Fuzzy and PSO Based Algorithm for driver's behavior modeling

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Abstract— *The study of human behavior during driving is of primary importance for the improvement of drivers' security. This study is complex because of numerous situations in which the driver may be involved. In this paper, we propose a hierarchical fuzzy system for human in a driver-vehicle-environment system to model takeover by different drivers. The driver's behavior is affected by the environment. We include climate, road and car conditions in a fuzzy mode. For obtaining fuzzy rules, we have provided three separate questionnaires on the effects of climate; road and car condition on driver's performance. The number of fuzzy rules is optimized by Particle Swarm Optimization algorithm. Also the precision, age and driving individuality are used to model the driver's behavior under difference environments. We investigate the behavior of different drivers when a driver intends to pass the leading car. The comparative study showed that the simulation result is in good agreement with the real situations.*

Keywords— Fuzzy, PSO, Driver's behaviour.

1 Introduction

In recent years, by using new control ideas, safety in driving has been improved. MacAdam (1980) developed an optimal preview control algorithm; however, this algorithm could only be applied to single input single output systems. Fenton applied Linear Quadratic algorithm (1988) to design a controller for steering. Ackermann and Sienel (1990) used parameter space robust control to design the automatic steering controller. These models did not take the driver's preview behavior into consideration. Lee (1989) developed a discrete time preview control algorithm for four-wheel steering passenger vehicles and found that the control accuracy was improved substantially by taking the preview behavior into account. The fuzzy logic has proven to be a very effective tool for handling imprecision and uncertainty, which are both very important characteristics of driving environments. This makes fuzzy logic a powerful candidate tool in most traffic engineering studies [1]. In [2] Kamada et al. proposed a fuzzy logic lateral controller. Hessburg and Tomizuka [6] developed a fuzzy logic controller for vehicle lateral guidance which consisted of three sub-controllers: preview, feedback and gain scheduling. Cai, Lin and Mourant investigated the influence of driver emotion on performance through platoon driving simulated with multiple simulators [4]. They induced two kinds of emotion states (anger and excitation) through realistic driver-driver interaction by using networked driving simulators. Drivers' psycho physiological parameters changes were the indicators of emotions. In the anger and excitation states, drivers showed poorer lane control capability. In [4] the author investigated emotional behavior (anger, neutral, and excitation) of drivers by collecting driving performance data. The results demonstrated the feasibility and efficiency of using multiple networked driving simulators to study driver emotional behavior, e.g., road rage.

In this paper, we use new parameters to identify uniqueness of driving maneuver of each driver under different environment, the precision, age and driving individuality. In modeling, the decision making process is based on three positions, one position in equal lane and two positions in opposite lane. By considering three positions, the speed, direction of car and the steering angle, a fuzzy model is presented for steering angle and speed control. We used two levels for modeling. The low level control model is responsible for modeling the steering angle and the speed variations enforced by the driver. The high level control model, models the decision making process of the driver. For this purpose, first the fuzzified low level control models are illustrated in section 2. The high level decision making model is designed in section 3 and the simulation results are presented in section 4. Finally section 5 describes conclusions.

2 Low level control

In order to implement the low-level control model, a simple car's model is required [5]. The car states include the Cartesian position (x,y) centered mid-way between the rear wheels and the car's orientation denoted by equations 1 to 3, where φ is the steering angle, V is the car's speed and θ is the angle of the car with respect to the X axis and L is the distance between center of rear and front wheels.

$$x_{n+1} = x_n + V_n \times \cos(\theta_n) \times \Delta t \tag{1}$$

$$y_{n+1} = y_n + V_n \times \sin(\theta_n) \times \Delta t \tag{2}$$

$$\theta_{n+1} = \theta_n + \frac{V_n \times \tan(\varphi_n) \times \Delta t}{L} \tag{3}$$

The driver controls V and φ. In order to model the complete low level control procedure, we have assumed that apart from the information from the environment that the driver perceives, other information such as age and driver's individuality are influential in the driver's control procedure. This can be formulated as:

$$\Delta V = f(x_n, y_n, \varphi_n, \theta_n, Environment_n, Driver_n) \tag{4}$$

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$$\Delta\varphi = f(x_n, y_n, \varphi_n, \theta_n, Environment_n, Driver_n) \quad (5)$$

Where $(x_n, y_n, \theta_n, \varphi_n)$ determine car's state, *Environment* is the information of the condition of *Climate*, *Road* and *Car* and *Driver* is the individual driver influence.

2-1) Environmental condition

The *Climate* condition is the information of luminosity, field of view, rain, temperature and humidity. The *Road* condition is about the traffic surrounding the driver, road safety, quality of road materials, moving obstacle and having enough signs and finally the *Car* condition is the information of car's ergonomic, safety equipments performance and agent of distraction in car. The information is considered as the input variables of fuzzy system (Figure 1).

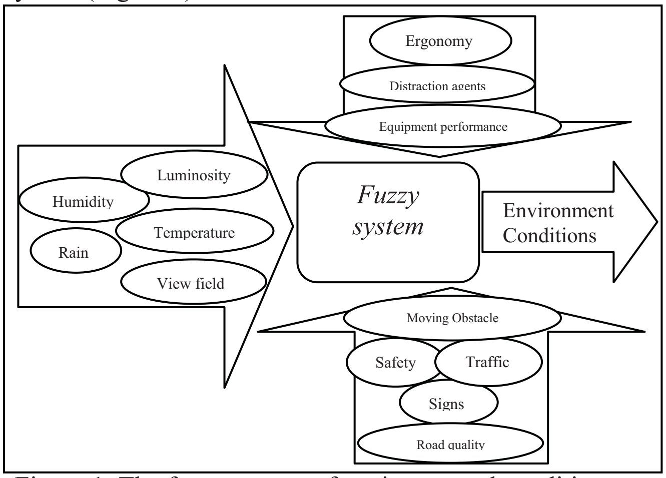

Figure 1. The fuzzy system of environmental condition

2-1-1) *Fuzzy rule base and membership functions*

Questionnaires have been provided to obtain the fuzzy rules, where the effects of climate, road and car condition in driving have been questioned separately. Each expert driver answered each question in three manners, percent value, graphic representation and linguistic term. We allocated a weight for each of them. For percent value $w_{per} = 1$, graphic representation $w_{gr} = 2$ and finally for linguistic term $w_{ling} = 0.5$ have been considered.

The membership functions of fuzzy values are supposed to be bell shape as follows:

$$\mu(x) = \frac{1}{1 + \frac{(x-c)^2}{d}} \quad (6)$$

where x is the member of universe, c is the median and d represents the shape factor.

By using collected data, the median value and shape factor for each expert driver is calculated as follows:

$$c_{ij} = \frac{w_{per} \times val_{per,j} + w_{gr} \times val_{gr,j} + w_{ling} \times val_{ling,j}}{w_{per} + w_{gr} + w_{ling}} \quad (7)$$

$$d_{ij} = \frac{\left(\left|val_{per,j} - val_{gr,j}\right|\right) + \left(\left|val_{per,j} - val_{ling,j}\right|\right) + \left(\left|val_{gr,j} - val_{ling,j}\right|\right)}{3} \quad (8)$$

where c_{ij} is median and d_{ij} is the shape factor suggested by i^{th} driver for the j^{th} parameter. So we have n values of c_{ij} and d_{ij} for n drivers.

Now we can obtain the overall membership function for each of environmental parameters by:

$$\mu_{P_j}(x) = \frac{1}{1 + \frac{(x - c_{P_j})^2}{d_{P_j}}} \quad (9)$$

where c_{P_j} and d_{P_j} are the proposed median and shape factor for the j^{th} parameter. c_{P_j} is obtained based on the number of linguistic terms which are optimized by PSO algorithm (section 2-1-2). For example, suppose the number of linguistic terms and range of universe for a variable are 5 and [0 1] respectively. Then values of medians for five verbal are: 0, 0.25, 0.5, 0.75 and 1 for *very bad*, *bad*, *medium*, *good* and *very good* respectively.

Also d_{P_j} is defined as:

$$d_{Pj} = \frac{1}{2} \times \frac{W_{univ_j} \times d_{ref_j}}{W_{ref\_univ_j} \times (N_{ling\_term_j} - 1)} \quad (10)$$

where W_{univ_j} is the width of universes for j^{th} parameter, $N_{ling\_term_j}$ is the number of linguistic terms for j^{th} parameter (obtained from PSO algorithm), $W_{ref\_univ_j}$ and d_{ref_j} are the width and the shape factor of reference universe for j^{th} parameter. The average of n value of the shape factors (obtained from eq. 8) is considered as d_{ref}. For all of parameters, $W_{ref\_univ_j}$ is fixed to 10.

The importance of the parameters of climate, road and car condition varies for different people. So we use a pair wise comparison table for determining the weights of different parameters. Table1 shows part of pair wise comparison table.

Table1. A part of compared table

Parameter	A	B	C	D
A		√	√	-

The above table shows that parameter A is more important than parameters B and C. But parameter D is more important than parameter A. The proposed method for determining weights of parameters in fuzzy rules is as follows:

First arrange the parameters. First parameter is the least important. Then a_i is assigned to i^{th} parameter such that $a_i = i \times w$. where i is the priority index of parameter and w is the priority weight which is considered as 2 in this paper.

When k parameters have equal importance, $a = w \times \frac{\sum i}{k}$ for all of k parameters. After that, we form the priority table as follows:

- If i^{th} parameter is more important than the j^{th} parameter, value of i^{th} row and j^{th} column in table is equal to $T_{ij} = a_i - a_j$.

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- If the *jth* parameter is more important than the i^{th} one then $T_{ij} = \frac{1}{a_j - a_i}$
- For diagonal elements $T_{ii} = 1$

Finally the weight of each parameter is obtained as follow:

$$M_i = (\prod_{j=1}^{m} T_{ij})^{\frac{1}{m}} , \quad W_i = \frac{M_i}{\sum_{j=1}^{m} M_j} \tag{11}$$

where m is the number of parameters. The obtained weights for parameters are used to generate valid fuzzy rules in section 2-1-2.

The general form of fuzzy rules for climate condition is as follows:

If field of View is … *and* Luminosity is … *and* *Rain* is … *and* Temperature is … *and* Humidity is … *Then* climate condition is …

For road condition:

If Traffic is … *and* Road quality is … *and* Sign is … *and* Moving obstacle is … *and* Safety is … *Then* Road condition is …

Finally for car condition, we have:

If Safety equipment operation is … *and* Ergonomic is … *and* Distract agent is … *Then* Car condition is …

2-1-2) *Particle Swarm Optimization*

Particle Swarm Optimization (PSO) is an optimization algorithm which uses properties of a swarm to find an optimal solution [4]. In this work, the swarm is represented by 100 individuals (or *particles*) whose values change at each iteration. The performance of each particle is measured at each position using a "fitness" function. This function increases as the optimality of the solution increases; in this way, a particle with a higher fitness is considered to fit better than the one with a lower fitness. Also, a record of the best position (*pbest*) for each particle, as well as the best overall position (*gbest*) for all particles, is kept in memory. The entire swarm then searches around the gbest solution and each of the pbest solutions, all the while trying to find even better solutions.

a) particle representation

The number of fuzzy rules depends on the number of linguistic terms of input variables. So, in order to optimize number of fuzzy rules, the number of linguistic terms of each parameter of climate, road and car condition is optimized using PSO. The number of linguistic terms for each input parameter is randomly selected 3, 5 or 7, so maximum number of fuzzy rules will be 7^m (*m* is the number of input variables). The number of linguistic terms of output fuzzy variable is set to 5.

To optimize the number of fuzzy rules and linguistic terms, the following particle is considered for PSO:

Particle=[*par_set par_rules*]

In the presented particle, the first part *par_*set is related to number of linguistic terms and is defined as follows:

$$par\_set = (N_{in1}, N_{in2}, \ldots, N_{in_j}, \ldots, N_{in_m})$$

Where m is the number of input variables and N_{in_j} shows the number of linguistic terms of j^{th} input variable. The number of linguistic terms of output variable is always equal to 5. So the *par_set* has *m* elements.

The second part of particle *par_rules* is:

$$par\_rules = (O_{R1}, O_{R2}, \ldots, O_{Ri}, \ldots, O_{R7^m})$$

The allele value at each location in the second part of particle contains either zero or the label of an output linguistic value to be used for a given rule. In other words, if O_{Ri} represents the allele at position *i*, its nonzero value gives the consequent part (i.e., the label of the corresponding fuzzy set on the output variable) of the rule which corresponds to the i^{th} location of the rules particle. A particle containing a zero allele value at the i^{th} position (i.e., R_i=0) indicates that the rule set represented by the rule particle has not selected any rule with the i^{th} antecedent clause.

As mentioned before, maximum number of fuzzy rules is 7^m. So in each rule_par, when the number of fuzzy rules is less than 7^m, other elements are considered to be zero. A simple example is considered which has 2 input variables. Both of variables have 3 linguistic terms (named Lt1, Lt, Lt3). So the maximum of fuzzy rules is nine.

All fuzzy rules are as follows:

Rule1: *If* input_1 is Lt_1 *and* input_2 is Lt_1 *Then* output is O_{R1}
Rule2: *If* input_1 is Lt_1 *and* input_2 is Lt_2 *Then* output is O_{R2}
Rule3: *If* input_1 is Lt_1 *and* input_2 is Lt_3 *Then* output is O_{R3}
Rule4: *If* input_1 is Lt_2 *and* input_2 is Lt_1 *Then* output is O_{R4}
Rule5: *If* input_1 is Lt_2 *and* input_2 is Lt_2 *Then* output is O_{R5}
Rule6: *If* input_1 is Lt_2 *and* input_2 is Lt_3 *Then* output is O_{R6}
Rule7: *If* input_1 is Lt_3 *and* input_2 is Lt_1 *Then* output is O_{R7}
Rule8: *If* input_1 is Lt_3 *and* input_2 is Lt_2 *Then* output is O_{R8}
Rule9: *If* input_1 is Lt_3 *and* input_2 is Lt_3 *Then* output is O_{R9}

Since the number of linguistic terms of output variable is 5, then $O_{Ri} \in \{0, 1, 2, 3, 4, 5\}$. Suppose linguistic terms of output variable are {*very bad*, *bad*, *medium*, *good* and *very good*}, therefore, the allele value is 0 when the corresponding rule hasn't been selected as a fuzzy rule, 1 when output variable is *very bad*, 2 when it is *bad*, and so on.

The optimized *par_rules* is obtained by PSO algorithm as follows:

par_rules =(0, 1, 2, 0, 3, 0, 0, 3, 5, 0, … , 0)

where first nine values are related to fuzzy rules. By considering the optimized *par_rules* , We have five rules: Rule2, Rule3, Rule5, Rule8 and Rule9. So optimized fuzzy rules are:

If input_1 is Lt_1 *and* input_2 is Lt_2 *Then* output is *very bad*
If input_1 is Lt_1 *and* input_2 is Lt_3 *Then* output is *bad*
If input_1 is Lt_2 *and* input_2 is Lt_2 *Then* output is *medium*
If input_1 is Lt_3 *and* input_2 is Lt_2 *Then* output is *medium*
If input_1 is Lt_3 *and* input_2 is Lt_3 *Then* output is *very good*

b) The fitness function

In the fitness function, we need to use some valid fuzzy rules. In order to generate valid fuzzy rules, we select the worse (value=0) and the best (value=1) state (verbal value) of each input variable. The linguistic terms of them are *very bad* and *very good* respectively. For the middle state (*medium*), value of 0.5 is assigned. If the input variable is defined by 5 linguistic terms, the state between the worse

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and middle state (*bad*) is set to 0.25 and the state between the best and middle (*good*) is set to 0.75. Also the center of gravity defuzzifier is applied as follows:

$$z^* = \frac{\sum_{i=1}^{m} z_i \times w_i}{\sum_{i=1}^{m} w_i} \tag{12}$$

where z_i *and* w_i are the value and weight (section 2-1-1, eq.11) of i^{th} input variable respectively. All of the rules where z^* gets one of values 0, 0.25, 0.5, 0.75 and 1, corresponding to linguistic terms of input variables, are considered as valid rules.

For example if linguistic term of traffic, road quality, sign, moving obstacle and safety are considered to be medium, then values of all of them is 0.5. Then by considering appropriate weight for each input variable (section 2-1-1, eq.11), z^* will be obtained as follows:

$$z^* = \frac{0.5\times0.21+0.5\times0.13+0.5\times0.11+0.5\times0.21+0.5\times0.34}{0.21+0.13+0.11+0.21+0.34} = 0.5$$

The obtained value is corresponding to *medium* linguistic term for z^*. By this way the following valid rule is obtained:

Rule: If Traffic is medium *and* Road quality is medium *and* Sign is medium *and* Moving obstacle is medium *and* Safety is medium *Then* Road condition is medium

Finally the fitness function used for the optimization of the membership functions is defined by:

$$\text{Fitness}= W_b \times n_c + \frac{W_r}{n_R} \tag{13}$$

Where n_R is the number of rules and W_r is its weighting factor, n_c is the number of input data set which have same output for valid fuzzy rules and the rules generated by PSO and W_r is its weighting factor.

2-2) Driver behavior

The personality (individuality) of each person is very important in the task performance. Because it affects on driver's decisions and acts. We consider drivers personality into three groups, risky person, normal person and attentive person. Also, the people have different reactions in different ages. So we include age of driver in modeling of driver's behavior. In addition, the precision of each person affect on calculating of distance. So we include it by considering graduating diploma and the measure of necessary precision in his work. Figure 2 shows the hierarchical fuzzy system which models driver behavior in decision making. For obtaining fuzzy rules in hierarchical fuzzy system, we use the applied method to generating valid rules in PSO algorithm. In proposed model, only by applying one coefficient in the universes of speed change and steering angle change also the ideal low and high speed for each person, we can easily model the different behavior under take over conditions.

3 High Level Control

3-1) Structure of road and existence cars

Two lanes road is considered as the movement trajectory of cars. In the simulation, four cars are considered (Figure 3). The *A* car is the car which we intend to control it by fuzzy rules, it is called *Controlled car*. The *B* car is the back car which intends to pass *Controlled car* and it is called *BEDOL*. The *C* car is the front car which moves in opposite lane. If *C* car moves in the same direction as *Controlled car,* then it is called *FEDOL* and if direction of movement is in opposite direction then it is called *FODOL*. The *D* car is the front car which moves in the same lane of *Controlled car*. If *D* car moves in the same direction as controlled car then it is called *FEDEL* and if it is in opposite direction then it is called *FODEL*.

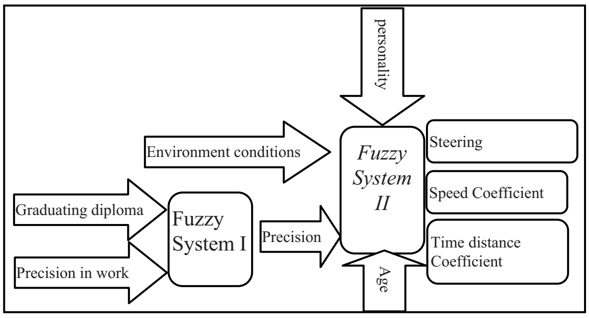


Figure 2. The driver's behavior hierarchy fuzzy system

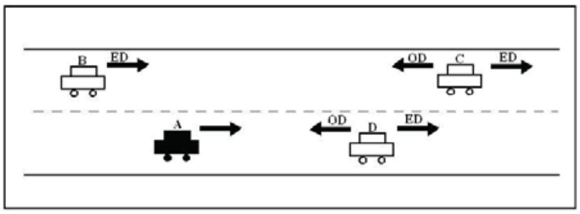
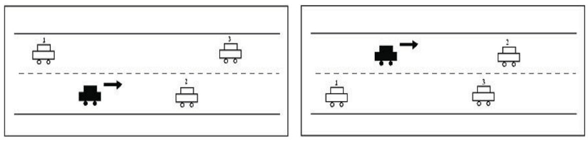


Figure 3. The movement trajectory of cars

3-2) Effective cars in the decision making of driver

When a person drives a car on the road, movements of other cars affect his/her decision making. For example, *FODEL* car is more important than *FEDEL* car and *FODOL* is more important than *FEDOL* car. When driver decides to pass *FEDEL* car, location of *BEDOL* and *FODOL* is very important. The three important cars in decision making of driver are shown in Figure 4.



(a) Controlled car is on the right lane   *(b) Controlled car* is on the left lane

Figure 4. The situations of important cars

3-3) Decision making process

By considering three positions, the speed and direction of car and the steering angle, the fuzzy variables for steering angle and speed control are presented as follows:

Td_{BOL}: (input variable) time distance of *Controlled car* with the back car in other lane, moving in the same direction.

Td_{FEL}: (input variable) Time distance with the front car, moving in the same lane

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Td_{FOL} : (input variable) Time distance with the car moving in opposite lane
V: (input variable) Speed of *Controlled car*
Dir: (input variable) *Controlled car*'s direction
Δv : (output variable) Change of speed
$\Delta\varphi$: (output variable) Direction change of steering.

Each of the input variables, Td_{BOL} , Td_{FEL} and Td_{FOL} has four linguistic values or fuzzy sets: The speed has three fuzzy sets. The car direction and the steering angle direction have seven fuzzy sets. Each of output variables is defined by using seven linguistic variables. We define a vector for Td_{BOL} , Td_{FEL} and Td_{FOL} separately. First element of each time distance vector represents the minimum time distance for collision with corresponding car. It is called very low. The second element is the lowest value of the middle time with corresponding car. We call it medium time. The last element is the lowest value as the highest time with corresponding car which is called high time. The above time distance vectors are defined for a *normal driver* who drives according to driving laws. But for modeling different behaviors of driver, we use the time distance coefficient which is obtained by hierarchical fuzzy system. The time distance coefficient is called *K_TD*. The purposed time distance vectors for different drivers are shown in table 2.
In table 2 we have

$$b = \begin{cases} (\sqrt{k\_TD})^{-1}, & K\_TD \geq 1 \\ \sqrt{k\_TD}, & K\_TD < 1 \end{cases}$$

$$Td_{FEL} = \begin{cases} Td_{FEDEL}, & \text{if } FEDEL \text{ exict} \\ Td_{FODEL}, & \text{oherwise} \end{cases}$$

$$Td_{FOL} = \begin{cases} Td_{FEDOL}, & \text{if } FEDOL \text{ exict} \\ Td_{FODOL}, & \text{oherwise} \end{cases}$$

Table 2: Time distance vector for different drivers

Left Lane:	Right Lane:
Td_{BOL}=*K_TD**[0.5/b 2/b 7]	Td_{BOL}=*K_TD**[3 10 15]
Td_{FEDEL}=*K_TD**[1 3 5]	Td_{FEDEL}=*K_TD**[4/b 8/b 12]
Td_{FEDOL}=*K_TD**[3 5 8]	Td_{FEDOL}=*K_TD**[1 3 7]
Td_{FODEL}=*K_TD**[2 4 6]	Td_{FODEL}=*K_TD**[4 7 20]
Td_{FODOL}=*K_TD**[3 7 20]	Td_{FODOL}=*K_TD**[3 7 15]

3-3-1) Road partitions in decision making of driver

Drivers drive in different positions of road. When a driver intends to pass the leading car, he/she moves toward the middle of road while in low speed and dangerous conditions, the car moves toward the shoulder of road. So in decision making, we divide the road to four divisions: Left lane, Middle Lane, Right lane and Shoulder of lane. Among four decision lanes, the middle of lane and the shoulder of road lane are the transient lanes. A driver is driving in the right lane and only when he/she is passing the leading car, he/she drives in the left lane.

3-3-2) Fuzzy rule base for decision making of driver

The decision making process is categorized into four scenarios:

1. Right lane
- Staying in the same lane and continuing the path

a) No car is in front. The car continues its path.
b) A car is in front and the time distance with it is low, the driver starts to make a decision based on his/her desired speed, safety priorities but *FODOL* car is near or there is *BEDOL* car, then the driver decreases the car's speed and continues the path.

- Going to the shoulder of road

A car is in front and the time distance with it is very low; but *FODOL* car is near and *BEDOL* car is near. So the takeover from the left lane is impossible. In order to avoid collision, the driver must move the car to the shoulder of road.

- Going to the middle lane to passing

When the driver decides to change lane and perform a takeover from the left lane. So he/she moves the car to the middle lane.

2. Middle lane

As mentioned before, this lane is a transient lane. If the takeover conditions are satisfied, the driver increases the speed and continues with the same direction to enter the left lane. Otherwise he/she decides to stay in middle lane or to return to right lane.
After taking over, driver with the same speed from this lane enters to right lane

3. Left lane
- Before taking over

If the takeover conditions are satisfied, the driver continues the path with high speed. Otherwise he/she goes to middle lane and decides to stay there until the takeover conditions are provided or he/she returns to right lane.

- After taking over

The driver with the same speed from this lane goes to middle lane in order to go to the right lane.

4. Shoulder of road lane

As mentioned before, a driver in order to avoid collision goes to this lane. So he/she must stay in this lane until he/she could return.

4 Results

The obtained weights of each of environmental parameters from eq. (11) are summarized in Table 3. This table shows that among climate parameters, view field is the most important parameter. Safety is the most important among the road parameters and safety equipment operation is the most important among the car parameters.

Table 3: The weights of environmental parameters in fuzzy rules

Climate parameter	*W*	Road parameter	*W*	Car parameter	*W*
View	0.37	Traff.	0.21	Eq.o.	0.47
Lum.	0.297	R.q.	0.13		
Rain	0.178	Sign	0.11	Er.	0.25
Temp.	0.098	M.obs	0.21	Dis.a.	0.28
Hum.	0.057	Safety	0.34		

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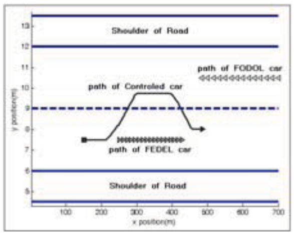
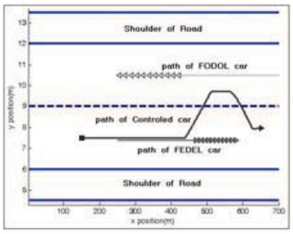
The obtained optimum number of fuzzy sets for environmental parameters input variables by PSO algorithm is shown in Table 4. The number of fuzzy sets of output variables (climate, road and car condition) is fixed and is equal to 5 sets.

Table 4. The optimum number of fuzzy sets for environmental parameters

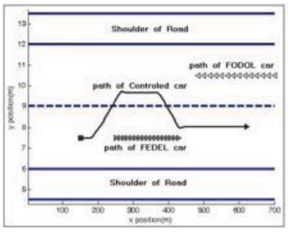
Climate parameter	number	Road parameter	number	Car parameter	number
View	5	Traff.	3	Eq.o.	5
Lum.	3	R.q.	5		
Rain	5	Sign	3	Er.	5
Temp.	3	M.obs.	5	Dis.a.	5
Hum.	3	Safety	3		



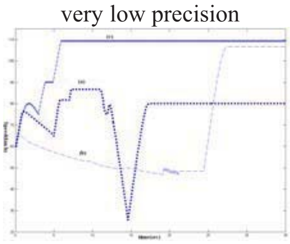
(a) Normal driver



(b) Attentive old driver with very low precision



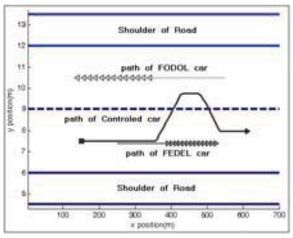
(c) Attentive old driver with very high precision



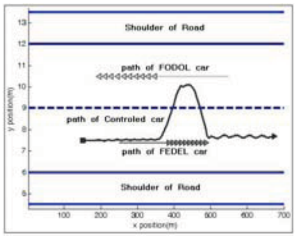
(d) Car's speed by (a), (b), (c) drivers

Figure 5: Comparison of different drivers in the same conditions

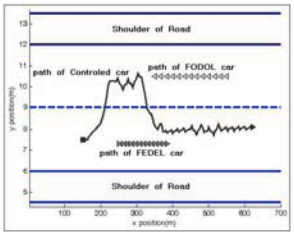
We investigate the behavior of different drivers under take over condition. The comparison of behavior of three drivers under equal passing conditions and the best environmental conditions is shown in Figures 5 and 6. As it is seen in Figure 5, *normal driver* and attentive old driver with very high precision pass the leading car. But attentive old driver with very low precision waits until the *FODOL* passes and then he/she passes the leading car. The paths of cars before passing are shown by solid lines. The very low precision person's error is higher than the very high precision person in calculating distance with other car. Because of being attentive, the driver waits for passing the leading car to collision avoidance. The car's speed of each driver shows the driver's behavior and decision under equal conditions. The *normal driver* is decided to passing and increases the speed. The movement of car is smooth. The old person with very high precision has more steering direction change because he/she is attentive and old and needs more time of passing than normal driver. The old person with very low precision is late in decision making and waits. After that he/she is passing the leading car and returns the right lane as soon as because of being attentive. Figure 6 compares a *normal driver* with a young driver. In equal conditions, the risky young driver passes the leading car. But the attentive young driver and normal driver waits until the *FODOL* car is passed. The speeds of cars are shown in figure (11- d). The results are obtained in good mental status.



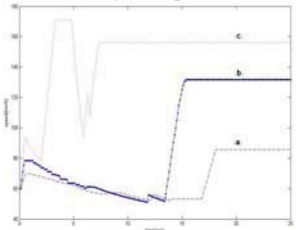
(a) Normal driver



(b) Attentive young driver with very low precision



(c) Risky young driver with very low precision



(d) Car's speed by (a), (b), (c) drivers

Figure 6: The comparison of different driving behavior in equal conditions

5 Conclusion

In this paper a fuzzy three positions model has been presented for the low-level control model and a fuzzy hierarchical system have been proposed for the high-level Control Model. The obtained results show that in equal conditions an attentive old driver with very high precision passes the leading car, but attentive old driver with very low precision waits until *FODOL* car passes and then he/she passes the leading car. The very low precision person's error is higher than that of the very high precision person in calculating distance with other car. This method also provides a basis for modeling individual driver behavior characteristics that may be tuned and used in automatically guided vehicles. It also provides a reference of natural driver behavior of each individual.

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