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Aircraft Landing Control Based on CMAC and GA Techniques

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Abstract: This paper presents an intelligent control scheme that uses a cerebellar model articulation controller (CMAC) and genetic algorithms (GA) in aircraft automatic landing control and to make automatic landing systems (ALS) more intelligent. The proposed intelligent controller can act as an experienced pilot and guide the aircraft to a safe landing in severe turbulence environment. Current flight control law is adopted in the intelligent design. Tracking performance and adaptive capability are demonstrated through software simulation.

1. INTRODUCTION

Conventional automatic landing system is enabled only under limited conditions. If severe wind disturbance is encountered, the pilot must handle the aircraft based on the limits of the automatic landing system. Aircraft pilots must not only be acquainted with the operation of instrument boards but also need flight sensitivity to the ever-changing environment, especially in the landing phase when turbulence is encountered. An inexperienced pilot may not be able to guide the aircraft to a safe landing at the airport. According to the National Transportation Safety Board report (NASDAC Review, 2004), between 1994 and 2003, there were 19562 aircraft accidents. Weather was a contributing factor in 4159 of these accidents and involved 4167 aircraft. Of the 4159 weather-related accidents, 2726 were due to wind conditions. In addition, a single accident may involve multiple weather conditions. According to the statistics of Flight International 10-16, January 2006 issue, there were 23 accidents/incidents affected by weather, causing total 324 (34 crew and 290 passengers) fatalities. The average accident fatality caused by weather is 14 people. It was apparent that most of cases were in the landing phase. It is therefore desirable to develop an intelligent ALS that expands the operational envelope to include safer responses under a wider range of conditions. The goal of this paper is to show that the proposed intelligent control system can relieve human operators and guide the aircraft to a safe landing in a severe turbulence environment.

In recent years, intelligent control is more and more popular in the control fields. Many intelligent concepts have been applied into various scientific and engineering researches, such as fuzzy system, neural network, cerebellar model articulation controller (CMAC), genetic algorithms (GA), and hybrid systems etc., for example. There are also obvious achievements in flight control domain (Jorgensen *et al.*, 1991; Cooper, 1995; Iiguni *et al.*, 1998; Chaturvedi *et al.*, 2002; Izadi *et al.*, 2003; Malaek *et al.*, 2004; Juang *et al.*, 2005). In the corresponding period of neural networks, the CMAC was developed by Albus in 1975. It imitates the structure of human cerebellum, which is a kind of associative memory neural network. Unlike the back-propagation based neural network which is using the global weight updating rule, CMAC is distinguished by the local weight updating rule. CMAC not only combines the advantages of rapid convergence speed and low computation but can also be realized easily by hardware. With increasing interest in neural networks, CMAC has attracted many investigators into this field. The applications of CMAC can be found such as robot control, unknown nonlinear systems, image and signal processing (Lin *et al.*, 2004; Hu *et al.*, 1999).

In this study, we introduce a hybrid fuzzy-CMAC-GA controller to automatic landing system. Because fuzzy set theory has been successfully employed in various fields, more and more researchers integrated the fuzzy concept into the conventional CMAC, such as Nie *et al.*,1993; Zhao *et al.*,2000; Hu *et al.*,2005; Su *et al.*,2006. The performance of the intelligent ALS under severe environment can be improved by the advantages of the fuzzy-CMAC which include local generalization, rapid learning convergence, and fuzzy interpretation capability. Besides, GA is utilized to the selection of optimal control gains, which are used to make the controller adaptive to different flight conditions. Robustness is obtained by choosing optimal control gains that allows wide range of disturbances to the controller. GA is search and optimization method based on the principle of natural evolution and population genetics. The basic principles of GA were first proposed by Holland (1975). GA presumes that the potential solution of any problem is an individual and can be represented by a set of parameters. These parameters are regarded as the genes of a chromosome and can be structured by a string of values in binary or real-value form. A positive value, generally known as a fitness value, is used to reflect the degree of "goodness" of the chromosome for the problem which would be highly related with its objective value. In this paper, a real-value GA using Adewuya crossover rule is applied to search optimal control parameters (Adewuya, 1996).

2. SYSTEM MODEL

At the aircraft landing phase, the pilot descends from the cruise altitude to an altitude of approximately 1200 ft above the ground. The pilot then positions the aircraft so that the

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aircraft is on a heading towards the runway centerline. When the aircraft approaches the outer airport marker, which is about 4 nautical miles from the runway, the glide path signal is intercepted, as shown in Fig. 1. As the airplane descends along the glide path, its pitch, attitude, and speed must be controlled. The descent rate is about 10 ft/sec and the pitch angle is between -5 to +5degrees. Finally, as the airplane descends 20 to 70 feet above the ground, the glide path control system is disengaged and a flare maneuver is executed. The vertical descent rate is decreased to 2 ft/sec so that the landing gear may be able to dissipate the energy of the impact at landing. The pitch angle of the airplane is then adjusted, between 0 to 5 degrees for most aircraft, which allows a soft touchdown on the runway surface.

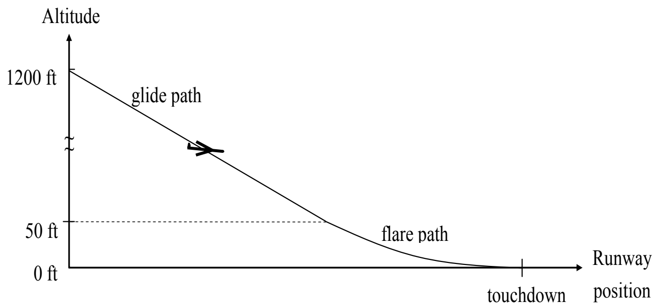

Fig. 1. Glide path and flare path

A simplified model of a commercial aircraft that moves only in the longitudinal and vertical plane is used in the simulations for implementation ease (Jorgensen *et al*.,1991). The motion equations of the aircraft are given as follows:

$$\dot{u} = X_u(u-u_g) + X_w(w-w_g) + X_q q - g(\frac{\pi}{180})\cos(\gamma_0)\theta + X_E\delta_E + X_T\delta_T \qquad (1)$$

$$\dot{q} = M_u(u-u_g) + M_w(w-w_g) + M_q q + M_E\delta_E + M_T\delta_T \qquad (2)$$

$$\dot{w} = Z_u(u-u_g) + Z_w(w-w_g) + (Z_q - \frac{\pi}{180}U_0)q + g(\frac{\pi}{180})\sin(\gamma_0)\theta + Z_E\delta_E + Z_T\delta_T \qquad (3)$$

$$\dot{\theta} = q \qquad (4)$$

$$\dot{h} = -w + \frac{\pi}{180}U_0\theta \qquad (5)$$

where u is the aircraft longitudinal velocity (ft/sec), w is the aircraft vertical velocity (ft/sec), q is the pitch rate (rate/sec), θ is the pitch angle (deg), h is the aircraft altitude (ft), δ_E is the incremental elevator angle (deg), δ_T is the throttle setting (ft/sec), γ_o is the flight path angle (-3deg), and g is the gravity (32.2 ft/sec^2). The parameters X_i, Z_i and M_i are the stability and control derivatives.

Reliable wind profiles are needed in this study. Two spectral turbulence forms models by von Karman and Dryden are mostly used for aircraft response studies. In this study the Dryden form (Jorgensen *et al.*, 1991) was used for its demonstration ease. The model is given by :

$$u_g = u_{gc} + N(0,1)\sqrt{\frac{1}{\Delta t}}\left(\frac{\sigma_u\sqrt{2a_u}}{s+a_u}\right) \qquad (6)$$

$$w_g = N(0,1)\sqrt{\frac{1}{\Delta t}}\left(\frac{\sigma_w\sqrt{3a_w}(s+b_w)}{(s+a_w)^2}\right) \qquad (7)$$

where $u_{gc} = -u_{wind510}[1 + \frac{\ln(h/510)}{\ln(51)}]$, $\sigma_u = 0.2|u_{gc}|$, $L_w = h$, $a_u = \frac{U_o}{L_u}$, $a_w = \frac{U_o}{L_w}$, $b_w = \frac{U_o}{L_w\sqrt{3}}$, $L_u = 100h^{1/3}$ for $h > 230$, $L_u = 600$ for $h \le 230$, $\sigma_w = 0.2|u_{gc}|$ for $h > 500$,

$\sigma_w = 0.2|u_{gc}|(0.5 + 0.00098\times h)$ for $0 \le h \le 500$.

The parameters are: u_g is the horizontal wind velocity (ft/sec), w_g is the vertical wind velocity (ft/sec), U_0 is the nominal aircraft speed (ft/sec), $u_{wind510}$ is the wind speed at 510 ft altitude, L_u and L_w are scale lengths (ft), σ_u and σ_w are RMS values of turbulence velocity (ft/sec), Δt is the simulation time step (sec), *N(0,1)* is the Gaussian white noise with zero mean and unity standards deviation, u_{gc} is the constant component of u_g, and h is the aircraft altitude (ft). Fig. 2 shows a turbulence profile with a wind speed of 30 ft/sec at 510 ft altitude.

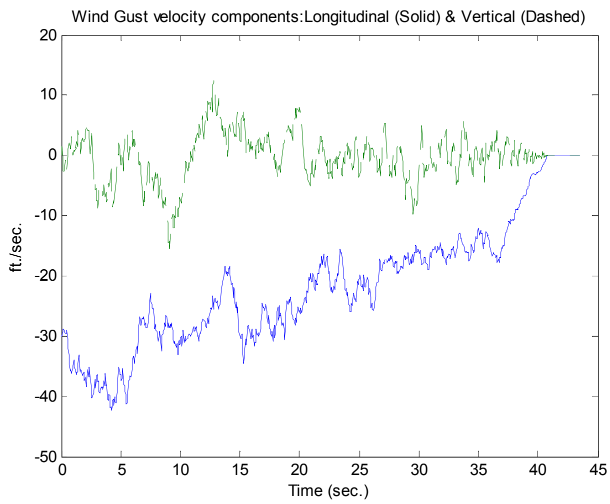

Fig. 2. Turbulence profile

3. INTELLIGENT CONTROL

PID controller is a simplified structure of an aircraft landing controller as shown in Fig. 3. Its inputs consist of altitude and altitude rate commands along with aircraft altitude and altitude rate. Via aircraft landing controller we can obtain the pitch command θ_c. Then, the pitch autopilot is controlled by pitch command. The pitch autopilot is shown in Fig. 4. Detail descriptions can be found in (Jorgensen *et al*.,1991). In order to enable aircraft to land more steady when an aircraft arrives to the flare path, a constant pitch angle will be added to the controller. In general, the PID controller is simple and effective but there are some drawbacks such as apparent overshoot and sensitive to external noise and disturbance. When severe turbulence is encountered the PID controller may not be able to guide the aircraft to land safely. With a fuzzy-CMAC compensator the proposed controller can overcome these disadvantages. The control scheme that we used was a combination design from Shi *et al*. (2006), Juang *et al*. (2005), and Miller *et al*. (1990). It uses a traditional PID controller to stabilize the plant and train the fuzzy-CMAC to provide precise control. The gains of PID controller are adjusted based on experiences, what it provides are tolerable solutions, not desired solutions. The fuzzy-CMAC can effectively improve these conditions. The overall control scheme is described in Fig. 5, in which the control signal U is the sum of the PID controller output and the fuzzy-CMAC output. The inputs for the fuzzy-CMAC and PID controller are: altitude, altitude command, altitude rate, and altitude rate command. The PID controller provides tolerable solutions. In each time step k, the fuzzy-CMAC involves a recall process and a learning process. In the recall process, it uses the desired system output of the next time step and the actual system output as the address to generate the control signal U_{FCMAC}. In the learning process, the control signal of the pitch autopilot, U, is treated as a desired output. It is used to modify the weights of fuzzy-CMAC stored at location which is addressed by the actual system output and the system output of the next time step. The output of the fuzzy-CMAC is the compensation for pitch command.

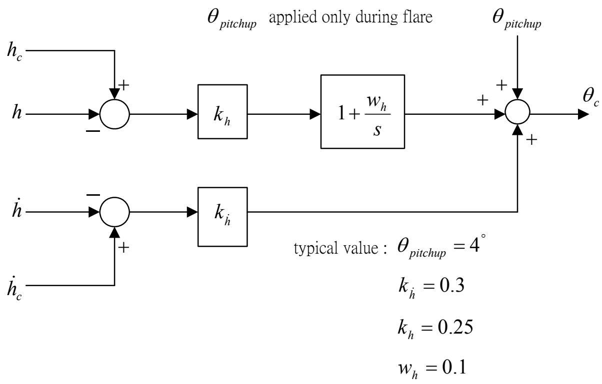

Fig. 3. PID-controller

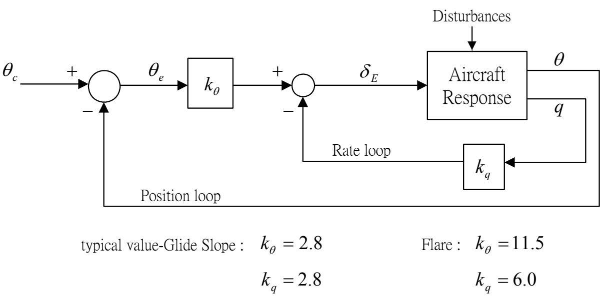

Fig. 4. Pitch autopilot

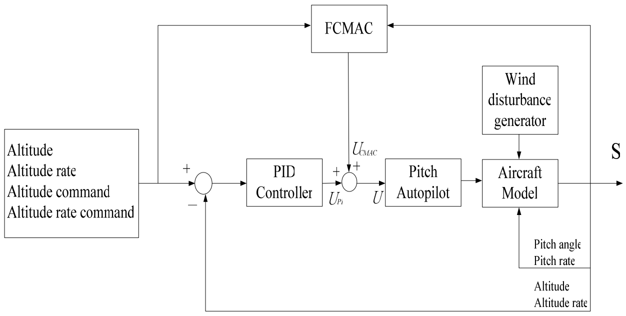

Fig. 5. The fuzzy-CMAC control scheme

CMAC is a kind of associative memory network. Not only it has faster self learning rate than normal neural network by quantities with a few adjustments of memory weights, but also it has good local generalization ability. The function of CMAC is similar to a look-up table, and the output of CMAC is figured from a linear combination of weights which are stored in memory. The concept of CMAC is to store data (knowledge) into overlapped storage hypercubes (remembering region) in an associative manner such that the stored data can easily be recalled. Two kinds of operations are included in the CMAC, one is calculating the output result and the other is learning and adjusting the weight. The output of CMAC can be obtained by the mapping process $U \rightarrow A \rightarrow Y$, which the input is $x \in U \subset R^N$ with a corresponding function $y \in Y \subset R^M$, and A stands for the M dimensioned storage space, $a \in A \subset R^M$ is the binary associative vector. Let the input x address N ($N < M$) storage hypercubes; the mapping $A \rightarrow Y$ is to compute the output as

$$y(x) = \sum_{j=1}^{N} w_j \cdot a_j(x) \qquad j = 1, 2, ..., N \tag{8}$$

where w_j is the weight of the j-th storage hypercube and $a_j(x)$ is a binary factor indicating whether the j-th storage hypercube is addressed by the input x. In the stage of network learning in CMAC, it is to modify the weight of storage hypercubes according to the error between the desired output and the real output. Its weight updating rule is

$$w_j^{(i)} = w_j^{(i-1)} + \frac{\alpha}{m} a_j (y_d - \sum_{j=1}^{N} w_j^{(i-1)} a_j) \tag{9}$$

where y_d is the desired output, m is the number of addressed hypercubes, α is the learning rate. At first, the input vector of CMAC is divided into certain blocks. The relation between input vector with these blocks is simply a crisp relation. The relation between the input condition and the association intensity is simply "activated" or "not activated". In order to improve the shortcoming of conventional CMAC on the crisp relation, fuzzy set theory is introduced while processing division of the input and activating association intensity. Then it can well reflect the fuzziness and the continuity of human brain's cognition. Manifold fuzzy-CMAC approaches have been proposed in the literatures (Nie *et al*.,1993; Zhao *et al*.,2000; Su *et al*.,2006). The approach proposed in Su et al. (2006) is adopted in our intelligent ALS. In this study, membership functions are adopted and the equations in (8) and (9) are modified to

$$y = \sum_{j=1}^{N} (w_j C_j(x) \Big/ \sum_{k=1}^{N} C_k(x)) \quad (10)$$

and

$$w_j^{(i)} = w_j^{(i-1)} + \frac{\alpha}{m}(y_d - y)C_j(x) \Big/ \sum_{i=1}^{N} C_i(x) \quad (11)$$

where $C_j(x)$ is the firing strength of j-th rule for an input x. The firing strengths are considered as the learning strengths. They are the weighting factors in the distribution of the forward mapping as in (9). The structure of fuzzy-CMAC is shown in Fig. 6. The fuzzy-CMAC is utilized to quantize input with fuzzy rules and the defuzzification is to sum weighted outputs of the fired rules.

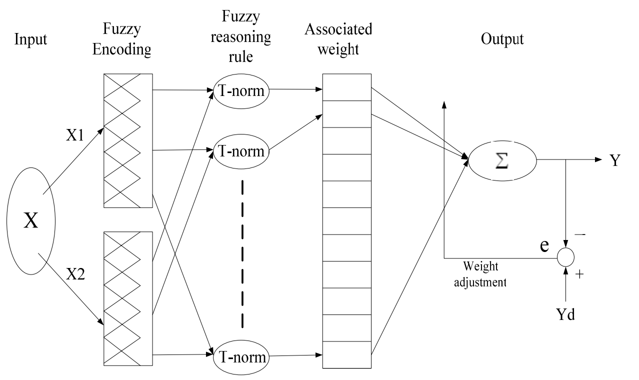

Fig. 6. The structure of fuzzy-CMAC

A real-value GA is utilized to parameter search of the hybrid fuzzy-CMAC-GA system. Unlike binary-coded genetic algorithm, the real-value GA does not require coding and decoding. In recent years most researches adopt real-value GA for its ability of exemption of coding and decoding operation time and enhancement of systematic accuracy. Therefore, in this paper we adopted a real-value GA to search the control parameters of the autopilot. The purpose of this procedure is to search more suitable control parameters for k_θ and k_q in glide path and flare path. Feedforward and feedback control parameters of the pitch autopilot are selected by the GA with different strength of disturbances. The wind disturbance strength increases progressively during the process of parameter search. The control parameters, k_θ and k_q, of the glide and flare paths are the chromosomes that need to be searched. The design of fitness function is to consider numbers of successful landing with different disturbance strengths as fitness function values. This method makes the aircraft adapt itself to wider range of wind disturbances. Figure 7 shows the flow chart of parameter search of the fuzzy-CMAC-GA control system. We utilized roulette wheel selection to choose better parents, which is according to the fitness function of populations. For each generation, the reproduction operator chooses populations that are placed into a mating pool, which is used as the basis for creating the next generation. Then, enter the next stage, crossover. The crossover process is divided into three steps, as shown below.

Step 1：Randomly choose a gene from each individual of a matching pair in parent generation, $P_{m\alpha}$ and $P_{n\alpha}$, as crossover site.

$$pattern_1 = [p_{m1} \quad p_{m2} \quad ..... \quad p_{m\alpha} \quad ..... \quad p_{ms}] \quad (12)$$
$$pattern_2 = [p_{n1} \quad p_{n2} \quad ..... \quad p_{n\alpha} \quad ..... \quad p_{ns}] \quad (13)$$

Step 2：Calculate new values of these selected genes as follows, where β is a random number and $0 \le \beta \le 1$.

$$p_{new1} = (1-\beta)\cdot p_{m\alpha} + \beta \cdot p_{n\alpha} \quad (14)$$
$$p_{new2} = \beta \cdot p_{m\alpha} + (1-\beta)\cdot p_{n\alpha} \quad (15)$$

Step 3：Replace $P_{m\alpha}$ and $P_{n\alpha}$ with P_{new1} and P_{new2}, respectively. The genes in the right side of the crossover site exchange with each other, which will obtain new offspring.

$$Newpattern_1 = [p_{m1} \quad p_{m2} \quad ..... \quad p_{new1} \quad ..... \quad p_{ns}] \quad (16)$$
$$Newpattern_2 = [p_{n1} \quad p_{n2} \quad ..... \quad p_{new2} \quad ..... \quad p_{ms}] \quad (17)$$

Finally an important process is the mutation, which permits the introduction of extra variability into the population. We pick out a population randomly, and change their gene information, but the new offspring must be in the range established after adding gene information. We use real number mutation process as follow

$$x_{new} = x_{old} + s \cdot rand\_noise \quad (18)$$

where s is the random value between 0 to 1.

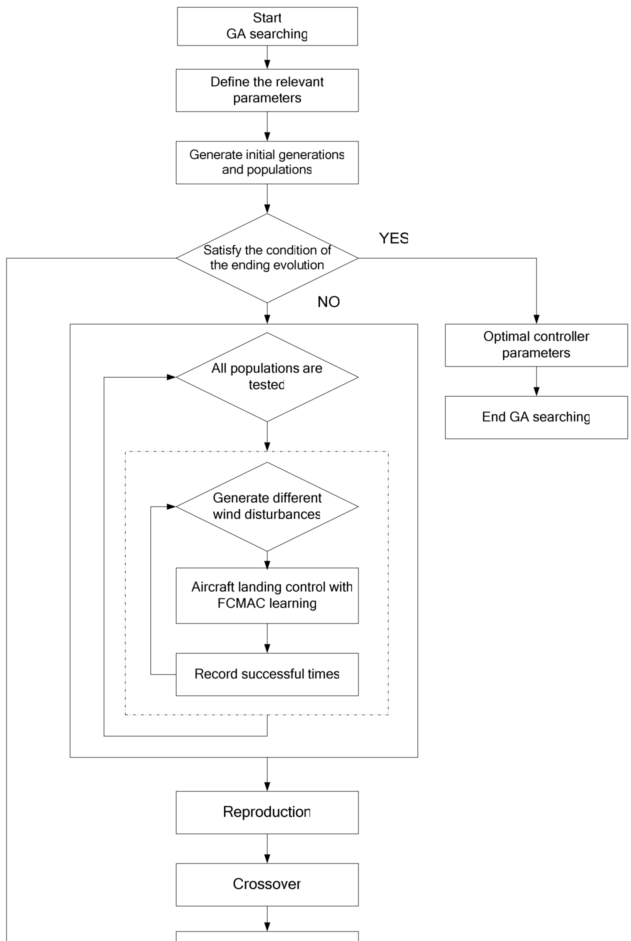

Fig. 7. Parameters search of the fuzzy-CMAC-GA scheme

4. SIMULATIONS

The aircraft starts the initial states of the ALS as follows: the flight height is 500 ft, the horizontal position before touching the ground is 9240 ft, the flight angle is -3 degrees, the speed of the aircraft is 234.7 ft/sec. Successful touchdown landing conditions are defined as follows:

$$-3 \le \dot{h}(T) \text{ ft/sec} \le 0, \quad 200 \le \dot{x}(T) \text{ ft/sec} \le 270,$$
$$-300 \le x(T) \text{ ft} \le 1000, \quad -10 \le \theta(T) \text{ degree} \le 5,$$

where T is the time at touchdown, $\dot{h}(T)$ is vertical speed of the aircraft at touchdown, $x(T)$ is the horizontal position at touchdown, $\dot{x}(T)$ is the horizontal speed, $\theta(T)$ is the pitch angle at touchdown.

Table 1 shows the results from using PID controller with different turbulence speeds. The conventional controller with original control gains can only successfully guide an aircraft flying through wind speeds of 0 ft/sec to 30 ft/sec. The situations at turbulence 30 ft/sec are that the pitch angle is -0.17 degrees, vertical speed is -2.19 ft/sec, horizontal velocity is 234.7 ft/sec, and horizontal position at touchdown is 844 ft. If the wind speed is higher than 30 ft/sec, the ALS will be unable to guide an aircraft to land safely. Table 2 shows the results from using CMAC controller with different turbulence speeds. This controller can guide the aircraft to land safely through wind speed at 0 ft/sec to 58 ft/sec. Table 3 shows the results from using fuzzy-CMAC controller. Simulations are done by using original control parameters of pitch autopilot. The learning rate α is 0.8, and the number of blocks m is 12 as well as the amount of membership functions. This controller can successfully guide the aircraft flying through wind speeds to 90 ft/sec.

Table 1. Results from using conventional controller

Wind speed	Landing point (ft)	Aircraft vertical speed (ft/sec)	Pitch angle (degree)
0	797	-2.83	-1.41
10	910	-2.55	-0.85
20	809	-2.38	-0.59
30	844	-2.19	-0.17
40	1020	-1.72	0.44

Table 2. Results from using CMAC controller

Wind speed	Landing point (ft)	Aircraft vertical speed (ft/sec)	Pitch angle (degree)
0	854	-2.55	-0.96
10	762	-2.76	-0.93
20	774	-2.51	-0.61
30	844	-2.72	-0.41
40	691	-1.93	0.21
50	586	-2.26	0.87
58	844	-2.58	0.98

Table 3. Results from using fuzzy-CMAC controller

Wind speed	Landing point (ft)	Aircraft vertical speed (ft/sec)	Pitch angle (degree)
10	797	-2.83	-1.41
30	938	-1.54	-0.58
50	891	-2.13	0.47
70	691	-2.21	1.41
90	926	-1.99	1.34

In order to further improve the performance of ALS, we utilize a GA to search the control parameters such that the fuzzy-CMAC is more robust to turbulence environment. The purpose of this procedure is to find the optimal control parameters k_q and k_θ in glide phase and flare phase. And then, the intelligent ALS can successfully guide the aircraft flying against turbulence strength to 120 ft/sec. Table 4 shows the results from different turbulence speeds, where K_1 and K_2 represent k_q and k_θ in the glide phase, K_3 and K_4 represent k_q and k_θ in the flare phase, respectively. The situations at wind turbulence 120 ft/sec are that the pitch angle is 4.23 degrees, vertical speed is -2.06 ft/sec, horizontal velocity is 234.7 ft/sec, and horizontal position at touchdown is 398 ft, as shown in Fig. 8 to Fig. 10.

Table 4. Results from using fuzzy-CMAC-GA controller (K_1=2.5409; K_2=6.8029; K_3=10.7398; K_4=13.4932)

Wind speed	Landing point (ft)	Aircraft vertical speed (ft/sec)	Pitch angle (degree)
30	738	-2.28	-0.16
50	598	-2.41	0.74
70	480	-2.94	1.15
90	644	-2.45	1.83
110	938	-1.90	1.51
120	398	-2.06	4.23

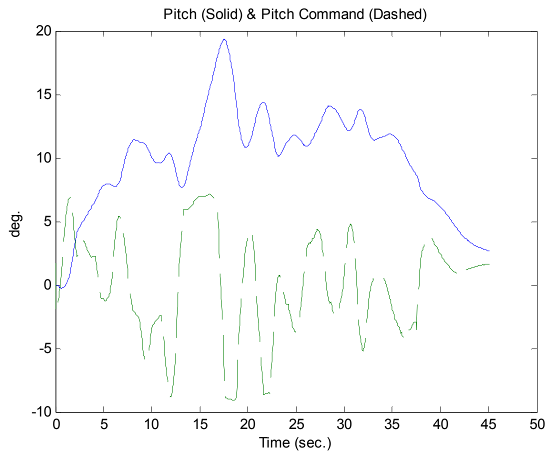

Fig. 8. Aircraft pitch and pitch command

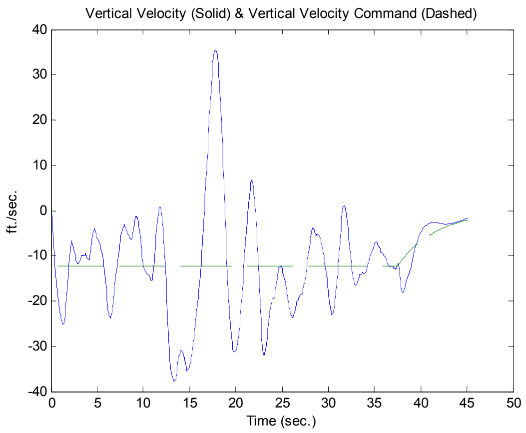

Fig. 9. Aircraft vertical velocity and command

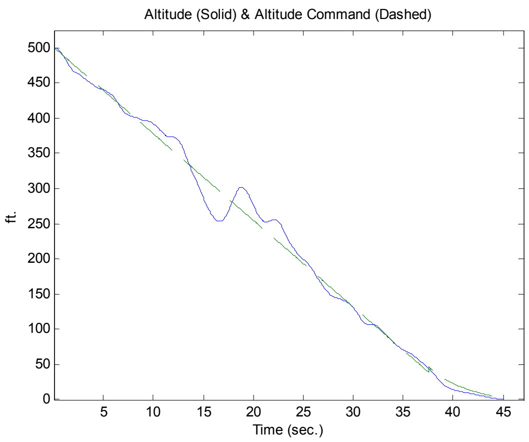

Fig. 10. Aircraft altitude and command

5. CONCLUSIONS

The purpose of this paper is to investigate the use of intelligent control techniques, which includes the conventional CMAC, the novel fuzzy-type CMAC, and a real-valued GA in the automatic landing system. Tracking performance and environment adaptive capability are demonstrated through software simulations. The conventional CMAC has better adaptive capability than conventional PID type controller; it can tolerate the turbulence strength to 58 ft/sec. The fuzzy interpretation raises the accuracy of the representation of the memory knowledge, the performance of the fuzzy-CMAC is more robust than CMAC, and it can guide the aircraft safely under the turbulence strength up to 90 ft/sec. Moreover, the accomplishment of fuzzy-CMAC with GA enhances obviously, it can reach the turbulence strength to 120 ft/sec.

REFERENCES

Adewuya, A.A. (1996). New Methods in Genetic Search with Real-valued Chromosomes, *M.S. thesis*, Dept. of Mechanical Engineering, Massachusetts Institute of Technology.

Albus, J. (1975). A new approach to manipulator control: the Cerebellar Model Articulation Controller. *Journal of dynamic Systems ,Measurement, and Control, Transactions of the ASME*, **97**, 220-227.

Chaturvedi, D.K., R. Chauhan, and P.K. Kalra (2002). Application of Generalized Neural Network for Aircraft Landing Control System. *Soft Computing*, **6**, 441-118.

Cooper, M.G. (1995). Genetic Design of Rule-Based Fuzzy Controllers. Ph.D. dissertation, University of California, Los Angeles.

Flight Safety Foundation-Taiwan, http://www.flightsafety.org.tw/news1.php?Code=1&main_id=3&pages=5

Hu, J.S., G.W. Hu, J.B. Wang, and B. Liu (2005). FCMAC based on minesweeping strategy. *Machine Learning and Cybernetics, Proc. of 2005 International Conference* , **2**, 784-787.

Hu, J., J. Pratt, and G. Pratt (1999). Stable Adaptive Control of a Bipedal Walking Robot with CMAC Neural Networks. *Proc. IEEE Int. Conf. Robot. Autom.*, **2**, 1050-1056.

Iiguni, Y., H. Akiyoshi, and N. Adachi (1998). An Intelligent Landing System Based on Human Skill Model. *IEEE Transactions on Aerospace and Electronic Systems*, **34(3)**,877-882.

Izadi, H., M. Pakmehr, and N. Sadati (2003). Optimal Neuro-Controller in Longitudinal Autolanding of a Commercial Jet Transport. *Proc. IEEE International Conference on Control Applications*, **CD-000202**, 1-6, Istanbul, Turkey.

Jorgensen, C.C. and C. Schley (1991). A Neural Network Baseline Problem for Control of Aircraft Flare and Touchdown. *Neural Networks for Control*, 403-425.

Juang, J.G. and J.Z. Chio (2005). Fuzzy Modeling Control for Aircraft Automatic Landing System. *International Journal of Systems Science*, **36(2)**, 77–87.

Lin, C.M., Y.F. Peng, and C.F. Hsu (2004). Robust Cerebellar Model Articulation Controller Design for Unknown Nonlinear Systems. *IEEE Transactions on Circuits and Systems II: Express Briefs*, **51(7)**, 354-358.

Malaek, S.M.B., N. Sadati, H. Izadi, and M. Pakmehr (2004). Intelligent autolanding controller design using neural networks and fuzzy logic. *Proc. IEEE* 5th Control Conference, **1**, 365–373.

Miller, W.T., R.P. Hewes, F.H. Glanz, and L.G. Kraft (1990). Real-time dynamic control of an industrial manipulator using a neural-network-based learning control. *IEEE Transactions on Robots and Automation*, **6(1)**, 1-9.

NASDAC Review of NTSB Weather-Related Accidents, http://www.nasdac.faa.gov/aviation_studies/weather_study/studyindex.html

Nie, J. and D.A. Linkens (1993). A fuzzified CMAC self-learning controller. *Proc. of IEEE International Conference on Fuzzy Systems*, **1**, 500-505.

Su, S.F., Z.J. Lee, and Y.P. Wang (2006). Robust and fast learning for fuzzy cerebellar model articulation controllers. *IEEE Transactions on Systems, Man and Cybernetics, Part B*, **36(1)**, 203-208.

Zhao, M., and Y. Cheng (2000). Fuzzy CMAC and its application in function learning. *Proc. of the 3rd World Congress on Intelligent Control and Automation,* **2**, 904-907.