Proceedings of the IEEE ITSC 2006
2006 IEEE Intelligent Transportation Systems Conference
Toronto, Canada, September 17-20, 2006

An Agent-based Controller for Vehicular Automation

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Abstract—**In this paper, we present a design of controller for vehicular automation based on mobile agent technology. In this approach, the control goal is conducted by coordinating active or default agents based on sensory feedback and vehicle conditions. A hosting mechanism determines which agent has the right to control the vehicle and make the decision. Those agents are divided into two groups: default agents which are developed by fuzzy rules, and active agents which are produced by neural networks. Fuzzy agents locate in the vehicle and neural network agents locate in remote server. Two types of agents have similar function but different performance, so those agents produced by neural network can transfer back to the vehicle after learning to replace default fuzzy agents according to mobile agent technology. The performance of the proposed technique is illustrated by simulation studies of a vehicle longitudinal control system.**

Index Terms—**ACC, CC, mobile agents, agent-based controllers, fuzzy controllers, neural network controllers**

I. Introduction

URBAN highway in most major cities is congested and needs effecting approach to reduce the congestion. With the advance of control, communication and computing technologies, most researchers are interested in resolving transportation problems according to information technologies. Currently, this field has attracted great interests in different programs, i.e. California PATH program, Ohio State University Center for Intelligent Transportation Research, The Robotics Institute of Carnegie Mellon University and Advanced Traffic & Logistics Algorithms & Systems Lab of University of Arizona in the United States; Daimler–Benz and MAN Project, PROMETHEUS Program, ARGO Car project and Project EZAuto in Europe; some programs under ITS Japan; and a number of growing projects in China[1].

Manuscript received March 1, 2006. This work was supported by the National Natural Science Foundation of China (No.60334020), the 973 Key Project (2002CB312200) from the Ministry of Science and Technology, China NSFC two-bases project under grant No.60440420130

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Most researchers believe that transportation system will become integral infrastructure in the future so that vehicles and roadsides can communicate by computer network. In this context, it is assumed that traffic in a lane travels in platoons. Inside a platoon, all the vehicles follow the leader with a small intraplatoon separation of one meter. The interplatoon spacing is assumed to be large, so as to isolate the platoons from each other. Studies illustrate this approach can promote additional capacity [2].

On the other side, as pointed out in [3], due to financial and practical limitation, the short-term tendency has switched from AHS (Advanced Highway Systems) to IVI (Intelligent Vehicle Initiative), since the driver assist systems can independently be implemented in today's generation of cars without the costly modifications in the infrastructure. ACC, stop and go cruise, collision warning and collision avoidance systems are being developed in this context.

Devices of ACC are currently being introduced by several car manufacturers in their latest cars. The ACC concept extends the conventional cruise control system to include car following. The ACC would have automatically adjusted the speed of the car to match the speed of the vehicle ahead and to maintain an appropriate distance.

Most implementations of ACC have been presented. Conventional methods based on analytical control generate good results but with high design and computational costs since the application object, a vehicle, is a nonlinear element and its representation is impossible. More importantly, the control devices of vehicles are embedded computing platform and the resource of computing and storing is scare. On the other side, skilled driver can achieve sophisticated driving in dynamic, unstructured and unpredictable environments. This leads to some researchers using behavior programming, fuzzy control and neural networks for development of ACC [4] [5].

This paper presents a design of controller for vehicular automation based on mobile agent technology. The driving condition is divided into two types: having no vehicles and having vehicles ahead. The situation assessment in the hosting mechanism classifies the current external traffic and internal system states into predefined cases upon which control agents can make decisions regarding their actions. An arbitrator in hosting mechanism will determine which agent has the right to handle the case. Those agents are developed by mobile agent technology and implemented though "Function Identity and Performance Difference". The agents of low performance (such as fuzzy agents) are located in the vehicle and the others of high performance (such as neural network agents) are located in remote server at the beginning. After the neural network agents complete learning, they are translated into fuzzy agents and transferred back to the vehicle. So we can implement "Local Simple and Remote Complexity" and promote control performance at same computing and storing resource.

The paper is organized as follows: Section II introduces the vehicle dynamics and control goal. Hosting mechanism is presented in Section III. Section IVimplements four control agents. Simulation result is presented in Section V. Finally, conclusion is drawn in Section VI.

II. VEHICLE DYNAMICS AND CONTROL GOAL

The model and corresponding parameters of the vehicle longitudinal dynamics are adopted from [6], and they are shown as follows:

$$\ddot{x} = \frac{F - c\dot{x} - d}{M} \tag{1}$$

$$\dot{F} = \frac{1}{\tau}(-F + u) \tag{2}$$

Where, in the equation (1), x, F, c, d, and M are the position, the engine traction force, effective aerodynamic drag coefficient, rolling resistance friction, and effective inertia, respectively. Equation (2) is engine dynamics, where the engine traction force F is modeled as a first-order system, and u is the control input. $c = 0.44\text{kg/m}$, $d = 352\text{kg.m/s}^2$, $\tau = 0.2\text{s}$, $M = 1500\text{kg}$.

The goal of CC is to follow the velocity set by user. The CC has two input information: the instantaneous speed and the time interval between two speed measures and the controller output is the stepping on the accelerator pedal. In the practical driving, driver controls the vehicle though brake pressure and the throttle position. In this paper, control performance of CC is assessed by current speed measure and three past speed measure:

$$\vartriangle v' = \vartriangle v(k) + \vartriangle v(k-1) + \vartriangle v(k-2) + \vartriangle v(k-3) \tag{3}$$

Where k is the current measure time.

The goal of ACC is to automatically adjust the speed of the vehicle to match the speed of the car ahead and to maintain an appropriate distance. The extreme situation is when the preceding car stops; then the ACC equipped car must stop too. This is a classical event in traffic jam driving, and is named Stop&Go. In this context, a sensor is needed to mount in the front of the car to measure the preceding vehicle distance. The sensor could either be of optical or radar type, but the radar sensor is often preferred since it is much less influenced by the weather conditions than the optical sensor. The ACC has four input information: the distance and velocity of preceded vehicle, the velocity of preceding vehicle and the time interval between two speed measures. Safe distance is decided by current velocity and brake condition of preceding vehicle. California rule is adopted and expressed as $S_d = \lambda_2 v = 0.225Lv$ where λ_2 is coefficient and L is vehicle length. If we assume:

$$\delta(t) = x_1 - x_2 - 0.225Lv \tag{4}$$

the goal of ACC is to make the $\delta(t)$ minimal. The performance of ACC can be assessed by the $\delta(t)$ of current speed measure and three past speed measures:

$$\delta' = \delta(k) + \delta(k-1) + \delta(k-2) + \delta(k-3) \tag{5}$$

III. HOSTING MECHNISM FOR VEHICLE CONTROL AGENTS

In agent-based vehicle control, a vehicle controller becomes a vehicle agent host where different agents reside at different times in response to different driving condition. Unlike in a traditional control system, where a control algorithm is an integral part of an isolated device and must be responsible for the entire operation, a control agent in an agent-based control system focuses on only a few specific operating condition. Figure 1 illustrates this hosting mechanism.

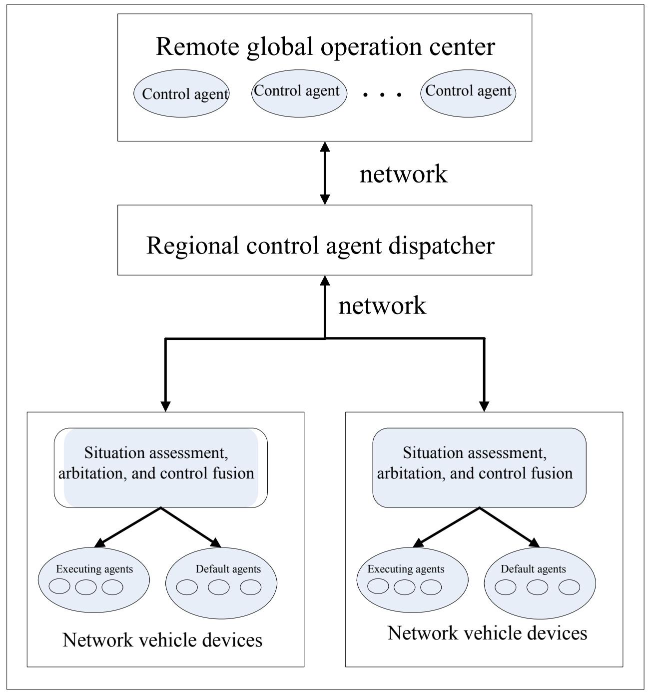

Figure1. A hosting mechanism for vehicle control agent.

There are two types of agents: default control agents and executing agent in the vehicle which is connected with remote operation center by network. Default control agents reside in the vehicle to ensure its basic operation and performance if connectivity isn't available. In this paper, fuzzy rule is used to develop default control agents. Executing control agents that can deal with current driving condition with reasonable performance is produced by neural network agents located in remote operation center.

The executing agents' decision-making process consists of situation assessment, arbitration, and control fusion. Situation assessment classifies the current external traffic and internal system states into predefined cases upon which control agents can make decisions regarding their actions. Arbitration will determine which executing agents have right to control the vehicle. If the arbitrator selects multiple agents, they'll make their individual decisions, which will be combined into a single decision for the vehicle by a control fusion algorithm. In this paper, fuzzy logic is used to address these issues.

Assuming that x_1, v_1 and a_1 are location, velocity and acceleration of preceded vehicle and x_2, v_2 and a_2 are location, velocity and acceleration of preceding vehicle, then $\delta = x_1 - x_2 - (\lambda_2 v_2 + \lambda_3), \dot{\delta} = \dot{x}_1 - \dot{x}_2 - \lambda_2 \dot{x}_2, \ddot{\delta} = \ddot{x}_1 - \ddot{x}_2 - \lambda_2 \ddot{x}_2$ are relative location, relative velocity and relative acceleration respectively. The fuzzy rule of arbitrator can be expressed as:

Rule 1: IF δ is PO, THEN *cc fuzzy control agent* control the vehicle;

Rule 2: IF δ is PO and $\triangle v'$ is PO, THEN download *new cc fuzzy control agent* to control the vehicle;
Rule 3: IF δ is NE, THEN *acc fuzzy control agent* control the vehicle;
Rule 4: IF δ is NE and δ' is NE, THEN download *new acc fuzzy control agent* to control the vehicle.

In this system, new fuzzy control agent is produced by neural network and transferred backto the vehicle as mobile agent.

IV. IMPLEMENTATION OF CONTROL AGENT

i. IMPLEMENTATION OF CC CONTROL AGENT

A. CC FUZZY CONTROL AGENT

CC fuzzy control agent gets input information through the sensors mounted in the vehicle: current instantaneous speed and the time interval between two speed measures. Speed deviation and acceleration can be denoted as:

$$\triangle v = v_d - v \tag{6}$$

$$a = \frac{v_t - v_{t-1}}{\triangle t} \tag{7}$$

The output of CC fuzzy control agent is the brake pressure and the throttle position, which is denoted as u in equation (2). Figure 2 is the control scheme.

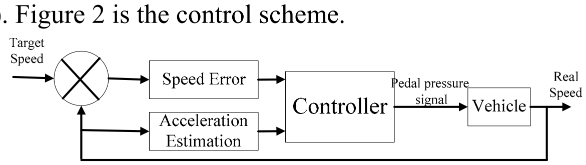

Figure 2. CC scheme including fuzzy control agent

There are three fuzzy variables in CC fuzzy control agent: speed deviation $\triangle v$, acceleration a and control output u. Figure 3, 4 and 5 give the membership function of above fuzzy variables.

Finally, fuzzy rule can be set as:
Rule 1: IF speed deviation $\triangle v$ is PO, THEN u is NE;
Rule 2: IF speed deviation $\triangle v$ is NE, THEN u is PO;
Rule 3: IF acceleration a is NE, THEN u is PO;
Rule 4: IF acceleration a is PO, THEN u is NE;

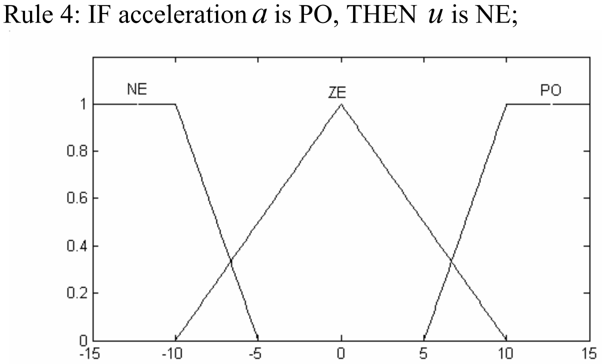

Figure 3. Speed deviation membership function.

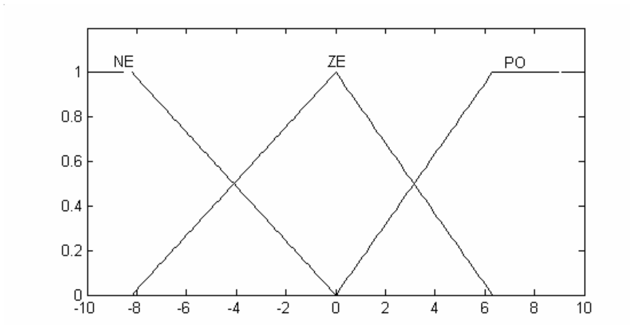

Figure 4. Acceleration membership function.

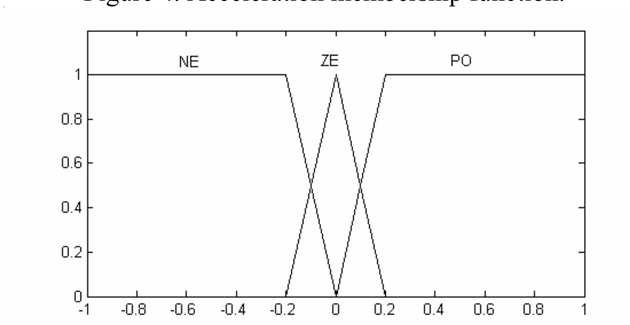

Figure 5. Output membership function.

B. CC NEURAL NETWORK CONTROL AGENT

CC neural network agents are located in remote server, which can produce promoting CC fuzzy agents. In this paper, the design paradigm in [8] is used to develop CC neural network. As we have mentioned earlier, in the conventional design, designer can only adjust the parameter of FLCS by trial-and-error. In [8], the procedure of decision-making of a FLCS leads to a neuro-fuzzy network consisting of three types of subnets for pattern recognition, fuzzy reasoning and control synthesis respectively. The unique knowledge structure embedded in this structured network enables it to carry out adaptive changes of fuzzy reasoning methods and membership functions for both input signal patterns and output control actions, and then recover these changes individually and completely later from its subnets. Figure 6 shows those three types of subnets.

Consider a process monitored through a signal vector s with m readings, $s = (s_1, s_2, ...s_m)$, and driven by a control vector u with n components, $u = (u_1, u_2, ..., u_n)$. Each of the sensor readings and control components is described by a set of linguistic terms, namely, $A_i = \{S_i^1, S_i^2, ...S_i^{p_i}\}$ and $B_j = (U_j^1, U_j^2, ..., U_j^{q_j})$ for s_i and u_j, $i = 1, ..., m$ $j = 1, ..., n$, respectively. For each signal readings s_i, a neural network SN_i in Figure 6(a) is constructed to match its values with the linguistic terms in the set of signal patterns A_i. In other words, the function of SN_i is to calculate membership functions $\mu_{S_i^k}(x)$ for $k = 1, ..., p_i$ $i = 1, ..., m$. For each decision rule r in the knowledge base of an FLCS, a neural network RN_r in Figure 6(b) is used to calculate the firing strength of the rule. Thus, RN_r is actually a network implementation of the conjunction operator. By changing its weights, this network can implement different conjunction operation. Figure 6(c) illustrates a two-layer neural network CN_j for the synthesis of control component u_j, $j = 1, ..., n$. It involves steps of

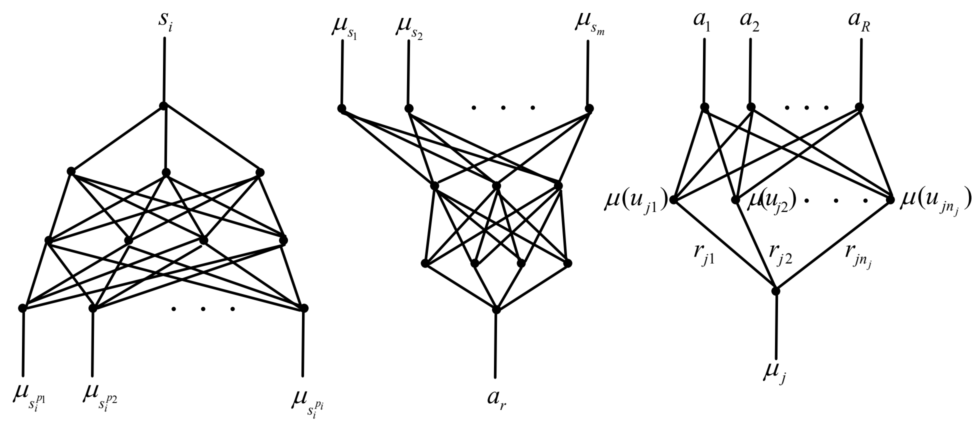

Figure 6. Construction of subnets.

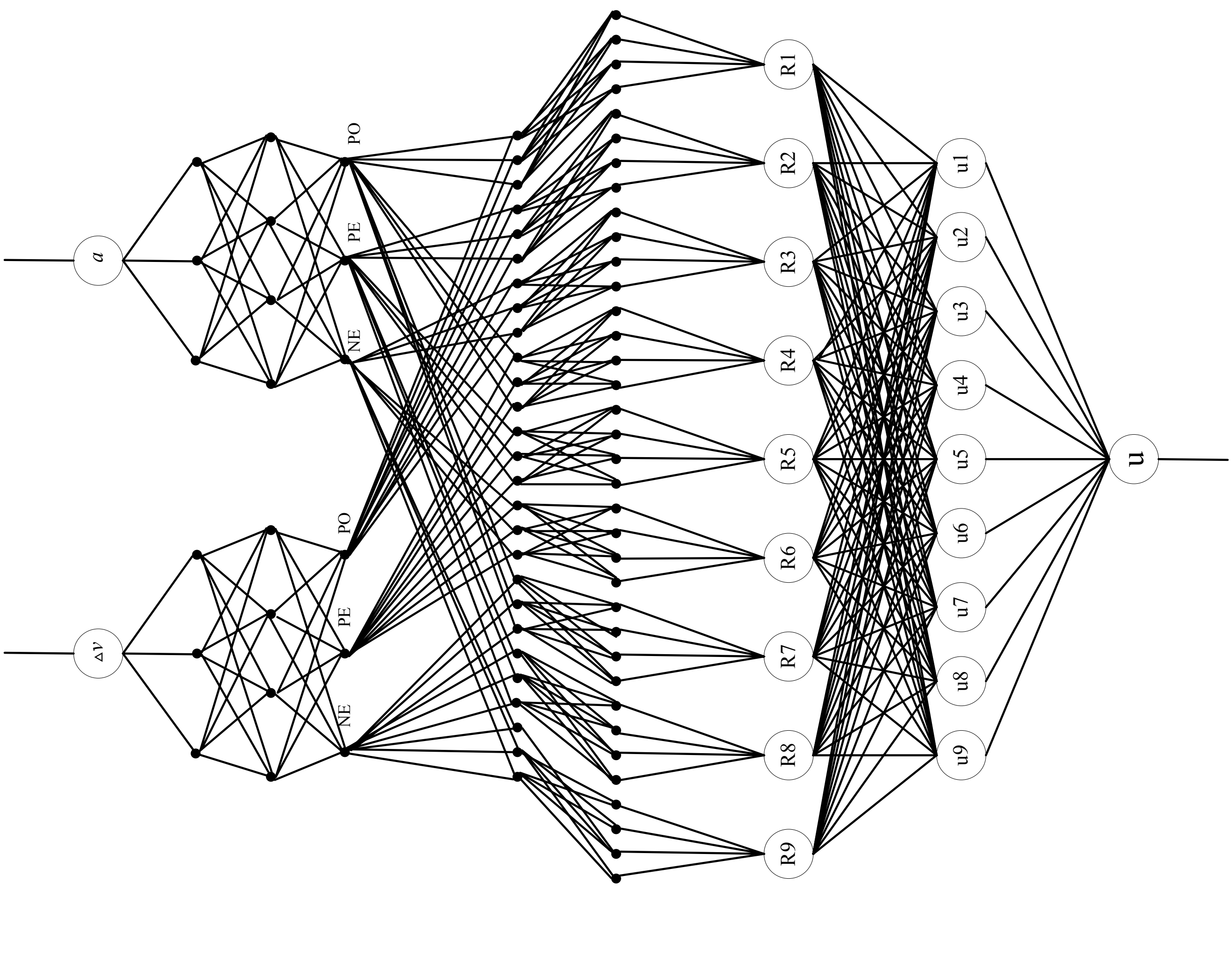

Figure 7. Neuro-fuzzy network for the CC fuzzy agent.

deducing consequences for individual rules, generating resultant fuzzy control and then converting it into a crisp value.

Once neural networks SN_i, RN_r and CN_j have been created, the final step toward a structured neuro-fuzzy network is to connect those networks appropriately according to the original FLCS. Figure 7 presents the neuro-fuzzy network for the four-rule CC fuzzy agent described in the previous section. It should be noted that this neuro-fuzzy network is nine-rule system, but not all rule will function. Through the adaptive changes of weight, the firing strength of other rules will become zero.

The neural network presented above is multilayer feedforward neural networks, which can be trained using backpropagation learning algorithm. This has been discussed in [8] [9], we will not more discuss this issue.

ii. IMPLEMENTATION OF ACC CONTROL AGENT

A. ACC FUZZY CONTROL AGENT

ACC fuzzy control agent gets the location information x_1 of the preceded vehicle through the sensor mounted in front and constructs another input reading $\delta(t)$ which has been mentioned in equation (4). Figure 8 is the control scheme.

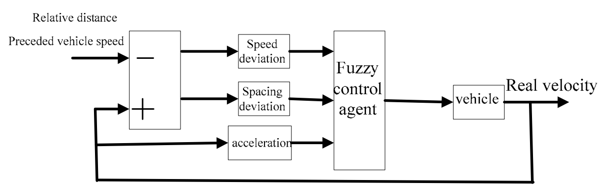

Figure 8. ACC scheme including fuzzy control agent

Assuming that the average velocity is $20\,m/s$, the length of the vehicle is $4m$, the safe distance needs $18m$ which includes the length of the vehicle. Figure 9 shows the membership function of $\delta(t)$. The membership functions of other variables are equal to that of CC fuzzy agent.

Finally, learning from skilled driver, the fuzzy rules are set as:

Rule 1: IF speed deviation $\triangle v$ is PO, THEN u is NE;

Rule 2: IF speed deviation $\triangle v$ is NE and $\delta(t)$ is PO, THEN u is PO;

Rule 3: IF accelerate a is PO, THEN u is NE;

Rule 4: IF accelerate a is NE and $\delta(t)$ is PO, THEN u is PO.

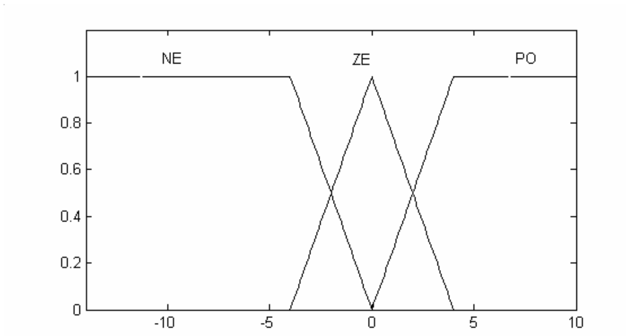

Figure 9. Spacing deviation membership function

B. ACC NEURAL NETWORK CONTROL AGENT

Using the three types of subnets described in previous section, ACC neural network control agent can be developed through similar process. We will no describe this process in detail in this section.

V. SIMULATION RESULT

The first set of simulation test the performance of CC. In Figure 10, the dotted line is the real velocity of the vehicle which is controlled by CC fuzzy agent, the dash-dot line is the real velocity of the vehicle which is controller by new CC fuzzy agent recovered from neural network agent, and the solid line is the velocity set by user.

At the first, CC fuzzy control agent as default agent controls the vehicle and the real velocity can follow the velocity set by user. But when the desired velocity changes suddenly, the real velocity can not follow the change. This fires Rule 2 in hosting mechanism, which leads to the executing agent produced by neural network to control the vehicle.

The second set of simulation test the performance of ACC, in Figure 11(a), solid line, the dotted line the dash-dot line are the velocity of preceded vehicle, real velocity of preceding vehicle which is controlled by ACC fuzzy agent, and real velocity of preceding vehicle which is controlled by new ACC fuzzy agent produced by ACC neural network. Figure 11(b) shows the spacing deviation between preceded vehicle and preceding vehicle.

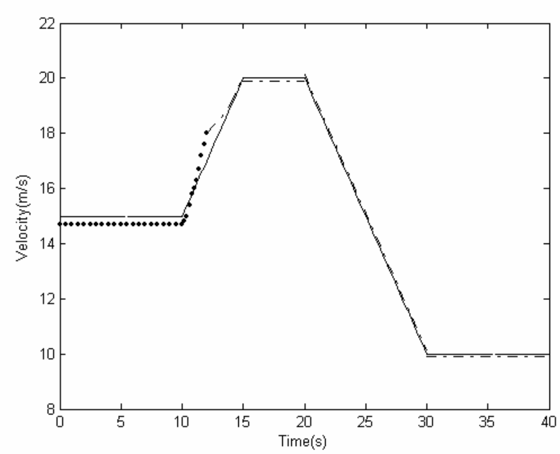

Figure 10. Velocity of the vehicle under CC agents

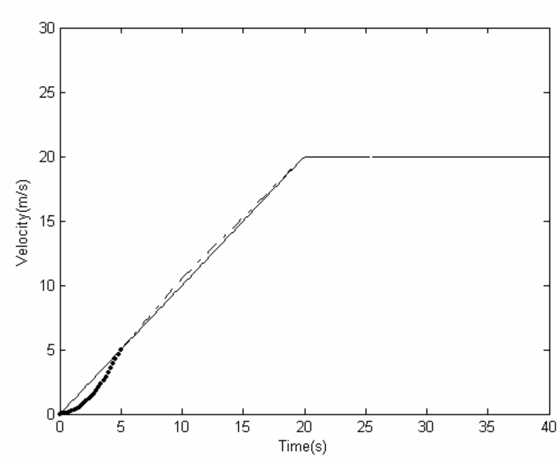

Figure 11(a). Velocity of the vehicle under ACC agents

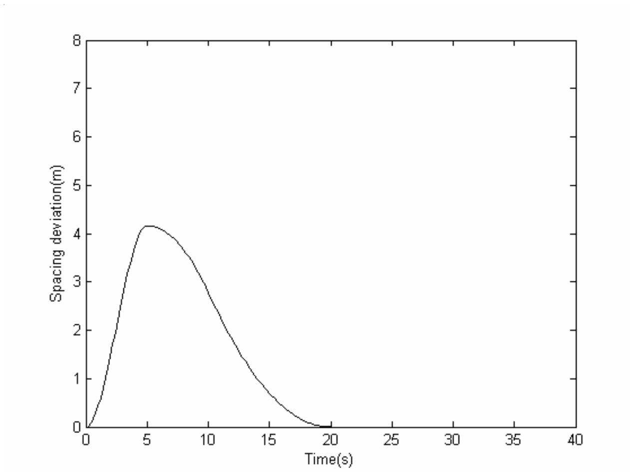

Figure 11(b). Spacing deviation between vehicles

VI. Conclusion

This paper studies the design of agent-based controller for vehicular automation. In this approach, the driving task is conducted by a group of control agent each of which focuses on only a few specific operating conditions. For each of default agent which is developed by fuzzy logic, a neural network agent is designed to produce new promoting fuzzy agent. Hosting mechanism determine which agent control the vehicle at specific driving condition. Simulation result demonstrated that the proposed control method can provide high performance at resource limitation.

Acknowledgment

This work is funded partly by National Natural Science Foundation of China (No.60334020), the 973 Key Project (2002CB312200) from the Ministry of Science and Technology, China NSFC two-bases project under grant No.60440420130.

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