Position Tracking Control of a Small Autonomous Helicopter by an LQR with Neural Network Compensation

Il Yong Eom* and Seul Jung**
Intelligent Systems and Emotional Engineering Lab.
Department of Mechatronics Engineering, Chungnam National University, Daejeon, Korea
(Tel : +82-42-821-6876; E-mail:{*princeom@hanmail.net, **jungs@cnu.ac.kr})

Abstract: In this paper, position tracking control of an autonomous helicopter is presented. Velocity is controlled by using an optimal state controller LQR. A position control loop is added to form a PD controller. To minimize a position tracking error, neural network is introduced. The reference compensation technique as a neural network control structure is used, and a position tracking error of an autonomous helicopter is compensated by neural network installed in the remotely located ground station. Considering time delays between an autonomous helicopter and the ground station, simulation studies have been conducted. Simulation results show that the LQR with neural network compensation performs better than that of the LQR itself.

Keywords: helicopter control, neural network, RCT

1. INTRODUCTION

Recently, research on unmanned aerial vehicles (UAV) has been rapidly increased due to great demand from military operations as well as commercial needs. To be fully autonomous for the UAVs, three basic technologies, localization, path planning, and control should be satisfied. The main goal of UAVs is to navigate to the destination autonomously and to come back safely with desired information. To do that, the UAV should know where it is and where the destination is. Localization is done by local and global sensor information with appropriate fusing algorithms. Performance of localization is very dependent upon sensors. Path planning is to determine the desired trajectory for the UAV to follow by avoiding possible collision with obstacles in the way to the destination. Finally, control has to be done to follow the pre-planned path accurately. Successful UAVs are able get information on specific objects on the ground or areas where human beings cannot easily access.

As a carrying vehicle, the helicopter system has been a very attractive research object to a robot community as well as a control community [1,2]. An unmanned RC helicopter is one kind of UAVs. Many researches of improving performance of navigation have been conducted. From optimal controllers to intelligent controllers, various control algorithms have also been proposed to improve speed control [3-7].

Recently, position control of the unmanned helicopter has been also demanding as the technology develops and needs. One specific advantage of the helicopter over other UAVs is that the helicopter can be a position-controlled system. While most of UAVs require fast speed and attitude control to navigate to the destination, the helicopter has the capability of dealing with objects since it can have a hovering posture. This means that position control of the helicopter can be done within a certain allowable accuracy.

By borrowing the concept of a position controlled robot system, in this paper, position tracking control of an unmanned autonomous helicopter (UAH) is presented. The velocity of the UAH is controlled by using the LQR method. Adding a position control loop forms a simple internal PD control structure. This PD controller is implemented in the UAH. However, since LQR control gains are selected from the linearized helicopter system model, the resultant position tracking errors occur due to nonlinear effects of the UAH system or outer disturbances.

To minimize a position tracking error, a neural network controller is separately installed to the ground station. Fig. 1 shows the overall system concept. The ground station receives information of the helicopter position from a GPS system, and processes it to generate position correction signals to the helicopter. In other words, a position tracking error of an autonomous helicopter is compensated by neural network installed in the remotely located ground station. As a neural network learning structure, the reference compensation technique is used.

Simulation studies are conducted with the small X-cell RC helicopter model that is mounted on the gimbal system for indoor use. Time delays between the UAV and the ground station are considered. Simulation results confirm that neural network compensation actually improves the performance of the PD controller even though there are time delays.

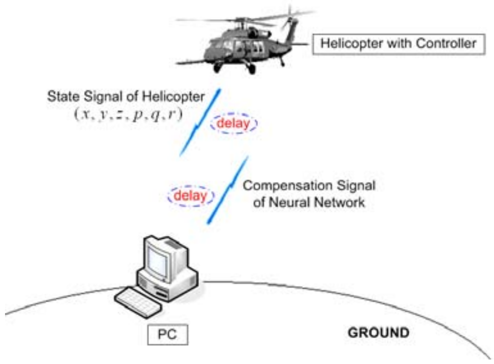

Fig.1. Overall system picture

2. HELICOPTER DYNAMICS

The model of a helicopter is shown in Fig. 2. The dynamics of a helicopter is as follows [8]:

$$\begin{aligned}
\dot{u} &= vr - wq - g\sin\theta + (X_{mr} + X_{fus})/m \\
\dot{v} &= wp - ur - g\sin\phi\cos\theta + (Y_{mr} + Y_{fus} + Y_{tr} + Y_{vf})/m \\
\dot{w} &= uq - vp + g\cos\phi\cos\theta + (Z_{mr} + Z_{ht})/m \\
\dot{p} &= qr(I_{zz} - I_{yy})/I_{xx} + (L_{mr} + L_{vf} + L_{tr})/I_{xx} \\
\dot{q} &= pr(I_{xx} - I_{zz})/I_{yy} + (M_{mr} + M_{ht})/I_{yy} \\
\dot{r} &= pq(I_{yy} - I_{xx})/I_{zz} + (-Q_e + N_{vf} + N_{tr})/I_{zz}
\end{aligned} \tag{1}$$

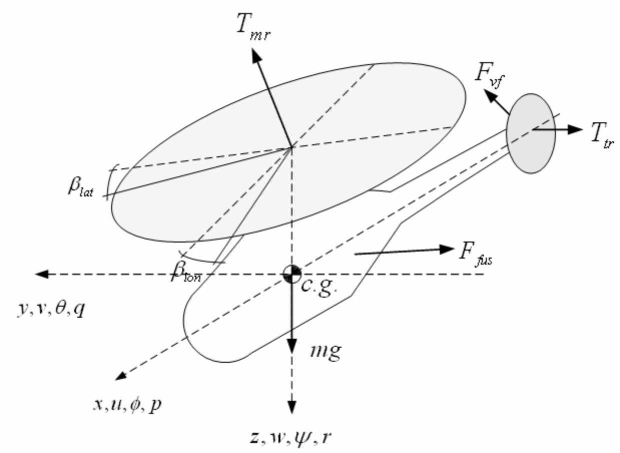

Fig. 2. Force and moment of a helicopter

$$\begin{aligned}
\dot{\phi} &= p + q\sin\phi\tan\theta + r\cos\phi\tan\theta \\
\dot{\theta} &= q\cos\phi - r\sin\phi \\
\dot{\psi} &= q\sin\phi\sec\theta + r\cos\phi\sec\theta
\end{aligned} \tag{2}$$

where u, v, w are velocities of longitudinal, lateral, and elevating directions, respectively. p, q, r are angular velocities of roll, pitch, and yaw, respectively, and ϕ, θ, ψ are Euler angles such as roll, pitch and yaw. Other parameters are defined as

m : mass

I_{xx}, I_{yy}, I_{zz} : moments of inertia around rolling, pitching and yawing axes

Y_{fus}, Y_{mr} : fuselage drag, main rotor induced force

Z_{fus}, Z_{mr} : fuselage drag, main rotor induced force

Y_{tr}, Y_{vf} : tail rotor induced force and vertical tail force in lateral direction

Z_{ht} : horizontal tail force in vertical direction

L_{mr}, L_{tr} : main and tail rotor induced rolling moment

L_{vt} : rolling moment from the vertical tail

M_{mr}, M_{tr} : main and tail rotor induced pitching moment

M_{ht} : rolling moment from the horizontal tail

N_{tr}, N_{vt} : yawing moment from the tail rotor and the vertical tail

Q_e : engine torque

$$X_{fus} = 0.5\rho S_x^{fus} u V_\infty, \quad X_{mr} = T_{mr} a_1 \tag{3}$$

$$Y_{fus} = 0.5\rho S_y^{fus} v V_\infty, \quad Y_{mr} = -T_{mr} b_1 \tag{4}$$

$$L_{mr} = (K_\beta + T h_{mr}) b_1 \tag{5}$$

$$M_{mr} = (K_\beta + T h_{mr}) a_1 \tag{6}$$

Flapping dynamics of the helicopter is defined as follows

$$b_1 = \frac{1}{1+s_\beta^2}\left\{ s_\beta \delta_{lon} + \delta_{lat} + \left(s_\beta + \frac{16}{\gamma} \right)\overline{p} - \left(s_\beta \frac{16}{\gamma} - 1 \right)\overline{q} \right\} \tag{7}$$

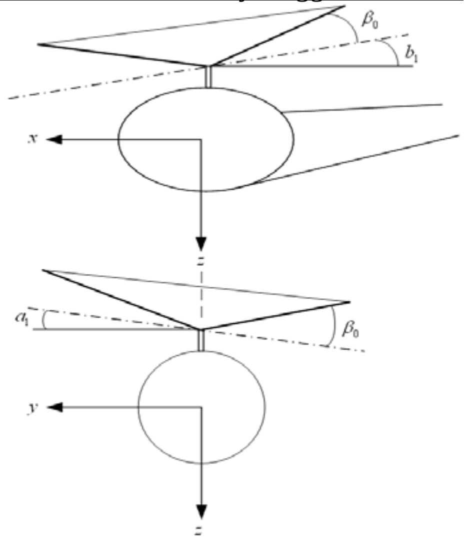

Fig. 3. Blade flapping of the helicopter

$$a_1 = \frac{1}{1+s_\beta^2}\left\{ s_\beta \delta_{lat} - \delta_{lon} + \left(s_\beta \frac{16}{\gamma} - 1 \right)\overline{p} + \left(s_\beta + \frac{16}{\gamma} \right)\overline{q} \right\} \tag{8}$$

where s_β is the stiffness number, γ is a lock number. Since equations (3) to (6) are nonlinear, linearization can be done by applying Taylor series expansion as

$$X = X_u u + X_v v + X_p p + X_q q + \cdots \tag{9}$$

Table I shows parameters of the small X-cell RC helicopter model.

TABLE I . PARAMETERS OF X-CELL

Parameter	Description
$m = 7.7kg$	Helicopter mass
$I_{xx} = 0.18 kg \cdot m^2$	Rolling moment of inertia
$I_{yy} = 0.35 kg \cdot m^2$	Pitching moment of inertia
$R_{mr} = 0.75m$	m.r. radius
$c_{mr} = 0.06m$	m.r. chord
$h_{mr} = 0.235m$	m.r. hub height above c.g.
$a_{mr} = 5.5 \ 1/rad$	m.r. blade lift curve slope
$\gamma_{fb} = 1.05$	Flybar Lock number
$\gamma_{mr} = 4.0$	m.r. blade Lock number
$\Omega_{mr} = 167 rad/\sec$	Nominal m.r. speed

The state space equation of the X-cell model becomes

$$A = \begin{bmatrix}
0 & 0 & 1 & 0 & 0 & 0 \\
0 & 0 & 0 & 1 & 0 & 0 \\
0 & 0 & \frac{M_q}{I_{yy}} & \frac{M_p}{I_{yy}} + \frac{r(I_{zz}-I_{xx})}{I_{yy}} & \frac{M_u}{I_{yy}} & \frac{M_v}{I_{yy}} \\
0 & 0 & \frac{L_q}{I_{xx}} + \frac{r(I_{yy}-I_{zz})}{I_{xx}} & \frac{L_p}{I_{xx}} & \frac{L_u}{I_{xx}} & \frac{L_v}{I_{xx}} \\
-g\cos\theta_e & 0 & \frac{X_q}{m} - W_e & \frac{X_p}{m} & \frac{X_u}{m} & R_e + \frac{X_q}{m} \\
0 & g\cos\theta_e & \frac{Y_q}{m} & W_e + \frac{Y_p}{m} & \frac{Y_u}{m} - U_e & \frac{Y_v}{m}
\end{bmatrix}
B = \begin{bmatrix}
0 & 0 \\
0 & 0 \\
\frac{M_{\delta_{lat}}}{I_{yy}} & \frac{M_{\delta_{lon}}}{I_{yy}} \\
\frac{L_{\delta_{lat}}}{I_{xx}} & \frac{L_{\delta_{lon}}}{I_{xx}} \\
\frac{X_{\delta_{lat}}}{m} & \frac{X_{\delta_{lon}}}{m} \\
\frac{Y_{\delta_{lat}}}{m} & \frac{Y_{\delta_{lon}}}{m}
\end{bmatrix} \tag{10}$$

Control and state parameters are given as

$$u = [\delta_{lat} \quad \delta_{lon}]^T \tag{11}$$

$$x = [\theta \quad \phi \quad q \quad p \quad u \quad v]^T \tag{12}$$

where δ_{lat} and δ_{lot} a longitudinal and a lateral cyclic pitch, respectively.

3. POSITON CONTROL OF LQR METHOD

From the state space model given in (10), velocity is controlled by the LQR method [9,10]. Extension from velocity control to position control requires another position controlled loop. Combining two control loops yields the internal PD controller of the helicopter system. The detailed block diagram is shown in Fig 4.

The position tracking error is defined as

$$e = x_D - x \tag{13}$$

where $x_D = [x_{Dp} \quad y_{Dp}]$ is the desired position of the helicopter, $x = [x_{RP} \quad y_{RP}]$ is the position of the helicopter obtained from the global positioning sensor.

The controller input is

$$u = k_P \cdot e + k_D \dot{e} \tag{14}$$

where k_P is the position controller gain and k_D is the velocity controller gain obtained from the LQR method.

However, position tracking errors are expected since the LQR controller gains for velocity control are optimized for the linearized model, and the position controller gain is not optimized. The position tracking error is compensated by neural network in the remotely located ground station.

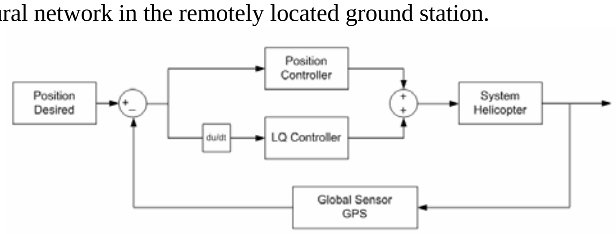

Fig.4. Position control block diagram.

4. NEURAL NETWOK COMPENSATION METHOD

The reference compensation technique (RCT) is one of the on-line learning algorithms for neural networks. The algorithm has been successfully applied to position control of robot manipulators as well as to mobile robots [11,12]. By borrowing the concept of the RCT algorithm, the separate control loop is introduced into the position control loop of the helicopter system as shown in Fig. 5. The ground station receives attitude information from the GPS mounted on the helicopter system. The information is used to correct positional errors by neural network that are caused by nonlinear effects. Whenever the desired path is delivered to the helicopter through wireless communication from the ground station at every sampling time, neural network compensation signals are also sent together. The control block diagram is shown in Fig. 5.

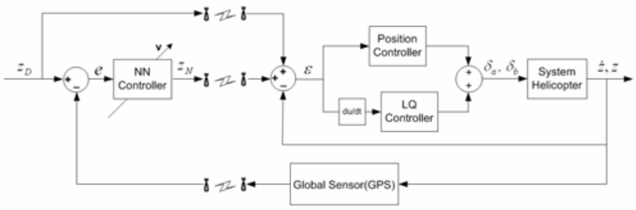

Fig. 5. Reference compensation technique scheme for a LQR controlled system.

The position tracking error with a compensating signal becomes

$$\varepsilon = e + C_N \tag{15}$$

where $e = z_D - z$ and $C_N = [x_N \quad y_N]$ is the compensation signal from the ground station.

The position controller input is

$$u = k_P(e + C_N) + k_D(\dot{e} + \dot{C}_N) \tag{16}$$

Define the error signal as

$$v = k_P e + k_D \dot{e} \tag{17}$$

The objective function to be minimized as

$$E = \frac{1}{2} v^T v \tag{18}$$

Differentiating (18) with respect to the weight w yields

$$\frac{\partial E}{\partial w} = \frac{\partial E}{\partial v}\frac{\partial v}{\partial w} = v\frac{\partial v}{\partial w} \tag{19}$$

From equations (16) and (17), the closed loop equation becomes

$$u - v = k_P C_N + k_D \dot{C}_N \tag{20}$$

Then the gradient can be obtained as

$$\frac{\partial E}{\partial w} = v\frac{\partial v}{\partial w} = -v\left(k_p \frac{\partial C_N}{\partial w} + k_p \frac{\partial \dot{C}_N}{\partial w}\right) \tag{21}$$

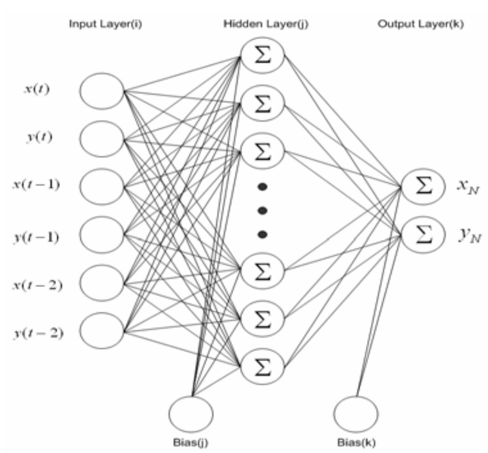

Fig. 6 neural network structure

5. SIMULATION RESULTS

5.1. Simulation Environment

Simulation environment is shown in Fig. 7. The small RC helicopter is mounted on the gymbal system. The gymbal system is designed for an indoor experiment. Simulation studies are conducted ahead in this environment before experiments are conducted. Virtual disturbance of vibration caused from the engine is given to the system. Time delay problems are also expected.

Fig. 7. Simulation environment

5.2. Step Position Tracking Control

For the first simulation study, position control of a step command is tested. From the initial position, the helicopter moves 1.5m in the longitudinal direction with the velocity of 0.1m/s and maintains a hovering attitude.

1) PD control scheme

The step response of the PD controller is shown in Fig. 8. Oscillation behaviors are observed due to disturbance. The corresponding position and velocity errors are also plotted in Fig. 9.

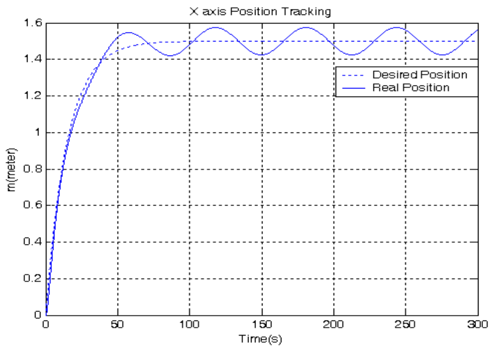

Fig.8. Position control response by a PD controller

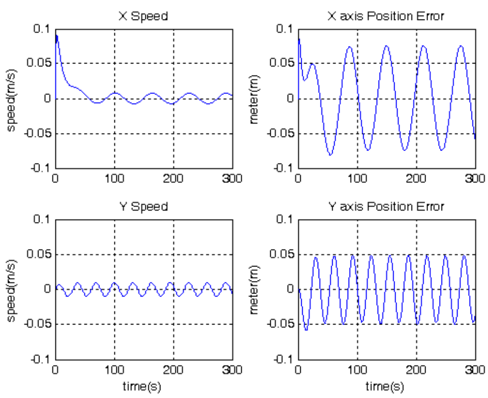

Fig. 9 Tracking errors by a PD controller

To compensate for those tracking errors, we add the compensation loop of neural network.

2) Neural Network control scheme

When the system is compensated by neural network, the tracking errors are minimized to almost zero. Several time delays are considered to see the communication delay effect on the system performance.

2.1) No time delay

First simulation is to see the performance of neural network compensation when there is no time delay. Fig. 10 shows the position tracking response, which is much better than that of Fig. 8. The corresponding errors are plotted in Fig. 11.

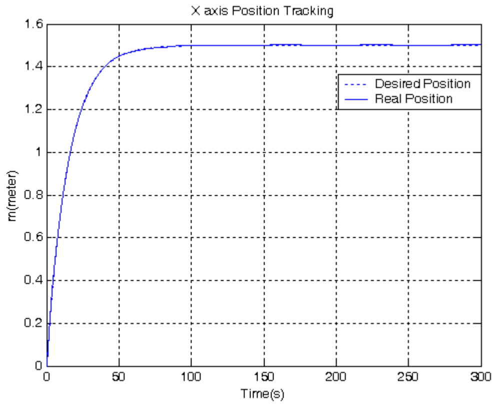

Fig. 10 Position tracking response of neural network compensation without time delay

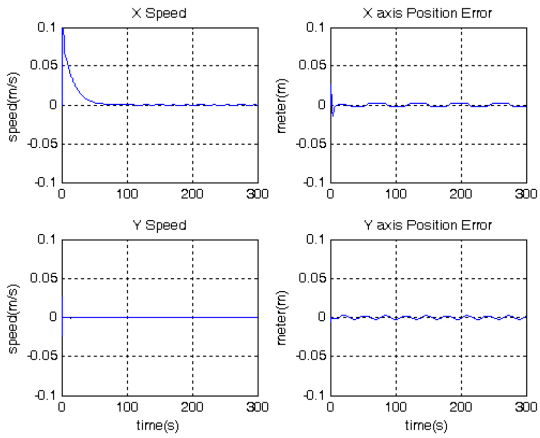

Fig. 11 Tracking errors by neural network

2.2) 1 second time delay

Assume that there is 1 second time delay in communication which is practical. The position tracking results are plotted in Fig. 12. Comparing it with the plot of Fig. 8 shows the better performance. We see the performance get worse as time delay is longer.

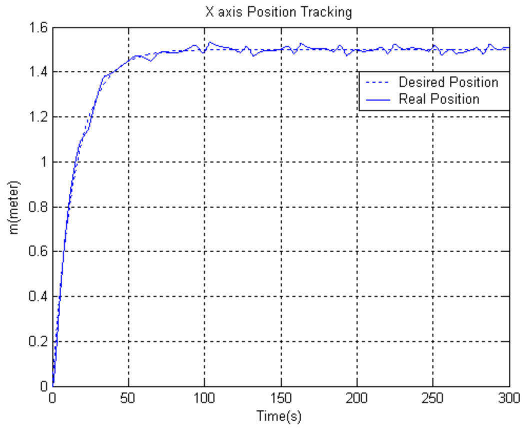

Fig. 12 Neural network compensation with 1 second delay

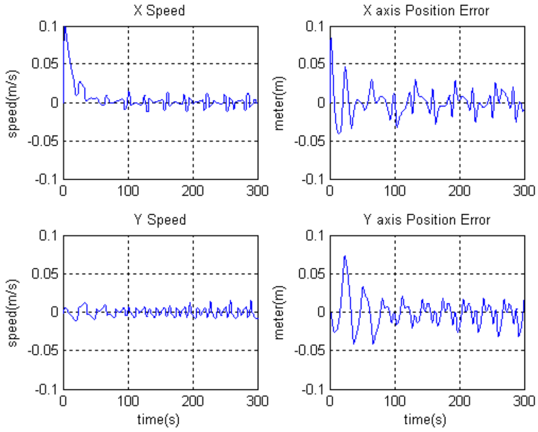

Fig. 13 Neural network compensation with 1 sec. delay

5.3 Circular Trajectory Tracking control

Next simulation is to follow the circular trajectory in Fig. 8.

The diameter of a circle is 1.5m and the complete traveling time takes 400 seconds.

1) PD control scheme

We see from Fig. 14 the ill position tracking performance.

Positional errors come from disturbance. The corresponding error plots are shown in Fig. 15. Positional error in x axis is about 15 and in y axis is about 10cm in magnitude.

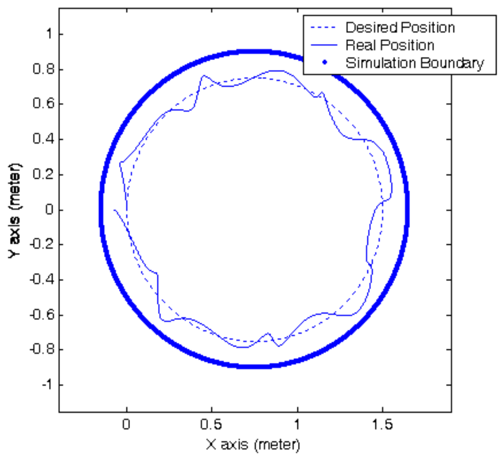

Fig. 14 Circular trajectory tracking by a PD controller

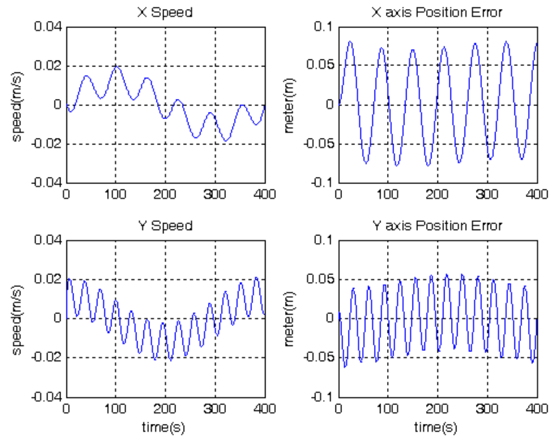

Fig. 15 Tracking errors by a PD controller

2) RCT Neural Network control scheme

2.1) No time delay

When there is no time delay, performance is excellent as shown in Fig. 16. We clearly see from Fig. 167that positional tracking error in x axis is about 4cm and in y axis is less than 1cm. There is much improvement in tracking.

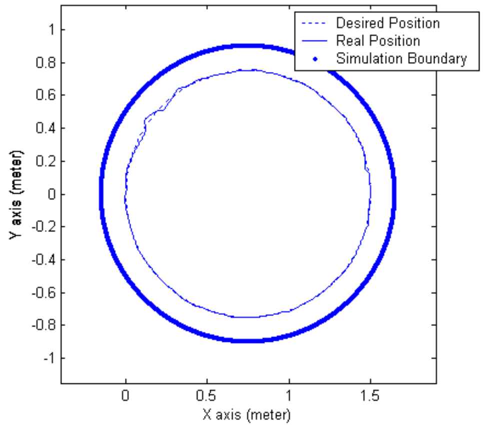

Fig.16. Tracking control without time delay

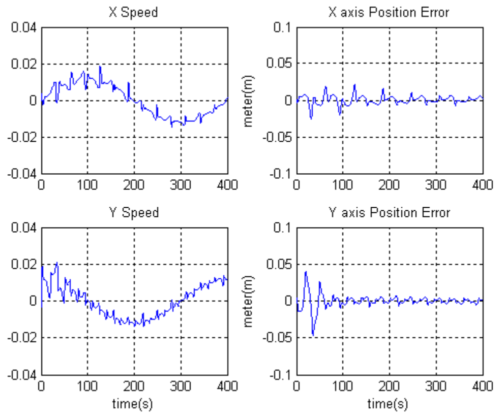

Fig. 17 Tracking errors

2.3) 1 second time delay

For 1 second time delay, Fig. 18 shows the tracking result. We see that tracking error is larger than that of Fig.16 of no time delay. The corresponding errors are plotted in Fig. 19.

However, it is much better than that of Fig. 14.

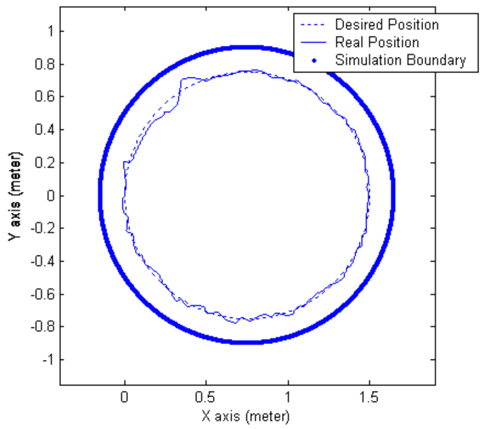

Fig. 18 Circular trajectory tracking with 1 second delay

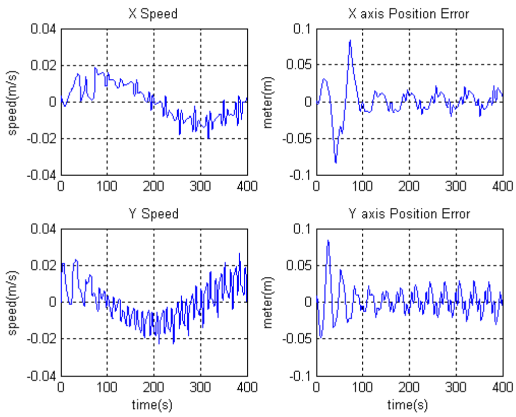

Fig. 19 Tracking errors due to 1 second delay

6. CONCLUSIONS

Position control of a small autonomous helicopter was presented. A PD controller was formed by combining an LQR velocity control method and a proportional position control. Position tracking errors were compensated by a neural network controller located remotely. External disturbance has been well rejected by a neural network compensator. Effects on the position tracking performance due to time delays in communication were investigated. Even though neural network learns on-line, there must be communication delays between the helicopter and the ground station.

There are several things to be addressed in the future:

- Full dynamic model should be considered.
- Neural network calculation should be fast enough for on-line control.
- GPS signals and Communication process should be stabilized.
- Time delay should be estimated by the optimal filters.
- Actual experimental studies should be conducted.

REFERENCES

[1] Mats Akesson, Erik Gustafson and Karl Hedrik Johansson. “Control Design for a Helicopter Lab Process”, *IFAC. 13th Triennial World congress*, San Francisco, USA. pp.41-46, 1996

[2] V. Gavrilets B. Mettler and E. Feron, “Nonlinear model for a Small-Size Acrobatic Helicopter”, *AIAA Guidance, Navigation, and Control Conference and Exhibit*, Montreal, Quebec, Canada, August, 2001

[3] P. A. Gili, M. Battipede, “A Comparative Design of a MIMO Neural Adaptive Rate Damping for a Nonlinear Helicopter Model”, *ESANN’2000 proceedings-European Symposium on Artificial Neural Networks*, Bruges, April 2000., pp.159-164

[4] Carla Cavalcante, Janette Cardoso, Josue J. G. Ramos, Othon R. Neves, “Design and Tuning of a Helicopter Fuzzy Controller”,1995. *Fourth IEEE International Conference on Fuzzy Systems and The Second IEEE International Fuzzy Engineering Symposium.*, Volume: 3 , 20-24 March 1995

[5] Amaral, T.G.B.; Crisostomo, M.M., “Automatic helicopter motion control using fuzzy logic”, 2001. *The 10th IEEE International Conference on Fuzzy Systems*, Volume: 2 , 2-5 Dec. 2001, Page(s): 860 -863 vol.3

[6] Amaral, T.G.B.; Crisostomo, M.M., “Neuro-fuzzy controller for helicopter motion control”, *2001. The 10th IEEE International Conference on Fuzzy Systems*, Volume: 2 , 2-5 Dec. 2001 Page(s): 594 -597 vol.3

[7] Amaral, T.G.; Crisostomo, M.M.; Pires, V.F., “Helicopter motion control using adaptive neuro-fuzzy inference controller”, *IEEE IECON 02* Volume: 3 , 5-8 Nov. 2002 , Page(s): 2090 -2095 vol.3

[8] Donald McLean, “Automatic flight Control System”, *Prentice Hall*, 1990

[9] Charles L. Phillips, “Digital Control System Analysis and Design”, *Prentice Hall*, 1995

[10] Peter J. Gawthrop, “Self tuning PID controller : algorithms and implementation”, *IEEE, Transaction on Automatic Control*, vol. AC-31, No.3, March, 1986

[11] S. Jung and T. C. Hsia, “Neural network Inverse Control Techniques for PD Controlled Robot Manipulator”, pp. 305-314, Vol. 19, No. 3, *ROBOTICA*, 2002

[12] S. Jung and H. T. Cho, "Decentralized neural network Reference Compensation Technique for PD Controlled Two Degrees of Freedom Inverted Pendulum," *International Journal of Control, Automations, and Systems*, vol. 2, no. 1, pp. 92-99, 2004.