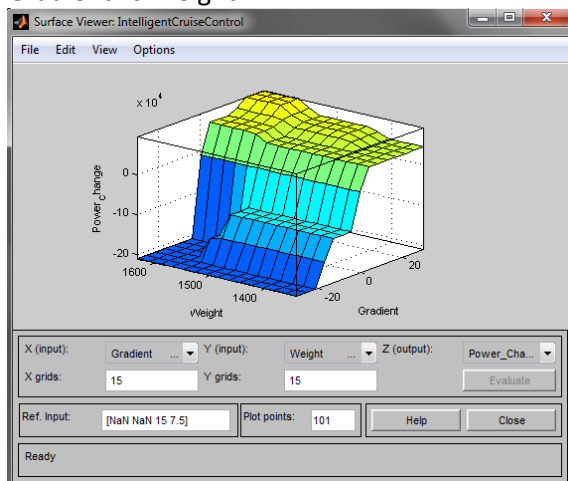
Variables [G W VP RS]	Rules Fired	Power Change (watts)
[18 1500 22 10]	93, 120	4.52×10^4
[-10 1430 13 1]	28,31,37,40	-1×10^5
[0 1620 6.5 7]	77,78,80,81	-1.75×10^5
[3 1600 10 2.5]	104,103,77,76	-7.2×10^4

Where [G W VP RS] stand for: Gradient, Weight, Vehicle Proximity and Relative Speed, respectively.

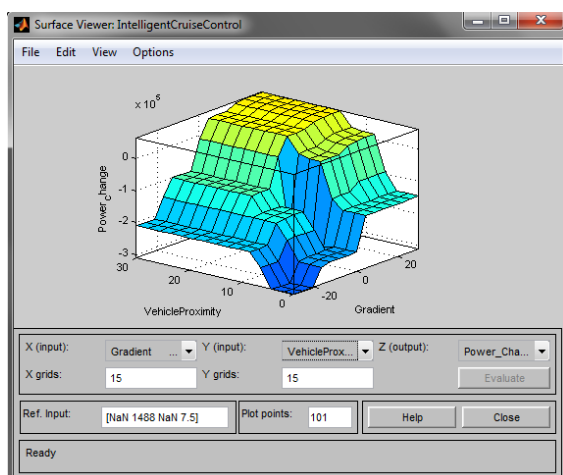
Using various mechanics formulae, we were satisfied that the outputs given for the power change were reasonable.

Below are screenshots of some of our surfaces:

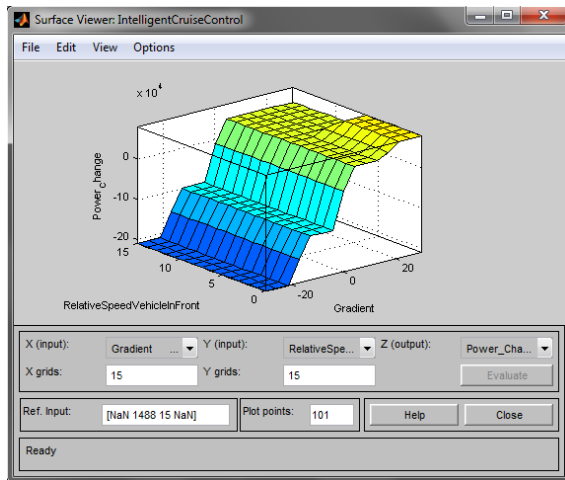
Gradient vs Weight



Gradient vs Vehicle Proximity



Gradient vs Relative Speed



Conclusions

The aim of our project was to develop a reasonably accurate fuzzy cruise control system that can deal with gradients and potentially avoid collisions. From our simulation results, we deemed our attempt a success. However we observed that there is significant scope for improvement, such as extra subcategories for the variables. We opted for less as any more would have led to several hundred rules.

Friction and weather may also be considered in a more accurate system.

Friction could be considered by analysing the difference between the velocity of the wheels (induced by the torque applied) and the actual velocity of the car (measured relative to the road). This could be done by using the laser/radar mounted on the front.

Weather could be considered by looking at how wind affects the aerodynamics of the vehicle. Note that this would be very difficult to do, as drag (without fluctuating winds) is difficult enough as it is.

Appendix

Power Calculation

To determine the maximum negative power change the following calculation was done.

We decided that the largest negative change in power would result from the situation where the vehicle is heaviest (1632kg), the gradient is steepest (-30 degrees) and the relative speed of the vehicle in front is highest (15m/s).

We used the conservation of energy to determine the change in energy.

$$E = \frac{1}{2}mv^2 + mgh$$
$$E = \frac{1}{2}(1632kg)(120kmh^{-1})^2 + (1632kg)(9.8ms^{-2})\left(\frac{1}{2}85.5m\right)$$
$$E = 1590kJ$$

The worst-case scenario for vehicle proximity was found to be 85.5m. A stopping time of 4.27s was determined using simple kinematics equations.

Thus the power change is:

$$P = \frac{E}{t} = \frac{1590kJ}{4.27s} = 372.4kW$$

We used Wolfram Alpha as it automatically deals with unit conversions.

References

http://www.rotr.ie/rules-for-driving/speed-limits/speed-limits_stopping-distances-cars.html

<http://www.carinf.com/en/2200417365.html>

<http://www.wolframalpha.com/>

<http://www.allcarrentacar.com/blog/the-pros-and-cons-of-cruise-control/>

<http://auto.howstuffworks.com/cruise-control.htm>