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Robust Autonomous Flight Control of an UAV by Use of Neural Networks ⋆

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Abstract: This paper describes a method to develop robust flight control systems for UAVs. It was difficult to develop flight control systems, because the helicopter dynamics is nonlinear. Moreover the flight environment is not fixed because of the atmospheric changes, such as the wind. The wind affects the attitude or velocities of the UAV, but the wind speed or direction is hard to predict, so the wind is usually categorized into stochastic uncertainties. An efficient method to design robust controllers by training neural networks is proposed in this paper. Neural networks trained by the proposed method are robust against stochastic uncertainties. In this paper, the small unmanned helicopter is focused on, and numerical results of altitude control are shown to demonstrate the effectiveness of our approach.

1. INTRODUCTION

To reduce the loss of disasters, such as earthquakes and so on, it is necessary to develop more effective disaster response system. In Japan, "Special Project for Earthquake Disaster Mitigation in Urban Areas" started in 2002 (Tadokoro [07]), and many researches on advanced rescue system which includes rescues robots and rescue information systems are going on. Considering the capabilities of robots, rescue robots will not be used to help and rescue victims directly. Rescue robots will be an advanced measure to collect information about the disaster site. From the viewpoint of information gathering activities, rescue robots can be categorized into two classes. One is a system to collect information of wide area quickly, and the other is a system to gather information of local area where rescuers can not enter. For examples, collapsed or firing buildings is too danger even for skilled rescuers. We are focusing of global information gathering activities and are carrying out a research on developing autonomous unmanned helicopter and its application to disaster response. Aerial vehicles can approach to the disaster site quickly, and can collect valuable bird's-eye information. Moreover unmanned aerial vehicle (UAV) can be applied to dangerous area such as volcanoes. Therefore UAV is useful in various rescue activities. Among various UAVs, unmanned helicopter is one of the most effective candidates for flying rescue robot. To realize flying rescue robots, autonomous flight control system(Omead [96]), which enables flying out of the sight, is inevitable, because the flying rescue robots must be able to fly out of the operator's sight. But the helicopter dynamics is complicated and nonlinear, so that designing flight controllers by conventional linear control theory is hard to use and linear controllers which has enough performance are difficult to design(Leitner [97]). Moreover flying rescue robot must be robust against various environmental changes, such as weather, wind and so on. Therefore it is required to develop a method to design advanced autonomous flight controllers for unmanned helicopters.

Many researches to apply neural networks to a control system are carried out. Feedback error learning is one of the most famous method in which a feedback controller and a feed-forward controller are used together, and a neural network is used as the feed-forward controller(Kawato [93]). In this method, error back propagation algorithm, which is based steepest decent method, is used to train the neural network, therefore the learning speed is very slow and moreover the learning is not stable. The robustness against the environmental changes or modeling error depends on the feedback controller. But in the feedback error learning, the feedback error learning is not focused on and given a priori. Because the designed neural network acts as feed-forward controller, it can not improve the robustness of the control system. To apply neural networks to real applications, robustness must be considered and assured so that design methods for feedback robust control systems by use of neural networks is required. Moreover robustness of the trained network should be quantified and assured in learning(Nakanishi [98, 00]).

In this paper, we propose a method to design robust control system by use of neural networks and applied the proposed method to design autonomous flight control system of an unmanned helicopter. For UAVs, wind is the most significant uncertainties. It is well-known that the wind speed or direction changes randomly. Therfore we focused on a method for stochastic uncertainties in this paper.

In Sec. 2, we explain autonomous unmanned helicopter developed for flying rescue robot. Formulations for designing robust controllers against robust controllers are given in

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Sec. 3. The proposed method is explained in Sec. 4 and numerical results of the proposed method are shown in Sec. 5. Sec. 6 is conclusion.

2. AUTONOMOUS UNMANNED HELICOPTER

YAMAHA RMAX(Sato [01], Nakanishi [ahs01]) is used in our study. It is a very small helicopter whose main rotor's diameter is about 3.1m and the maximum payload is 30kg, so that it can perform many activities. Figure 1 shows a photo of RMAX modified for the experiments for our study. The specification of RMAX can be found in the web pages(http://www.yamaha-motor.co.jp).

In this section, equipments for autonomous flight control are described. The helicopter equips an attitude sensor and a GPS sensor. The attitude sensor consists of a geomagnetic azimuth sensor, 3 gyros and accelerometers. To ensure the accuracy of measurement of position and velocity, a RTK-GPS is used. It is necessary to measure more accurate states of the helicopter, such as position, velocities, and the attitude to improve the performance and reliability of autonomous flight controllers, Therefore GPS-INS integrated navigation system using the extended Kalman Filter is developed and used for autonomous flight control. The integrated navigation system is also able to cancel the effect of the offsets of gyros and accelerometers and the effect of distance from the GPS antenna to the center of gravity respectively. Moreover, it is also able to compensate time delay in data transmission or measurement delay in GPS. A small laptop PC is also equipped on the helicopters to carry computations not only for the integrated navigation system but also for the flight controller using neural networks. Real time processing is required and RT-Linux is used as the operation system for the laptop. In flight experiments, flight data were stored in the hard disk of the laptop.

Figure 2 shows the signal block diagram of the autonomous unmanned helicopter. As the Figure 2 shows, the flight control system consists of two feedback loop, the inner loop and the outer loop. The outer loop is the positioning and velocity controller. In this paper, we focus on altitude control so the outer loop controller is mainly discussed. The outer controller sends a signal to the inner loop as the desired attitude. The inner loop is attitude controller to stabilize the attitude of the helicopter.

The flight simulator was offered from YAMAHA Motor Co., LTD. It is nonlinear 6-DOF flight simulator for RMAX and we can build flight controller into the simulators and it can demonstrate the autonomous flight numerically.

But any information about the dynamics of the helicopter, such as aerodynamic coefficients, isn't open to public. The flight simulator offered from YAMAHA was originally developed for checking code of the designed controller works well or not. So the simulator did not help to improve the performance of the flight controller. In conventional methods, it is almost impossible to design effective controllers without information of the dynamics of the controlled object

3. DESIGN OF ROBUST CONTROL SYSTEM BY USE OF NEURAL NETWORKS

3.1 Formulations

Consider a nonlinear system described as

$$\boldsymbol{x}(t+1) = \boldsymbol{f}(\boldsymbol{x}(t), \boldsymbol{u}(t), \boldsymbol{w}(t)) \tag{1}$$

where $\boldsymbol{x}(t)$ is a state vector and $\boldsymbol{u}(t)$ is the control vector. $\boldsymbol{w}(t)$ describes a disturbance or modeling error. It is assumed that $\boldsymbol{x}(t)$ is measurable. If a noise exists in the measurement, then measured state $\boldsymbol{y}(t)$ is described

$$\boldsymbol{y}(t) = \boldsymbol{x}(t) + \boldsymbol{v}(t) \tag{2}$$

where $\boldsymbol{v}(t)$ is noise vector. Measurement noise can be classified as stochastic uncertainties. It is assumed that there is no modeling error and only stochastic disturbance and measurement noise must be considered. $\boldsymbol{z}(t)$ is a reference output vector of the system described as

$$\boldsymbol{z}(t) = \boldsymbol{h}(\boldsymbol{y}(t), \boldsymbol{u}(t)) \tag{3}$$

The aim of our research is to design feedback controllers described as

$$\boldsymbol{u}(t) = \boldsymbol{g}(\boldsymbol{y}(t)) \tag{4}$$

which can reduce the influence of the stochastic uncertainties. We use a multi-layered feed-forward neural network as the feedback controller. The block diagram of the whole control system is described in Figure 3. In this paper, three layered neural networks are used to train because it can emulate any continuous functions to any desired accuracyFunahashi [89]. For simplicity, it is also assumed that averages of stochastic uncertainties are equal to 0, that is,

$$E[\boldsymbol{v}] = \boldsymbol{0}, \quad E[\boldsymbol{w}] = \boldsymbol{0} \tag{5}$$

If $E[\boldsymbol{v}]$ and $E[\boldsymbol{w}]$ are not zero, the proposed method must be extended. Dynamic controllers in which include at least

Fig. 1. Autonomous Unmanned Helicopter

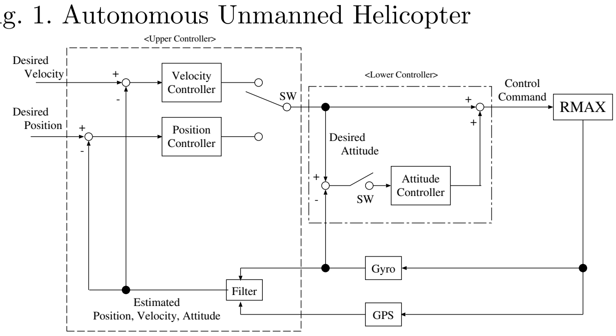

Fig. 2. Block Diagram of Autonomous Flight Control System

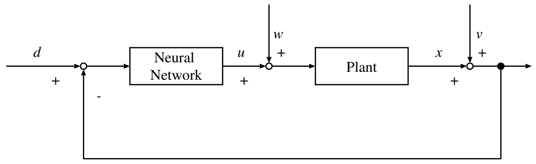

Fig. 3. Block diagram of a control system using a neural network

one integral operator are necessary for this case, and we can easily extend the proposed method to design dynamic robust controllers.

3.2 Training Algorithm for Design Control Systems using Neural Networks

Learning can be categorized into on-line training and off-line training. On-line training is useful for adaptive control system. But error back propagation method is too slow for adaptive control systems. Moreover it is difficult to assure the stability of the controlled system. So learning algorithms based on Lyapunov direct theorem are widely used. But these on-line training algorithms can not use the a-priori information about the controlled object and the designed controller might be limited and be not very efficient. On the other hand, a-priori information about the plant is fully used in off-line training methods and it has an advantages to develop efficient controllers(Nakanishi [97]). Among of off-line training algorithms, an algorithm using Powellfs conjugate direction method(Powell [64]) is effective in designing various controllers, because it does not require the Jacobian of the plant. The neural network can learn only by use of the value of the performance index. Details and examples of the training algorithm using Powellfs conjugate direction method can be found in Nakanishi [97]. This advantage of the training algorithm using Powellfs conjugate direction method is useful in designing not only optimal controllers but also robust controllers.

4. ROBUST CONTROLLER DESIGN FOR STOCHASTIC UNCERTAINTIES

4.1 Performance index for training robust controllers

A performance index J of the control system which is described as (6) is disturbed by stochastic uncertainties.

$$J = \sum_{t=0}^{T} |\boldsymbol{z}(t)|^2 \tag{6}$$

To learn robust control systems, statistical functions of the performance index J must be used. Sampled values of the performance index J are distributed around the center with variances. The center and the variance of the distribution of J means the expected performance and the degree of effect of uncertainties. If the controller is robust against uncertainties, the variance of the distribution is small. It is impossible to remove the effect of uncertainties perfectly in actual problems, there is an upper limit of the robustness. But too big robustness is harmful because robustness against uncertainties often causes the degradation of the performance of the controller. Therefore trade-off between performance and robustness is important in designing robust controllers, so a performance index in which trade-off can be taken into account is required.

To learn robust control systems, we propose to use a performance index J_γ described as

$$J_\gamma = \frac{1}{2\gamma}\log(E[\exp(2\gamma J)]) \tag{7}$$

where J is a sampled performance index(6) and γ is a scalar parameter. If the performance index (7) can be expanded about γ, we can obtain an approximated index described as

$$J_\gamma = E[J] + \gamma Var[J] + O(\gamma^2) \tag{8}$$

The approximated index(8) shows that training can be classified into three cases, $\gamma > 0$, $\gamma = 0$, and $\gamma < 0$. Training using negative γ leads to solutions whose variance is big, so the trained controller is fragile against the stochastic uncertainties. Therefore $\gamma \geq 0$ must be used in training robust controllers. According to Whittle [90], γ^{-1} is equal to induced L_2 gain from stochastic uncertainties to reference output $\boldsymbol{z}$. Using small gain theorem, the trained controller can tolerate uncertainties whose L_2 norm is less than γ(DGKF [89]). Therefore robustness of the trained controller can be quantified by γ, which is used in training. We can carry out trade-off between robustness and performance by choosing γ in training.

4.2 Modular Robust Controller

Neural networks trained by use of the training performance index (7) become robust against stochastic uncertainties. If γ is equal to zero, a controller which has the least robustness is designed. The training performance index, whose γ is positive, results in the controller whose robustness is improved. But what is required to improve robustness is stored as the weights of the trained neural network but it is difficult to understand directly. If what is the key property to improve the robustness is clear, such knowledge will contribute to design other kinds of nonlinear controllers, which have simpler structure than neural networks and are more comprehensive. For example, it will help to design gain scheduling controllers, which have much simpler structure than neural network based controllers but are also difficult to design.

If the controller can be divided into 2 parts and one has the least robust control module and the other is robust module. We define the mixing gain a of robust module shown in Fig. 4. Then we can control the robustness by changing the gain a of the trained module for the robustness. If stochastic uncertainties are bigger than expected, the mixing gain a should be increased, then he controller's performance degrades but the controller's robustness increases. Therefore, design of robust control systems which have modular structure will be useful in many cases, and the proposed training method can be easily applied to design modular structured controllers. At first, γ is set to 0 and then a controller which has the least robustness is trained. Secondary, a controller module for robustness is incrementally trained by using the training performance index (7) where $\gamma > 0$ and the mixing gain a is 1. Because training neural network takes times, it is difficult to prepare many neural network modules trained by use of different γ. Modularization helps

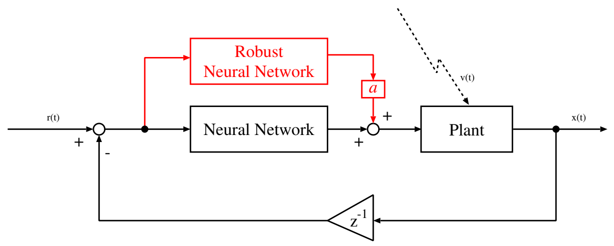

Fig. 4. Block diagram for learning of the modules of robust control systems

to design robust control system that has approximately appropriate robustness.

5. NUMERICAL SIMULATIONS OF ALTITUDE CONTROL OF AN UNMANNED HELICOPTER

To confirm the effectiveness of proposed methods, flight controllers for an autonomous unmanned helicopter are designed. Results of altitude control are shown in this section, but the proposed method can be applied to design other controllers, such as attitude controllers or horizontal positioning controllers.

For the aerial vehicles, wind must be considered in designing controllers. Wind speed or direction change almost randomly, and it should be treated as stochastic uncertainties. Vertical wind has significant effect on the altitude control of the aerial vehicles. Unmanned helicopter flies at low altitude less than 150m. Therefore the altitude control is very important part of the autonomous unmanned helicopter. For simplicity, we assumed that only vertical wind exists and no horizontal wind exists in our simulations. Other controllers were well-tuned linear PD controllers and results of control for other axis didn't have significant effect on the altitude controller. Altitude controllers of the helicopter were trained neural networks which acted as nonlinear state feedback controllers. Inputs of neural networks are altitude error and vertical velocity. Output of neural networks is collective input of the helicopter. In our simulations, 3 layered neural networks with 7 hidden units were used.

The sampled index J described as (9)

$$J = \sum_{t=0}^{60sec} (z(t) - d(t))^2 + v_z^2(t) \tag{9}$$

is used in training, where d is the desired altitude, and z is the actual altitude, and v_z is the actual vertical velocity.

The performance index (9) does not include control u explicitly. This might not familiar case. These kind of performance index leads to the diversity the control therefore (9) must be applied to problems with input constraints. In the flight simulator used in our simulations, both upper and lower limit of the collective input were imposed therefore infinite input is prohibited. Optimal control problems where the performance index does not include the control input explicitly often results in singular optimal solutions. In the singular solutions, the states are constrained to a certain sub-space of the whole state space. The sub-space where the state is constrained is determined only by the performance index. In case of (9), the singular solution forms a line described as

$$(z(t) - d(t)) + v_z = 0 \tag{10}$$

Input and states map of the trained neural network using proposed method at $\gamma = 0$ is shown in Fig. 5 and step response of the controlled altitude when the desired altitude d is changed from 0m to -5m is shown in Fig. 6. In training, γ equals to 0 so that the trained neural network is the least robust control module. According to these figures, it turns out that the neural network learned the singular optimal solution described as (10) by the proposed method and the input suddenly changed around the singular solution.

Results of modular control systems combined the least robust module and a robust module neural network trained at $\gamma = 0.1$ and $\gamma = 0.25$ are shown in Fig. 9. According to Fig. 9, the robustness of the whole control system was improved by increasing γ but the performance degraded simultaneously. Fig. 9 shows that the robustness of neural networks trained by the proposed method is quantified by γ. Moreover input and state map of the modular control system combined the least robust module and the robust module neural network trained at $\gamma = 0.1$ is shown in Fig. 7. Compared with the map shown in Fig. 5, we could find other sharp change of the input around $v_z = 0$ except for the singular solution. Input and state map of the robust module neural network trained at $\gamma = 0.1$ is shown in Fig. 8, and we also could find the sharp change of the input in the map. Theses results shows that gains of the controller for descending should be different from those of the controller for ascending to make altitude control of the helicopter robust. That is, variable structural control is effective for robust altitude control. This result is consistent with the fact that gain scheduling controller, whose gains are different depending simply on the velocity, is very simple but effective to make altitude control robust against the vertical wind(Nakanishi [03])

Fig. 10 describes the result of modular controllers.

$$u = u_f + a \cdot u_r \tag{11}$$

$$0 \le a \le 1 \tag{12}$$

where u_l is the output of the least robust neural network, and u_r is the output of the robust neural network, which is trained at $\gamma = 0.1$. a is a mixing gain of the robust neural network. Fig. 10 shows that very simple linear interpolation is used in the modular control system but it works well and modular controllers have approximately appropriate robustness.

6. CONCLUSION

A methods to design robust control systems by use of a neural network against stochastic uncertainties are proposed in this paper, and it is applied to design autonomous flight control of an rotorcraft UAV. In the proposed method, the robustness is quantified by γ. Stochastic disturbance, such as wind, exits in many systems, therefore robustness against stochastic uncertainties is very important factor of control systems. Simulation results of altitude control of rotorcraft UAV demonstrate the effectiveness of the by proposed method, and designed altitude controllers have good performance and robustness. Robust controllers is necessary to improve the reliability of the

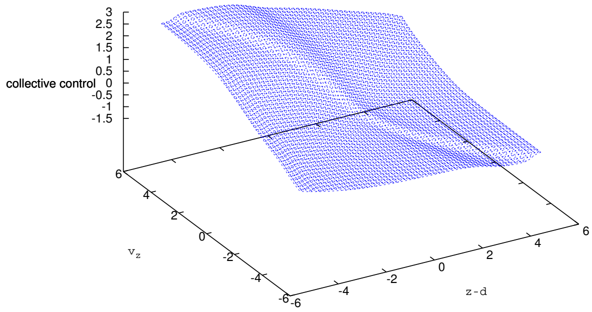

Fig. 5. Input and states map of the trained neural network using proposed method($\gamma = 0$)

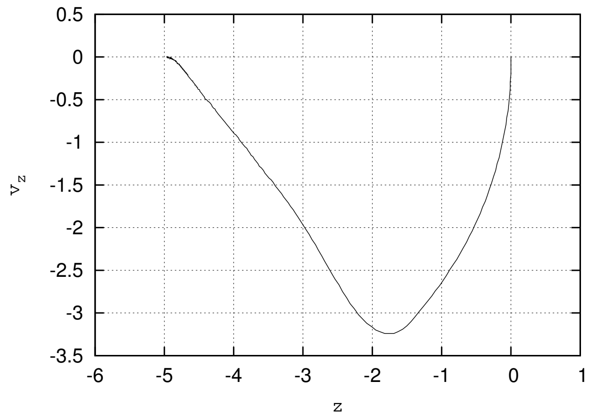

Fig. 6. Trajectory of the state by the trained neural network using proposed method($\gamma = 0$). Singlar solution can be found near (-5,0)

autonomous flight for various activities, such as disaster response and disaster prevention

Fig. 7. Input and the states map of the trained neural networks using proposed method($\gamma = 0$)($\gamma = 0.25$)

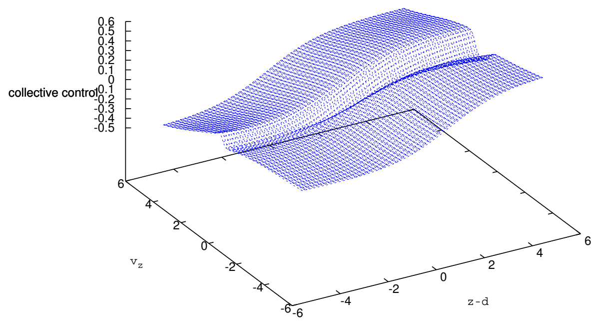

Fig. 8. Input and the states map of the trained robustify neural network using proposed method($\gamma = 0.25$)

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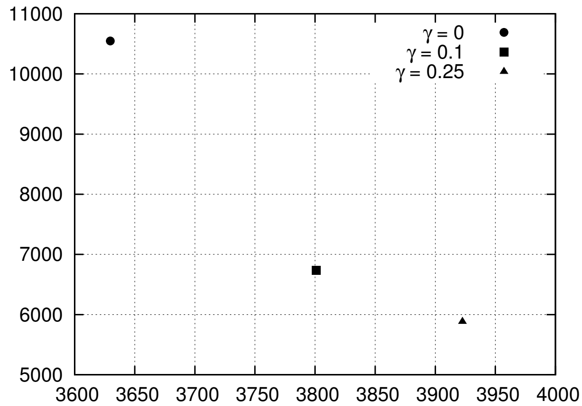

Fig. 9. Results of modular robust controllers:As γ increases, the variance of the result becomes smaller but the average performance is degraded.

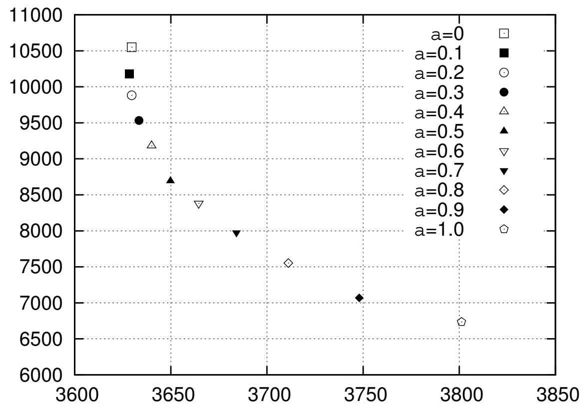

Fig. 10. Relation between α and robustness:If sthe mixing gain a increases, then the controller's performance degrades but the controller's robustness increases.