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中文摘要

隨著車輛數量的成長，駕駛員所可能遇到的行車安全之威脅也相對地提高，車輛的行車安全考量問題就顯得重要，所以本計畫在本年度利用適應性控制與模糊類神經網路為基礎來設計“智慧車輛跟車控制系統”，藉以提昇車輛行駛時的安全性，以減少交通事故以及傷亡發生的機率。所提出之控制系統包括一個類神經控制器與一個強健控制器，其中類神經控制器利用具有網路建構能力之非對稱歸屬函數模糊類神經網路，主要用來線上學習近似理想控制器，而強健控制器主要用來確保系統穩定。整個系統學習過程包含網路架構學習與網路參數學習兩部分：網路架構學習考慮到當網路學習能力不佳時，類神經網路可自動生長模糊規則來加強網路學習能力，同時亦可自動刪除一些不重要之神經元來減少運算量。網路參數學習依據李亞普諾夫穩定定理推導出之學習法則來即時調整網路參數，如此可確保整個系統穩定性。最後，在驗證測試所提出控制器效能方面，如果要設置完整的實驗場所將需要花費眾多的時間和金錢，且實車驗證工作還存在一定程度的危險性，而本子計畫利用虛擬實境技術來取代實車測試來解決這些問題。經由 MATLAB 模擬與虛擬實境技術模擬均可驗證本計畫在本年度所提出之控制器可達到不錯的響應。

關鍵詞：車輛跟車控制；適應性控制；類神經網路控制；網路架構學習；網路參數學習；虛擬實境

Abstract

Vehicle and highway automation is believed to reduce the risk of accidents, improve safety, increase capacity, reduce fuel consumption and enhance overall comfort and performance for drivers. This project proposes an intelligent car-following control (ICFC) system. The proposed ICFC system is comprised of a neural controller and a robust controller. The neural controller using an asymmetric self-organizing fuzzy neural network (ASOFNN) is designed to mimic an ideal controller, and the robust controller is designed to compensate for the approximation error between the neural controller and the ideal controller. The structure of the ASOFNN can online grown or prune. The proposed structure learning algorithm not only can create the new fuzzy rules online if the approximation performance is inappropriate, but can also prune the insignificant fuzzy rules online. Moreover, the adaptation laws of the ICFC system are derived in the sense of Lyapunov stability theorem, thus the stability of the closed-loop control system can be guaranteed. Finally, in order to verify the effectiveness of the proposed ICFC system, a real-car experimental setup should be applied. There must have spent much time, manpower and money to build or to conserve the equipment. This project utilizes the virtual-reality (VR) technique to solve the all above problem. Experimental results demonstrate the proposed ICFC system can achieve favorable performance and the VR simulation is comparatively good.

Keyword: car-following control, adaptive control, neural control, structure learning, parameter learning, virtual-reality

I. INTRODUCTION

Transportation technology is one of the most influential areas in the human life. The traffic congestion is a global problem. Vehicle and highway automation is believed to reduce the risk of accidents, improve safety, increase capacity, reduce fuel consumption and enhance overall comfort and performance for drivers. There has been enough reason to assume that more automated automobiles relieve the driver from many undesirable routines of driving task [1]. Automated highway systems by not only a free agent but also a platoon have been demonstrated over the past several years [2-4]. In a model-based controller design, if exact model of controlled system's dynamic is well known, there exists an ideal controller scheme to achieve favorable control performance by canceling all the system dynamics [5]. A tradeoff between system performance and model accuracy is necessary for the ideal controller design.

Recently, the fuzzy-neural-network-based control techniques have been used as an alternative design method for identification and control of dynamic systems [6-8]. The key element of the fuzzy neural network is the capability of approximating mapping through choosing adequately learning method. Though the control performances in [6-8] 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 fuzzy rules is chosen too large, the computation loading is heavy so that they are not suitable for online practical applications. If the number of the fuzzy rules is chosen too small, the learning performance may be not good enough to achieve desired control performance.

To solve this problem, several self-organizing fuzzy neural networks (SOFNNs) have been developed [9]. The self- organizing approach demonstrates the property of automatically generating rules of fuzzy neural networks without the preliminary knowledge. In general, a new membership function is generated when a new input signal is too far away from the current clusters, and an existing rule is canceled when the fuzzy rule is insignificant [9]. Recently, the SOFNNs have been adopted widely for the control of complex dynamic systems [10-12]. Some of them use the gradient descent method to derive the parameter learning algorithms [10]; however, stability analysis has not been performed yet. Some of them use the Lyapunov function to derive the parameter learning algorithms; however, the complex design procedure is not suitable for practical applications [11, 12].

In order to verify the effectiveness of the proposed control system, a real-car experimental setup should be applied. However, there must have spent much time, manpower and money to build or to conserve the equipment. The virtual-reality (VR) technique can solve the all above problem [13]. The VR technology is applied to make the operators believe they are in a different geographic location with different velocity and orientation than they have in the real world [13].

This project describes the technologies for a flexible automated platoon. First, this project proposed an asymmetric self-organizing fuzzy neural network (ASOFNN) with the asymmetric Gaussian membership functions. The structure adaptation is described as follows. A new rule of ASOFNN is generated when a new input signal is too far from the current clusters. If the fuzzy rule of ASOFNN is insignificant, it will be removed to reduce the computation load. Thus, the ASOFNN can self- organizing the fuzzy rules online to achieve an optimal network structure. Then, an intelligent car-following control (ICFC) system is proposed. The adaptation laws of the ICFC system are derived in the sense of Lyapunov stability theorem, thus the stability of the closed-loop control system 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 ICFC system though Matlab and VR simulation, respectively.

II. PROBLEM FORMULATION

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_l. From the platoon configuration, the spacing error e_i can be written as [1]

$$e_i = \begin{cases} x_l - x_1 - H_1 & for\ i = 1 \\ x_{i-1} - x_i - H_i, & for\ i = 2,3,...,N \end{cases}. \tag{1}$$

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. The dynamics of the car following system for the vehicle in a platoon are modeled as follows [1]

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

$$\ddot{x} = \frac{1}{m}(\xi - K_d \dot{x}^2 - d_m) \quad (3)$$

where ξ denotes the driving force produced by the vehicle engine; τ 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 Newtons'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 $\dot{\xi}$ in term of v and a, yields

$$\dot{a} = f(v,a) + \text{g}u \quad (4)$$

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

The control objective is to design a control system such that the tracking error 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 [5]

$$u^* = \text{g}^{-1}(-f + x_{i-1}^{(3)} + k_3\ddot{e} + k_2\dot{e} + k_1 e)\,. \quad (5)$$

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

$$e^{(3)} + k_3\ddot{e} + k_2\dot{e} + k_1 e = 0\,. \quad (6)$$

If k_1, k_2 and k_3 are chosen to correspond to the coefficients of a Hurwitz polynomial, then it implies $\lim_{t\to\infty} e = 0$ [5]. 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.

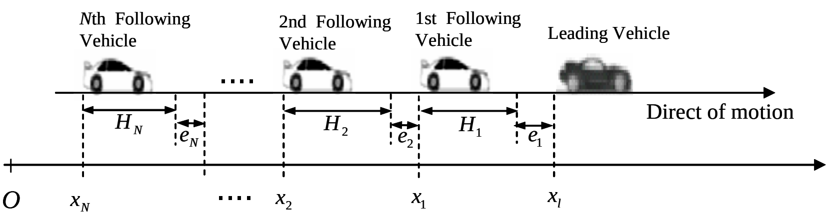

Fig. 1. Configuration of car-following platoon.

III. DESCRIPTION OF ASOFNN

A. Structure of ASOFNN

Figure 2 shows the configuration of the proposed ASOFNN which is composed of the input, the membership, the rule, and the output layers. The output of the ASOFNN with N existing fuzzy rules is given as [8]

$$y_o = \sum_{k=1}^{N} w_k \phi_k(\mathbf{x}) \quad (7)$$

in which w_k is the output action strength associated with the k-th rule and ϕ_k is the response of the firing weight for an input vector $\mathbf{x} = [x_1\, x_2 \cdots x_L]^T$ and composed of membership function defined as

$$\zeta_{ij} = \begin{cases} \exp\left(-\frac{(x_i - m_{ij})^2}{(\sigma_{ij}^l)^2}\right), & if \ -\infty < x_i \le m_{ij} \\ \exp\left(-\frac{(x_i - m_{ij})^2}{(\sigma_{ij}^r)^2}\right), & if \ m_{ij} \le x_i < \infty \end{cases}, \quad j = 1, 2, \cdots, M \quad (8)$$

where M is the total number of membership functions with respect to the respective input node and m_{ij}, σ_{ij}^{l}, and σ_{ij}^{r} are the mean, left-side variance, and right-side variance of the asymmetric Gaussian function in the *j*-th term of the *i*-th input linguistic variable x_i, respectively. And, the associated fuzzy rule can be obtain as

$$\phi_k = \prod_{j=1}^{M} \zeta_{jk} . \tag{9}$$

For ease of notation, define vectors $\mathbf{m}$, $\boldsymbol{\sigma}_\mathbf{l}$ and $\boldsymbol{\sigma}_\mathbf{r}$ collecting all parameters of ASOFNN as

$$\mathbf{m} = [m_{11} \cdots m_{L1}\ m_{12} \cdots m_{L2} \cdots\cdots m_{1M} \cdots m_{LM}]^T \tag{10}$$

$$\boldsymbol{\sigma}_\mathbf{l} = [\sigma_{11}^{l} \cdots \sigma_{L1}^{l}\ \sigma_{12}^{l} \cdots \sigma_{L2}^{l} \cdots\cdots \sigma_{1M}^{l} \cdots \sigma_{LM}^{l}]^T \tag{11}$$

$$\boldsymbol{\sigma}_\mathbf{r} = [\sigma_{11}^{r} \cdots \sigma_{L1}^{r}\ \sigma_{12}^{r} \cdots \sigma_{L2}^{r} \cdots\cdots \sigma_{1M}^{r} \cdots \sigma_{LM}^{r}]^T . \tag{12}$$

Then, the output of the ASOFNN can be represented in a vector form as

$$y_o = \mathbf{w}^T \boldsymbol{\varphi}(\mathbf{x}, \mathbf{m}, \boldsymbol{\sigma}_\mathbf{l}, \boldsymbol{\sigma}_\mathbf{r}) \tag{13}$$

where $\mathbf{w} = [w_1\ w_2\ \cdots\ w_N]^T$ and $\boldsymbol{\varphi} = [\phi_1\ \phi_2\ \cdots\ \phi_N]^T$.

B. Structure Learning

In the structure growing process, the mathematical description of the existing rules can be expressed as a cluster. Each cluster in the product space of the input-output data represents a rule in the rule base. 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 [9]. If the value of firing strength is too small, it represents that the input value is on the edge of range of the existing membership functions. Under this situation, the output will cause an unsatisfactory performance. Therefore, a new membership function and a new fuzzy rule should be generated to improve the performance. According to the above mention, the firing strength obtained from (9) is used as the degree measure

$$\beta_k = \phi_k , \quad k = 1, 2, ..., N(t) \tag{14}$$

where $N(t)$ is the number of the existing fuzzy rules at the time *t*. Find the maximum degree $\beta_{\max}$ defined as

$$\beta_{\max} = \max_{1 \le k \le N(t)} \beta_k . \tag{15}$$

It can be observed that the maximum degree $\beta_{\max}$ is small when the incoming data is far away from the universe of discourse of fuzzy rules. If $\beta_{\max} \le G_{th}$ is satisfied, where $G_{th} \in (0,1)$ is a pre-given threshold, a new membership function is generated. The mean and the standard deviation of the new membership function and the fuzzy rule are selected as follows

$$m_i^{new} = x_i \tag{16}$$

$$\sigma_i^{l,new} = \sigma_i \tag{17}$$

$$\sigma_i^{r,new} = \sigma_i \tag{18}$$

$$w^{new} = 0 \tag{19}$$

where x_i is the new incoming data and σ_i is a pre-specified constant. The number $N(t)$ is incremented

$$N(t+1) = N(t) + 1 . \tag{20}$$

To avoid the unbounded growing of network structure and the overload computation load, the structure pruning algorithm is developed to eliminate irrelevant fuzzy rules. When the *r*-th firing strength β_r is smaller than the threshold value P_{th}, it means that the relationship becomes weak between the input and the *r*-th rule, then the significant index of *r*-th fuzzy rules will be decayed. When the *r*-th firing strength β_r is larger than the threshold value P_{th}, it means that the incoming inputs fall into the range of the *r*-th fuzzy rule under this situation, then the significant index of *r*-th fuzzy rules will be risen. The significance index is determined for the importance of the *r*-th rules can be given as

$$I_r(t+1)=\begin{cases} I_r(t)\cdot\exp(-\tau_1), & if\ \beta_r < P_{th} \\ I_r(t)\cdot\left[2-\exp\left(-\tau_2\left(1-I_r(t)\right)\right)\right], & if\ \beta_r \geq P_{th} \end{cases},\quad r=1,2,\cdots,N(t) \tag{21}$$

where I_r is the significant index of the *r*-th rule and its initial value is 1, P_{th} is the pruning threshold value, and τ_1 and τ_2 are the designed constant. If $I_r \leq I_{th}$ is satisfied, where I_{th} is another pre-given threshold, the *r*-th fuzzy rule will canceled. For the real-time implemented, if the computation loading is the important issue for practical implement, the P_{th} can be chosen as a large value so that more fuzzy rules can be pruned. Hence, the computation load should be decreased.

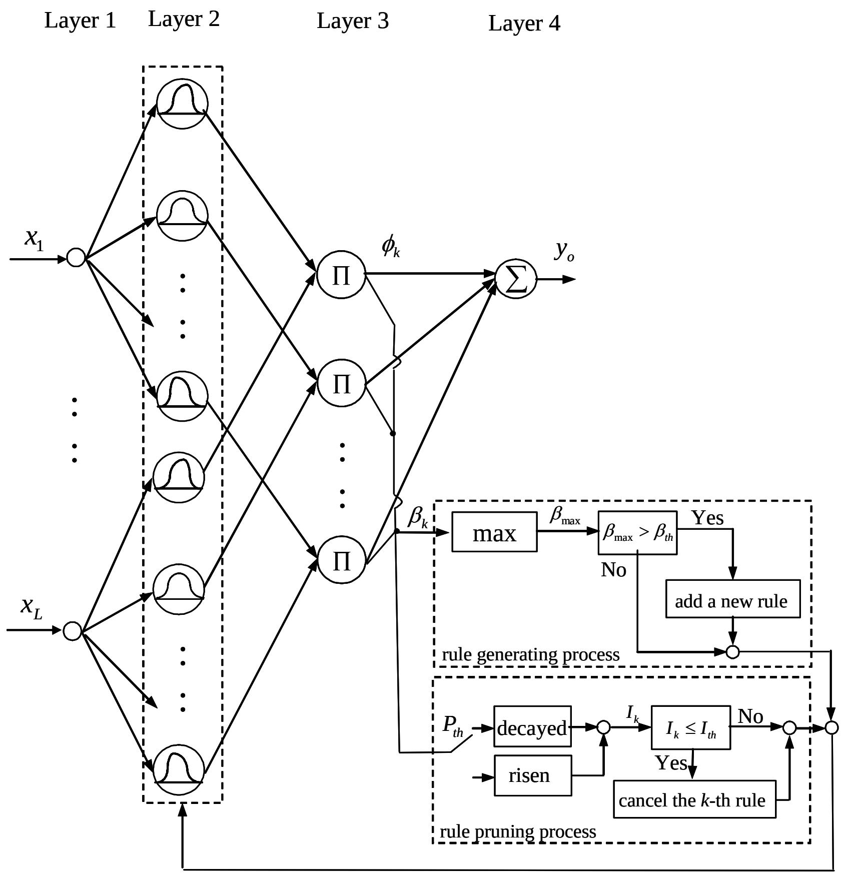

Fig. 2. Asymmetric self-organizing fuzzy neural network.

C. Approximation of ASOFNN

By the universal approximation theorem, an optimal SOFNN can be designed to approximate the controlled system dynamics, such that [8]

$$u^* = u^*_{nc} + \Delta = \mathbf{w}^{*T}\boldsymbol{\varphi}(\mathbf{x},\mathbf{m}^*,\boldsymbol{\sigma}^*_{\mathbf{l}},\boldsymbol{\sigma}^*_{\mathbf{r}}) + \Delta = \mathbf{w}^{*T}\boldsymbol{\varphi}^* + \Delta \tag{22}$$

where Δ denotes the approximation error; $\mathbf{w}^*$ and $\boldsymbol{\varphi}^*$ are the optimal parameters of $\mathbf{w}$ and $\boldsymbol{\varphi}$, respectively, and $\mathbf{m}^*$, $\boldsymbol{\sigma}^*_{\mathbf{l}}$ and $\boldsymbol{\sigma}^*_{\mathbf{r}}$ are the optimal parameters of $\mathbf{m}$, $\boldsymbol{\sigma}_{\mathbf{l}}$ and $\boldsymbol{\sigma}_{\mathbf{r}}$, respectively. In fact, the optimal parameter vectors that are needed to best approximate a given nonlinear function are difficult to determine. Then, an estimation neural controller will be introduced to mimic the ideal controller as

$$u_{nc} = \hat{\mathbf{w}}^T\boldsymbol{\varphi}(\mathbf{x},\hat{\mathbf{m}},\hat{\boldsymbol{\sigma}}_{\mathbf{l}},\hat{\boldsymbol{\sigma}}_{\mathbf{r}}) = \hat{\mathbf{w}}^T\hat{\boldsymbol{\varphi}} \tag{23}$$

where $\hat{\mathbf{w}}$ and $\hat{\boldsymbol{\varphi}}$ are the optimal parameters of $\mathbf{w}$ and $\boldsymbol{\varphi}$, respectively, and $\hat{\mathbf{m}}$, $\hat{\boldsymbol{\sigma}}_{\mathbf{l}}$, $\hat{\boldsymbol{\sigma}}_{\mathbf{r}}$ are the estimated vectors of $\mathbf{m}$, $\boldsymbol{\sigma}_{\mathbf{l}}$ and $\boldsymbol{\sigma}_{\mathbf{r}}$, respectively. Define an approximation error, $\tilde{u}$, as

$$\tilde{u} = u^* - u_{nc} = \tilde{\mathbf{w}}^T\tilde{\boldsymbol{\varphi}} + \hat{\mathbf{w}}^T\tilde{\boldsymbol{\varphi}} + \tilde{\mathbf{w}}^T\hat{\boldsymbol{\varphi}} + \Delta \tag{24}$$

where $\tilde{\mathbf{w}} = \mathbf{w}^* - \hat{\mathbf{w}}$ and $\tilde{\boldsymbol{\varphi}} = \boldsymbol{\varphi}^* - \hat{\boldsymbol{\varphi}}$. In the following, the linearization technique is employed to transform the nonlinear fuzzy function into a partially linear form so that the expansion $\tilde{\boldsymbol{\varphi}}$ can be expressed as [8]

$$\tilde{\boldsymbol{\varphi}} = \boldsymbol{\varphi}_{\mathbf{m}}^{T}\tilde{\mathbf{m}} + \boldsymbol{\varphi}_{\sigma_l}^{T}\tilde{\boldsymbol{\sigma}}_{\mathbf{l}} + \boldsymbol{\varphi}_{\sigma_r}^{T}\tilde{\boldsymbol{\sigma}}_{\mathbf{r}} + \mathbf{h} \tag{25}$$

where $\mathbf{h}$ is a vector of higher-order terms, $\tilde{\mathbf{m}} = \mathbf{m}^* - \hat{\mathbf{m}}$, $\tilde{\boldsymbol{\sigma}}_{\mathbf{l}} = \boldsymbol{\sigma}_{\mathbf{l}}^* - \hat{\boldsymbol{\sigma}}_{\mathbf{l}}$ and $\tilde{\boldsymbol{\sigma}}_{\mathbf{r}} = \boldsymbol{\sigma}_{\mathbf{r}}^* - \hat{\boldsymbol{\sigma}}_{\mathbf{r}}$. Substituting (25) into (24), (24) can be rewritten as

$$\begin{aligned} \tilde{u} &= \tilde{\mathbf{w}}^T\hat{\boldsymbol{\varphi}} + \hat{\mathbf{w}}^T(\boldsymbol{\varphi}_{\mathbf{m}}^{T}\tilde{\mathbf{m}} + \boldsymbol{\varphi}_{\sigma_l}^{T}\tilde{\boldsymbol{\sigma}}_{\mathbf{l}} + \boldsymbol{\varphi}_{\sigma_r}^{T}\tilde{\boldsymbol{\sigma}}_{\mathbf{r}} + \mathbf{h}) + \tilde{\mathbf{w}}^T\tilde{\boldsymbol{\varphi}} + \Delta \\ &= \tilde{\mathbf{w}}^T\hat{\boldsymbol{\varphi}} + \tilde{\mathbf{m}}^T\boldsymbol{\varphi}_{\mathbf{m}}\hat{\mathbf{w}} + \tilde{\boldsymbol{\sigma}}_{\mathbf{l}}^T\boldsymbol{\varphi}_{\sigma_l}\hat{\mathbf{w}} + \tilde{\boldsymbol{\sigma}}_{\mathbf{r}}^T\boldsymbol{\varphi}_{\sigma_r}\hat{\mathbf{w}} + \varepsilon \end{aligned} \tag{26}$$

where $\tilde{\mathbf{m}}^T\boldsymbol{\varphi}_{\mathbf{m}}\hat{\mathbf{w}} = \hat{\mathbf{w}}^T\boldsymbol{\varphi}_{\mathbf{m}}^T\tilde{\mathbf{m}}$, $\tilde{\boldsymbol{\sigma}}_{\mathbf{l}}^T\boldsymbol{\varphi}_{\sigma_l}\hat{\mathbf{w}} = \hat{\mathbf{w}}^T\boldsymbol{\varphi}_{\sigma_l}^T\tilde{\boldsymbol{\sigma}}_{\mathbf{l}}$, $\tilde{\boldsymbol{\sigma}}_{\mathbf{r}}^T\boldsymbol{\varphi}_{\sigma_r}\hat{\mathbf{w}} = \hat{\mathbf{w}}^T\boldsymbol{\varphi}_{\sigma_r}^T\tilde{\boldsymbol{\sigma}}_{\mathbf{r}}$, and $\varepsilon = \hat{\mathbf{w}}^T\mathbf{h} + \tilde{\mathbf{w}}^T\tilde{\boldsymbol{\varphi}} + \Delta$.

IV. ICFC System Design

The proposed ICFC system is comprised of a neural controller and a robust controller as shown in Fig. 3, where a tracking error index is defined as

$$s = \ddot{e} + k_3\dot{e} + k_2 e + k_1\int_0^t e\,d\tau\ . \tag{27}$$

The neural controller using the ASOFNN is designed to mimic an ideal controller, and the robust controller is designed to compensate for the approximation error between the neural controller and the ideal controller. The control law of the intelligent car-following control (ICFC) system is taken as

$$u = u_{nc} + u_{rc} \tag{28}$$

where u_{nc} is the neural controller and u_{rc} is the robust controller. Substituting (28) into (4) and using (5) and (27), yields

$$\dot{s} = g\,(u^* - u_{nc} - u_{rc})\ . \tag{29}$$

From (26), the error equation can be rewritten as

$$\dot{s} = \tilde{\mathbf{w}}^T\hat{\boldsymbol{\varphi}} + \tilde{\mathbf{m}}^T\boldsymbol{\varphi}_{\mathbf{m}}\hat{\mathbf{w}} + \tilde{\boldsymbol{\sigma}}_{\mathbf{l}}^T\boldsymbol{\varphi}_{\sigma_l}\hat{\mathbf{w}} + \tilde{\boldsymbol{\sigma}}_{\mathbf{r}}^T\boldsymbol{\varphi}_{\sigma_r}\hat{\mathbf{w}} + \varepsilon - u_{rc}\ . \tag{30}$$

To dispel the effect of minimum approximation error ε, the robust controller is chosen as

$$u_{rb} = \hat{E} + \kappa s \tag{31}$$

where $\hat{E}$ is the estimated value of ε, and κ is a positive constant. To guarantee the stability of the ICFC system, the Lyapunov function candidate is defined as

$$V = \frac{s^2}{2} + \frac{\tilde{\mathbf{w}}^T\tilde{\mathbf{w}}}{2\eta_w} + \frac{\tilde{\mathbf{m}}^T\tilde{\mathbf{m}}}{2\eta_m} + \frac{\tilde{\boldsymbol{\sigma}}_{\mathbf{l}}^T\tilde{\boldsymbol{\sigma}}_{\mathbf{l}}}{2\eta_{\sigma_l}} + \frac{\tilde{\boldsymbol{\sigma}}_{\mathbf{r}}^T\tilde{\boldsymbol{\sigma}}_{\mathbf{r}}}{2\eta_{\sigma_r}} + \frac{\tilde{E}^2}{2\eta_E} \tag{32}$$

where η_w, η_m, η_{σ_l}, η_{σ_r}, η_E are the positive-constant learning rates and $\tilde{E} = \varepsilon - \hat{E}$. Differentiating (32) with respect to time and using (30), yields

$$\begin{aligned} \dot{V} &= s\dot{s} + \frac{\tilde{\mathbf{w}}^T\dot{\tilde{\mathbf{w}}}}{\eta_w} + \frac{\tilde{\mathbf{m}}^T\dot{\tilde{\mathbf{m}}}}{\eta_m} + \frac{\tilde{\boldsymbol{\sigma}}_{\mathbf{l}}^T\dot{\tilde{\boldsymbol{\sigma}}}_{\mathbf{l}}}{\eta_{\sigma_l}} + \frac{\tilde{\boldsymbol{\sigma}}_{\mathbf{r}}^T\dot{\tilde{\boldsymbol{\sigma}}}_{\mathbf{r}}}{\eta_{\sigma_r}} + \frac{\tilde{E}\dot{\tilde{E}}}{\eta_E} \\ &= s(\tilde{\mathbf{w}}^T\hat{\boldsymbol{\varphi}} + \tilde{\mathbf{m}}^T\boldsymbol{\varphi}_{\mathbf{m}}\hat{\mathbf{w}} + \tilde{\boldsymbol{\sigma}}_{\mathbf{l}}^T\boldsymbol{\varphi}_{\sigma_l}\hat{\mathbf{w}} + \tilde{\boldsymbol{\sigma}}_{\mathbf{r}}^T\boldsymbol{\varphi}_{\sigma_r}\hat{\mathbf{w}} + \varepsilon - u_{rc}) \\ &\quad + \frac{\tilde{\mathbf{w}}^T\dot{\tilde{\mathbf{w}}}}{\eta_w} + \frac{\tilde{\mathbf{m}}^T\dot{\tilde{\mathbf{m}}}}{\eta_m} + \frac{\tilde{\boldsymbol{\sigma}}_{\mathbf{l}}^T\dot{\tilde{\boldsymbol{\sigma}}}_{\mathbf{l}}}{\eta_{\sigma_l}} + \frac{\tilde{\boldsymbol{\sigma}}_{\mathbf{r}}^T\dot{\tilde{\boldsymbol{\sigma}}}_{\mathbf{r}}}{\eta_{\sigma_r}} + \frac{\tilde{E}\dot{\tilde{E}}}{\eta_E} \\ &= \tilde{\mathbf{w}}(s\hat{\boldsymbol{\varphi}} + \frac{1}{\eta_w}\dot{\tilde{\mathbf{w}}}) + \tilde{\mathbf{m}}^T(s\boldsymbol{\varphi}_{\mathbf{m}}\hat{\mathbf{w}} + \frac{1}{\eta_m}\dot{\tilde{\mathbf{m}}}) + \tilde{\boldsymbol{\sigma}}_{\mathbf{l}}^T(s\boldsymbol{\varphi}_{\sigma_l}\hat{\mathbf{w}} + \frac{1}{\eta_{\sigma_l}}\dot{\tilde{\boldsymbol{\sigma}}}_{\mathbf{l}}) \\ &\quad + \tilde{\boldsymbol{\sigma}}_{\mathbf{r}}^T(s\boldsymbol{\varphi}_{\sigma_r}\hat{\mathbf{w}} + \frac{1}{\eta_{\sigma_r}}\dot{\tilde{\boldsymbol{\sigma}}}_{\mathbf{r}}) + s(\varepsilon - u_{rb}) + \frac{\tilde{E}\dot{\tilde{E}}}{\eta_E}\ . \end{aligned} \tag{33}$$

Choose the adaptive laws as

$$\dot{\tilde{\mathbf{w}}} = -\dot{\hat{\mathbf{w}}} = -\eta_w s\hat{\boldsymbol{\varphi}} \tag{34}$$

$$\dot{\tilde{\mathbf{m}}} = -\dot{\hat{\mathbf{m}}} = -\eta_m s\boldsymbol{\varphi}_{\mathbf{m}}\hat{\mathbf{w}} \tag{35}$$

$$\dot{\tilde{\boldsymbol{\sigma}}}_l = -\dot{\hat{\boldsymbol{\sigma}}}_l = -\eta_{\sigma_l} s\boldsymbol{\varphi}_{\sigma_l}\hat{\mathbf{w}} \tag{36}$$

$$\dot{\tilde{\boldsymbol{\sigma}}}_r = -\dot{\hat{\boldsymbol{\sigma}}}_r = -\eta_{\sigma_r} s \boldsymbol{\varphi}_{\boldsymbol{\sigma}_r} \hat{\mathbf{w}} \tag{37}$$

and

$$\dot{\hat{E}} = \eta_E s \tag{38}$$

then (19) can be rewritten as

$$\dot{V} = -\kappa s^2 \le 0 \, . \tag{39}$$

By Barbalat's lemma [5], it can be concluded that $s(t) \to 0$ as $t \to \infty$. In summary, the ICFC system is presented in (28), where u_{nc} is given in (23) with the parameters adjusted by (34)~(37); u_{rb} is given in (31) with the parameters $\hat{E}$ adjusted by (38). By applying this online tuning law, the ICFC system can be guaranteed to be stable in the Lyapunov sense.

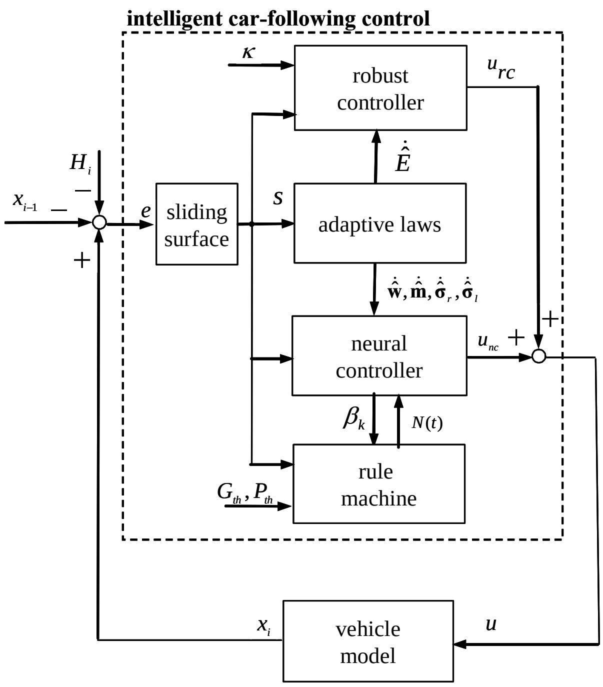

Fig. 3. The block diagram of intelligent car-following control system.

V. SIMULATION RESULTS

A. Matlab Simulation

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 $\tau = 0.2$, $m = 916kg$, $K_d = 0.44Ns^2/m^2$ and $d_m = 67.7$ Nm [1]. In scenario 1, assumes that one following vehicle (FV) follows the leading vehicle (LV). The safety spacing is initialized with H_1 =10m first, and after the 15th, 30th, 45th, 60th, and 75th seconds the safety space is changed between H_1 =5m and H_1 =10m, respectively. The initial values of the LV and FV are chosen as $v_l(0) = 20m/\sec$, $a_l(0) = 0m/\sec^2$, $v_1(0) = 20m/\sec$ and $a_1(0) = 0m/\sec^2$ and the LV in the platoon has no acceleration. In scenario 2, assumes that the FVs follow the LV with the safety space H_i =5m. The vehicle acceleration and velocity of the LV are shown in Fig. 4(a) and 4(b), respectively. For numerical simulations, the initial values of the vehicle following system are chosen as $v_l(0) = 20m/\sec$, $a_l(0) = 0m/\sec^2$, $v_i(0) = 20m/\sec$ and $a_i(0) = 0m/\sec^2$.

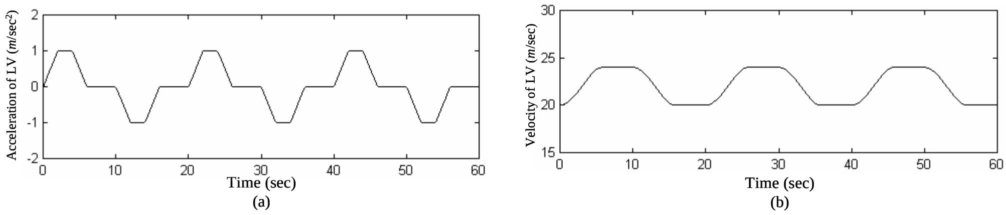

Fig. 4. LV's acceleration and velocity time profile for scenario 2.

For both scenarios (scenario 1 and scenario 2), the control parameters of the ICFC system are selected as $k_1 = 2$, $k_2 = 5$, $k_3 = 4$, $\eta_w = 1000$, $\eta_m = \eta_{\sigma_i} = \eta_{\sigma_r} = 10$, $\eta_E = 1$, $\sigma_i = 1.0$, $G_{th} = 0.5$, $P_{th} = 0.1$, $\tau_1 = \tau_2 = 0.01$ and $I_{th} = 0.01$. These parameters are chosen through some trials to achieve satisfactory transient control performance. The simulation results of scenario 1 are shown in Fig. 5. From the simulation results, it can be seen that the proposed the ICFC system can achieve satisfactory performance for the one-vehicle following system even in the change of the safety spacing command. The simulation results of scenario 2 are shown in Fig. 6. From the simulation results, it can be seen that the proposed the ICFC system can also achieve satisfactory performance even in the changes of acceleration and velocity of the LV.

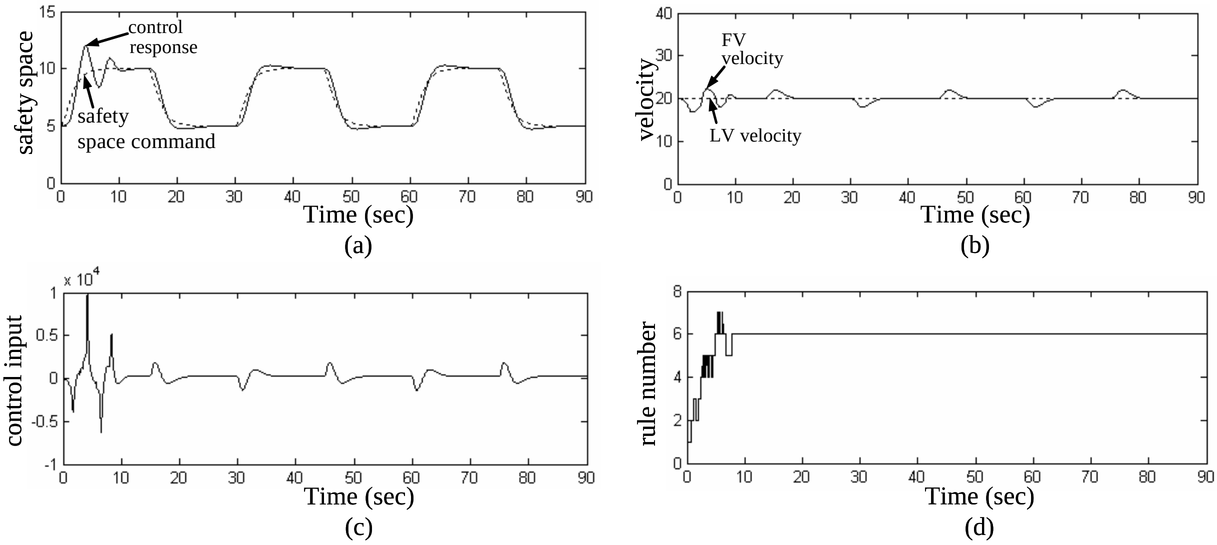

Fig. 5. Simulation results for scenario 1.

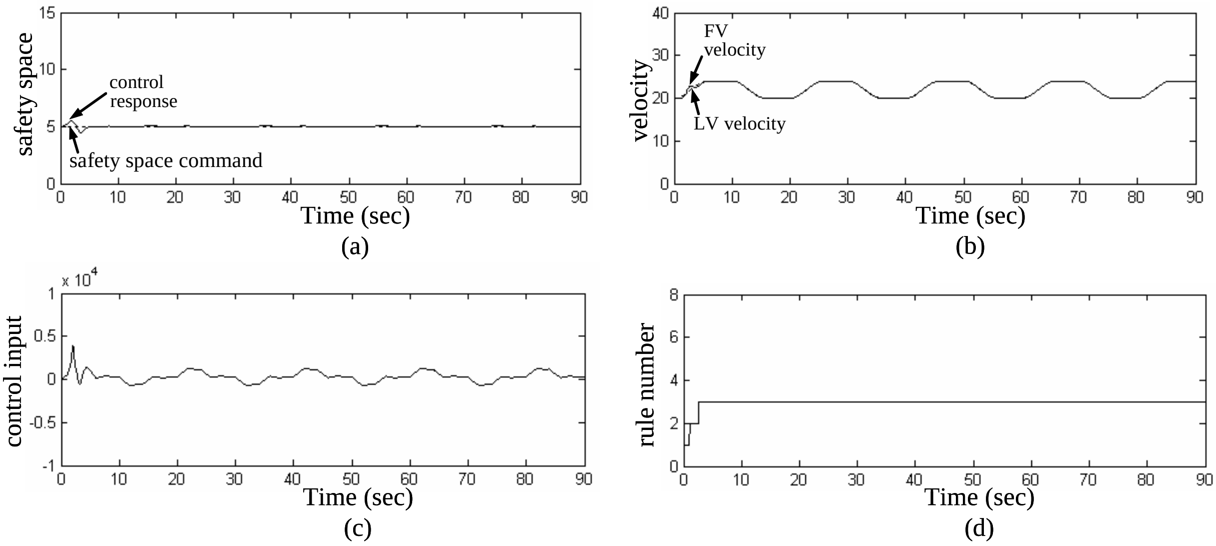

Fig. 6. Simulation results for scenario 2.

B. VR Simulation

A visual system is the most significant part in a simulator, because the operators on board recognize driving environments with their eyes. Therefore, graphic scenes with high resolution are needed to realistically feel the virtual driving environments. In the virtual driving environments development, we use the 3DS-max [14] software to create the 3D models, and use the WorldToolKit (WTK) library [15] to program the VR scenes. The 3DS-max software is popular graphic software to create 3D model. The WTK library is an advanced cross-platform development environment for high-performance and 3D graphics applications. To possess a realistic driving feeling, the virtual driving environment must be very similar to the real world. However, since it is very difficult to process this environment in real-time, the virtual driving environment is set by compromising between a realistic driving feeling and real-time ability. The development flow of the VR scene is shown in Fig. 7. First, we use 3DS-max to accurately build 3D models for a true system (such as car, boat, tree and terrain, etc.) and define the parameters of each model (such as length and width of the car, and radius of the wheel, etc.). Then, we use C program including the WTK library and call its library function to move the 3D models. For VR dynamic simulation system can virtually capture the behavior of the true system, a system dynamic equation is used to describe the system's dynamic behavior.

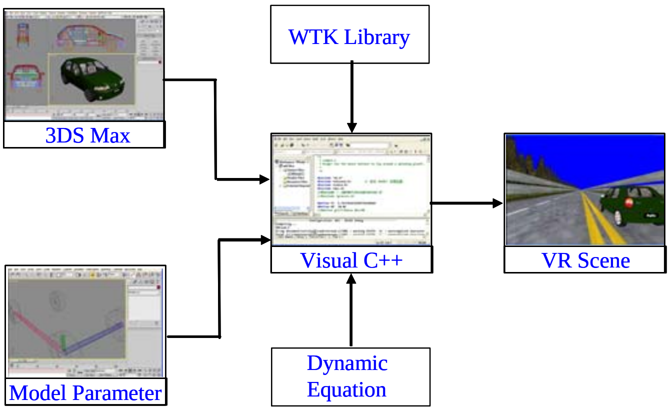

Fig. 7. Development flow of the VR scene.

VI. CONCLUSIONS

This paper has successfully developed an asymmetric self-organizing fuzzy neural network (ASOFNN). And, an intelligent car-following control (ICFC) system with adaptive control approach for the vehicle-following system is proposed. In the ASOFNN design, a dynamic rule generating/pruning mechanism is developed to cope with the tradeoff between the approximation accuracy and computational loading. In the ICFC design, the on-line adaptation laws are derived based on the Lyapunov stability theorem to guarantee the closed-loop controller's stability. Finally, the Matlab simulation and the virtual-reality (VR) technique are applied to show the effectiveness of the proposed ICFC system, respectively.

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計畫成果自評

本計畫研究報告內容與原計畫相符並有達到預期目標成果，歸納本計畫在本年度之貢獻可歸納如下

(1) 完成具有網路建構能力之非對稱歸屬函數模糊類神經網路開發工作。

(2) 完成智慧車輛跟車控制系統開發工作。

(3) 完成虛擬實境跟車駕駛模擬器。

(4) 完成 MATLAB 模擬與虛擬實境實現。

(5) 成果已投稿至 2009 CACS IACC 國際研討會。

行政院國家科學委員會補助國內專家學者出席國際學術會議報告

98 年　4 月　12 日

報告人姓名	許駿飛	服務機構 及職稱	中華大學電機系 助理教授
會議 時間 地點	自 98 年 3 月 26 日 至 98 年 3 月 29 日 日本，岡山	本會核定 補助文號	
會議 名稱	（中文）2009 電氣和電子工程師協會網路、感測與控制國際研討會 （英文）2009 IEEE International Conference on Networking, Sensing and Control		
發表 論文 題目	**第一篇：** (中文) 回饋小波類神經網路運用於無刷馬達適應性位置追蹤控制 (英文) Adaptive Position Tracking Control of a BLDC Motor Using a Recurrent Wavelet Neural Network		
	第二篇： (中文)具有模糊補償之小波類神經適應性控制器設計 (英文) Design of a Wavelet-Neural-Based Adaptive Controller with a Fuzzy Compensator		

報告內容應包括下列各項：

一、　參加會議經過

近年來晚輩延續之前的研究成果，持續積極朝向更具有智慧型且更符合實際需求之控制器設計工作，並將所獲得之成果整理投稿至 2009 IEEE International Conference on Networking, Sensing and Control (2009 ICNSC)國際研討會發表。在論文被 2009 ICNSC 國際研討會接受後，晚輩便開始陸續準備出國的相關事宜，包含向研討會主辦單位註冊、來回飛機票、住宿飯店與欲發表之論文內容。而 2009 ICNSC 國際研討會今年度於 3 月 26 日至 3 月 29 日在日本岡山大學舉行，整個研討會將所有接受的論文分成 30 多個 session 分別進行討論。

晚輩共投稿兩篇論文於 2009 ICNSC 國際研討會，分別是

第一篇：
(中文) 回饋小波類神經網路運用於無刷馬達適應性位置追蹤控制
(英文) Adaptive Position Tracking Control of a BLDC Motor Using a Recurrent Wavelet Neural Network
第二篇：
(中文)具有模糊補償之小波類神經適應性控制器設計
(英文) Design of a Wavelet-Neural-Based Adaptive Controller with a Fuzzy Compensator

第一篇論文在 3 月 27 日上午之“Control of Network”集會中發表，與第二篇論文在 3 月 28 日下午之“Control Theory II”集會中發表。在此會議中，參與的十多位學者包含了來自芬蘭、阿拉伯聯合大公國、中國大陸、台灣以及日本等地區。對於晚輩所報告之內容，有多位學者提出了許多值得參考的意見與建議，對於未來之研究提供了許多的新研究方向與改善空間。

2009 ICNSC 會場

2009 ICNSC 會場

二、　與會心得

晚輩在此次研討會中，除了藉由發表報告和與外國學者接觸來增加外語練習機會外，更重要的是體驗到外國學者對於學術研究之態度。在此次報告的"Control of Network "集會中，雖然都是以各種不同類神經網路架構在進行各項系統的控制與應用，但所應用之方向與範圍都有極大的差異。雖外國學者對於不同領域之研究，都依然保有極大的興趣，對於不了解之部份都會積極提問，並且依自己的經驗給予建議與協助，這是晚輩認為非常值得學習的精神。同時，亦有國外學者建議晚輩目前之實驗成果表現令他無法明確得知所設計控制器之優點，其建議晚輩應該要適當改善才能凸顯論文之價值。

三、 考察參觀活動(無是項活動者省略)

在藉由此次研討會參觀日本岡山大學中，學生也發現到日本大學的教學環境規劃的十分良好，而整體的管理也井然有序，學生認為這對整體教學品質一定會有莫大的幫助，非常值得我們學習。

四、 建議

經由這次的國際研討會，可以發現來自世界各國之專家學者們均投注眾多的心力於計算機科學方面之研究工作，並運用至眾多不同之運用領域，由此可知其重要性，更可以看到國外學者做研究的態度，也獲得了許多來自國外學者的建議與協助，讓我得到更多努力研究之動力。

另外，本次 2009 ICNSC 國際研討會，晚輩也帶領一位碩士班研究生前往參加，但光兩篇論文之論文刊登費用即花費全部之國科會補助金額，建議需提供更多申請經費補助管道，以私立大學研究生要申請到國科會補助實在很難申請到，這是十分困擾的問題，應該要多鼓勵學生出國參與國際會議並上台英文報告練習自我表達能力，使真正認真且優秀的學生能獲得更多學習之機會與空間。

五、 攜回資料名稱及內容

攜回資料有完整論文光碟片一片與論文摘要紙本一本。

六、 其他

無。