Self-Organizing Fuzzy Learning CLOS Guidance Law Design

CHIH-MIN LIN
Yuan-Ze University
Taiwan

CHUN-FEI HSU
National Chiao-Tung University
Taiwan

YI-JEN MON
Yuan-Ze University
Taiwan

A new self-organizing fuzzy logic control (SOFLC) design method is proposed. The proposed method is applied to the command line-of-sight (CLOS) guidance law design. The SOFLC contains two sets of fuzzy inference logic. One is the fuzzy logic controller and the other is the rule modifier. The new learning method of the rule modifier is developed based on a fuzzy learning algorithm. The modification value of each rule is based on the fuzzy firing weight, so that learning of the rule bases is reasonable. Finally, two engagement scenarios are examined, and a comparison between a fuzzy logic control (FLC), an optimal learning FLC, and the proposed SOFLC CLOS guidance laws is made. Simulation results show that the proposed SOFLC guidance law can achieve better guidance performance than the other guidance laws.

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Authors' addresses: C-M. Lin and Y-J. Mon, Dept. of Electrical Engineering, Yuan-Ze University, Chung-Li, Tao-Yuan, 320, Taiwan, Republic of China, E-mail: (cml@ee.yzu.edu.tw); C-F. Hsu, Dept. of Electrical and Control Engineering, National Chiao-Tung University, Hsinchu 300, Taiwan, Republic of China.

I. NOMENCLATURE

ψ_t	Yaw angle of target
θ_t	Pitch angle of target
ψ_m	Yaw angle of missile
θ_m	Pitch angle of missile
ϕ_{mc}	Roll angle command
σ_t	Azimuth angle of line-of-sight (LOS) to target
γ_t	Elevation angle of LOS to target
σ_m	Azimuth angle of LOS to missile
γ_m	Elevation angle of LOS to missile
$\Delta\sigma$	$\sigma_m - \sigma_t$
$\Delta\gamma$	$\gamma_m - \gamma_t$
T	Thrust force
D	Drag force
M	Mass of missile
g	Gravity acceleration
a_x	Axial acceleration of missile
$\tilde{a}_{yc}$	Yaw acceleration command
$\tilde{a}_{zc}$	Pitch acceleration command
a_{ty}	Yaw acceleration of target
a_{tz}	Pitch acceleration of target
R_m	Missile range from ground tracker
R_t	Target range from ground tracker
v_m	Missile velocity
v_t	Target velocity
a_t	Target acceleration
$s\theta$	$\sin(\theta)$
$c\theta$	$\cos(\theta)$
(X_I, Y_I, Z_I)	Missile inertial frame
(X_M, Y_M, Z_M)	Body frame
(X_L, Y_L, Z_L)	LOS frame
(x_t, y_t, z_t)	Target position in inertial frame
(x_m, y_m, z_m)	Missile position in inertial frame.

II. INTRODUCTION

The guidance law design makes use of the relative target-missile states to produce command accelerations for the autopilot of a missile. The guidance system is a nonlinear, time-varying, and multiobjective problem [1, 2]. Command line-of-sight (CLOS) guidance represents a derivative of the command guidance technique. The principle of CLOS guidance is to force a missile to fly as close as possible along the instantaneous LOS joining the ground tracker and the target. CLOS guidance has been regarded as a low-cost guidance concept because it emphasizes the placement of avionics on the launch platform as opposed to the on board expendable weapon [3, 4].

FLC using a rule-based algorithm can model the qualitative aspects of human knowledge and reasoning processes without employing precise quantitative analyses. It also possesses several advantages such as robustness and no need of system model [5, 6].

Recently, FLC has been applied to guidance systems [7–9]. However, these fuzzy-logic-based guidance law design methods are based on fuzzy inference rules that are constructed based on the qualitative aspects of human knowledge. The design of satisfactory fuzzy rules needs time-consuming trial-and-error. To tackle this problem, an attractive approach is provided by self-organizing fuzzy logic control (SOFLC) [10–12]. The SOFLC proposed in [10, 11] contains a learning algorithm to modify the control rules based on an evaluation of the system's performance. The modification of the control rules is achieved by assigning a credit to the control action based on present performance. In [12], a negative gradient modification method for the optimal performance is expressed, in which the local optimal control performance can be obtained. This rule modification approach is called optimal learning fuzzy logic control (OLFLC) here. However, the convergence time of the control action for this method is long since only one rule is modified each time.

A new SOFLC design method is proposed here. The proposed SOFLC contains two sets of fuzzy inference logic. One is the fuzzy logic controller and the other is the rule modifier. The new learning method of the rule modifier is developed based on a fuzzy learning algorithm. Since more than one rule will be fired at each inferring process and the fired grade is different for each rule, one rule modification algorithm presented in [12] and the fixed value modification algorithm presented in [10, 11] are not the most suitable ones. In the proposed SOFLC design method, the modification value of each rule is based on the fuzzy firing weight, so that the learning of the rule bases is more reasonable than that in [10–12]. Finally, the proposed SOFLC is applied for the CLOS guidance law design. For simulations, two engagement scenarios are considered; one is an antiaircraft scenario and the other is an anti-intercontinental-ballistic-missile scenario. A comparison between an FLC, an OLFLC, and the proposed SOFLC guidance laws is made. Simulation results show that the SOFLC guidance law can achieve smaller miss distance than the other fuzzy-logic-based guidance laws and the performance index of SOFLC guidance law is smaller than the OLFLC guidance law, so that the proposed self-organizing fuzzy learning algorithm is more suitable for CLOS guidance law design.

III. FORMULATION OF MISSILE-TARGET ENGAGEMENT

The three-dimensional CLOS guidance problem can be formulated as a tracking problem for a time-varying nonlinear system. Fig. 1 depicts the three-dimensional pursuit situation. The origin of the inertial frame is located at the ground tracker.

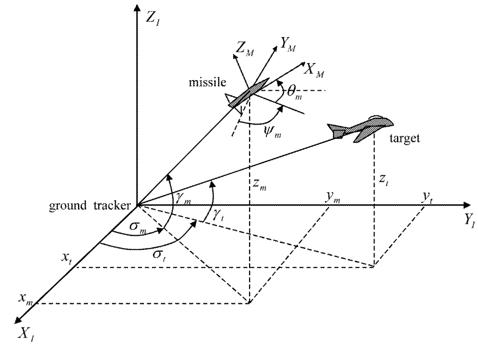

Fig. 1. Three-dimensional pursuit scenario.

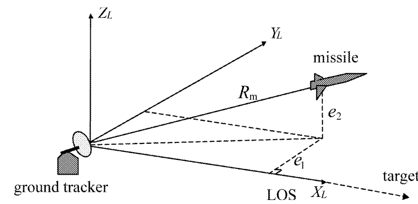

Fig. 2. CLOS pursuit scenario.

The origin of the missile body frame is fixed at the missile center of mass. For simulations, the motion of the missile in the inertial frame can be represented as follows [4]:

$$
\begin{aligned}
\ddot{x}_m &= a_x c\theta_m c\psi_m - \tilde{a}_{yc}(s\phi_{mc} s\theta_m c\psi_m + c\phi_{mc} s\psi_m) \\
&\quad - \tilde{a}_{zc}(c\phi_{mc} s\theta_m c\psi_m - s\phi_{mc} s\psi_m) \\
\ddot{y}_m &= a_x c\theta_m s\psi_m - \tilde{a}_{yc}(s\phi_{mc} s\theta_m s\psi_m - c\phi_{mc} c\psi_m) \\
&\quad - \tilde{a}_{zc}(c\phi_{mc} s\theta_m s\psi_m + s\phi_{mc} c\psi_m) \\
\ddot{z}_m &= a_x s\theta_m + \tilde{a}_{yc} s\phi_{mc} c\theta_m + \tilde{a}_{zc} c\phi_{mc} c\theta_m - g \\
\dot{\psi}_m &= \tilde{a}_{yc} c\phi_{mc}/(v_m c\theta_m) - \tilde{a}_{zc} s\phi_{mc}/(v_m c\theta_m) \\
\dot{\theta}_m &= \tilde{a}_{yc} s\phi_{mc}/v_m + \tilde{a}_{zc} c\phi_{mc}/v_m - g c\theta_m/v_m
\end{aligned}
\tag{1}
$$

where v_m denotes the velocity of the missile given by

$$
v_m \triangleq (\dot{x}_m^2 + \dot{y}_m^2 + \dot{z}_m^2)^{1/2} \tag{2}
$$

and a_x represents the axial acceleration of the missile given by

$$
a_x \triangleq (T - D)/M. \tag{3}
$$

A tracking error is defined in order to convert the CLOS guidance problem into a tracking problem. The CLOS guidance involves guiding the missile onto the LOS to target. Define the LOS frame as depicted in Fig. 2. The X_L axis forwards along the LOS to target and the Y_L axis is horizontally directed to the left of the $X_L - Z_L$ plane. Then, the coordinates (e_1, e_2) indicated in Fig. 2 represent the missile position in the LOS frame. The tracking error is defined as [4]

$$
e \triangleq \begin{bmatrix} e_1 \\ e_2 \end{bmatrix} = \begin{bmatrix} -x_m s\sigma_t + y_m c\sigma_t \\ -x_m s\gamma_t c\sigma_t - y_m s\gamma_t s\sigma_t + z_m c\gamma_t \end{bmatrix}. \tag{4}
$$

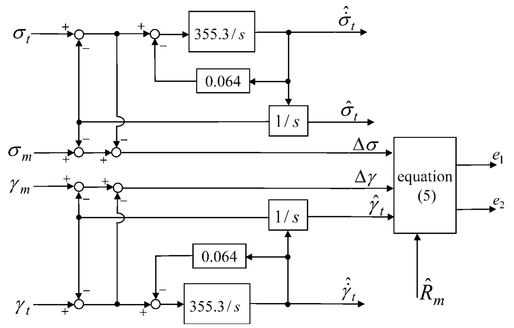

Fig. 3. Block diagram representation of estimation algorithm for guidance information.

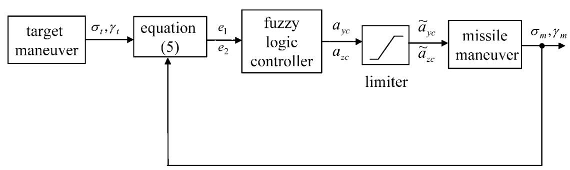

Fig. 4. Guidance system for FLC CLOS guidance law.

Note that $|e|$ represents the distance from the missile to the LOS. Therefore, the missile will eventually hit the target if the tracking error is driven to zero before the target crosses the missile. Since e_1 and e_2 cannot be measured directly, these quantities ought to be computed indirectly using the polar position data of the missile available from the ground tracker as

$$e \overset{\Delta}{=} \begin{bmatrix} e_1 \\ e_2 \end{bmatrix} = \begin{bmatrix} R_m c(\Delta\gamma + \gamma_t) s\Delta\sigma \\ R_m s(\Delta\gamma + \gamma_t) c\gamma_t - R_m c(\Delta\gamma + \gamma_t) s\gamma_t c\Delta\sigma \end{bmatrix}. \tag{5}$$

The control object is to drive the error and the change-of-error (e and $\dot{e}$) to zero.

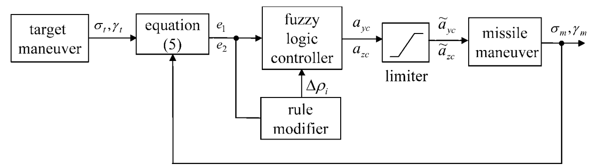

Fig. 6. Guidance system for SOFLC CLOS guidance law.

IV. FUZZY LOGIC CONTROL

The basic FLC should be viewed as a linguistic conditional statement symbolized in the form of a relation matrix R given by the Cartesian product

$$R = E \times \dot{E} \times U \tag{6}$$

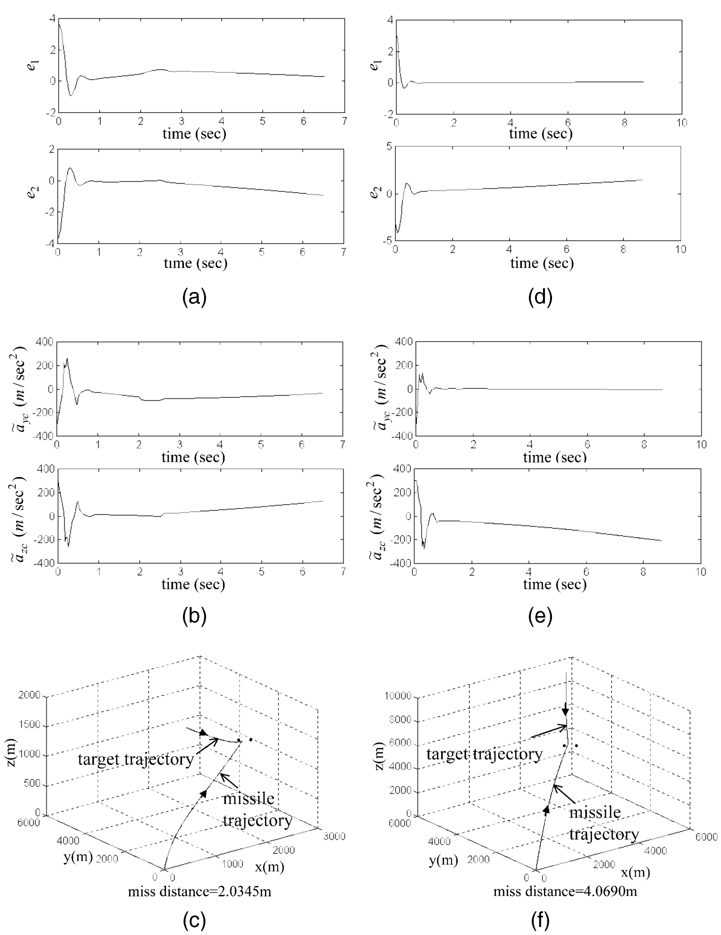

Fig. 5. Engagement responses of FLC CLOS guidance law.

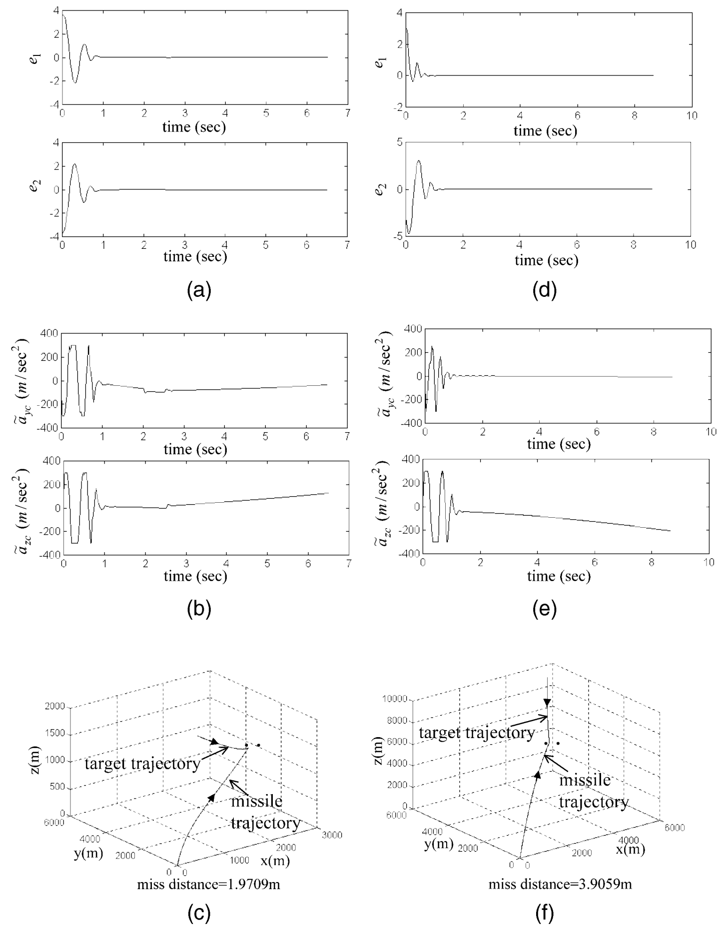

Fig. 7. Engagement responses of SOFLC CLOS guidance law.

where R is the control rule base; E and $\dot{E}$ are the fuzzified values of e and $\dot{e}$, respectively; U is the fuzzy output of the controller; $\times$ means the Cartesian product. The overall relation matrix R obtained from the fuzzy control rules is calculated as the union of m individual relation matrices

$$R = R_1 \cup R_2 \cup \cdots \cup R_m = \bigcup_{i=1}^{m} R_i. \tag{7}$$

Therefore, the output U from the fuzzy controller can be obtained from its inputs E and $\dot{E}$. Zadeh's compositional rule is employed for rule inference:

$$U = (E \times \dot{E}) \circ R \tag{8}$$

where $\circ$ denotes the compositional rule of inference.

The fuzzy control rules are in the following form:

$$\text{Rule } i: \quad \text{If} \quad e \text{ is } F_e^i \quad \text{and} \quad \dot{e} \text{ is } F_{\dot{e}}^i \quad \text{then} \quad u \text{ is } \rho_i \tag{9}$$

where F_e^i and $F_{\dot{e}}^i$ represent the fuzzy sets; ρ_i, $i = 1,2,\ldots,n$ are the singleton control actions. The defuzzification of the controller output is accomplished by the method of center-of-gravity [5]

$$u(e,\dot{e},\rho_i) = \frac{\sum_{i=1}^{n} w_i \times \rho_i}{\sum_{i=1}^{n} w_i} \tag{10}$$

where w_i is the firing weight of the ith rule. The defuzzified value in (10) represents the control force.

V. SELF-ORGANIZING FUZZY LOGIC CONTROL

The objective of the control is to bring the system from any initial state to a desired state, and the dynamic behavior of the system should be insensitive to the variations of the system parameters and external disturbances. To achieve the objective an iterative learning algorithm is adopted to adjust control efforts ρ_i, $i = 1,2,\ldots,n$ that are initiated from zero and are learned from the fuzzy rule modifier. The central part of the iterative learning algorithm for a SOFLC system is to change the control effort in the direction of the negative gradient of a performance index I which is defined as a function of e and $\dot{e}$

$$I = \sum_{k=1}^{g} \sqrt{e^2(k) + h[\dot{e}(k)]^2} \tag{11}$$

where k is the kth time interval, g is the total number of time intervals, and $h > 0$ is a weighting factor. The partial derivatives of I with respect to e and $\dot{e}$ can be

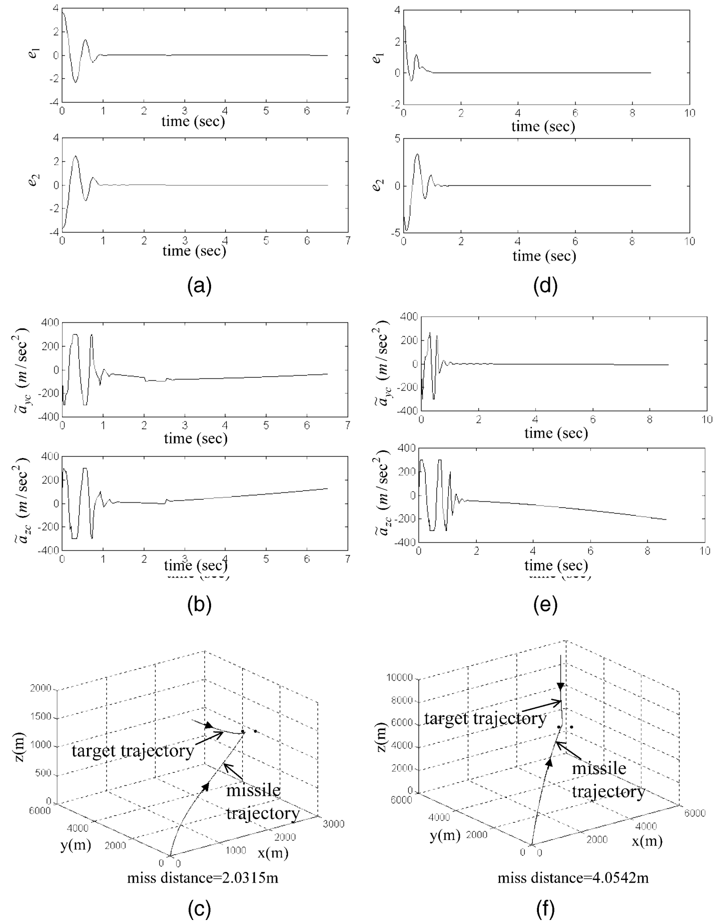

Fig. 8. Engagement responses of OLFLC CLOS guidance law.

obtained as follows:

$$\frac{\partial I}{\partial e(k)} = \frac{e(k)}{\sqrt{e^2(k) + h[\dot{e}(k)]^2}} \tag{12}$$

$$\frac{\partial I}{\partial \dot{e}(k)} = \frac{h\dot{e}(k)}{\sqrt{e^2(k) + h[\dot{e}(k)]^2}}. \tag{13}$$

The negative gradient for the optimal performance can be expressed as

$$-|\nabla I| = -\left\{\left|\frac{e(k)}{\sqrt{e^2(k) + h[\dot{e}(k)]^2}}\right| + h\left|\frac{\dot{e}(k)}{\sqrt{e^2(k) + h[\dot{e}(k)]^2}}\right|\right\}. \tag{14}$$

Based on the optimal control, the adjust control signal δu is chosen as

$$\delta u(k) = \eta(-|\nabla I|)\begin{bmatrix} e(k) \\ \dot{e}(k) \end{bmatrix} \tag{15}$$

where η is the learning rate with positive constant.

The modification algorithm for each fuzzy control rule is proposed as follows:

$$\Delta\rho_i(k) = \delta u(k) \cdot \frac{w_i}{\sum_{i=1}^{n} w_i} \tag{16}$$

where $\Delta\rho_i$ is a modification value to be added to the ith control rule in (9), i.e.

$$\rho_i(k+1) = \rho_i(k) + \Delta\rho_i(k). \tag{17}$$

Equation (16) represents that the modification value of each control rule is proportional to its firing weight of fuzzy inference. This is more reasonable than the rule modification methods proposed in [10–12].

Taking a summary, the fuzzy rules of SOFLC are given in (9) with the control efforts ρ_i updated with (17). And then the defuzzified control force is given in (10).

VI. SIMULATION RESULTS

For simulations, the simplified dynamics of target motion can be represented in the inertial frame as follows [4]:

$$\begin{aligned}
\ddot{x}_t &= -a_{ty}s\psi_t - a_{tz}s\theta_t c\psi_t \\
\ddot{y}_t &= a_{ty}c\psi_t - a_{tz}s\theta_t s\psi_t \\
\ddot{z}_t &= a_{tz}c\theta_t - g \\
\dot{\psi}_t &= a_{ty}/(v_t c\theta_t) \\
\dot{\theta}_t &= (a_{tz} - gc\theta_t)/v_t
\end{aligned} \tag{18}$$

TABLE I
Initial Data Used for Simulations

State	Scenario	Scenario 1	Scenario 2
$x_t(0), y_t(0), z_t(0)$	[m]	$2500, 5361.9, 1000$	$5000, 5000, 10000$
$\dot{x}_t(0), \dot{y}_t(0), \dot{z}_t(0)$	[m/s]	$0, -340, 0$	$0, 0, -750$
$\psi_t(0), \theta_t(0)$	[deg]	$-90, 0$	$-90, 0$
$x_m(0), y_m(0), z_m(0)$	[m]	$14.32, 39.34, 3.36$	$14.44, 17.20, 26.52$
$\dot{x}_m(0), \dot{y}_m(0), \dot{z}_m(0)$	[m/s]	$70.84, 151.92, 28.32$	$250, 250, 450$
$\psi_m(0), \theta_m(0)$	[deg]	$65, 9.59$	$45, 54.73$
$\Delta\sigma(0), \Delta\gamma(0)$	[deg]	$5, -5$	$5, -5$

TABLE II
Parameter Data Used for Simulations

$(T-D)/M$	$\begin{cases} 340\ \text{m/s}^2 & 0 < t < 2 \\ -44.1\ \text{m/s}^2 & t > 2 \end{cases}$ for scenario 1; $\begin{cases} 100\ \text{m/s}^2 & 0 < t < 10 \\ -44.1\ \text{m/s}^2 & t > 10 \end{cases}$ for scenario 2
ϕ_{mc}	0 deg
guidance command frequency	50 Hz
autopilot damping ratio	0.6
autopilot natural frequency	6π rad/s

where v_t is given by

$$v_t \stackrel{\Delta}{=} (\dot{x}_t^2 + \dot{y}_t^2 + \dot{z}_t^2)^{1/2}. \tag{19}$$

It should be emphasized that the derivation of self-organizing fuzzy learning CLOS guidance law does not need to use the missile model in (1) and target model in (18). These models are used only for simulations. The pitch and yaw autopilot dynamics are chosen as the second-order time invariant linear systems and the ground tracker as a simplified differential tracking system with damping ratio 0.6 and nature frequency 6π rad/s as depicted in Fig. 3. The ground tracker provides the estimated values of σ_t, γ_t, $\dot{\sigma}_t$, and $\dot{\gamma}_t$ as well as the measurement data of $\Delta\sigma$ and $\Delta\gamma$. In the follows, the estimated value is distinguished from its true value by inserting the upper $\wedge$ to the corresponding variable. Two simulation scenarios are examined to justify the proposed design methods. The detailed data used for the simulations are listed in Tables I and II. For simulations, a $30g$ ($g = 9.8$ m/s^2) limiter is included to represent the maneuverability of the missile. Thus, the acceleration commands are expressed as

$$\tilde{a}_{yc} = \text{sat}(a_{yc}, 30g) \tag{20}$$

and

$$\tilde{a}_{zc} = \text{sat}(a_{zc}, 30g) \tag{21}$$

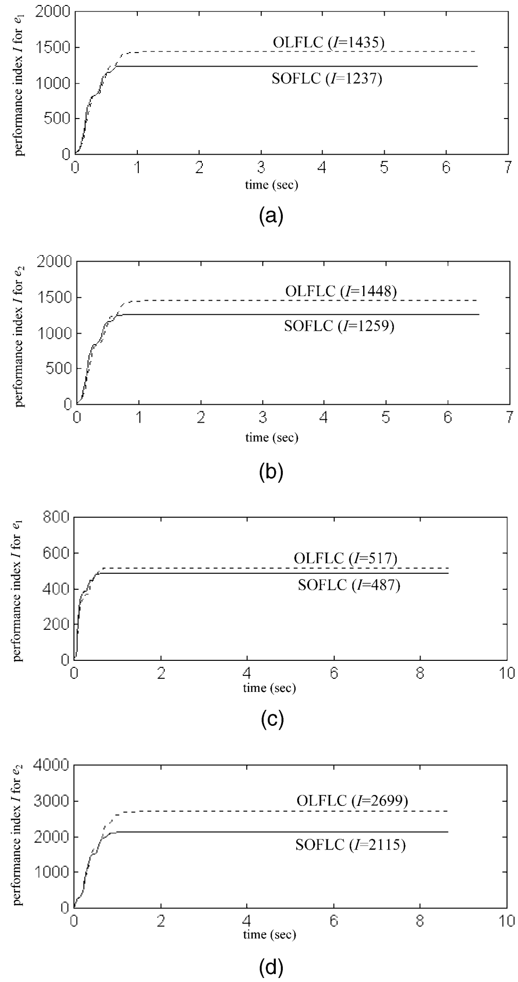

Fig. 9. Performance index of OLFLC and SOFLC guidance laws.

where

$$\text{sat}(a,b) = \begin{cases} a & \text{for} \quad a \le |b| \\ b \cdot \text{sgn}(a) & \text{for} \quad a > |b| \end{cases} \tag{22}$$

and $\tilde{a}_{yc}$ and $\tilde{a}_{zc}$ denote the acceleration command for azimuth-loop and elevation-loop, respectively. Scenario 1 represents an antiaircraft scenario. Assume that the target maneuvers with $a_{ty} = 5g$ and $a_{tz} = -g$ for the first 2.5 s and then with $a_{ty} = -5g$ and $a_{tz} = 5g$ until interception. For scenario 2, assume that the target maneuvers with $a_{ty} = 0g$ and $a_{tz} = 1g$ for the first 2.5 s and then with $a_{ty} = 0.5g$ and $a_{tz} = 1g$ until interception, which represents a simplified model of intercontinental ballistic missile with a lateral maneuver in the final aiming phase.

A comparison between an FLC, an OLFLC, and the proposed SOFLC guidance laws is made. The performance evaluation consists of miss distance and the responses of tracking errors. The FLC CLOS guidance system is depicted in Fig. 4 and its fuzzy inference rules are summarized in Table III where triangular membership functions are employed. The fuzzy labels used in this paper are negative big (NB), negative small (NS), zero (ZO), positive small (PS),

TABLE III
Fuzzy Inference Rules

e	$\dot{e}$ NB	NS	ZO	PS	PB
NB	1.00	1.00	1.00	0.43	0.00
NS	1.00	1.00	0.43	0.00	−0.43
ZO	1.00	0.43	0.00	−0.43	−1.00
PS	0.43	0.00	−0.43	−1.00	−1.00
PB	0.00	−0.43	−1.00	−1.00	−1.00

TABLE IV
Miss Distances (m) for Fuzzy-Logic-Based Guidance Laws

Design Method	Scenario	
	Scenario 1	Scenario 2
fuzzy logic control guidance law	2.0345	4.0690
optimal learning fuzzy logic control guidance law	2.0315	4.0542
self-organizing fuzzy logic control guidance law	1.9709	3.9059

and positive big (PB). By using the FLC guidance law, the simulation results are depicted in Fig. 5(a) to Fig. 5(c) for scenario 1, and Fig. 5(d) to Fig. 5(f) for scenario 2, respectively. The proposed SOFLC CLOS guidance system is depicted in Fig. 6. By using the proposed SOFLC guidance law with $\eta = 0.1$ and $h = 10$, the simulation results are shown in Fig. 7(a) to Fig. 7(c) and Fig. 7(d) to Fig. 7(f) for scenario 1 and scenario 2, respectively. By using the OLFLC guidance law with $\eta = 0.1$ and $h = 10$, in which only one rule is modified at each inferring process, the simulation results are shown in Fig. 8(a) to Fig. 8(c) and Fig. 8(d) to Fig. 8(f) for scenario 1 and scenario 2, respectively. The comparison of simulation results is summarized in Table IV, which shows that the SOFLC guidance law can achieve smaller miss distance than the other fuzzy-logic-based guidance laws. However, the SOFLC pays the price of larger transient responses of tracking errors and control efforts than the FLC at the initial learning phase, since the control rules are initiated from zero. The performance index I in (11) for the OLFLC and SOFLC guidance laws are shown in Figs. 9(a) and 9(b) and Figs. 9(c) and 9(d) for scenario 1 and scenario 2, respectively. From the simulations, it is shown that the performance index of the proposed SOFLC is smaller than that of the OLFLC. This also shows that the learning algorithm of the proposed SOFLC is better than the OLFLC.

VII. CONCLUSIONS

In this paper, a new SOFLC learning method is developed and this design method is applied for the CLOS guidance law design. A comparison between an FLC, an optimal learning FLC, and the proposed SOFLC guidance laws for two engagement scenarios is made. Simulation results demonstrate that the proposed SOFLC guidance law can achieve satisfactory performance for different engagement scenarios. Furthermore, the proposed SOFLC guidance law is found to perform better than the other fuzzy-logic-based guidance law in terms of the miss distance and performance index. It is revealed that the proposed SOFLC learning algorithm is suitable for the CLOS guidance law design.

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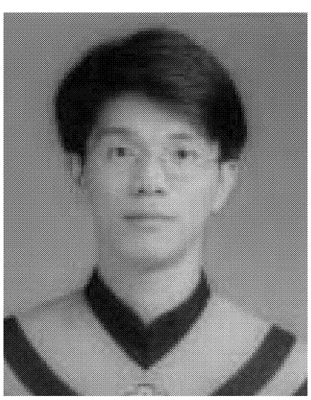
Chih-Min Lin received the B.S. and M.S. degrees in control engineering and a Ph.D. degree in electronics engineering from National Chiao Tung University, Taiwan, Republic of China in 1981, 1983, and 1986, respectively.

During 1986–1992, he was with the Chung Shan Institute of Science and Technology as a deputy director of system engineering of missile systems. He also served concurrently as an associate professor at Chiao Tung University and Chung Yuan University, Taiwan. He joined the faculty of the Department of Electrical Engineering, Yuan-Ze University, Taiwan, in 1993 and is currently a professor and the Chairman of the Department of Electrical Engineering. During 1997–1998, he was the honor research fellow in the University of Auckland, New Zealand. His research interests include fuzzy neural network, cerebellar model articulation control, guidance and flight control, and systems engineering.

He has served as the committee member of Chinese Automatic Control Society and the Deputy Chairman of IEEE Control Systems Society, Taipei Section.



Chun-Fei Hsu received the B.S., M.S., and Ph.D. degrees in electrical engineering from Yuan-Ze University, Taiwan, Republic of China in 1997, 1999, and 2002, respectively.

He joined the Department of Electrical and Control Engineering, National Chiao-Tung University, Taiwan, Republic of China, in 2002. His research interests include servomotor drives, flight control and intelligent control using fuzzy system and neural network technologies.