

# Autonomous Aero-Robot and Disaster Response

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## Abstract:

After a not-widely-known fact is revealed that Japan is a leading country in production and use of industrial unmanned helicopters, a kind of UAV. The voice command system and the autonomous flight control system with a variety of control algorithms including neural network, robust and adaptive control that have been developed in collaboration between Kyoto University and Yamaha Motor Co., and funded by the Ministry of Education and Science of Japan are described in some detail. Both already-proven and promising future applications of the autonomous unmanned helicopters are given.

## 1. Introduction

Numerous studies to develop unmanned helicopters and their flight control systems have recently been conducted in the United States, Europe and Japan. But it is not widely known that Japan is on the top in production of unmanned helicopters, a type of UAV, for non-military uses. In Japan, about 1,500 unmanned helicopters have been produced and they have been used mainly for crop dusting in paddy fields. Yamaha unmanned helicopters have established an overwhelming 80% share of this market. Yamaha Motor Co. began developing industrial-use, unmanned helicopters in the 1980s. In 1990 they delivered "R-50" the first unmanned helicopter with a 20kg effective load capacity for agricultural use, such as crop dusting, chemical spray and pest control. To date, a total of 1,200 units of Yamaha unmanned helicopter have been sold in Japan. Since then, these unmanned helicopters have become the focus of attention as economical, environment-friendly next-generation agricultural devices that are now being used primarily for crop dusting. For example, in the case of dusting rice paddies, an unmanned helicopter can do the job in about 1/15th the time it takes by hands of an aging farmer [1].

At the first stage of the development, they already realized the difficulties of controlling unmanned helicopters. Their target has been to develop an unmanned helicopter that could be operated easily by everyone. They also started to develop control devices for unmanned helicopters at the same time. At the initial stage of control system development, they developed altitude and direction control devices that could enhance the stability of altitude and direction for flight performance. These devices consist of a laser range sensor, an accelerometer and a geomagnetic azimuth sensor. A laser range sensor measures the distance between ground and helicopter by counting the reflecting time of light. Since 1995 Yamaha

helicopters have mounted the attitude control devices called “Yamaha Attitude Control System (YACS)”, which has three fiber optic rate gyros and three accelerometers. It greatly increases flight stability and ease of operation through the use of flight pattern control models based on extensive flight analysis. With YACS, all the flight control elements including, rudder and elevation are subject to computer control that provides constant adjustments according to the parameters of three different flight modes that the operator can select from, according to the type of use. Thanks to this system, new operators with just a short period of training can now master helicopter operation, which was previously considered a very difficult skill. This in turn has succeeded in expanding the demand for these helicopters.

The latest model, named Yamaha Aero Robot “RMAX”, made its debut in October of 1997, mounting a specially developed horizontally opposed, liquid-cooled, 2-stroke, 246cc engine rated at 21hp. This made possible an effective load capacity of 30kg at an operating weight of 64kg. See Fig. 1 and Table 1 for details.

Taking an RMAX as the base-model, a joint project to develop an autonomous unmanned helicopter for use in case of disaster prevention and monitoring purpose between Kyoto University and Yamaha Motor Co. was started in the year 2000, funded by the Ministry of Education and Science of Japan (3-year project with the grant-in-aid of 30,600,000 JPY).



**Fig. 1 RMAX in Spraying Chemical over Paddy Field**

## 2. Autonomous Unmanned Helicopter

In this section, equipments for our autonomous unmanned helicopter, which is a modified version of the RMAX, named Kyoto Univ. version. See Fig. 2. 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 real time kinematics type of differential GPS (RTK D-GPS) is installed. To improve the performance and reliability of autonomous flight controllers, it is necessary to use more accurate states of the helicopter, such as the position, velocity, and attitude. Therefore GPS-INS integrated navigation system using the extended Kalman filter with 15 dimensions is

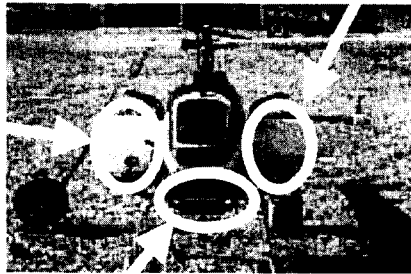
|                         | R50          | RMAX  |
|-------------------------|--------------|-------|
| Main Rotor              |              |       |
| Diameter (mm)           | 3,070        | 3,115 |
| Tail Rotor              |              |       |
| Diameter (mm)           | 520          | 545   |
| Complete helicopter     |              |       |
| Overall Length (mm)     | 3580         | 3630  |
| Overall Height (mm)     | 1,080        | 1,080 |
| Overall Width (mm)      | 700          | 720   |
| Weight                  |              |       |
| Empty (kg) (With Fuel)  | 47           | 64    |
| Payload (kg)            | 20           | 30    |
| Engine                  |              |       |
| Displacement ( $cm^3$ ) | 98           | 246   |
| Category                | Water cooled |       |
| Maximum Output (KW)     | 8.8          | 15.4  |

**Table 1. Specifications of R-50 and RMAX**

developed. The integrated navigation system can cancel the effect of the offset of gyros and accelerometers and the effect of distance from the GPS antenna to the center of gravity respectively.

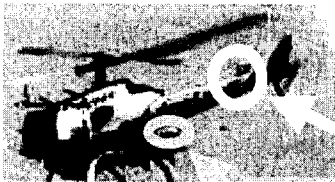
**Data Modem**

**Controller**  
 Note PC with  
 Pentium3 650Mz  
 OS RT-Linux



**Inertial Sensor (3 axis platform)**

- G-Sensors
- Gyroscopes

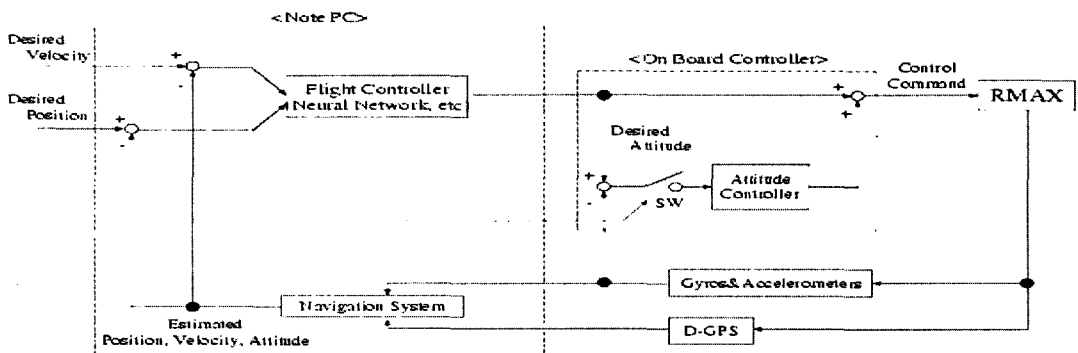


**D-GPS**

**Magnetic Compass**

**Fig. 2 Modified RMAX (Kyoto Univ. Version)**

Moreover, it is also able to compensate time delay in transmission of GPS measurement data. Much computation is required for the integrated navigation system and for the neural network in the flight control, so that a note PC is also equipped on the helicopter. Real time processing is required in the computation, so that RT-Linux is used as the operation system. Because the Note PC and RT-Linux are used, it becomes possible to reduce the total of the cost and time to develop flight control system. Fig. 3 shows the signal block diagram of the autonomous unmanned helicopter. In flight experiments, a Note PC, of which CPU is Intel Pentium III 650MHz, is used and it has enough capability to perform computation required in the flight control system. As the Fig. 3 shows, the flight control system consists of two



**Fig. 3 Block Diagram of Autonomous Flight Control System**

feedback loops, the inner loop and the outer loop. The outer loop is the positioning and velocity controller, which is computed by the Note PC. In our study, the outer loop controller is mainly discussed. The outer controller sends a signal to the inner loop as the desired attitude. In the inner loop, an attitude controller was used for the helicopter to track the desired attitude. The attitude controller is fixed and it have already programmed on the board computer. But outer controller can stop using the attitude controller, because the attitude controller may not have enough performance. If the attitude controller was turned off, the outer controller controls the helicopter directly. The flight simulator developed by Yamaha Motor Co. can simulate the flight controlled by the flight control system described in Fig. 3. But any information about the dynamics of the helicopter, such as aerodynamic coefficients, is not open to public, so that the flight simulator was used only to check if the designed controller works or not. Even if a simulator can be used, it is almost impossible to design effective controllers without knowing the dynamics of the controlled object in the conventional design methods.

### 3. Advanced Voice Command Control System

In Japan, many unmanned helicopters are used for agricultural purposes, and they are controlled remotely using PROPO. But controlling UAVs remotely needs the skill. For a novice operator, it is not easy to control an UAV remotely, not only for agricultural purposes but also for many purposes. A semi-autonomous flight mode of UAVs will be able to overcome such difficulty. We propose that a voice command system is one of the most suitable command interfaces for the semi-autonomous flight mode [2]. Since communication by voice is quite common for human, the voice command system can be used very easily even by novice operators. Operators can give commands with their own voices and can know the state of UAVs by voice messages issued by the voice command system.

In order to examine the effectiveness, we developed a voice command system for RMAX and experiments using a flight simulator of RMAX were carried out as well as real experimental flight tests.

Fig. 4 is a conceptual figure, which shows the voice command system is connected to the terminal computer of RMAX by RS-232C. To concentrate on developing the interface of the voice command system, a commercial

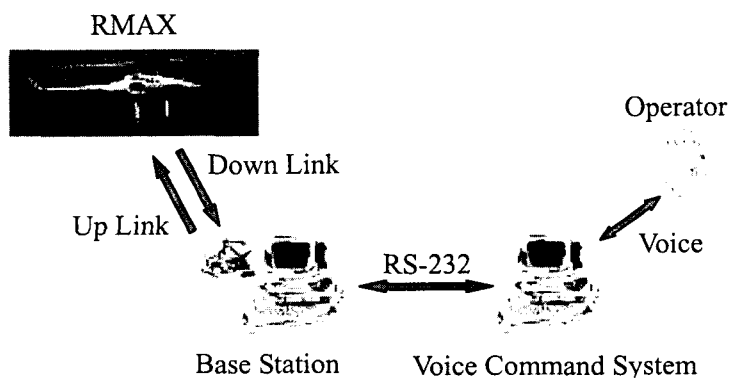


Fig. 4 Advanced Voice Command Control System

software (IBM ViaVoice) was at first used as a speech-recognition part, which is vital to the whole voice command system. The rate of recognition of a speech-recognition system had big influence on the whole degree of satisfaction and surrounding noise had influence on the rate of recognition of the command. The

ViaVoice was not satisfactory to our purpose. So we adopt the “Julius” developed in Kyoto Univ., as the speech-recognition system, which results in the satisfactory recognition rate. For novice operators, commands used in this system are very much simplified. For example, in order to make RMAX hover, simply say, “hover”.

Results of experiments were analyzed based on human interface design principles and they were fed-back to improve the whole system. The results of interviews and questionnaires performed to the subjects for the system show that the voice command system is well accepted for the semi-autonomous flight of UAVs.

Moreover, it becomes clear that the function by which the operator can check the state of an UAV by a voice message contributes to the improvement in operability and the achievement of the purpose greatly. This system equipped only minimum functions for the navigation of RMAX. Therefore the function to guide operator by voice messages should be improved for the degree of satisfaction and we are now investigating in depth what kinds of functions are required.

#### 4. Autonomous Flight Control System by Training a Neural Network

##### 4.1 Neural network and training algorithm

Because a neural network can emulate any continuous function to any desired accuracy, numerous studies on applying the neural network to control engineering are conducted.

Fig. 5 shows a typical structure of a multi-layered neural network. Among training algorithms of neural networks, the Back-Propagation algorithm is the most famous. But the desired response, which is called the teacher signal, is necessary in the algorithm. Moreover the Jacobian matrix of the system must be computed in training algorithms based on gradient [3], so that it requires an exact mathematical model of a controlled object. It, however, is

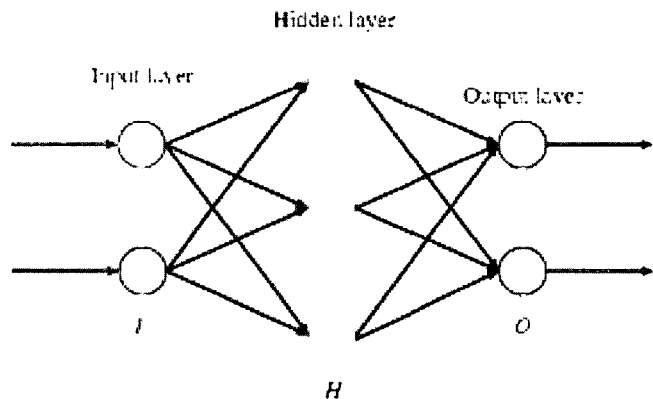


Fig. 5 Multi-layered Neural Network

difficult to obtain an exact model of UAVs, and knowledge of many experts is inevitable to construct the model. Nevertheless, to develop a flight simulator of an UAV is very important because it can help to reduce the total cost of developing UAV, especially of developing autonomous flight control systems. In conventional methods, detail information about the dynamics of UAVs is necessary in developing controllers, so that a designer of the autonomous flight control system of UAV must have integrated knowledge. So it is difficult to develop autonomous flight controllers, therefore a method to design control systems much easier is required. If controllers can be designed by use of a flight simulator without knowing detail information about the UAV, distributed knowledge can be used more effectively, so that

efficiency of development of autonomous flight control systems is much improved because a designer of the flight controller does not need to know the detail of the dynamics of the UAV.

For the purpose, we proposed to use neural networks in designing controllers, and the proposed training method can be built in any flight simulators without knowing almost anything about the dynamics. The proposed training method is based on Powell's conjugate direction algorithm, which can be applied to problems which include not-differentiable functions. Neither any derivatives nor the teacher signal are not needed in training neural networks, therefore it is much suitable for developing controllers by use of neural networks. Moreover in the training algorithm, any information about the controlled object, such as state equation, is not required so that it can easily built in flight simulators of any UAVs. Therefore various expert's knowledge can be easily and perfectly absorbed in the system, so that the training algorithm is much effective in designing autonomous control systems of UAVs. In this study, a flight simulator of RMAX is used. Although not all information about RMAX is open to public, our training algorithm is built in the simulator very easily. Methods to design typical control systems, which are useful in autonomous flight control of UAVs, are discussed in the following sections.

#### 4.2 Neural network for feedback linearization in autonomous flight control

Consider a nonlinear system with  $n$  degrees of freedom in general form:

$$\ddot{y} = f(y, \dot{y}, u) \quad (1)$$

where  $y$  and  $\dot{y}$  are the state variables and  $u$  is the control variable.  $U$  is a pseudo-control variables, such that

$$U = f(y, \dot{y}, u) \quad (2)$$

If  $f$  is a known and invertible function with respect to control  $u$ , control  $u$  described as (3) can linearize the map between control and output.

$$u = f^{-1}(y, \dot{y}, U) \quad (3)$$

If the pseudo-control is chosen as (4), the closed loop dynamics can be expressed as (5).

$$U = -K_p(y - d) - K_D\dot{y} \quad (4)$$

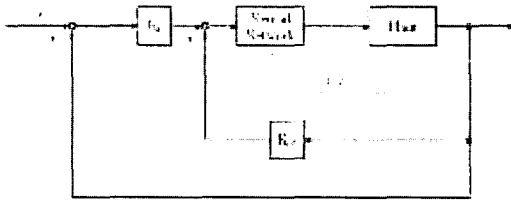
$$\ddot{y} = -K_p(y - d) - K_D\dot{y} \quad (5)$$

In this section, to develop a method to design a controller for feedback linearization, it is assumed that  $f$  is invertible but not known. A neural network is used as feedback linearizing transformation shown in Fig. 6. But the block diagram shown in Fig. 6 cannot be used in training directly, so that the block diagram shown in Fig. 7 is used in training the neural network. The performance index  $J$  described as (6)

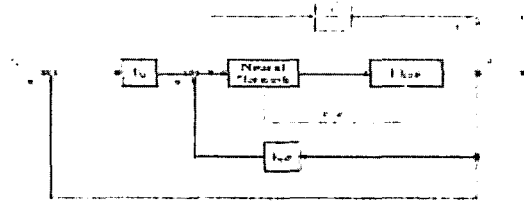
$$J = \sum_{t=0}^T e^2(t) \quad (6)$$

is used for training, where  $e$  is an inversion error. Training is equivalent to minimization of the performance index  $J$ .  $K_p$  and  $K_D$  are parameters that determine the response of UAVs, and

$K_p = 1.0$  and  $K_D = 2.0$  are used in training. After training is completed, the neural network can be used as the controller for linearizing the dynamics of UAVs. Fig. 8 shows the response of RMAX controlled by the trained neural network and it is shown linearizing transformation by the network is successful.

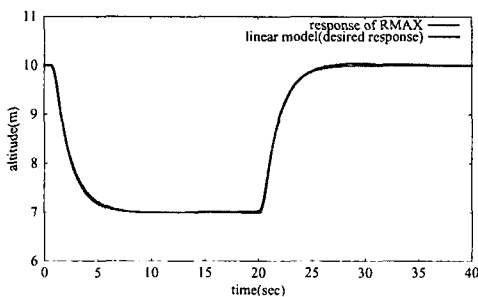


**Fig. 6** Control network linearization by neural network

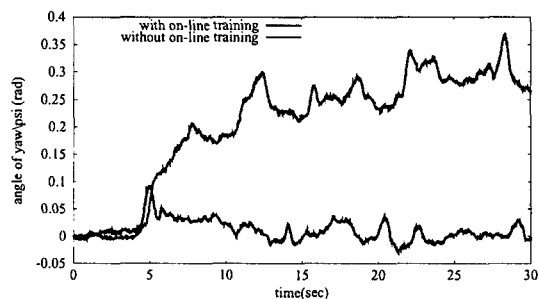


**Fig. 7** Block diagram for training a neural network

But modeling errors must remain, however, in any flight simulators. Therefore control systems must be tolerable for the modeling error or can adapt it on-line. The neural network that is trained by the method described above can be used together on-line training of another neural network easily, so that controllers by which the modeling error is compensated can be developed easily. Experimental results of yaw control of a small electrically powered helicopter are shown in Figs. 9 and 10. It is shown that the on-line training can easily compensate modeling error and the effect of a wind, and it turns out that the hybrid controller has excellent performance. Fig. 10 shows that the hybrid controller still has excellent performance, even if the efficiency of the control is 50% reduced. The hybrid controller can be a fault tolerant control system. Therefore it is shown that the proposed method can improve the reliability of the autonomous flight controllers.



**Fig. 8** Altitude response controlled by a trained neural network



**Fig. 9** The effect of on-line training (side wind blows at 5 sec.)

### 4.3 Training neural network for robust controller against stochastic uncertainties

Generally speaking, some uncertainties are inevitable in developing controllers, so that designing robust control system becomes important. We had already proposed methods to design robust controllers by use of neural networks [4, 5], but only deterministic uncertainties are considered in those methods. But stochastic disturbance is also one of the most typical uncertainties, so that controllers must be designed to reduce its influence on the performance [6]. Our purpose in this section is to develop the method to design

a robust neural controller against stochastic disturbances.

The most typical stochastic uncertainty (6) that exists in flight of UAVs is a wind, and time series of wind speed and its direction belong to stochastic process. The flight of an UAV is disturbed by a wind, so that a performance index of a sampled flight becomes stochastic. Training using a particular wind is quite danger because the trained controller doesn't have proper robustness. Any stochastic values cannot be used as the index for training. Therefore a statistical value of the stochastic process is suitable for the index for training. Even some statistical values, such as max or median, are not differentiable, but our training algorithm can use not-differentiable values as the index in training. To design robust controller against winds, we proposed to use a performance index described as (7),

$$L = \frac{1}{\gamma} \log(E[\exp(2\gamma \cdot J)]) \quad (7)$$

where  $J$  is a sampled index. If the performance index (7) can be expanded about  $\gamma$ , we can obtain an approximated index described as (8),

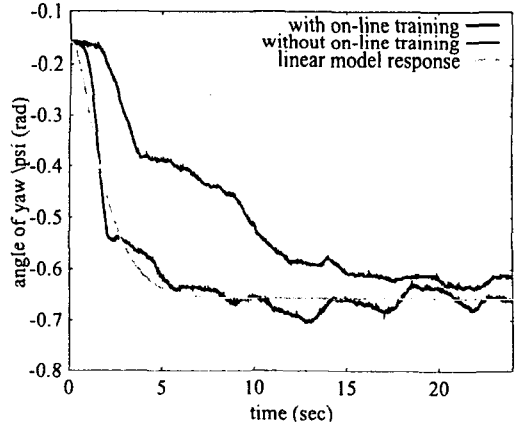
$$L = E[J] + \gamma \cdot \text{Var}[J] + O(\gamma^2) \quad (8)$$

$\gamma \geq 0$  is a scalar parameter and it quantifies the robustness of the trained controller.  $\gamma$  is an induced  $L_2$ -gain from stochastic disturbances to reference outputs. From (8), it is shown that not only average but variance are considered in this method. The bigger  $\gamma$  is used in training, the smaller the variance of the performance is, that is, the trained neural network has robustness against stochastic disturbances. Therefore its robustness can be quantified by  $\gamma$ , and this is the most advantageous point of our method.

To confirm the effectiveness of the proposed method, it is assumed that only vertical wind exists and horizontal wind does not exist in simulations. Altitude controllers of RMAX, which are nonlinear state feedback controllers, are designed by use of neural networks. The sampled index  $J$  described as (9) is used in training, where  $d$  is the desired altitude.

$$J = \sum_{t=0}^{40 \text{ sec}} (z(t) - d(t))^2 + v_z^2(t) \quad (9)$$

Average and variance of the sampled index  $J$  are shown in Fig. 11. The average indicates the performance of the controller, and the variance indicates the extent of the influence of the disturbance, therefore these values are very important parameters for robust controllers against stochastic disturbances. Both the average and the variance of a neural network, which is trained without considering any wind, is big. Therefore the network fails in reducing the influence of the wind, and the performance is not good enough. But both average and variance of neural networks trained by the proposed method are small, so



**Fig. 10 The effect of on-line training (efficiency of the rudder is decreased to 50%)**



that Fig. 11 shows that neural networks trained by the proposed method have excellent robustness and performance. Moreover, this figure shows that a designer can perform the tradeoff between robustness and performance by choosing  $\gamma$ . Quantified robustness against the stochastic disturbance is the most noteworthy property of the proposed method, and it can be combined with training for deterministic uncertainties very easily, so that more excellent training method will be brought.

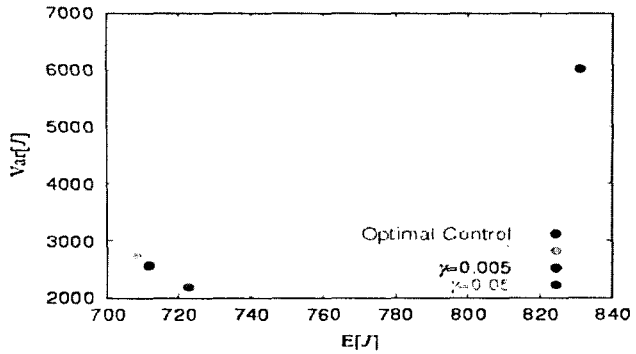
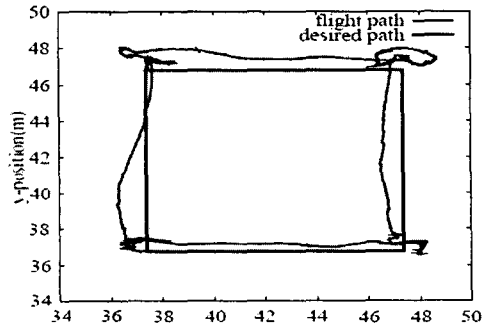


Fig. 11 Average and variance of the performance index

#### 4.4 Flight Experiments

In this section, results of flight experiments using the flight control system designed by the proposed methods are shown [7]. The proposed method can be applied to design various kinds of controllers, such as velocity controllers, positioning controllers and so on. Although we had already tested various controllers actually, only positioning control is demonstrated in this section because it is important in many activities. In flight experiments, the four controllers, that is, elevator controller, aileron controller, yaw controller, and altitude controller, are used, and each controller is designed independently.



##### (1) Positioning Control in a Horizontal Plane

Fig. 12 shows the result of positioning control in a horizontal plane. The programmed path is a square of 10 meters. The helicopter is also controlled to keep the initial altitude and the initial direction. In Fig. 12  $x$  and  $y$  axes mean the direct forward and the right respectively. Only controllers that were trained offline were used in this experiment. The day of flight experiments was very windy, but the helicopter was controlled with enough accuracy but there was some steady-state error. the cause will be as follows:

(1)The average of wind speed isn't 0,

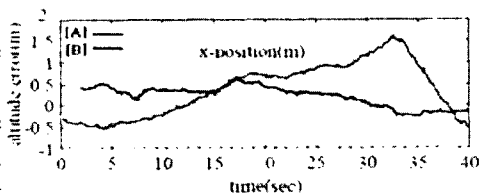


Fig. 12 Flight path in horizontal plane

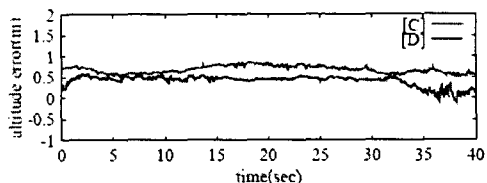
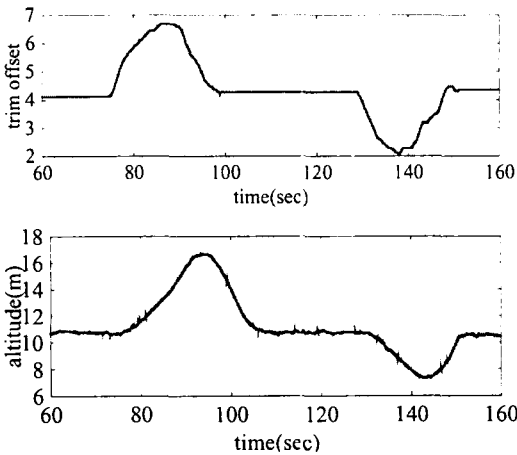


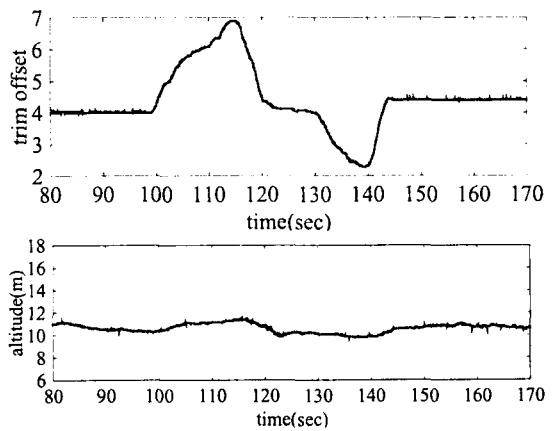
Fig. 13 Results of altitude controllers

- (2) Installation error angles of the main rotor, and
- (3) Trim error.

Such steady-state error is not desirable, but it is difficult to remove only by the state feedback controller that is trained offline.



**Fig. 14** changes of trim  
(Controller [C])



**Fig. 15** Response to change of trim  
(Controller [D])

## (2) Altitude Control

To check the performance in hovering, results of altitude control by the four different controllers are compared with.

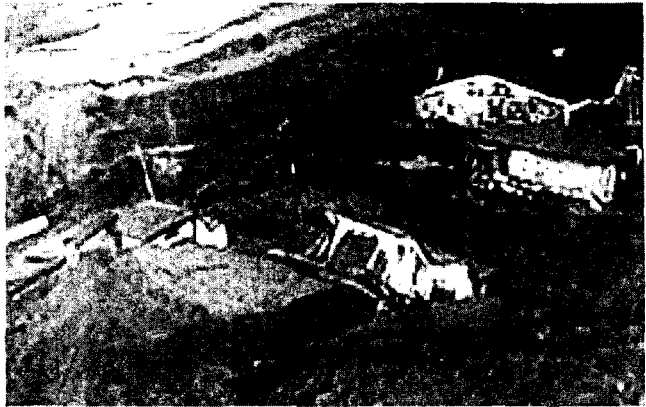
- [A] PD controller,
- [B] Controller [A] + online training neural network,
- [C] A neural network which is trained offline, and
- [D] Controller [C] + online training neural network

To determine the PD gain in [A] and [B], the optimal gain is searched using the flight simulator by try-and-errors. In the online training rule, sigma modification with dead zone is used. Fig. 13 shows the results of each controller and it is proved that the performance of the controller is much improved by adding online training controller. Moreover the neural network trained by the proposed method has good performance and robustness even without the online training controller. To confirm the effectiveness of the online training controller, the trim of collective was changed during the flight. This is the emulated experiment to check if the online training controller can reduce the influence of the gust, failures and so on. In Figs. 14 and 15, responses to the change of trim are shown. Because Controller [C] is only a state feedback controller, the change of trim had a great influence on the altitude. But Fig. 15 shows that the online training controller can make the influence very small.

## 5. Applications

### 5.1 Observation Flight at Erupting Volcanoes

At the end of March 2000, Mt. Usu, on Japan's northern island of Hokkaido, erupted. The surrounding area was quickly declared a no-entry zone and several thousand local inhabitants were evacuated to temporary housing that they occupied for several months. With the possibility of further volcanic activity still strong, the government-established field headquarters was continuing observation and information gathering on a full-time basis. Receiving ask for cooperation from the Public Works Research Institute of the Ministry of Construction in observation operations in the volcano's vicinity, Yamaha Motor Co. sent a team to Mt. Usu and it was the first time that the autonomous unmanned helicopter was used to observe erupting volcanoes. The field headquarters had been set up in tents at a position just 2.5km from the active crater of the



**Fig. 16 Destroyed houses**

volcano. Fortunately, the air conditions were relatively calm during the actual observation flights and there was little disturbance of the airwaves. Everything worked according to the plan. During three days, the autonomous unmanned helicopter made six observation flights, filming the targeted areas and successfully relaying the images back to the headquarters. See Fig. 16 for a sample photo. The result gave us many clear, live images of changes in topography of the mountain and build-up of volcanic ash that could not be seen by the manned helicopters or the Defense Forces' aerial photographs. In addition to sending out these images, the unmanned helicopter has been proven valuable in a number of unexpected ways, such as for dropping scales to actually measure the depth of volcanic ash and gravel build-up, an important indicator for predicting dangerous mudslides.

Furthermore, the autonomous unmanned helicopter was used for observation of erupting Mt. Oyama on Miyakejima Island, Tokyo, Japan, on February 2001. The autonomous unmanned helicopter was used again to make estimates of the thickness of the mudslide layers. Also, an equipped gas sensor measured densities of volcanic gas. The data gathered from these observation flights is expected to play an important role in the future for studies concerning the construction of "landslide dams" designed to prevent the spread of land/mudslide damage.

The autonomous unmanned helicopter has enabled to gather of previously unavailable data such as low-flight observation images from the high-danger areas near the volcano.

### 5.2 Possible Future Applications

### **(1) Disaster Prevention**

Very recently the Minister of Education and Science of Japan launched “Special Project on Prevention and Reduction of Losses caused by Earthquake in Megalopolises” and they solicited research proposals from universities, research institutions and business firms. We, a joint team consists of Kyoto University and Yamaha Motor, made a research proposal “Developing Intelligent Aero-robot for Disaster Prevention” to the Ministry, and fortunately our proposal has been selected. In the four-year project, we plan

- (1) To develop an advanced and integrated navigation system by use of sensor fusion technique,
- (2) To develop an advanced autonomous flight control system,
- (3) To make risk and reliability analysis of the proposed intelligent aero-robot in rescue activities,
- (4) To make basic research on the cooperation between robots on the land and aero-robots in the air.

### **(2) Humanitarian Detection and Removal of Anti-personnel Mines**

The Minister of Education and Science of Japan launched vary lately another very interesting research project on “Research and Development of Sensing and Access/Control Techniques witch supports Humanitarian Detection and Removal of Anti-personnel Mines”. We, a team of two universities, two research institutions and a firm, have proposed a research plan on “Development of Hybrid Minefield Access System using All Terrain Unmanned Vehicles”, but at present we do not know if the proposal is selected or not. In the proposal, we plan to develop a hybrid minefield access system using unmanned vehicles and unmanned helicopters. The proposed project include

- (1) Effective access to the minefield based on cooperative operation,
- (2) Easy teleoperation with information fusion utilizing the helicopters and the vehicles, and
- (3) Reliable infrastructure for mine marking and mapping using Intelligent Data Carriers (IDC).

### **5.3 Other Area of Possible Applications**

The Japanese government and other industries have been interested in the operation of unmanned helicopters. For example,

- (1) Hokkaido Regional Development Bureau has already decided to buy an unmanned helicopter for the observation role of volcanoes including Mt.Usu.
- (2) The Japan Meteorological Agency has also decided to use unmanned helicopters for gas sampling and putting measuring devices for earthquakes in dangerous sites.
- (3) Japan Coast Guard is also contemplating their use for search and rescue operations.
- (4) Electric power plant companies, which have many nuclear power plants all over Japan, are very interested in unmanned helicopters to watch radioactivity accidentally released. Because there was an unfortunate accident at a nuclear fuel processing plant in Tokai-mura in 1999.

## **6. Conclusions**

After an introduction to the brief history on the production and use of unmanned helicopters in Japan, the command and control systems for UAVs including unmanned helicopters are discussed in this paper. It is shown that the voice command system is very suitable for the semi-autonomous flight mode of UAVs,

and that even a novice operator can control UAVs easily. It is also pointed out that more investigation from the viewpoint of the human interface, that is user-friendly interface, is needed before the technology is widely accepted. A very convenient and effective method to design autonomous flight control systems by use of neural networks and their training is described and some results obtained from the real flight tests together with numerical results obtained from the flight simulator and from the simple indoor experiments. The already-proven and possible-in-the-future applications of autonomous unmanned helicopters mainly in the area of safety and disaster prevention are given.

We believe an unmanned helicopter has a lot of potential, because it can go in and perform operations in areas too dangerous for humans. But in order to realize this potential we first have to increase the reliability of the technologies. And eventually we would like to have a system that is so foolproof that even people who know nothing about helicopter can fly it.

### Acknowledgements

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At last but not at least, for the authors to express their sincere thanks to each members of the joint team of Kyoto Univ. and Yamaha Motor Co., a photo taken at a flight experimental test at Yamaha Test Flight Field is shown in Fig. 17.



Fig. 17 RMAX Kyoto Univ. Version and Team KU and YM

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