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Abstract

Transportation technology is one of the most influential areas in the human life. Therefore, researchers have been involving in wide scope of related research activities aiming to enhance efficiency, comfort, and safety of transportation systems. Due to the ever growing number of vehicles on the roads, urban highways are congested and need additional capacity. Upon entering the intelligent automated highway system, the longitudinal control of the car-following collision prevention system will drive a vehicle along the fully automated highway. To achieve this objective, this subproject proposes a self-structuring fuzzy neural network control (SSFNNC) system for the vehicle platoons system. The proposed SSFNNC system is comprised of a neural controller and a robust controller. The neural controller using a self-structuring fuzzy neural network (SFNN) is designed to mimic an ideal controller, and the robust controller is designed to achieve $L^2$ tracking performance with desired attenuation level. The adaptation laws of the control system are derived in the sense of Lyapunov stability theorem, so that the stability of the control system can be guaranteed. Moreover, the learning phase of the SFNN is considered about structure and parameter learning phases. The structure learning phase possesses the ability of online generation and elimination of fuzzy rules to achieve optimal neural structure, and the parameter learning phase adjusts the interconnection weights of neural network to achieve favorable approximation performance. Finally, some simulation scenarios are examined to verify the effectiveness of the proposed SSFNNC system.

keywords: car-following, self-structuring learning phase, fuzzy neural network, robust control

I. Introduction

Transportation technology is one of the most influential areas in the human life. Many researchers have been involved in a wide scope of related research activities aiming to enhance efficiency, comfort, and safety of transportation systems. Among them, the traffic congestion is a global problem. One solution of this problem is to increase the traffic flow by decreasing the inter-vehicular spacing. To achieve this objective, car following for traffic safety has been an active area of research [1, 2]. However, human driving involves reaction time, delay, and human error that affect safe driving adversely. One way to eliminate human error and delay in vehicle
following is to integrate an automated car-following control system in the driving system. Inside
the vehicle platoon, all the vehicles follow the leading vehicle with a small intraplatoon
separation. To enable this, each vehicle will be equipped with control systems which coordinate
control between the brakes, engine and steering subsystems.

The neural-network-based control techniques have been used as an alternative design
method for identification and control of dynamic systems [3-6]. The key element of the neural
network is the capability of approximating mapping through choosing adequately learning
method. Based on this property, the neural-network-based controllers have been developed to
compensate for the effects of nonlinearities and system uncertainties, so that the stability,
convergence and robustness of the control system can be improved. Although the control
performances in [3-6] are acceptable, the learning algorithm only includes the parameter learning
phase, and they have not considered the structure learning phase of the neural network. If the
number of the hidden neurons is chosen too large, the computation loading is heavy so that they
are not suitable for online practical applications. If the number of the hidden neurons is chosen
too small, the learning performance may be not good enough to achieve desired control
performance.

To solve this problem, several self-structure neural-network-based control have been
developed [7-9]. However, some of them use the gradient descent method to derive the parameter
learning algorithms which can’t guarantee the system stability. Some of them use the Lyapunov
function to derive the parameter learning algorithms; however, the neurons in the hidden layer
only can automatic split-up to achieve satisfactory performance without considering how to
eliminate the neuron.

This paper combines the advantages of the self-structuring fuzzy neural network (SFNN)
approach and adaptive control technique to develop an intelligent longitudinal control for vehicle
platoon systems. The proposed self-structuring fuzzy neural network control (SSFNNC) system is
comprised of a neural controller and a robust controller. The neural controller exploiting a SFNN
is the principal controller. The SFNN is used to online estimate the ideal controller with the
structure and parameter learning phases, simultaneously. The structure learning phase possesses
the ability of online generation and elimination of fuzzy rules to achieve optimal neural structure,
and the parameter learning phase adjusts the interconnection weights of neural network to
achieve favorable approximation performance. The robust controller is used to achieve $L_2$
tracking performance with desired attenuation level. Moreover, all the parameter learning
algorithms are derived based on the Lyapunov function, thus the system stability can be
guaranteed. Finally, two simulation scenarios (one-vehicle following scenario and multi-vehicles
following scenario) are examined to verify the effectiveness of the proposed SSFNNC system.

II. Problem Formulation
A. Platoon Dynamic

Figure 1 describes a platoon of $N$ vehicles following a lead vehicle on a straight lane of
highway. The position of the rear bumper of the $i$th vehicle with respect to a fixed reference point
$O$ on the road is denoted by $x_i$. The position of the lead vehicle’s rear bumper with respect to the
same fixed reference point is denoted by $x_1$. From the platoon configuration, the spacing error
$e_i$ can be written as

$$
e_i = \begin{cases} 
x_i - x_1 - H_i & \text{for } i = 1 \\
x_{i-1} - x_i - H_i & \text{for } i = 2,3,\ldots,N 
\end{cases}$$

(1)

where $H_i$ denotes the safety spacing of the $i$th vehicle in the platoon. In the following, the
variables and parameters are assumed to be associated with the $i$th vehicle, unless subscripts
indicate otherwise.

B. Vehicle Model

The dynamics of the car following system for the vehicle in a platoon are modeled as follows

$$\dot{\xi} = \frac{1}{\tau}(-\xi + u)$$

(2)
\[ \ddot{x} = \frac{1}{m}(\xi - K_d \dot{x}^2 - d_m) \]  

where \( \xi \) denotes the driving force produced by the vehicle engine; \( \tau \) denotes the engine time lag to the vehicle; \( u \) denotes the throttle command input to the vehicle’s engine (if \( u > 0 \), then it represents a throttle input and if \( u < 0 \), it represents a brake input); \( m \) denotes the mass of the vehicle; \( K_d \) denotes the aerodynamic drag coefficient for the vehicle; and \( d_m \) denotes the vehicle’s mechanical drag. Equation (2) represents the vehicle’s engine dynamics, and (3) represents Newton’s second law applied to the vehicle modeled as a particle of mass. Differentiating both sides of (3) with respect to time and substituting the expression for \( \xi \) in term of \( v \) and \( a \), yields

\[ \ddot{a} = f(v,a) + g \]  

where \( f(v,a) = \frac{1}{\tau} \left[ a + \frac{K_d}{m} v^2 + \frac{d_m}{m} \right] - 2K_d \frac{va}{m} \) is a nonlinear function, \( g = \frac{1}{m\tau} \) is a positive constant, \( v \) denotes the velocity of the vehicle, and \( a \) denotes the acceleration of the vehicle.

III. Control Algorithm Design

The control objective is to design a control system such that the tracking error \( e \) can be driven to zero. Assume that the parameters of the platoon system in (4) are well known, an ideal controller of the following vehicle can be constructed as [10]

\[ u^* = g^{-1}(-f + x^{(3)} + k_3 \dot{e} + k_2 \dot{e} + k_1 e). \]  

Substituting (5) into (4), gives the following equation

\[ e^{(3)} + k_3 \dot{e} + k_2 \dot{e} + k_1 e = 0. \]  

If \( k_1, k_2 \) and \( k_3 \) are chosen to correspond to the coefficients of a Hurwitz polynomial, then it implies \( \lim_{t \to \infty} e = 0 \). However, the system dynamics \( f \) and \( g \) always cannot be precisely obtained in the real-time practical applications, thus the ideal controller \( u^* \) in (5) is always unachievable.

A. Structure of SSFNN

A self-structuring fuzzy neural network (SSFNN) is shown in Fig. 2, which is comprised of the input, the membership, the rule and the output layers. The interactions for the layers are given as follows.

Layer 1 - Input layer: For every node \( i \) in this layer, the net input and the net output are represented as

\[ \text{net}_i = x_i \]  

\[ y_i = f_i(\text{net}_i) = \text{net}_i, \quad i = 1,2,\ldots,l \]  

where \( x_i \) represents the \( i \)-th input to the node of layer 1.

Layer 2 - Membership layer: In this layer, each node performs a membership function and acts as an element for membership degree calculation, where the Gaussian function is adopted as the membership function. For the \( j \)-th node, the reception and activation functions are written as

\[ \text{net}_j = \frac{(x_j^2 - m_j)^2}{(\sigma_j)^2} \]  

Fig. 1. Configuration of car-following platoon.
\[ y_j^2 = f_j^2(\text{net}_j^2) = \exp(\text{net}_j^2), \quad j = 1, \ldots, m \]  

where \( m_j \) and \( \sigma_j \) are the mean and standard deviation of the Gaussian function in the \( j \)-th term of the \( i \)-th input linguistic variable \( x_i^j \), respectively, and \( m \) is the total number of the linguistic variables with respect to the input nodes.

Layer 3 - Rule layer: Each node \( k \) in this layer is denoted by \( \prod \), which multiplies the incoming signals and outputs the result of the product. For the \( k \)-th rule node

\[ \text{net}_k^3 = \prod_j x_j^3 \]  

\[ y_k^3 = f_k^3(\text{net}_k^3) = \text{net}_k^3, \quad k = 1, \ldots, n \]

where \( x_j^3 \) represents the \( j \)-th input to the node of layer 3.

Layer 4 - Output layer: The single node \( o \) in this layer is labeled as \( \Sigma \), which computes the overall output as the summation of all incoming signals

\[ \text{net}_o^4 = \sum_k w_k^4 x_k^4 \]  

\[ y_o^4 = f_o^4(\text{net}_o^4) = \text{net}_o^4 \]

where the link weight \( w_k^4 \) is the output action strength associated with the \( k \)-th rule, \( x_k^4 \) represents the \( k \)-th input to the node of layer 4, and \( y_o^4 \) is the output of the SOFNN. For ease of notation, by defining vectors \( \mathbf{m} \) and \( \mathbf{\sigma} \) collecting all parameters of SOFNN, the output of the SOFNN can be represented in a vector form

\[ y_o^4 = \mathbf{w}^T \Phi(\mathbf{m}, \mathbf{\sigma}) \]  

B. Structure Learning of SFNN

The first step in the structure learning phase is to determine whether or not to add a new node (membership function) in layer 2 and the associated fuzzy rule in layer 3, respectively. In the rule generating process, the mathematical description of the existing rules can be expressed as a cluster. Since one cluster formed in the input space corresponds to one potential fuzzy logic rule, the firing strength of a rule for each incoming data \( x_i \) can be represented as the degree that the incoming data belong to the cluster. The firing strength obtained from (11) is used as the degree measure

\[ \beta_k = y_k^3, \quad k = 1, 2, \ldots, n(t) \]  

where \( n(t) \) is the number of the existing rules at the time \( t \). According to the degree measure, the criterion of generating a new fuzzy rule for new incoming data \( x_i \) can be represented as the degree that the incoming data belong to the cluster. The firing strength obtained from (11) is used as the degree measure

\[ \beta_k = y_k^3, \quad k = 1, 2, \ldots, n(t) \]  

where \( n(t) \) is the number of the existing rules at the time \( t \). According to the degree measure, the criterion of generating a new fuzzy rule for new incoming data is described as follows. Find the maximum degree \( \beta_{\text{max}} \) defined as

\[ \beta_{\text{max}} = \max_{1 \leq k \leq n(t)} \beta_k. \]

It can be observed that if the maximum degree \( \beta_{\text{max}} \) is smaller as the incoming data is far away the existing fuzzy rules. If \( \beta_{\text{max}} \leq \beta_{\text{th}} \) is satisfied, where \( \beta_{\text{th}} \in (0,1) \) a pre-given threshold, then a new membership function is generated. The mean and the standard deviation of the new membership function and the output action strength are selected as follows:

\[ m_{i,\text{new}} = x_i \]  

\[ \sigma_{i,\text{new}} = \sigma_i \]  

\[ w_{\text{new}} = 0 \]

where \( x_i \) is the new incoming data and \( \sigma_i \) is a pre-specified constant.

Next the structure learning phase is considered to determine whether or not to eliminate the existing fuzzy rules which are inappropriate. A significance index is determined for the importance of the \( k \)-th rules can be given as follows

\[ I_k(t+1) = \begin{cases} I_k(t) \exp(-\tau), & \text{if } \beta_k < \rho \\ I_k(t), & \text{if } \beta_k \geq \rho \end{cases}, \quad k = 1, 2, \ldots, n(t) \]  

where \( \tau \) and \( \rho \) are the learning parameters.
where $I_k$ is the significance index of the $k$-th rule its initial value is 1, $\rho$ is the elimination threshold value and $\tau$ is the elimination speed constant. The proposed elimination algorithm is derived from the observation that if the significance index gets fading when the rule firing weight $\beta_k$ is smaller than elimination threshold value $\rho$. 

![Fig. 2. Self-structuring fuzzy neural network.](image)

C. SSFNNC Design

The proposed SSFNNC system, comprised of a neural controller and a robust controller, for the vehicle platoon is shown in Fig. 3, where a tracking error index is defined as

$$s = \ddot{e} + k_3 \dot{e} + k_2 e + k_1 \int_0^t e \, d\tau.$$  \hfill (22)

The control law of the intelligent longitudinal controller is taken as

$$u = u_{nc} + u_{rc}$$  \hfill (23)

where $u_{nc}$ is the neural controller and $u_{rc}$ is the robust controller. By substituting (23) into (4), it is revealed that

$$\dot{a} = f + g(u_{nc} + u_{rc}).$$  \hfill (24)

Multiplying (5) with $g_i^{-1}$, adding to (20) and using (7), the error equation can be obtained as

$$\dot{\delta} = g(u^* - u_{nc} - u_{rc}).$$  \hfill (25)

By the universal approximation theorem, an optimal SOFNN can be designed to approximate the controlled system dynamics, such that [11]

$$u^* = u_{nc} + \Delta = w^* \Phi^* (m^*, \sigma^*) + \Delta$$  \hfill (26)

where $\Delta$ is the approximation error, $w^*$ and $\Phi^*$ are the optimal parameter vectors of $w$ and $\Phi$, respectively, and $m^*$ and $\sigma^*$ are the optimal parameters of $m$ and $\sigma$, respectively. Let the number of optimal neurons be $n^*$ and the neurons be divided into two parts. The first part contains $n$ neurons which are the activated part and the secondary part contains $n^* - n$ neurons which do not exist yet. Thus, the optimal weights $w^*$, $\Phi^*$, $m^*$ and $\sigma^*$ are classified in two parts such as

$$w^* = \begin{bmatrix} w_{a}^* \\ w_i^* \end{bmatrix}, \quad \Phi^* = \begin{bmatrix} \Phi_a^* \\ \Phi_i^* \end{bmatrix}, \quad m^* = \begin{bmatrix} m_a^* \\ m_i^* \end{bmatrix} \quad \text{and} \quad \sigma^* = \begin{bmatrix} \sigma_a^* \\ \sigma_i^* \end{bmatrix}$$  \hfill (27)
where $\mathbf{w}_a^*$, $\Phi_a^*$, $\mathbf{m}_a^*$ and $\sigma_a^*$ are activated parts, and $\mathbf{w}_i^*$, $\Phi_i^*$, $\mathbf{m}_i^*$ and $\sigma_i^*$ are inactivated parts, respectively. Since these optimal parameters are unobtainable, a SFNN is defined as

$$\hat{u}_{nc} = \hat{\mathbf{w}}_a^T \hat{\Phi}_a (\hat{\mathbf{m}}_a, \hat{\sigma}_a)$$

(28)

where $\hat{\mathbf{w}}_a$, $\hat{\Phi}_a$, $\hat{\mathbf{m}}_a$ and $\hat{\sigma}_a$ are the estimated values of $\mathbf{w}_a^*$, $\Phi_a^*$, $\mathbf{m}_a^*$ and $\sigma_a^*$, respectively. Define the estimated error $\hat{u}$ as

$$\hat{u} = u^* - \hat{u}_{nc}$$

$$= \mathbf{w}_a^T \Phi_a + \mathbf{w}_i^T \Phi_i - \hat{\mathbf{w}}_a^T \hat{\Phi}_a + \Delta$$

$$= \mathbf{w}_a^T \Phi_a + \mathbf{w}_i^T \Phi_i + \hat{\mathbf{w}}_a^T \hat{\Phi}_a + \mathbf{w}_i^T \Phi_i + \Delta$$

(29)

where $\hat{\mathbf{w}}_a = \mathbf{w}_a^* - \mathbf{w}_a$ and $\hat{\Phi}_a = \Phi_a^* - \Phi_a$. Some adaptive laws will be proposed to on-line tune the mean and standard deviation of the Gaussian function of the SFNN to achieve favorable estimation of the dynamic function. The Taylor expansion linearization technique is employed to transform the nonlinear radial basis function into a partially linear form, i.e.

$$\hat{\Phi}_a = \mathbf{A}^T \hat{\mathbf{m}}_a + \mathbf{B}^T \hat{\sigma}_a + \mathbf{h}$$

(30)

where $\mathbf{A} = \left[ \frac{\partial \Phi_1}{\partial \mathbf{m}_a}, \ldots, \frac{\partial \Phi_n}{\partial \mathbf{m}_a} \right]_{\mathbf{m}_a = \mathbf{m}_a^*}$, $\mathbf{B} = \left[ \frac{\partial \Phi_1}{\partial \sigma_a^*}, \ldots, \frac{\partial \Phi_n}{\partial \sigma_a^*} \right]_{\sigma_a = \sigma_a^*}$, $\mathbf{h}$ is a vector of higher-order terms, $\hat{\mathbf{m}}_a = \mathbf{m}_a^* - \mathbf{m}_a$, $\hat{\sigma}_a = \sigma_a^* - \sigma_a^*$, and $\frac{\partial \Phi_k}{\partial \mathbf{m}_a}$ and $\frac{\partial \Phi_k}{\partial \sigma_a^*}$ are defined as

$$\left[ \frac{\partial \Phi_k}{\partial \mathbf{m}_a} \right]^T = \left[ 0 \ldots \frac{\partial \Phi_k}{\partial \mathbf{m}_a} \right]_{(k-1) \ldots 0}^{0 \ldots 0}$$

(31)

$$\left[ \frac{\partial \Phi_k}{\partial \sigma_a^*} \right]^T = \left[ 0 \ldots \frac{\partial \Phi_k}{\partial \sigma_a^*} \right]_{(k-1) \ldots 0}^{0 \ldots 0}$$

(32)

Substituting (30) into (29), it is obtained that

$$\hat{u} = \mathbf{w}_a^T \Phi_a + \hat{\mathbf{w}}_a^T \hat{\Phi}_a + \mathbf{w}_i^T \Phi_i + \hat{\mathbf{w}}_i^T \hat{\Phi}_i + \Delta$$

(33)

where $\mathbf{w}_a^T \mathbf{A}^T \hat{\mathbf{m}}_a = \hat{\mathbf{w}}_a^T \hat{\Phi}_a$ and $\mathbf{w}_i^T \mathbf{B}^T \hat{\sigma}_a = \hat{\mathbf{w}}_i^T \hat{\Phi}_i$ are used since they are scales; and the uncertain term $\varepsilon = \mathbf{w}_a^T \mathbf{h} + \hat{\mathbf{w}}_a^T \hat{\Phi}_a + \mathbf{w}_i^T \Phi_i + \Delta$.

From (25), the error equation can be rewritten as

$$\dot{s} = g (\hat{\mathbf{w}}_a^T \hat{\Phi}_a + \hat{\mathbf{m}}_a^T \hat{\mathbf{A}} \hat{\mathbf{w}}_a + \hat{\sigma}_a^T \hat{\mathbf{B}} \hat{\mathbf{w}}_a + \varepsilon - u_{nc})$$

(34)

Then, the following theorem can be stated and proven.

**Theorem 1**: Consider a car-following system represented by (4). The vehicle’s control law is designed as $u = u_{nc} + u_{rc}$. The neural controller $u_{nc}$ is designed as (28), in which the parameter vectors are tuned by

$$\dot{\mathbf{w}}_a = -\mathbf{w}_a = -\eta_1 \mathbf{w}_a$$

(35)

$$\dot{\mathbf{m}}_a = -\mathbf{m}_a = -\eta_2 \mathbf{A} \dot{\mathbf{w}}_a$$

(36)

$$\dot{\sigma}_a = -\sigma_a = -\eta_3 \mathbf{B} \dot{\mathbf{w}}_a$$

(37)

where $\eta_1$, $\eta_2$ and $\eta_3$ are the learning-rates. The robust controller $u_{rc}$ is designed as

$$u_{rc} = \frac{2 \delta^2 + 1}{2 \delta^2} s$$

(38)

where $\delta$ is a prescribed attenuation constant. Then the stability of the intelligent longitudinal control system can be guaranteed.

Proof: Consider a Lyapunov function candidate in the following form

$$V(s, \hat{\mathbf{w}}_a, \hat{\mathbf{m}}_a, \hat{\sigma}_a) = \frac{1}{2} s^2 + g (\frac{\hat{\mathbf{w}}_a^T \hat{\mathbf{w}}_a}{2 \eta_1} + \frac{\hat{\mathbf{m}}_a^T \hat{\mathbf{m}}_a}{2 \eta_2} + \frac{\hat{\sigma}_a^T \hat{\sigma}_a}{2 \eta_3})$$

(39)

Differentiating (39) with respect to time and using (34), it gives
\[ \dot{V} = s \dot{s} + g(\tilde{\omega}_a^{T} \tilde{\omega}_a + \tilde{m}_a^{T} \tilde{m}_a + \tilde{\sigma}_a^{T} \tilde{\sigma}_a) \]

\[ = s(\tilde{\omega}_a^{T} \dot{\tilde{\omega}}_a + \tilde{m}_a^{T} A \tilde{\dot{m}}_a + \tilde{\sigma}_a^{T} B \tilde{\dot{\sigma}}_a + \varepsilon - u_{rc}) + g(\tilde{\omega}_a^{T} \tilde{\omega}_a + \tilde{m}_a^{T} \tilde{m}_a + \tilde{\sigma}_a^{T} \tilde{\sigma}_a) \]

\[ = \tilde{\omega}_a^{T} (s \hat{\Phi}_a + s \hat{\tilde{\omega}}_a) + \tilde{m}_a^{T} (sA \hat{\dot{m}}_a + s \hat{\tilde{m}}_a) + \tilde{\sigma}_a^{T} (sB \hat{\dot{\sigma}}_a + s \hat{\tilde{\sigma}}_a) + s(e - u_{rc}) \]

\[ = s \varepsilon - \frac{(\delta^2 + 1)s^2}{2\delta^2} \]

\[ = -\frac{s^2}{2} \left( \frac{s}{\delta} - \delta \varepsilon \right)^2 + \frac{1}{2} \delta^2 \varepsilon^2 \]

\[ \leq -\frac{s^2}{2} + \frac{1}{2} \delta^2 \varepsilon^2 \quad (40) \]

Assume \( \varepsilon \in L_2[0,T), \forall T \in [0,\infty) \), integrating the above equation from \( t = 0 \) to \( t = T \), yields

\[ V(T) - V(0) \leq -\frac{1}{2} \int_0^T s^2 \, dt + \frac{1}{2} \delta^2 \int_0^T \varepsilon^2 \, dt \quad (41) \]

Since \( V(T) \geq 0 \), the above inequality implies the following inequality

\[ \frac{1}{2} \int_0^T s^2 \, dt \leq V(0) + \frac{1}{2} \delta^2 \int_0^T \varepsilon^2 \, dt \quad (42) \]

If the system starts with initial conditions \( s(0) = 0, \tilde{\omega}_a = 0, \tilde{m}_a(0) = 0 \) and \( \tilde{\sigma}_a(0) = 0 \), the \( L_2 \) tracking performance can be rewritten as

\[ \sup_{\varepsilon \in L_2[0,T]} \left\| \varepsilon \right\| \leq \delta \quad (43) \]

where \( \left\| s \right\|^2 = \int_0^T s^2(t) \, dt \) and \( \left\| \varepsilon \right\|^2 = \int_0^T \varepsilon^2(t) \, dt \).

**IV. Simulation Results**

To investigate the effectiveness of the proposed intelligent longitudinal control system, two simulation scenarios are carried out. The specific constants of the vehicle parameters used in this paper are chosen as \( \tau = 0.2 \), \( m = 916 \text{kg} \), \( K_d = 0.44 \text{Ns}^2/\text{m}^2 \) and \( d_m = 67.7 \text{Nm} \). For both scenarios, the control parameters of SSFNNC are selected as \( k_1 = 2, k_2 = 5, k_3 = 4, \)

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**Fig. 3. Self-structuring fuzzy neural network control for the longitudinal system.**
$\eta_1 = \eta_2 = \eta_3 = 1000$, $\delta = 0.5$, $\sigma_i = 2.0$, $\beta_{ih} = 0.6$, $\tau = 0.01$, $\rho = 0.3$, and $I_{ih} = 0.01$. These parameters are chosen through some trials to achieve satisfactory transient control performance.

In scenario 1, assumes that one following vehicle (FV) follows the leading vehicle (LV). The safety spacing is initialized with $H_1 = 10 m$ first, and after the 15th, 30th, 45th, 60th, and 75th seconds the safety space is changed between $H_1 = 5 m$ and $H_1 = 10 m$, respectively. The initial values of the LV and FV are chosen as $v_i(0) = 20 m/sec$, $a_i(0) = 0 m/sec^2$, $v_f(0) = 20 m/sec$ and $a_f(0) = 0 m/sec^2$ and the LV in the platoon has no acceleration. The simulation results of intelligent longitudinal control for scenario 1 are shown in Fig. 4. The safety spacing of the FV is shown in Fig. 4(a), the vehicle of the FV is shown in Fig. 4(b), the control input of FV is shown in Fig. 4(c), and the rule number of SFNN is shown in Fig. 4(d). From the simulation results, it can be seen that the proposed SSFNNC system can achieve satisfactory performance for the one-vehicle following system even in the change of the safety spacing command.

In scenario 2, assumes that three FVs follow the LV with the safety space $H_i = 15 m$. The vehicle acceleration and velocity of the LV are shown in Fig. 5(a) and 5(b), respectively. For numerical simulations, the initial values of the vehicle following system are chosen as $v_i(0) = 20 m/sec$, $a_i(0) = 0 m/sec^2$, $v_f(0) = 20 m/sec$ and $a_f(0) = 0 m/sec^2$. The simulation results of intelligent longitudinal control for scenario 2 are shown in Fig. 6. The safety spacing of the FV is shown in Fig. 6(a), the vehicle of the FV is shown in Fig. 6(b), the acceleration of the FV is shown in Fig. 6(c), the control input of FV is shown in Fig. 6(d), and the rule number of SFNN is shown in Fig. 6(e). From the simulation results, it can be seen that the proposed SSFNNC system can also achieve satisfactory performance even in the changes of acceleration and velocity of the LV.
Fig. 6. Simulation results for scenario 2.

V. Conclusions
This paper has successfully developed an intelligent longitudinal control system via the self-structuring fuzzy neural network (SFNN) approach and adaptive control approach for the vehicle-following system. The on-line adaptation laws of the proposed self-structuring fuzzy neural network control scheme are derived based on the Lyapunov stability theorem, so that the tracking stability can be guaranteed for the control system. In the SFNN design, a dynamic rule generating/elimination mechanism is developed to cope with the tradeoff between the approximation accuracy and computational loading. Finally, two different simulation scenarios are carried out and simulation results have demonstrated that the proposed control system can achieve favorable tracking performance for the vehicle-following control even under the leading vehicles safety space change and acceleration maneuver.

VI. References