CONTROL SYSTEM DESIGN FOR AN AUTONOMOUS HELICOPTER USING PARTICLE SWARM OPTIMIZATION

Byoung-Mun Min*, Hyo-Sang Shin*, and Min-Jea Tahk*
***Korea Advanced Institute of Science and Technology (KAIST)**

Keywords: *control system design, autonomous helicopter, nonlinear dynamics, particle swarm optimization (PSO), sequential quadratic programming (SQP)*

Abstract

This paper presents a control system design method for an autonomous helicopter using the Particle Swarm Optimization (PSO) method. In this paper, the nonlinear dynamic model of a miniature helicopter is directly used to design a control system without linearization process. The nonlinear dynamics of model helicopter is represented by sixteen state variables including flapping dynamics, engine dynamics, and rotor speed dynamics. PSO algorithm is adopted as an optimization solver. In the proposed method, controller gains are selected to minimize the error between the desired response and the actual response of helicopter control system. To improve the convergence speed, sequential quadratic programming (SQP) is integrated to the basic PSO algorithm. The performance of the designed control system for an autonomous helicopter is evaluated through fully nonlinear simulation.

1 Introduction

The helicopter system is a versatile flight machine because of its hovering capability, vertical take-off and landing, and aggressive maneuverability. Recently, the interest in unmanned helicopter system has been abruptly increased for surveillance and reconnaissance. For successful application to these missions, control system for an autonomous flight should be designed and implemented. Therefore, some researches for an autonomous flight using unmanned helicopter were performed. In these previous researches, YAMAHA RMAX system is the most successful one. The autonomous flight control system of RMAX was completed using linear PD controller [1].

The flight control system design based on conventional approach [2] can be performed in such a way of yielding linear models at several reference flight conditions, designing linear controller for each condition, and blending these design points with gain scheduling scheme. However it is very difficult to develop an autonomous flight control system of unmanned helicopter based on the conventional method because the dynamics of helicopter is usually highly nonlinear and many uncertainties. In order to overcome this difficulty, various kinds of nonlinear control techniques have been studied. Among them, adaptive control using neural network was gracefully employed for unmanned helicopter system [3-5]. Though the nonlinear control techniques have some advantages in comparison to the conventional approach, the proportional-integral-derivative (PID) controller has been widely used in the real flight control system because of its simple structure and robust performance. Unfortunately, it is quite tedious and time-consuming to tune properly the gains of PID controller. In this paper, a heuristic method for the gain tuning of PID controller is proposed and applied to flight control system design for an autonomous helicopter. The proposed method determines the controller gains from numerical optimization approach. Fig. 1 shows the main process of the new method. In the new approach, the controller gains are selected to minimize the error between the desired response and the actual response of flight control system using particle swarm optimization (PSO) method [6,7]. Moreover, a hybrid PSO method integrated with sequential quadratic programming (SQP) algorithm [8,9] is developed to improve the convergence speed.

The paper is organized as follows. Section 2 presents the nonlinear dynamics of unmanned helicopter. In Section 3, a hybrid PSO algorithm is proposed. Section 4 outlines a helicopter application of the new approach developed in Section 3. Conclusions are given in Section 5.

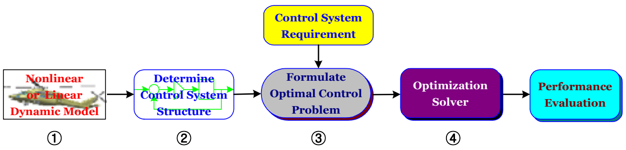

Fig. 1. The main process of proposed control system design method

2 Nonlinear Helicopter Model

In implementing the designed controller to the real system, modeling fidelity is an important factor to guarantee the performance of flight control system. The unmanned helicopter model for control system design is a Voyager GRS 260 developed by JR PROP. As shown in Fig. 1, this miniature helicopter features a conventional type: two-blades, clockwise rotating main rotor, stabilizer bar, and tail rotor. Also, the physical parameters of our miniature helicopter are summarized in Table 1.

Fig. 2. Voyager GRS 260 miniature helicopter

Table 1. Parameters of Voyager GRS 260 helicopter

Engine	23cc Gasoline Engine, 3HP
Fuselage Length	1570 mm
Main/Tail Rotor Dia.	1770 mm / 289 mm
Empty Weight	6.6 kg
Max. Payload	5.0 kg

2.1 Rigid Body Dynamics

Referring to Gavrilets [10], if the cross products of inertia are neglected, the rigid body equations of motion for a helicopter are given by

$$\begin{aligned} \dot{u} &= vr - wq - g\sin\theta + \left(X_{mr} + X_{fus}\right)/m \\ \dot{v} &= wp - ur + g\sin\phi\cos\theta + \left(Y_{mr} + Y_{fus} + Y_{tr} + Y_{vf}\right)/m \\ \dot{w} &= uq - vp + g\cos\phi\cos\theta + \left(Z_{mr} + Z_{fus} + Z_{ht}\right)/m \end{aligned} \quad (1)$$

$$\begin{aligned} \dot{p} &= qr\left(I_{zz} - I_{yy}\right)/I_{xx} + \left(L_{mr} + L_{vf} + L_{tr}\right)/I_{xx} \\ \dot{q} &= pr\left(I_{xx} - I_{zz}\right)/I_{yy} + \left(M_{mr} + M_{ht}\right)/I_{yy} \\ \dot{r} &= pq\left(I_{yy} - I_{xx}\right)/I_{zz} + \left(-Q_e + N_{vf} + N_{tr}\right)/I_{zz} \end{aligned} \quad (2)$$

where the subscript *mr*, *fus*, *tr*, *vf*, and *ht* indicate main rotor, fuselage, tail rotor, vertical fin, and horizontal stabilizer, respectively. In Eq. (2), Q_e is the torque produced by the engine to counteract the aerodynamic torque on the main rotor blades. Since the helicopter blades rotate clockwise, Q_e is always positive ($Q_e > 0$).

2.2 Flapping Dynamics

From the previous research on modeling of a small-scale unmanned helicopter [11], flapping dynamics of the main rotor and stabilizer bar can be lumped and represented by a pair of first-order tip-path plane dynamics. The lateral and longitudinal flapping dynamics are

$$\dot{b}_1 = -p - \frac{b_1}{\tau_e} - \frac{1}{\tau_e}\frac{\partial b_1}{\partial \mu_v}\frac{v - v_w}{\Omega R} + \frac{B_{\delta_{lat}}}{\tau_e}\delta_{lat} \quad (3)$$

$$\dot{a}_1 = -q - \frac{a_1}{\tau_e} + \frac{1}{\tau_e}\left(\frac{\partial a_1}{\partial \mu}\frac{u - u_w}{\Omega R} + \frac{\partial a_1}{\partial \mu_z}\frac{w - w_w}{\Omega R}\right) + \frac{A_{\delta_{lon}}}{\tau_e}\delta_{lon} \quad (4)$$

where $B_{\delta_{lon}}$ and $A_{\delta_{lon}}$ are effective steady-state lateral and longitudinal gains from the cyclic inputs to the main rotor flap angles, δ_{lat} and δ_{long} are the lateral and longitudinal cyclic control inputs, and τ_e is the effective rotor time constant for a rotor with the stabilizer bar. The control moments produced by the flapping motion is the dominant rolling and pitching moments of main rotor.

2.3 Engine and Rotor Speed Dynamics

The rotor speed dynamics and the engine dynamics to the commanded torque are

$$\dot{\Omega} = -\dot{r} + \frac{1}{I_{rot}} \left(Q_e - Q_{mr} - n_{tr} Q_{tr} \right) \qquad (5)$$

$$\dot{Q}_e = -\frac{1}{\tau_{eng}} Q_e + \frac{1}{\tau_{eng}} \left(Q_e^0 + K_{gov} \left(Q_c - \Omega \right) \right) \qquad (6)$$

In Eq. (5), $\dot{Q}_e$ is the engine torque, which is positive when the main rotor rotates clockwise, and Q_{mr} is the main rotor torque, which has an opposite sign to the engine torque. Q_{tr} and n_{tr} represent the tail rotor torque and the gear ratio between the main rotor and tail rotor, respectively. In the engine dynamics modeled as a first order lag system, τ_{eng} is an engine time constant, Q_e^0 is the main rotor torque at hover, and Ω is the rotor speed. K_{gov} is a governor gain of the engine. Governor plays a role of maintaining a constant engine rotational speed.

The nonlinear dynamics represented in this section is available in low advance ratio flight envelope: from hover to *20m/sec* (equivalent advance ratio is *0.15*) [10].

3 A Hybrid Particle Swarm Optimization

The particle swarm optimization (PSO) method is one of the evolutionary computation techniques. It was introduced by Kennedy and Eberhart based on observations of the social behavior of animals such as bird flocking, fish schooling, and swarm theory. PSO is different from evolutionary algorithm (EA) in that it does not need reproduction or mutation for producing the next generation.

In this paper, a hybrid PSO algorithm is developed to improve the computation time and the convergence speed. The proposed hybrid PSO algorithm changes the optimization solver to sequential quadratic programming (SQP) algorithm when the given convergence criterion is met.

3.1 The Basic PSO Algorithm

The basic feature of PSO method is that each particle in the swarm is searching for the optimum with its position and velocity. In this process, each particle remembers the position it was in where, it had its best result so far. Also, the particles in the swarm co-operate each other in the way of exchanging the information where they have discovered the best position in the searching space. The basic PSO algorithm can be summarized as follows;

PSO algorithm

1. Randomly, initialize the position and the velocity of the particles.

$$\begin{aligned} x_0^i &= x_{\min} + rand \times \left(x_{\max} - x_{\min} \right) \\ v_0^i &= v_{\min} + rand \times \left(v_{\max} - v_{\min} \right) \end{aligned} \qquad (7)$$

2. For each particle, evaluate the fitness value with the given cost function.
3. Compare a particle's fitness evaluation with particle's *pbest* (p_k^i). Exchange the particle's fitness value and location with *pbest* , if it is better.
4. Compare a particle's fitness evaluation with the population's overall previous best, *gbest* (p_k^g). Exchange the particle's fitness value and location with *gbest*, if it is better.
5. Update the velocity and the position of the particle according to the following equations.

$$v_{k+1}^i = w v_k^i + c_1 r_1 \left(p_k^i - x_k^i \right) + c_2 r_2 \left(p_k^g - x_k^i \right) \qquad (8)$$

$$x_{k+1}^i = x_k^i + v_{k+1}^i \qquad (9)$$

6. Loop to step 2 until a criterion is met.

In the velocity update equation of Eq. (8), w , c_1 , and c_2 mean inertia weight, self and swarm confidence factors, respectively. r_1 and r_2 are random numbers on the interval [0, 1].

3.2 Integration of SQP Algorithm

The termination criterion of the basic PSO algorithm is chosen as the fitness value does not vary during five generations. However, the amount of update rates in position and velocity is gradually decreased as all particles are gathered around the optimal solution. Since the convergence speed is decreased as well as the computation time is increased in the small region containing an optimal solution. To avoid this problem, an optimization solver is changed from PSO algorithm to SQP algorithm when all particles are converged within 10% of an initial search area. Here, the final positions of all particles position determined by PSO algorithm are used as the initial values of SQP algorithm. The flow chart of the proposed hybrid PSO algorithm is shown in Fig. 3.

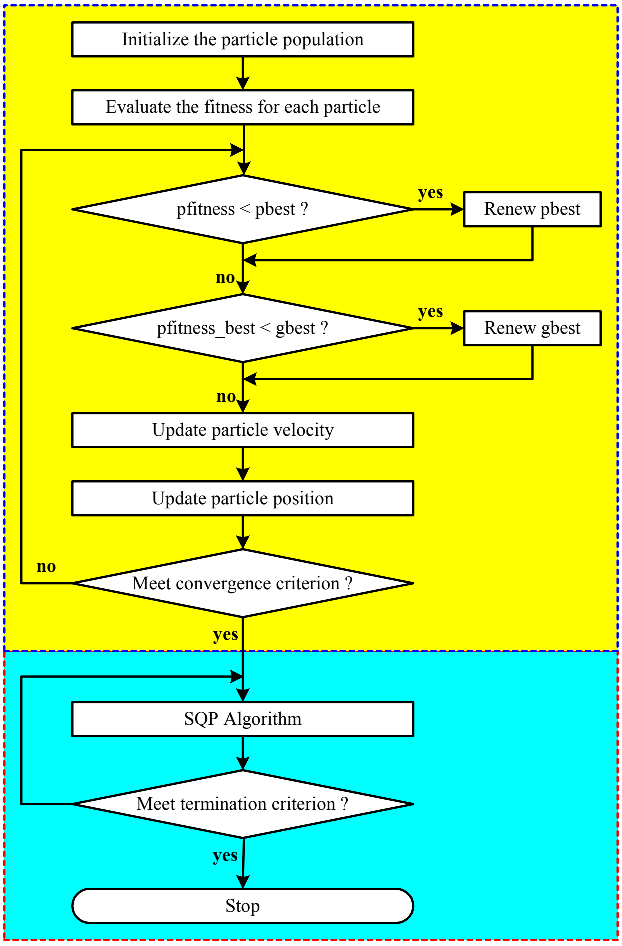

Fig. 3. The flow chart of a hybrid PSO algorithm

4 Control System Design for an Autonomous Helicopter

It is important to design flight control system for an autonomous or semi-autonomous flight of unmanned helicopter. The autonomous flight control system of our unmanned helicopter is shown in Fig. 4. Considering the mission that this unmanned helicopter has to accomplish, the outer-loop flight control system involves four channels, i.e. vertical, longitudinal, lateral, and yaw channels, for altitude control, longitudinal velocity control, lateral velocity control, and heading angle control with main rotor collective pitch, longitudinal cyclic, lateral cyclic, and tail rotor collective pitch as control inputs. The outer-loop controllers have PI controller except for the altitude controller. Both the longitudinal and the lateral channels have an inner-loop controller formed by pitch/roll angular rate and pitch/roll attitude angle feed-back. All actuator dynamics are modeled as first order system with the time constant of *0.05sec*.

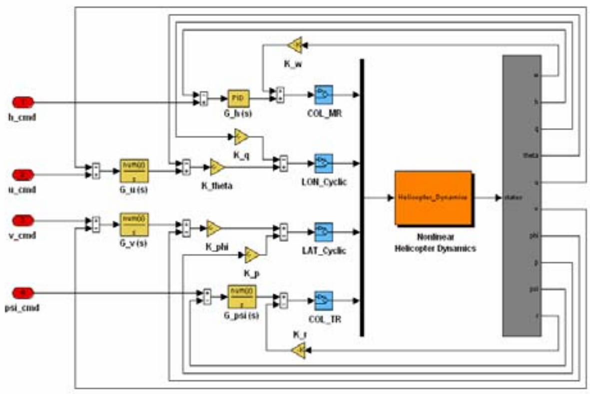

Fig. 4. Block diagram of autonomous flight control system for unmanned helicopter

4.1 Desired Response and Cost Function

As mentioned in "Introduction", controller gains are selected to minimize the error between the desired response and the actual response of flight control system. The desired response of autonomous flight control system is chosen that the output shows a second order system's response:

$$\frac{y}{y_c} = \frac{\omega_n^2}{s^2 + 2\xi\omega_n s + \omega_n^2} \tag{10}$$

Parameters of the desired response for four control channels are summarized in Table 2. Natural frequencies of vertical channel and yaw channel are faster than those of longitudinal and lateral channels. The reason is that, in a miniature helicopter characteristics, main rotor collective and tail rotor collective directly response to the control stick inputs, while longitudinal cyclic and lateral cyclic responses have some time delay caused by the *90 deg.* gyroscopic phase lag between the main rotor and a stabilizer bar.

Table 2. Parameters of the desired responses

	Vertical Channel	Longitudinal and Lateral Channels	Yaw Channel
ξ	0.7	0.5	1.0
ω_n	3.0	1.5	3.0

The optimization results are sensitively affected by the cost function in an optimization system. In this paper, we use the following cost function

$$J = \int_{t_0}^{t_f} \left[w(t) \times \left\{ \left(e(t)\right)^2 + \left(\frac{u(t)}{|u(t)|} \right)^2 \right\} \right] dt \qquad (11)$$

$$w(t) = \begin{cases} w_1 \ , & t_0 \le t \le t_{tr} \\ w_2 \ , & t_{tr} \le t \le t_f \end{cases} \qquad (12)$$

where t_0 is the initial time, t_{tr} is the transient time, t_f is the final time. $e(t)$ is the error between the desired response and the actual response of flight control system and $u(t)$ is the control input. In this cost function, different weightings can be given from the initial to transient time period and transient to final time period.

4.2 Optimal Controller Gains

In this paper, the optimal controller gains for each control channel are selected by directly using the nonlinear dynamic model described in Section 2. In the proposed hybrid PSO algorithm, the number of particles for each parameter is *30* and the self and swarm confidence factor is $c_1 = c_2 = 1.5$. The optimal controller gains are calculated 10 times by using pure PSO algorithm and the proposed hybrid PSO algorithm to comparison of convergent efficiency. Fig. 5 shows the variations of the cost in the case that the pure PSO algorithm and the proposed hybrid PSO algorithm are applied to vertical control channel. Though initial costs are different because of the randomly initialized particles, the convergence speeds to reach a certain cost value are same. However, the proposed hybrid PSO algorithm can rapidly reduce the cost with a few number of fitness evaluation. Moreover, cost calculated by the proposed method is smaller than that of pure PSO algorithm. This implies that the controller gain set determined by the proposed method represents a superior optimality. The average computation time of the pure PSO algorithm and the proposed hybrid PSO algorithm are, respectively, 1508 sec. and 591 sec.

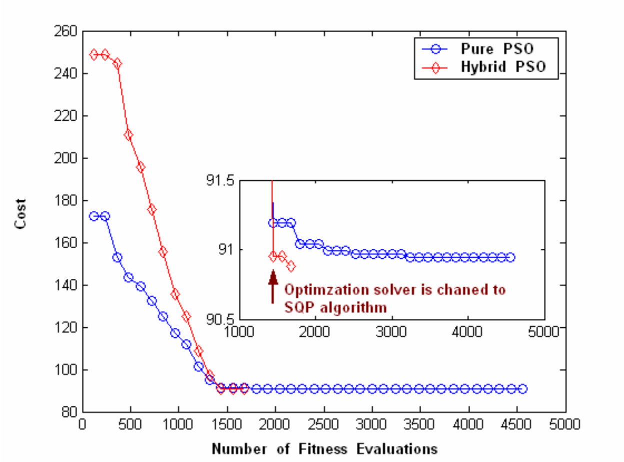

Fig. 5. The cost variations of the pure PSO algorithm and the hybrid PSO algorithm

The optimal gain set obtained by the proposed method are presented in Table 3.

Table 3. The optimal gain set of four control channels

Vertical Channel	K_w	0.35465
	K_p^h	9.50293
	K_i^h	0.00000
	K_d^h	2.66968
Longitudinal Channel	K_q	1.56747
	K_θ	3.81011
	K_p^u	5.86340
	K_i^u	1.91380
Lateral Channel	K_p	0.68155
	K_ϕ	2.86800
	K_p^v	4.22963
	K_i^v	2.71701
Yaw Channel	K_r	1.48218
	K_p^ψ	5.74388
	K_i^ψ	0.00000

To analyze the performance of our flight control system, we observe the time responses of each control channel to step input and illustrated the results in Fig. 6. Here, the longitudinal and lateral velocity commands are limited to *5 m/sec*. From the results shown in Fig. 6, we conclude that the designed control system might be adopted as a possible autonomous flight control system for an unmanned helicopter.

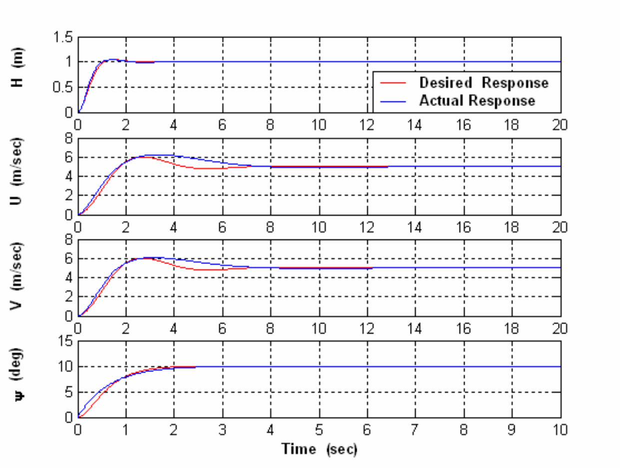

Fig. 6. Responses of four control channels to step input

4.3 Nonlinear Simulation Results

The pirouette maneuver requires that a helicopter points its nose toward a point defining the center of a circle with a specified radius and then maneuvers around the circle holding a constant altitude. To satisfy these requirements, even though an excellent pilot, pirouette maneuver is a difficult flight. In this paper, to verify a potential capability of the designed autonomous flight control system, we perform a nonlinear simulation for pirouette maneuver. For this simulation, *2 m/sec* lateral velocity command, *6 deg*. heading angle command per second, and *20 m* altitude command are engaged. The simulation results are shown in Fig. 7 ~ Fig. 10. From these simulation results, the autonomous flight control system of our unmanned helicopter successfully achieves a pirouette maneuver. Also, the altitude control performance and tracking performances of longitudinal velocity command and heading angle command are perfect.

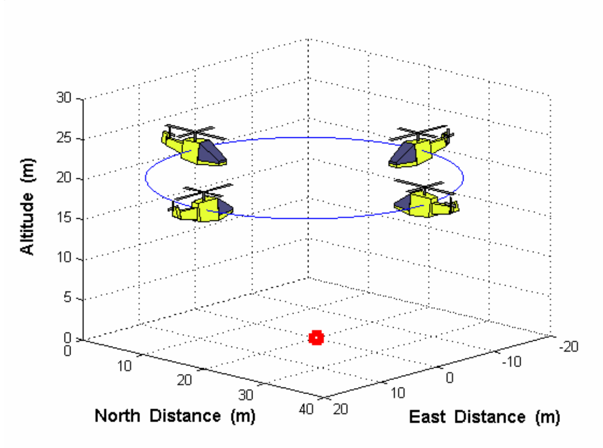

Fig. 7. Flight trajectory during pirouette maneuver

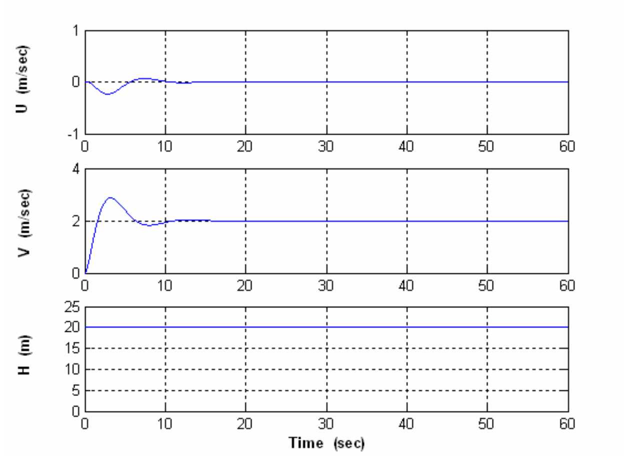

Fig. 8. Responses of longitudinal velocity, lateral velocity, and altitude

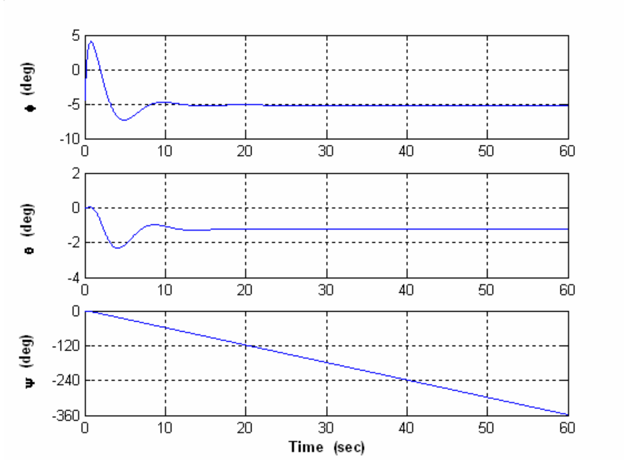

Fig. 9. Time histories of attitude angles

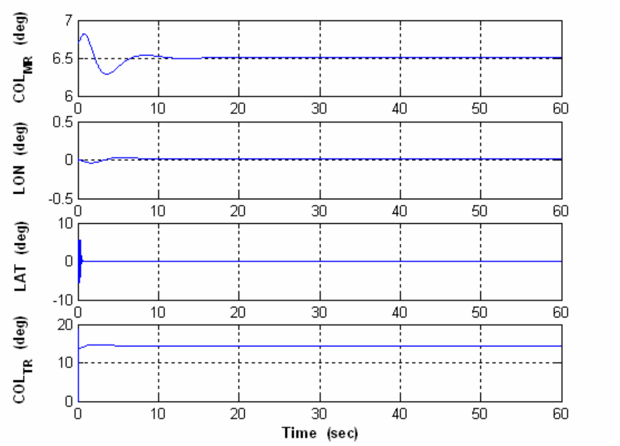

Fig. 10. Control stick inputs during pirouette maneuver

5 Conclusions

The paper suggests a control system design method for autonomous helicopter using a hybrid PSO algorithm. The proposed hybrid PSO algorithm combines the basic PSO algorithm and SQP algorithm to improve the convergence speed. The proposed method is successfully applied to the problem of optimal gain selection for unmanned helicopter system. The performance of the designed autonomous flight control system for unmanned helicopter is evaluated through fully nonlinear simulation on pirouette maneuver.

Implementation the proposed autonomous flight control system on the real system and flight test are remained for future work.

Acknowledgement

This paper was performed for Smart UAV Development Program, one of the 21st Century Frontier R&D Programs funded by the Ministry of Commerce, Industry, and Energy of Korea.

References

[1] Sato A. Research and Development and Civil Application of an Autonomous, Unmanned Helicopter. *Proceedings of AHS International Forum 57*, 2001.

[2] Stevens B. L. and Lewis F. L. *Aircraft Control and Simulation*, John Wiley & Sons, Inc., 1992.

[3] Calise A. J., Kim B. S., Leitner J., and Prasad J. V. R. Helicopter Adaptive Flight Control Using Neural Networks. *Proceedings of the 33rd Conference on Decision and Control*, Lake Buena Vista, FL, pp 3336-3341, 1994.

[4] Leitner J., Calise A. J., and Prasad J. V. R. Analysis of Adaptive Neural Networks for Helicopter Flight Control. *Journal of Guidance, Control, and Dynamics*. Vol. 20, No. 5, pp 972-979, 1997.

[5] Nakanishi H. and Inoue K. Development of Autonomous Flight Control Systems for Unmanned Helicopter by Use of Neural Networks. *Proceedings of the 2002 International Joint Conference on Neural Networks*. pp 2626-2631, 2002.

[6] Kennedy J. and Eberhart R. Particle Swarm Optimization. *Proceedings of the IEEE International Conference on Neural Network*. Perth, Australia, pp 1942-1945, 1995

[7] Kennedy J. and Eberhart R. *Swarm Intelligence*. 1st edition, Academic Press, 2001.

[8] Gill P. E., Murray W., and Wright M. H. *Practical optimization*. Academic Press, 1981.

[9] Bryson Jr. A. E. *Dynamic Optimization*. Addison-Wesley, 1999.

[10] Gavrilets V., Mettler B., and Feron E. Nonlinear model for a small-size acrobatic helicopter. *Proceedings of the AIAA Guidance, Navigation, and Control Conference*. Montreal, Canada, AIAA 2001-4333, 2001.

[11] Mettler B., Tischler M., and Kanade T. System identification modeling of a small-scaled unmanned rotorcraft for flight control design. *Journal of the American Helicopter Society*, Vol. 47, No. 1, pp 50-63, 2002.