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中文摘要

汽車科技發展百餘年以來，雖然帶動交通產業的蓬勃發展，但大幅增加的車輛數與駕駛人口，也使得行車環境變得日益複雜，造成事故死傷率急速攀升，所以本計畫在本年度開發設計智慧車輛自動控制系統，整個控制系統主要將利用適應性控制與模糊類神經網路為基礎來設計，期望所開發之智慧型控制系統可以有效地提昇車輛行駛時的安全性，以減少交通事故以及傷亡的發生。整個車輛自動控制系統包含車輛跟車控制系統與車道切換控制系統兩大部分，其中車輛跟車控制系統已在之前計畫中完成，本年度計畫著重在車道切換控制系統的開發工作，所提出之控制系統包括一個狀態回授控制器與一個類神經控制器，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。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，本子計畫利用縮小實驗小車建立一虛擬實境來取代實車測試，藉以模擬與分析所開發方法之效能與實用性。經由一些結果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：適應性控制；類神經網路控制；網路架構學習；網路參數學習；實驗小車

Abstract

Transportation technology is one of the most influential areas in the human life. Vehicle automation is believed to reduce the risk of accidents, improve safety, increase capacity, reduce fuel consumption and enhance overall comfort and performance for drivers. Analyzing the spot of car accidents, there are about 1/3 accidents happened near crossroad. In this sub-project, an intelligent vehicle control system has been developed in two years. In the first year, an intelligent car-following control (ICFC) system is developed. In the second year (this year), an intelligent lane-change control (ILCC) system with a bump avoidance system is expected. The proposed ILCC system is comprised of a state feedback controller and a neural 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. This project utilizes the virtual-reality (VR) technique to solve the requirement of time, manpower and money in the real-word experimental tests. A small model car based on a FPGA application is designed. From the simulation and experimental results, the proposed ILCC system can achieve favorable performance and the VR simulation is comparatively good.

Keyword: adaptive control, neural control, structure learning, parameter learning, small model car

I. INTRODUCTION

Transportation technology is one of the most influential areas in the human life. The purpose of intelligent transportation systems (ITS) is to increase transportation safety and efficiency by integrating human beings, vehicles, roadways and call-centers. Vehicle automation is believed to reduce the risk of accidents, improve safety, increase capacity, reduce fuel consumption and enhance overall comfort and performance for drivers. Many researchers have been involved in a wide scope of related research activities aiming to enhance efficiency, comfort, and safety of transportation systems [1-3]. The automation of the overtaking maneuver is considered to be one of the toughest challenges in the development of autonomous vehicles. Automated highway systems by not only a free agent but also a platoon have been demonstrated over the past several years [4, 5]. For car-following collision prevention problem, the control objective is to maintain a desired safety space for the following vehicles. Moreover, analyzing the spot of car accidents, there are about 1/3 accidents happened near crossroad. Most of these accidents are critical. A lane changing system for a vehicle with two exterior rear view mirrors including at least one video sensor wherein the video sensor detects objects in motion which are moving relative to the vehicle. Lane-change maneuvers have been used to move into or out of a circulation lane or platoon; however, overtaking operations have not received much coverage in the literature [6-9].

In this sub-project, an intelligent vehicle control system has been developed in two years.

In the first year, an intelligent car-following control (ICFC) system is developed. This project proposes 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 ICFC system with the advantages of the ASOFNN 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. The simulation results denominate the proposed ICFC system can achieve favorable tracking performance for a safe car-following control.

In the second year (this year), an intelligent lane-change control (ILCC) system with a bump avoidance system is expected. The proposed ILCC system is comprised of a state feedback controller and a neural controller. The neural controller uses an ASOFNN to online estimation a robust controller. 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. The adaptation laws of the ILCC system are derived in the sense of Lyapunov stability theorem, thus the stability of the closed-loop control system can be guaranteed. In the simulation examples, the simulation results show the proposed ILCC system can achieve favorable control performance.

II. DESCRIPTION OF ASOFNN

2.A. Structure of ASOFNN

Figure 1 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 [10-12]

$$y_o = \sum_{k=1}^{N} w_k \phi_k(\mathbf{x}), \quad o = 1,2,...,N \tag{1}$$

in which N is the total number of output; 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

$$\zeta_{ij} = \begin{cases} \exp(-\dfrac{(x_i - m_{ij})^2}{(\sigma_{ij}^l)^2}), \; if \; -\infty < x_i \le m_{ij} \\ \exp(-\dfrac{(x_i - m_{ij})^2}{(\sigma_{ij}^r)^2}), \; if \; m_{ij} \le x_i < \infty \end{cases}, \quad j = 1, 2, \cdots, M \tag{2}$$

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

$$\phi_k = \prod_{j=1}^{M} \zeta_{jk}, \quad k = 1, 2, \cdots, M \; . \tag{3}$$

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

$$\mathbf{m} = [m_{11} \cdots m_{L1} \; m_{12} \cdots m_{L2} \cdots\cdots m_{1M} \cdots m_{LM}]^T \tag{4}$$

$$\boldsymbol{\sigma}_\mathbf{l} = [\sigma_{11}^l \cdots \sigma_{L1}^l \; \sigma_{12}^l \cdots \sigma_{L2}^l \cdots\cdots \sigma_{1M}^l \cdots \sigma_{LM}^l]^T \tag{5}$$

$$\boldsymbol{\sigma}_{\mathbf{r}} = [\sigma_{11}^r \cdots \sigma_{L1}^r \ \sigma_{12}^r \cdots \sigma_{L2}^r \cdots\cdots \sigma_{1M}^r \cdots \sigma_{LM}^r]^T . \tag{6}$$

Then, the output of the ASOFNN can be represented as

$$y_o = \mathbf{w}_o^T \boldsymbol{\varphi}(\mathbf{x}, \mathbf{m}, \boldsymbol{\sigma}_{\mathbf{l}}, \boldsymbol{\sigma}_{\mathbf{r}}) , \quad o = 1,2,..., N \tag{7}$$

where $\mathbf{w}_o = [w_{01} \ \ w_{02} \ \cdots \ w_{0M}]^T$ and $\boldsymbol{\varphi} = [\phi_1 \ \ \phi_2 \ \cdots \ \phi_M]^T$. The outputs of ASOFNN expresses in a vector notation as

$$\mathbf{y} = \mathbf{W}^T \boldsymbol{\varphi}(\mathbf{x}, \mathbf{m}, \boldsymbol{\sigma}_{\mathbf{l}}, \boldsymbol{\sigma}_{\mathbf{r}}) \tag{8}$$

where $\mathbf{y} = [y_1 \ \ y_2 \ \cdots \ y_N]^T$ and $\mathbf{W} = [\mathbf{w}_1 \ \ \mathbf{w}_2 \ \cdots \ \mathbf{w}_N]^T$.

2.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. 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 [13, 14]. According to the above mention, the firing strength obtained from (3) is used as the degree measure

$$\beta_k = \phi_k , \quad k = 1,2,..., N(t) \tag{9}$$

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

$$\beta_{\max} = \max_{1 \le k \le N(t)} \beta_k . \tag{10}$$

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

$$m_i^{new} = x_i \tag{11}$$

$$\sigma_i^{l,new} = \sigma_i \tag{12}$$

$$\sigma_i^{r,new} = \sigma_i \tag{13}$$

$$w^{new} = 0 \tag{14}$$

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

$$N(t+1) = N(t) + 1 . \tag{15}$$

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 [15]

$$I_r(t+1) = \begin{cases} I_r(t) \cdot \exp(-\tau_1), & \text{if } \beta_r < P_{th} \\ I_r(t) \cdot \left[2 - \exp\left(-\tau_2 \left(1 - I_r(t)\right)\right)\right], & \text{if } \beta_r \ge P_{th} \end{cases}, \quad r = 1, 2, \cdots, N(t) \tag{16}$$

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 $I_r \le I_{th}$ 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.

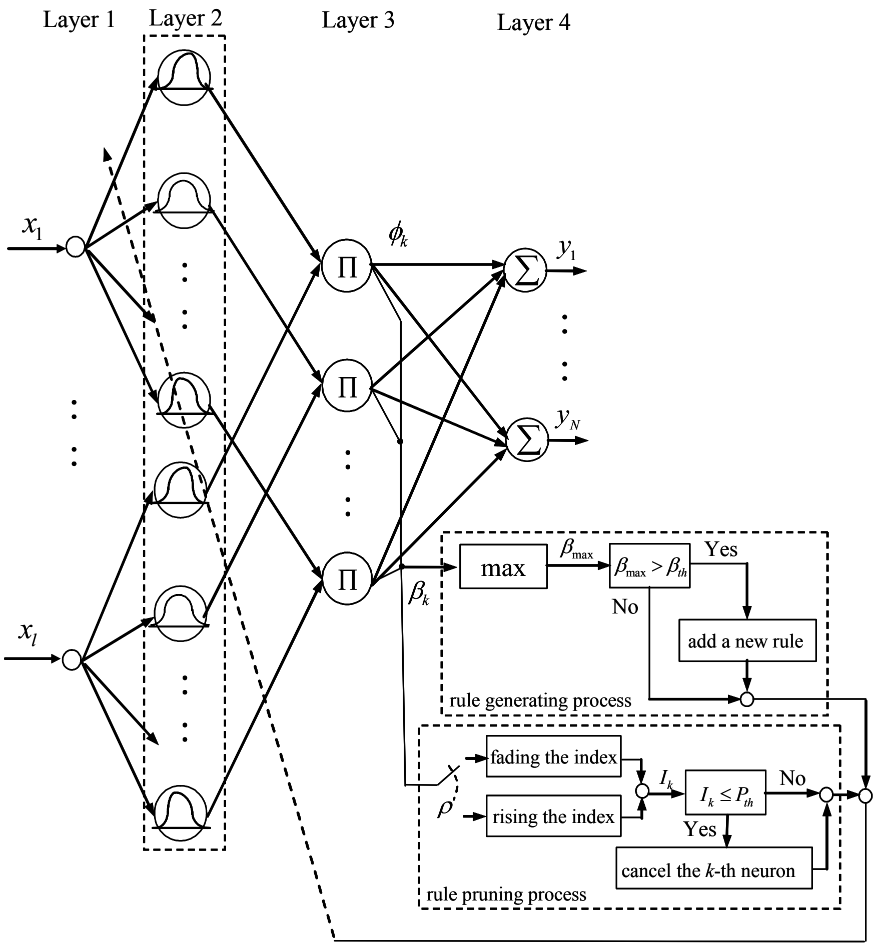

Fig. 1. Asymmetric self-organizing fuzzy neural network.

2.C. Approximation of ASOFNN

By the universal approximation theorem, an optimal ASOFNN can be designed to approximate any dynamical function, such that [16, 17]

$$\mathbf{\Omega} = \mathbf{W}^{*T}\boldsymbol{\varphi}(\mathbf{x},\mathbf{m}^*,\boldsymbol{\sigma}_l^*,\boldsymbol{\sigma}_r^*) + \Delta = \mathbf{W}^{*T}\boldsymbol{\varphi}^* + \boldsymbol{\Delta} \tag{17}$$

where $\boldsymbol{\Delta}$ denotes the approximation error; $\mathbf{W}^*$ and $\boldsymbol{\varphi}^*$ are the optimal parameters of $\mathbf{W}$ and $\boldsymbol{\varphi}$, respectively, and $\mathbf{m}^*$, $\boldsymbol{\sigma}_l^*$ and $\boldsymbol{\sigma}_r^*$ are the optimal parameters of $\mathbf{m}$, $\boldsymbol{\sigma}_l$ and $\boldsymbol{\sigma}_r$, 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

$$\hat{\mathbf{y}} = \hat{\mathbf{W}}^T\boldsymbol{\varphi}(\mathbf{x},\hat{\mathbf{m}},\hat{\boldsymbol{\sigma}}_l,\hat{\boldsymbol{\sigma}}_r) = \hat{\mathbf{W}}^T\hat{\boldsymbol{\varphi}} \tag{18}$$

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

$$\tilde{\mathbf{y}} = = \tilde{\mathbf{W}}^T\tilde{\boldsymbol{\varphi}} + \hat{\mathbf{W}}^T\tilde{\boldsymbol{\varphi}} + \tilde{\mathbf{W}}^T\hat{\boldsymbol{\varphi}} + \boldsymbol{\Delta} \tag{19}$$

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

$$\tilde{\boldsymbol{\varphi}} = \boldsymbol{\varphi}_m^T\tilde{\mathbf{m}} + \boldsymbol{\varphi}_{\sigma_l}^T\tilde{\boldsymbol{\sigma}}_l + \boldsymbol{\varphi}_{\sigma_r}^T\tilde{\boldsymbol{\sigma}}_r + \mathbf{h} \tag{20}$$

where $\mathbf{h}$ is a vector of higher-order terms, $\tilde{\mathbf{m}} = \mathbf{m}^* - \hat{\mathbf{m}}$, $\tilde{\boldsymbol{\sigma}}_l = \boldsymbol{\sigma}_l^* - \hat{\boldsymbol{\sigma}}_l$ and $\tilde{\boldsymbol{\sigma}}_r = \boldsymbol{\sigma}_r^* - \hat{\boldsymbol{\sigma}}_r$. Substituting (20) into (19), (19) can be rewritten as

$$\begin{aligned}\tilde{\mathbf{y}} &= \tilde{\mathbf{W}}^T\tilde{\boldsymbol{\varphi}} + \hat{\mathbf{W}}^T(\boldsymbol{\varphi}_m^T\tilde{\mathbf{m}} + \boldsymbol{\varphi}_{\sigma_l}^T\tilde{\boldsymbol{\sigma}}_l + \boldsymbol{\varphi}_{\sigma_r}^T\tilde{\boldsymbol{\sigma}}_r + \mathbf{h}) + \tilde{\mathbf{W}}^T\hat{\boldsymbol{\varphi}} + \boldsymbol{\Delta} \\ &= \tilde{\mathbf{W}}^T\hat{\boldsymbol{\varphi}} + \tilde{\mathbf{m}}^T\boldsymbol{\varphi}_m\hat{\mathbf{W}} + \tilde{\boldsymbol{\sigma}}_l^T\boldsymbol{\varphi}_{\sigma_l}\hat{\mathbf{W}} + \tilde{\boldsymbol{\sigma}}_r^T\boldsymbol{\varphi}_{\sigma_r}\hat{\mathbf{W}} + \boldsymbol{\varepsilon}\end{aligned} \tag{21}$$

where $\tilde{\mathbf{m}}^T\boldsymbol{\varphi}_m\hat{\mathbf{W}} = \hat{\mathbf{W}}^T\boldsymbol{\varphi}_m^T\tilde{\mathbf{m}}$, $\tilde{\boldsymbol{\sigma}}_l^T\boldsymbol{\varphi}_{\sigma_l}\hat{\mathbf{W}} = \hat{\mathbf{W}}^T\boldsymbol{\varphi}_{\sigma_l}^T\tilde{\boldsymbol{\sigma}}_l$, $\tilde{\boldsymbol{\sigma}}_r^T\boldsymbol{\varphi}_{\sigma_r}\hat{\mathbf{W}} = \hat{\mathbf{W}}^T\boldsymbol{\varphi}_{\sigma_r}^T\tilde{\boldsymbol{\sigma}}_r$, and $\boldsymbol{\varepsilon} = \hat{\mathbf{W}}^T\mathbf{h} + \tilde{\mathbf{W}}^T\tilde{\boldsymbol{\varphi}} + \boldsymbol{\Delta}$.

III. ILCC SYSTEM DESIGN

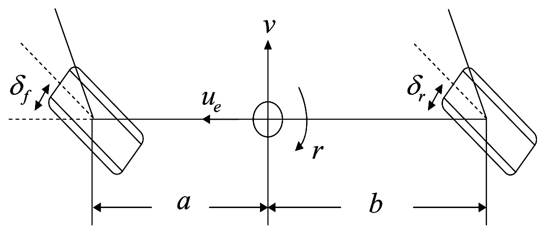

Fig. 2. Bicycle model for car steering.

The simplified car steering dynamic, as shown in Fig. 2, the response of 4WS can be expressed as follows [6]

$$\begin{bmatrix} \ddot{x} \\ \ddot{\psi}_r \end{bmatrix} = \begin{bmatrix} a_{11} & a_{12} \\ a_{21} & a_{22} \end{bmatrix} \begin{bmatrix} \dot{x} \\ \dot{\psi}_r \end{bmatrix} + \begin{bmatrix} b_{11} & b_{12} \\ b_{21} & b_{22} \end{bmatrix} \begin{bmatrix} \delta_f \\ \delta_r \end{bmatrix} \tag{22}$$

where $a_{11} = -\dfrac{k_1 + k_2}{mu_e}$; $a_{12} = \dfrac{bk_2 - ak_1}{mu_e} - u_e$; $a_{21} = \dfrac{bk_2 - ak_1}{I_z u_e}$; $a_{22} = -\dfrac{a^2 k_1 + b^2 k_2}{I_z u_e}$; $b_{11} = \dfrac{k_1}{m}$; $b_{12} = \dfrac{k_2}{m}$; $b_{21} = \dfrac{ak_1}{I_z}$ and $b_{22} = -\dfrac{bk_2}{I_z}$. Equation (22) can be expressed as a state equation

$$\ddot{\mathbf{x}} = \mathbf{f}(\underline{\mathbf{x}}) + \mathbf{G}(\underline{\mathbf{x}})\mathbf{u} \tag{23}$$

where $\underline{\mathbf{x}} = [x \quad \psi]^T$; $\mathbf{f} = \begin{bmatrix} a_{11} & a_{12} \\ a_{21} & a_{22} \end{bmatrix}$; $\mathbf{G} = \begin{bmatrix} b_{11} & b_{12} \\ b_{21} & b_{22} \end{bmatrix}$, and $u = [\delta_f \quad \delta_r]^T$. The lateral position error and yaw angle error is defined as $\tilde{\mathbf{x}} = \mathbf{x_d} - \mathbf{x}$ and $\tilde{\psi} = \psi_d - \psi$ where x_d and ψ_d is the desired lateral position and yaw angle, respectively. The objective of a control system is to design a control law $\mathbf{u}$ such that the system output $\mathbf{x}$ can track a desired signal $\mathbf{x_d}$. The tracking error e is defined as

$$\mathbf{e} \underline{\underline{\Delta}} \mathbf{x_d} - \mathbf{x} \tag{24}$$

Assume the nonlinear functions $\mathrm{f}(\underline{\mathrm{x}})$ and $\mathrm{G}(\underline{\mathrm{x}})$ can be exactly known, an ideal control law u^* can be designed as [18]

$$\mathbf{u}^* = \mathbf{G}^{-1}(\underline{\mathbf{x}})[\ddot{\mathbf{x}}_\mathbf{d} - \mathbf{f}(\underline{\mathbf{x}}) - \mathbf{d} + \mathbf{K}\underline{\mathbf{e}}] = \mathbf{G}^{-1}(\underline{\mathbf{x}})\mathbf{K}\underline{\mathbf{e}} + \mathbf{u_{rb}} \tag{25}$$

where $\mathbf{G}^{-1}(\underline{\mathbf{x}})\mathbf{K}\underline{\mathbf{e}}$ is a state feedback controller and the robust controller dealing with the unknown system dynamics and external disturbance is given as

$$\mathbf{u}_{\mathrm{rb}} = \mathbf{G}^{-1}(\underline{\mathbf{x}})[\ddot{\mathbf{x}}_\mathbf{d} - \mathbf{f}(\underline{\mathbf{x}})] \tag{26}$$

Furthermore, the state feedback gain

$$\mathbf{K} = [\mathbf{K}_2 \quad \mathbf{K}_1] \tag{27}$$

which contains real numbers. Substituting (25) into (23), yields

$$\ddot{\underline{\mathbf{e}}} + \mathbf{K}_1 \dot{\underline{\mathbf{e}}} + \mathbf{K}_2 \underline{\mathbf{e}} = 0 \tag{28}$$

By properly choosing $\mathbf{K}$ such that all roots of the polynomial $\ddot{\mathbf{s}} + \mathbf{K}_1 \dot{\mathbf{s}} + \mathbf{K}_2 \mathbf{s} = 0$ lie in the open left-half plane, then the tracking error vector $\underline{\mathrm{e}}$ will converge to zero. However, unmodeled dynamics and external disturbance are always unknown in practice, so that u_{rb} in (25) is generally unavailable. Thus, the controller is designed as

$$\mathbf{u} = \mathbf{B}^{-1}\mathbf{K}\underline{\mathbf{e}} + \hat{\mathbf{u}}_\mathbf{nc} \tag{29}$$

where the neural controller $\hat{\mathbf{u}}_\mathbf{nc}$ used a ASOFNN to approximate the robust controller u_{rb}. Substituting (29) into (23) and using (25), yields

$$\dot{\underline{\mathbf{e}}} = \mathbf{A}\underline{\mathbf{e}} + \mathbf{B}(\mathbf{u_{rb}} - \hat{\mathbf{u}}_\mathbf{nc}) \tag{30}$$

where $\mathbf{A} = \begin{bmatrix} 0 & \mathbf{I} \\ -\mathbf{K}_2 & -\mathbf{K}_1 \end{bmatrix}$ and $\mathbf{B} = \begin{bmatrix} 0 \\ \mathbf{G}(\underline{\mathbf{x}}) \end{bmatrix}$. If the neural controller $\hat{\mathbf{u}}_\mathbf{nc}$ can approximate the robust controller $\mathbf{u_{rb}}$, that means $\hat{\mathbf{u}}_\mathbf{nc} \cong \mathbf{u_{rb}}$, and then (30) becomes $\dot{\underline{\mathbf{e}}} \cong \mathbf{A}\underline{\mathbf{e}}$. Since $\mathbf{A}$ can be designed as a Hurwitz matrix, this implies $\lim_{t\to\infty} \underline{\mathbf{e}} = \mathbf{0}$. By the substitution of (21) into (30), the error dynamics become

$$\dot{\underline{\mathbf{e}}} = \mathbf{A}\underline{\mathbf{e}} + \mathbf{B}(\tilde{\mathbf{W}}^T\hat{\boldsymbol{\varphi}} + \tilde{\mathbf{m}}^T\boldsymbol{\varphi}_{\mathbf{m}}\hat{\mathbf{W}} + \tilde{\boldsymbol{\sigma}}_{\mathbf{l}}^T\boldsymbol{\varphi}_{\boldsymbol{\sigma}_{\mathbf{l}}}\hat{\mathbf{W}} + \tilde{\boldsymbol{\sigma}}_{\mathbf{r}}^T\boldsymbol{\varphi}_{\boldsymbol{\sigma}_{\mathbf{r}}}\hat{\mathbf{W}} + \boldsymbol{\varepsilon}) \tag{31}$$

To derive the stabilizing adaptive laws of the ILCC system, choose the following Lyapunov function

$$V = \frac{1}{2}\underline{\mathbf{e}}^T\mathbf{P}\underline{\mathbf{e}} + \frac{1}{2\eta_1}tr(\tilde{\mathbf{W}}^T\tilde{\mathbf{W}}) + \frac{1}{2\eta_2}\tilde{\mathbf{m}}^T\tilde{\mathbf{m}} + \frac{1}{2\eta_3}\tilde{\boldsymbol{\sigma}}_{\mathbf{l}}^T\tilde{\boldsymbol{\sigma}}_{\mathbf{l}} + \frac{1}{2\eta_4}\tilde{\boldsymbol{\sigma}}_{\mathbf{r}}^T\tilde{\boldsymbol{\sigma}}_{\mathbf{r}} \tag{32}$$

where $\mathbf{P}$ is a symmetric positive definite matrix; and η_1, η_2, η_3 and η_4 are positive constants. Since A is a Hurwitz matrix, there exist symmetric positive definite matrices $\mathbf{P} > 0$ and $\mathbf{Q} > 0$ such that a Lyapunov equation

$$\frac{1}{2}(\mathbf{A}^T\mathbf{P} + \mathbf{PA}) = -\mathbf{Q} \tag{33}$$

The derivative of the Lyapunov function is given by

$$\begin{aligned}\dot{V} &= \frac{1}{2}(\dot{\underline{\mathbf{e}}}^T\mathbf{P}\underline{\mathbf{e}} + \underline{\mathbf{e}}^T\mathbf{P}\dot{\underline{\mathbf{e}}}) + \frac{1}{\eta_1}tr(\tilde{\mathbf{W}}^T\dot{\tilde{\mathbf{W}}}) + \frac{1}{\eta_2}\tilde{\mathbf{m}}^T\dot{\tilde{\mathbf{m}}} + \frac{1}{2\eta_3}\tilde{\boldsymbol{\sigma}}_{\mathbf{l}}^T\dot{\tilde{\boldsymbol{\sigma}}}_{\mathbf{l}} + \frac{1}{2\eta_4}\tilde{\boldsymbol{\sigma}}_{\mathbf{r}}^T\dot{\tilde{\boldsymbol{\sigma}}}_{\mathbf{r}} \\ &= -\frac{1}{2}\underline{\mathbf{e}}^T\mathbf{Q}\underline{\mathbf{e}} + \underline{\mathbf{e}}^T\mathbf{PB}(\tilde{\mathbf{W}}^T\hat{\boldsymbol{\varphi}} + \tilde{\mathbf{m}}^T\boldsymbol{\varphi}_{\mathbf{m}}\hat{\mathbf{W}} + \tilde{\boldsymbol{\sigma}}_{\mathbf{l}}^T\boldsymbol{\varphi}_{\boldsymbol{\sigma}_{\mathbf{l}}}\hat{\mathbf{W}} + \tilde{\boldsymbol{\sigma}}_{\mathbf{r}}^T\boldsymbol{\varphi}_{\boldsymbol{\sigma}_{\mathbf{r}}}\hat{\mathbf{W}} + \boldsymbol{\varepsilon}) \\ &\quad + \frac{1}{\eta_1}tr(\tilde{\mathbf{W}}^T\dot{\tilde{\mathbf{W}}}) + \frac{1}{\eta_2}\tilde{\mathbf{m}}^T\dot{\tilde{\mathbf{m}}} + \frac{1}{\eta_3}\tilde{\boldsymbol{\sigma}}_{\mathbf{l}}^T\dot{\tilde{\boldsymbol{\sigma}}}_{\mathbf{l}} + \frac{1}{\eta_4}\tilde{\boldsymbol{\sigma}}_{\mathbf{r}}^T\dot{\tilde{\boldsymbol{\sigma}}}_{\mathbf{r}}\end{aligned} \tag{34}$$

Noting that

$$tr(\tilde{\mathbf{W}}^T\dot{\tilde{\mathbf{W}}}) = \sum_{i=1}^{2}\tilde{\mathbf{w}}_i^T\dot{\tilde{\mathbf{w}}}_i \tag{35}$$

where $\tilde{\mathbf{w}}_i$ is i–th column of matrix $\tilde{\mathbf{W}}$. Then (34) becomes

$$\begin{aligned}\dot{V} &= -\frac{1}{2}\underline{\mathbf{e}}^T\mathbf{Q}\underline{\mathbf{e}} + \underline{\mathbf{e}}^T\mathbf{PB}\boldsymbol{\varepsilon} + \tilde{\mathbf{m}}^T(\underline{\mathbf{e}}^T\mathbf{PB}\boldsymbol{\varphi}_{\mathbf{m}}\hat{\mathbf{W}} + \frac{\dot{\tilde{\mathbf{m}}}}{\eta_2}) + \tilde{\boldsymbol{\sigma}}_{\mathbf{l}}^T(\underline{\mathbf{e}}^T\mathbf{PB}\boldsymbol{\varphi}_{\boldsymbol{\sigma}_{\mathbf{l}}}\hat{\mathbf{W}} + \frac{\dot{\tilde{\boldsymbol{\sigma}}}_{\mathbf{l}}}{\eta_3}) \\ &\quad + \tilde{\boldsymbol{\sigma}}_{\mathbf{r}}^T(\underline{\mathbf{e}}^T\mathbf{PB}\boldsymbol{\varphi}_{\boldsymbol{\sigma}_{\mathbf{r}}}\hat{\mathbf{W}} + \frac{\dot{\tilde{\boldsymbol{\sigma}}}_{\mathbf{r}}}{\eta_4}) + \sum_{i=1}^{2}\tilde{\mathbf{w}}_i^T(\underline{\mathbf{e}}^T\mathbf{PB}\hat{\boldsymbol{\varphi}} + \frac{\dot{\tilde{\mathbf{w}}}_i}{\eta_1})\end{aligned} \tag{36}$$

Choose adaptation laws as

$$\dot{\hat{\mathbf{w}}}_i = -\dot{\tilde{\mathbf{w}}}_i = \eta_1\underline{\mathbf{e}}^T\mathbf{PB}\hat{\boldsymbol{\varphi}}, \quad i = 1,2 \tag{37}$$

$$\dot{\hat{\mathbf{m}}} = -\dot{\tilde{\mathbf{m}}} = \eta_2\underline{\mathbf{e}}^T\mathbf{PB}\boldsymbol{\varphi}_{\mathbf{m}}\hat{\mathbf{W}} \tag{38}$$

$$\dot{\hat{\boldsymbol{\sigma}}}_{\mathbf{l}} = -\dot{\tilde{\boldsymbol{\sigma}}}_{\mathbf{l}} = \eta_3\underline{\mathbf{e}}^T\mathbf{PB}\boldsymbol{\varphi}_{\boldsymbol{\sigma}_{\mathbf{l}}}\hat{\mathbf{W}} \tag{39}$$

$$\dot{\hat{\boldsymbol{\sigma}}}_{\mathbf{r}} = -\dot{\tilde{\boldsymbol{\sigma}}}_{\mathbf{r}} = \eta_4\underline{\mathbf{e}}^T\mathbf{PB}\boldsymbol{\varphi}_{\boldsymbol{\sigma}_{\mathbf{r}}}\hat{\mathbf{W}} \tag{40}$$

then (36) becomes

$$\dot{V} = -\frac{1}{2}\underline{\mathbf{e}}^T\mathbf{Q}\underline{\mathbf{e}} + \underline{\mathbf{e}}^T\mathbf{PB}\boldsymbol{\varepsilon} \le -\|\underline{\mathbf{e}}\|\lambda_{\min}(\mathbf{Q}) + \|\underline{\mathbf{e}}\|\|\mathbf{P}\|\|\mathbf{B}\|\boldsymbol{\varepsilon} \tag{41}$$

Then, the proposed ILCC system can guarantee system stable [18].

IV. SIMULATION RESULTS

These in-vehicle electronic systems monitor the position of a vehicle within a roadway lane and warn a driver if it is unsafe to change lanes or merge into a line of traffic. These systems are rearward-looking, radar-based systems. They assist drivers who are intentionally changing lanes by detecting vehicles in the driver's blind spot. A simulation case is applied to investigate the effectiveness of the proposed ILCC system. In case, control the vehicle’s lateral position of first lane and second lane at $0m$ and $1.2m$, respectively. The controller parameters of the ILCC system are selected as $\mathbf{P} = \begin{bmatrix} 380 & 60 & 16 & 3.5 \\ 59 & 106 & 1 & 6.4 \\ 16 & 1.1 & 2.1 & 0 \\ 3.4 & 6.3 & 0 & 2.1 \end{bmatrix}$; $\mathbf{K}_1 = \begin{bmatrix} 272.4 & 472.2 \\ 942.3 & 291.4 \end{bmatrix}$; $\mathbf{K}_2 = \begin{bmatrix} 227 & 62.8 \\ 78.5 & 38.8 \end{bmatrix}$; $\eta_1 = 10$ and $\eta_2 = \eta_3 = \eta_4 = 1$. These parameters are selected through trails. The simulation result is show in Fig. 3. The lateral velocity of vehicle is shown in Fig. 3(a); the lateral position of vehicle is shown in Fig. 3(b); the yaw velocity of vehicle is shown in Fig. 3(c); the yaw position of vehicle is shown in Fig. 3(d); the controller effort is shown in Fig. 3(e); and the number of fuzzy rules is shown in Fig. 3(f). The simulation results show the proposed ILCC system can achieve favorable control performance.

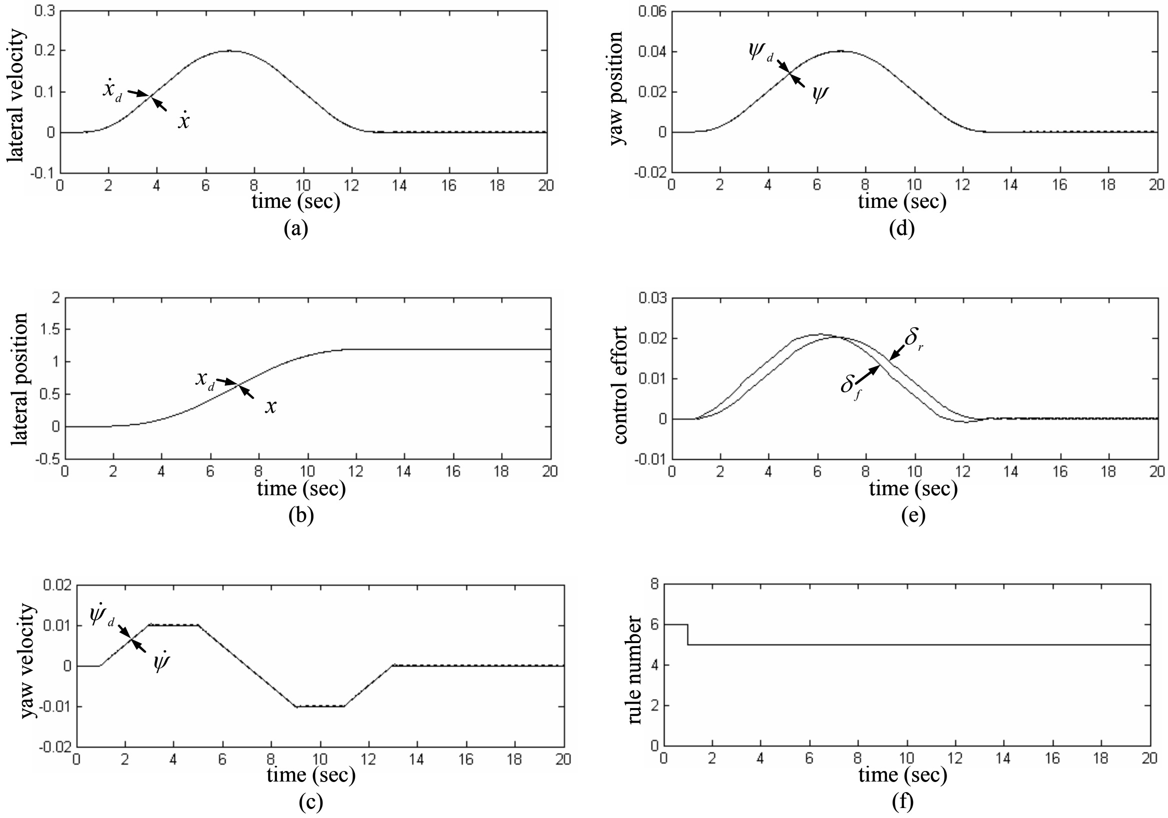

Fig. 3. Simulation results of the proposed ILCC system.

V. VR-BASED EXPERIMENTAL CAR

Public security has become an important issue everywhere. Especially, the safe manipulation and control of various machines and vehicles has gained special attention such that the authorities keep emphasizing the strict training of human operators. Currently, such training process usually relies on the actual machines or vehicles in the real sites. This not only has high demands in space, time and cost, but also causes another phase of public security problem. So this project develops a VR-based experimental car via field programmable gate array (FPGA) approach as shown in Fig. 4. FPGA is a fast prototyping IC component. This kind of IC incorporates the architecture of a gate array and programmability of a programmable logic device [19]. The advantage of controller implement by FPGA includes shorter development cycles, lower cost, small size, fast system execute speed, and high flexibility. This project uses Altera Stratix II series FPGA chip; Altera Quartus II software; Nios II processor and verilog hardware description language to implement the hardware control system. The Quartus II software is the development tool for programmable logic devices. The Nios II processor is a configurable, versatile, RISC embedded processor. Based on this hardware implementation, we can easily apply our proposed algorithm to test its effectiveness.

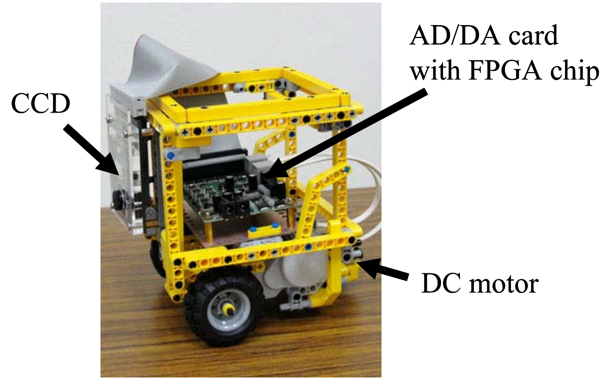

Fig. 4. VR-based experimental car.

VI. Conclusions

This paper has successfully developed an asymmetric self-organizing fuzzy neural network (ASOFNN). And, an intelligent lane-change control (ILCC) system is proposed. In the second year (this year), an intelligent lane-change control (ILCC) system with a bump avoidance system is expected. The proposed ILCC system is comprised of a state feedback controller and a neural controller. In the ASOFNN design, a dynamic rule generating/pruning mechanism is developed to cope with the tradeoff between the approximation accuracy and computational loading. The adaptation laws of the ILCC system are derived in the sense of Lyapunov stability theorem, thus the stability of the closed-loop control system can be guaranteed. In the simulation example, the simulation results show the proposed ILCC system can achieve favorable control performance.

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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多輸出非對稱歸屬函數模糊類神經網路開發工作。

(2) 完成智慧車輛車道切換控制開發工作。

(3) 完成 MATLAB 模擬與效能分析。

(4) 建構一台實驗小車，用於驗證所開發之演算法。

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

99 年 6 月 21 日

報告人姓名	許駿飛	系所 職稱	電機系 助理教授
會議 時間 地點	2009 年 6 月 6 日 ~ 6 月 9 日 中國，上海	本會核定 補助文號	NSC 98-2221-E-216-040-
會議 名稱	（中文）2010 第七屆類神經網路國際研討會 （英文）2010 The Seventh International Symposium on Neural Networks		
發表 論文 題目	（中文）使用小波類神經網路設計於具非線性未知參數下之渾沌系統同步控制 （英文）Master-slave chaos synchronization of uncertain nonlinear gyros using wavelet neural network		

報告內容應包括下列各項：

一、　參加會議經過

2010 The Seventh International Symposium on Neural Networks (第七屆類神經網路國際研討會)於 99 年 6 月 6 日至 6 月 9 日於中國大陸上海市舉行。並由世界各國頂尖之學者專家共同與會進行論文口頭報告及研究經驗交流分享，其亦爲國際上重要的類神經網路應用領域研討會。會議之議程一共有 4 天，大會邀請了四位教授來專題演講，包括

1. DeLiang Wang (The Ohio State University, US)

題目：**Cocktail Party Problem as Binary Classification**

摘要：Speech segregation, or the cocktail party problem, has proven to be extremely challenging. Part of the challenge stems from the lack of a carefully analyzed computational goal. The effectiveness of the ideal binary mask implies that sound separation may be formulated as a case of binary classification, which opens the cocktail party problem to a variety of neural network classification methods. This new formulation has led to major recent advances towards solving the cocktail party problem.

2. Gary G. Yen (Oklahoma State University, US)

題目：**A Textual Data Visualization Approach Based on the Self-Organizing Map**

摘要：The Self-Organizing Map (SOM) is an unsupervised neural network model that provides topology-preserving mapping from high-dimensional input spaces onto a commonly two-dimensional output space. In this study, the clustering and visualization capabilities of the SOM, especially in the analysis of textual data, i.e., document collections, are reviewed and further developed. A novel clustering and visualization approach based on the SOM is proposed for the task of text data mining.

3. Chin-Teng Lin (National Chiao-Tung University, Taiwan, China)

題目：**Computational Intelligent Brain Computer Interaction and Its Applications on Driving Cognition**

摘要：Human cognitive functions such as perception, attention, memory and decision making are omnipresent in our daily life activities. In this lecture, we briefly introduce the fundamental physiological changes of the human cognitive functions in driving first and then explain how to utilize these main findings to develop the monitoring and feedback systems based on Fuzzy logic and Fuzzy Neural technologies in the following two topics: (1) EEG-based cognitive state monitoring and prediction by using the self-constructing fuzzy neural systems; and (2) Spatial and temporal physiological changes and estimation of motion sickness. These research advancements can provide us new insights into the understanding of complex cognitive functions and lead to novel application enhancing our productivity and performance in face of real-world complications.

4. Andrzej Cichocki (Riken Brain Science Institute, JAPAN)

題目：**Computational Intelligent Brain Computer Interaction and Its Applications on Driving Cognition**

摘要：In many fields of neuroscience, medicine, engineering, and economics, large-scale massive data sets are routinely collected and often are gradually increased and dynamically modified in time as data stream (e.g., time series with an increasing length). In many cases, the data represented by tensors (multi-array), or set of matrices has a spatial temporal and spectral information. Multi-way blind sources separation, multimodal signal decompositions and statistical machine learning methods have turned out to be promising solutions.

專題三之主講者爲交通大學林進燈教授，主題爲探討人類的知覺、注意力、記憶及決策等認知能力。而其中駕駛行爲更是日常生活中無所不在的決策認知行爲。駕駛員疲勞、嗜睡、分心或暈車爲導致許多交通意外的主要原因；當司機失去注意力，也將明顯降低對車輛的控制能力。有鑒於此，如何有效地預防和提高人的認知功能已成爲一個非常重要的研究課題。因此該專題演講則簡要地介紹了人類在駕駛時的基本生理變化；並解釋如何利用這些特徵來發展出基於模糊邏輯和模糊神經網路的監測及回授系統之技術；林教授的這些創新技術使大家更了解複雜的認知功能，並提供許多類神經網路與生醫訊號更新穎的應用價值。

<6 月 6 日>

當天早上從桃園機場搭機前往至上海浦東機場(Pudong)，接著轉乘公車至上海市區，先到住宿飯店，當至飯店櫃臺辦理完成入住程序後，晚輩搭乘地鐵至研討會會場完成註冊程序，本次類神經網路國際研討會會議共有來自世界各地三百餘篇論文分別於 40 組分組議題中發表討論。上海只花了不到十五年的時間建設改革，真的值得深思。

ISNN 2010 會場看板

<6 月 7 日>

當天本人並沒有論文發表，故與中華大學王志湖教授與田慶誠教授及幾位研究所學生參訪同濟大學信息與通信工程學系，該系薛小平教授等就目前其所承接之 RFID 相關計劃及目前研究概況與經驗作一系列的簡介、討論及分享。

<6 月 8 日>

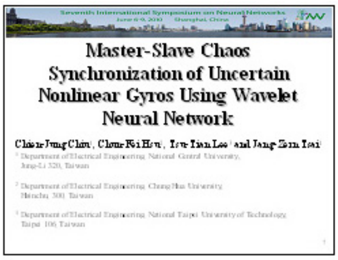
當天一早，本人與台北科技大學李祖添教授共同組了一個 **Special Session： Design of an Intelligent, Smart and Safe Vehicle**，其中共有 6 篇論文進行口頭發表，主要探討為智慧型安全車輛之未來趨勢，包含 ABS 防鎖死剎車系統，車道障礙物之偵測與辨識技術及智慧型泊車系統之研究等。最後，當天晚上與參與學者一同參與了此次研討會的頒獎晚宴，場面非常盛大且熱鬧。

Special Session 主持情狀

晚宴會場

<6月9日>

當天有一篇論文需要發表，本人發表論文題目是“使用小波類神經網路設計於具非線性未知參數下之渾沌系統同步控制”，參與的專家學者約有十餘人左右，大家互相分享論文研究心得以及觀念溝通。演講投影片如下：



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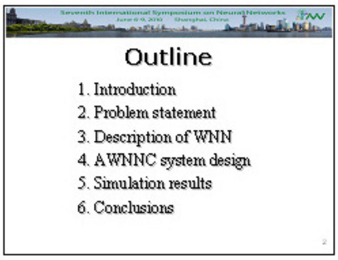

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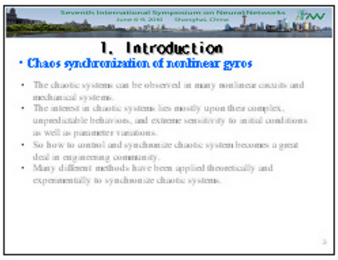

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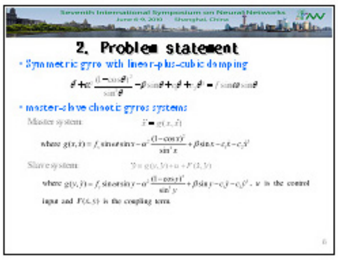

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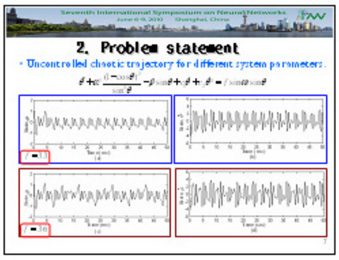

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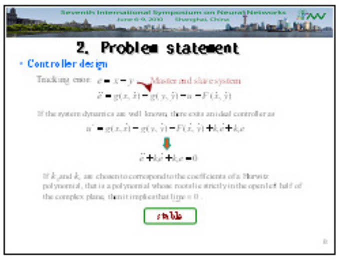

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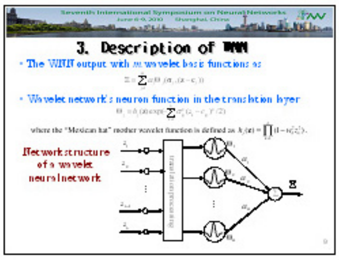

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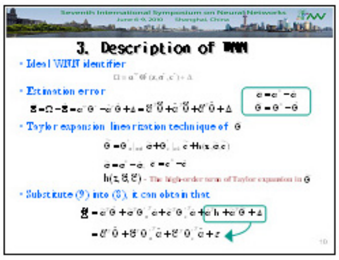

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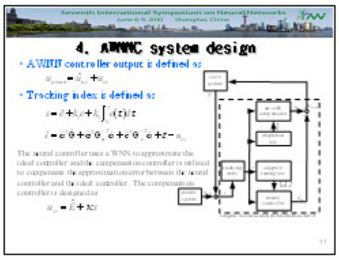

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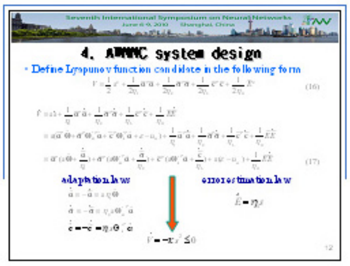

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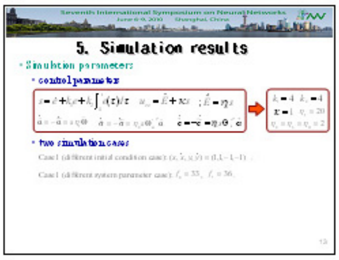

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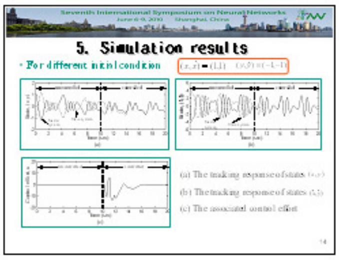

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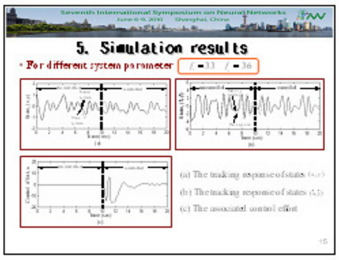

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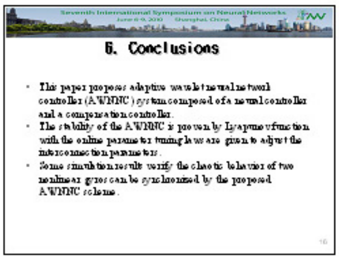

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二、 與會心得

首先感謝中華大學補助機票費使本人有機會到上海參加 2010 第七屆類神經網路國際研討會，並在會議中發表論文，藉由此次機會認識眾多國外一些優秀研究先進。本研討會匯集了來自全世界各地的菁英學者，許多研究成果都讓人十分振奮，同時也發現來自世界各國之專家學者先進皆熱衷於投入研究智慧型運輸系統、類神經網路控制等領域；與本人之研究領域相近，非常具有參考及學習之價值；因此本次研討會之參與收穫頗為豐碩，對於日後的研究都有相當好的助益。在交流過程中，不但能從其他學者專家的演講中產生新的研究方向與想法，更能在其他不同領域的研究裡學到新的東西，並且看到許多學者提出新的想法，實現各項理念，不排除也可以往這個方面去發展。

三、 考察參觀活動(無是項活動者省略)

無任何考察參觀活動。

四、 建議

經由這次參與 2010 第七屆類神經網路國際研討會(ISNN 2010)，本會議主要參與者大都是中國當地專家學者，可以發覺中國大陸之專家學者無不兢兢業業投注心血於此方面之研究發展工作，研發新的演算法，設計新的架構，應用新的問題，尤其在類神經網路各種應用領域也有多篇論文朝向智慧型機器人之控制與實現。而且從會中得到寶貴的經驗及知識，對將來的研究有更進一步的發展，倘若我們想要趕上國際水準勢必將投入更多心血才足以擠身已開發國家之列，稍一鬆懈極很可能很容易被中國大陸迎頭趕上。

五、 攜回資料名稱及內容

1. ISNN 2010 論文光碟片一張。

六、其他

無研發成果推廣資料

98年度專題研究計畫研究成果彙整表

<table>
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<tr><td rowspan="2">專利</td><td>申請中件數</td><td>0</td><td>0</td><td>100%</td><td rowspan="2">件</td><td></td></tr>
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<tr><td rowspan="2">技術移轉</td><td>件數</td><td>0</td><td>0</td><td>100%</td><td>件</td><td></td></tr>
<tr><td>權利金</td><td>0</td><td>0</td><td>100%</td><td>千元</td><td></td></tr>
<tr><td rowspan="4">參與計畫人力（本國籍）</td><td>碩士生</td><td>1</td><td>1</td><td>100%</td><td rowspan="4">人次</td><td></td></tr>
<tr><td>博士生</td><td>0</td><td>0</td><td>100%</td><td></td></tr>
<tr><td>博士後研究員</td><td>0</td><td>0</td><td>100%</td><td></td></tr>
<tr><td>專任助理</td><td>0</td><td>0</td><td>100%</td><td></td></tr>
<tr><td rowspan="12">國外</td><td rowspan="4">論文著作</td><td>期刊論文</td><td>0</td><td>1</td><td>100%</td><td rowspan="3">篇</td><td></td></tr>
<tr><td>研究報告/技術報告</td><td>0</td><td>0</td><td>100%</td><td></td></tr>
<tr><td>研討會論文</td><td>1</td><td>1</td><td>100%</td><td></td></tr>
<tr><td>專書</td><td>0</td><td>0</td><td>100%</td><td>章/本</td><td></td></tr>
<tr><td rowspan="2">專利</td><td>申請中件數</td><td>0</td><td>0</td><td>100%</td><td rowspan="2">件</td><td></td></tr>
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<tr><td>權利金</td><td>0</td><td>0</td><td>100%</td><td>千元</td><td></td></tr>
<tr><td rowspan="4">參與計畫人力（外國籍）</td><td>碩士生</td><td>0</td><td>0</td><td>100%</td><td rowspan="4">人次</td><td></td></tr>
<tr><td>博士生</td><td>0</td><td>0</td><td>100%</td><td></td></tr>
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<tr><td>專任助理</td><td>0</td><td>0</td><td>100%</td><td></td></tr>
</table>

其他成果 (無法以量化表達之成果如辦理學術活動、獲得獎項、重要國際合作、研究成果國際影響力及其他協助產業技術發展之具體效益事項等，請以文字敘述填列。)	無

	成果項目	量化	名稱或內容性質簡述
科教處計畫加填項目	測驗工具(含質性與量性)	0	
	課程/模組	0	
	電腦及網路系統或工具	0	
	教材	0	
	舉辦之活動/競賽	0	
	研討會/工作坊	0	
	電子報、網站	0	
	計畫成果推廣之參與（閱聽）人數	0	

國科會補助專題研究計畫成果報告自評表

請就研究內容與原計畫相符程度、達成預期目標情況、研究成果之學術或應用價值（簡要敘述成果所代表之意義、價值、影響或進一步發展之可能性）、是否適合在學術期刊發表或申請專利、主要發現或其他有關價值等，作一綜合評估。

1. 請就研究內容與原計畫相符程度、達成預期目標情況作一綜合評估 ■達成目標 □未達成目標（請說明，以 100 字為限） □實驗失敗 □因故實驗中斷 □其他原因 說明：
2. 研究成果在學術期刊發表或申請專利等情形： 論文：□已發表 □未發表之文稿 ■撰寫中 □無 專利：□已獲得 □申請中 ■無 技轉：□已技轉 □洽談中 ■無 其他：（以 100 字為限）
3. 請依學術成就、技術創新、社會影響等方面，評估研究成果之學術或應用價值（簡要敘述成果所代表之意義、價值、影響或進一步發展之可能性）（以 500 字為限） 大幅增加的車輛數與駕駛人口，也使得行車環境變得日益複雜，造成事故死傷率急速攀升，所以本計畫在本年度開發設計智慧車輛自動控制系統，整個控制系統主要將利用適應性控制與模糊類神經網路為基礎來設計，期望所開發之智慧型控制系統可以有效地提昇車輛行駛時的安全性，以減少交通事故以及傷亡的發生。所提出之控制系統包括一個狀態回授控制器與一個類神經控制器，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，本子計畫利用縮小實驗小車建立一虛擬實境來取代實車測試，藉以模擬與分析所開發方法之效能與實用性。經由一些結果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。