Developing Autonomous Flight Control Systems for Unmanned Helicopter by Use of Neural Network Training

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The 16th JISR-IIASA CSM'2002 Workshop

July 15-17, IIASA, Laxenburg, Austria

Research Project, Grant-in-Aid for Scientific Research (A):

"Development of Autonomous Aero-Robot and its Applications to Safety and Disaster Prevention"

Collaborative Research between Yamaha Motor Co. Ltd.
and Kyoto University

Principal Investigator: Prof. Koichi Inoue

Funding Agency: Ministry of Education and Science

Term: July 2000 to March 2003 (3years)

Grant: \30,600,000JPY ($255,000USD)

Objective: To develop an autonomous unmanned helicopter and to apply it for monitoring and rescue activities in case of natural or manmade disaster

Autonomous Flight of Unmanned Aerial Vehicles

Investigations on UAVs

US Army and Navy, DARPA — Unmanned Bomber
NASA — Unmanned Reconnaissance Planes
Georgia Tech.(Prof. Calise)
CMU（The Robotics Institute Prof. Kanade）
UC Berkeley, Stanford

Kyoto University – YAMAHA Motor Co. LTD. (1995-now）

Purpose

- Agricultural Purpose(Automatic Chemical Spray)
- Observation Activities at Dangerous Area
- Security Activities and Surveillance Activities

Unmanned Helicopters

YAMAHA R-50

YAMAHA RMAX

More than 1,500 Units of RMAX
and R-50 had been sold in Japan.
An Average of Flight Time = 80h/year
Total of Flight Times > 10000h/year

	R50	RMAX
Main Rotor Diameter(mm)	3,070	3,115
Tail Rotor Diameter(mm)	520	545
Overall Length(mm)	3,580	3,630
Overall Height(mm)	1,080	1,080
Overall Width(mm)	700	720
Empty Weight(kg)	47	64
Payload(kg)	20	30
Engine		
Displacement(cc)	98	246
Category	Water Cooled Stroke	
Maximum Output(KW)	8.8	15.4

Towards Autonomous Flight of UAVs

Hierarchy structure of Autonomous Flight Control of UAVs

- Situation Awareness
- Command Interface

Top

- Switching Flight Mode
  Velocity Control ⇔ Positioning Control etc.
- Reconfiguring Flight Control
- Fault Detection

Middle

- Flight Controller

Bottom

Designing Flight Controller

- **Knowledge of Many Experts**
- **Results of Many Experiments**

→ **Flight Simulators**

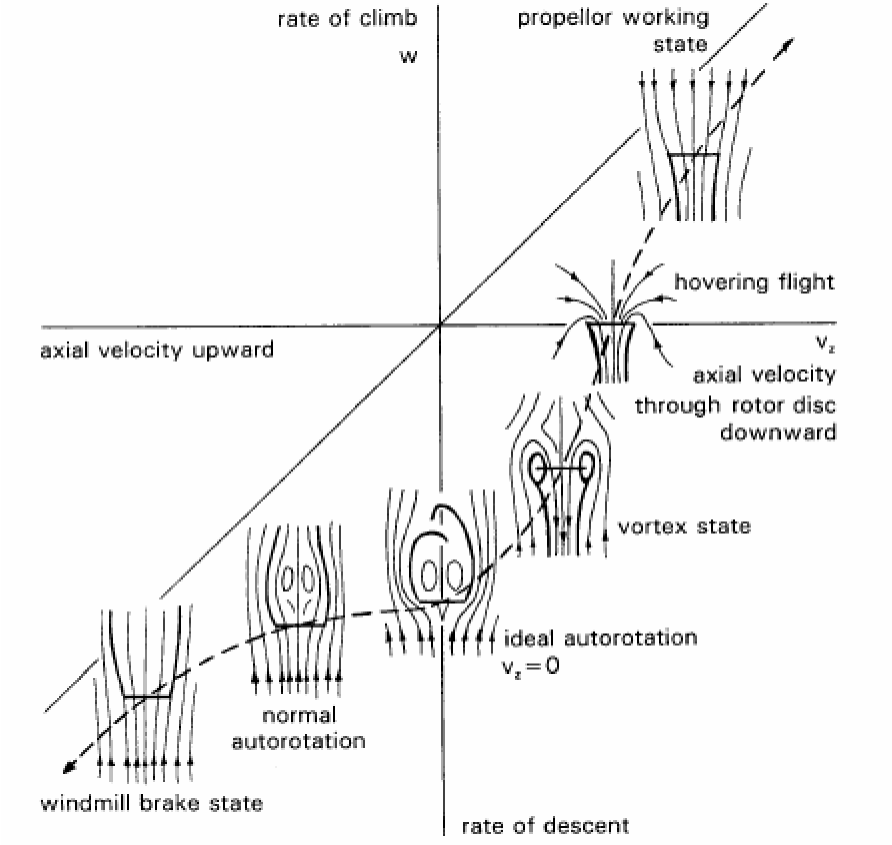
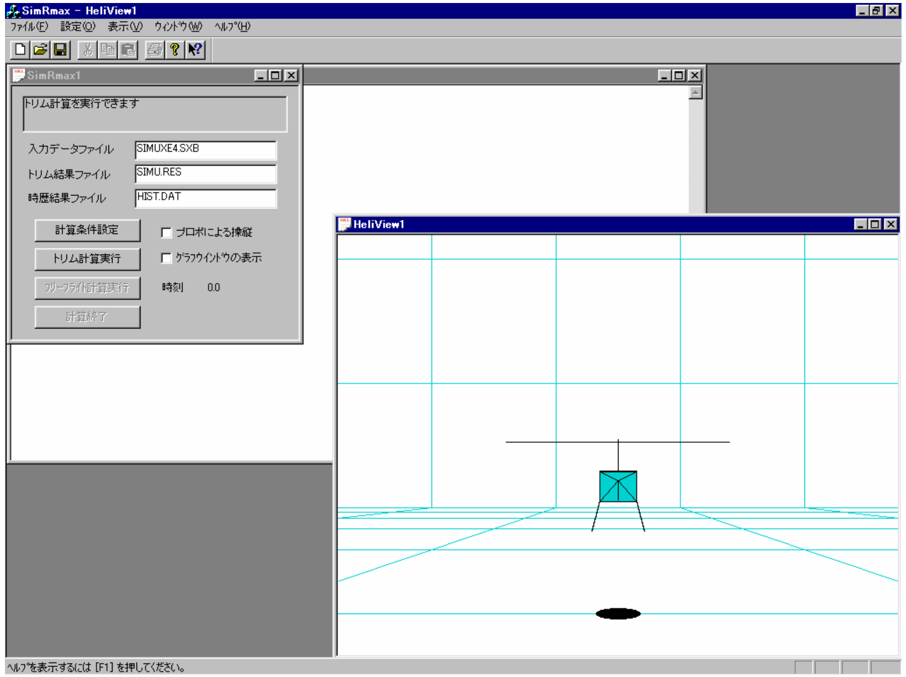


Fig. 2.8 Rotor flow states in axial flight



Nonlinear 6-DOF Flight Simulator of ***RMAX***

Too complex to design control systems

Designing Control Systems for Complex Systems

Conventional methods

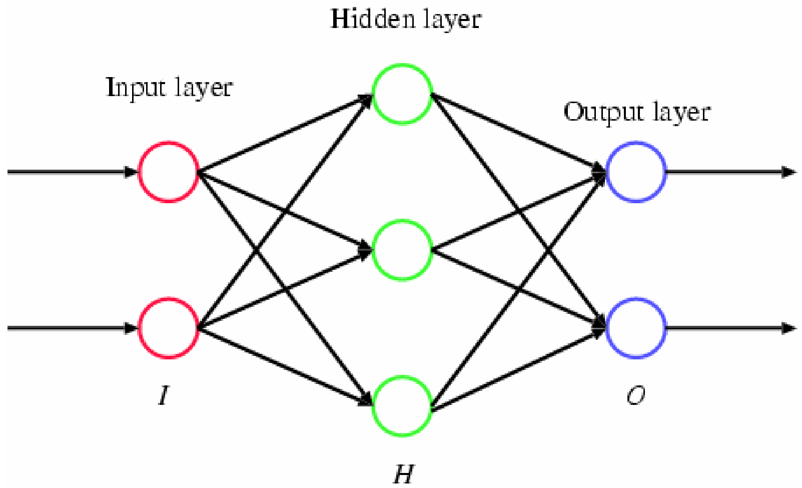
- Linearizing of nonlinear dynamics
- Switching linear controllers
  (Gain Scheduling Controllers)
- Reduction or Truncation
  (Ignoring the dynamics of high-frequency or some effects)
- Dividing the whole system into some sub-systems
  (Singular Perturbation)

are required to design control systems.

Proposed method

- Using neural network training
- Treating complex systems directly and in holistic approach

Controller using Neural Network



Multi-layered neural network

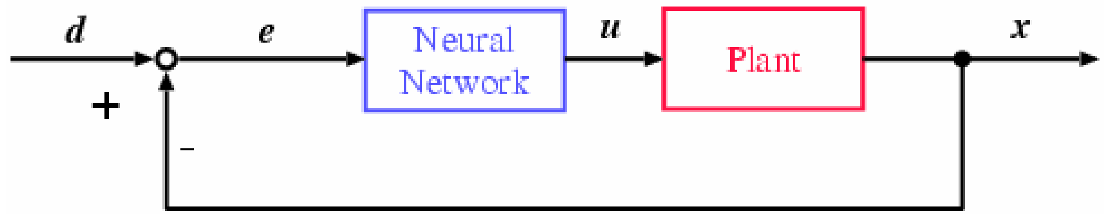
Ability of neural network

- A neural network can emulate any continuous function
- Learning

Useful in designing controllers

Training

Off-line Training



- Training method based on Gradient
- Training method based on Powell's conjugated direction algorithm

Designing and Developing Control Systems

On-line Training

Reconstruction or Reconfiguring Control Systems

Method to Design Controllers by Use of Neural Networks

Training a neural network

Optimization of a performance index

$$J = \int_0^T L(x(t), u(t))\, dt$$

or

$$J = \sum_{t=0}^{T} L(x(t), u(t))$$

Training algorithms

- Training method based on Gradient
- **Training method based on Powell's conjugated direction algorithm**

Training algorithm can be built in the flight simulator!!

In developing autonomous flight controller of UAVs, the algorithm enables to use complex knowledge.

Training Controller for Linearization

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

Linearizing Transformation

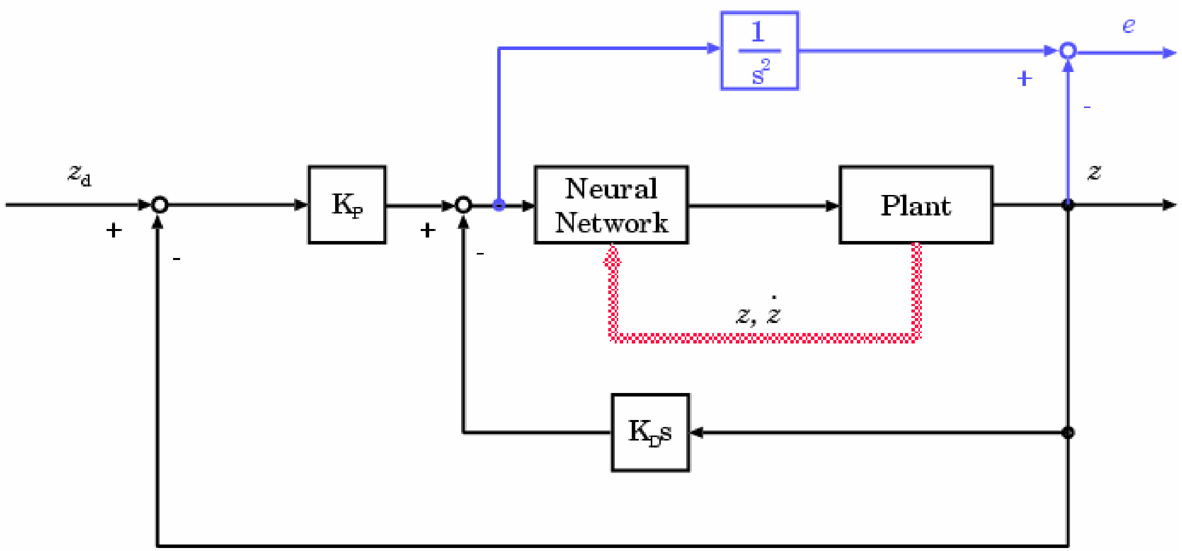
$$U = f(y, \dot{y}, u) = -K_p \cdot (y - d) - K_d \dot{y}$$
$$u = f^{-1}(y, \dot{y}, U)$$

$\ddot{y} = -K_p \cdot (y - d) - K_d \dot{y}$ linear

f : **Unknown**

Index for Training

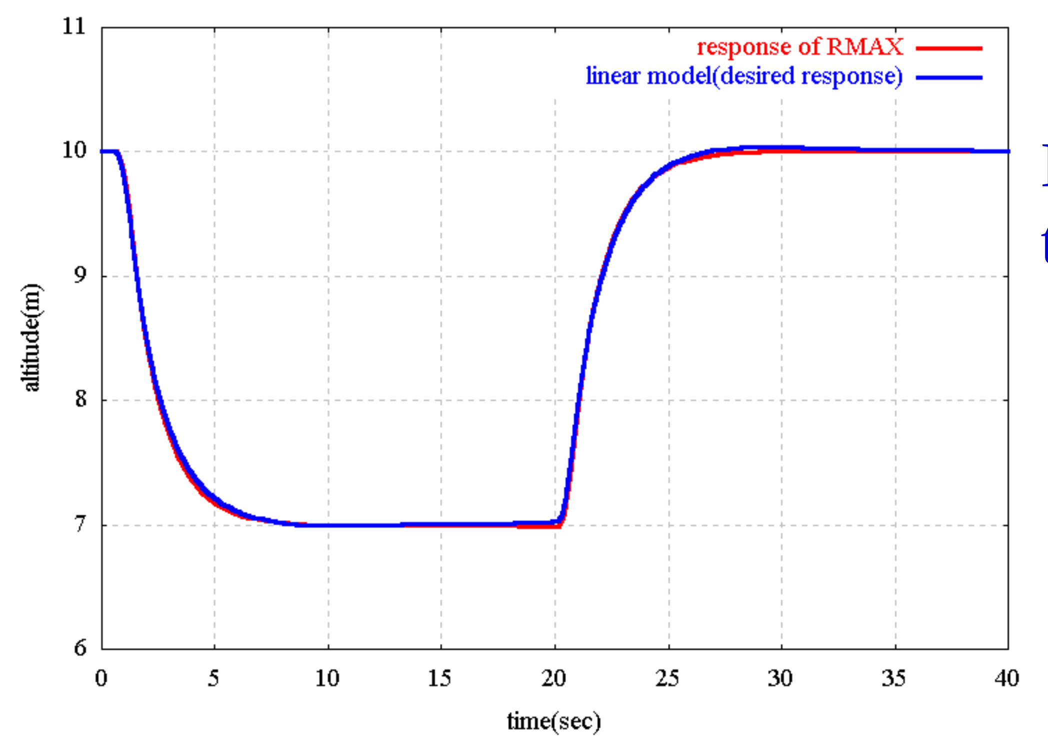
$$J = \sum_{t=0}^{T} e^2(t)$$



Numerical Simulations

Altitude Control

- Inputs of a neural network
  Altitude z velocity v_z
  Pseudo-Input $U = -K_p(z-d) - K_d v_z$
- Output of a neural network
  Collective control $\delta_{collective}$



Nonlinear dynamics is easily transformed to a linear dynamics

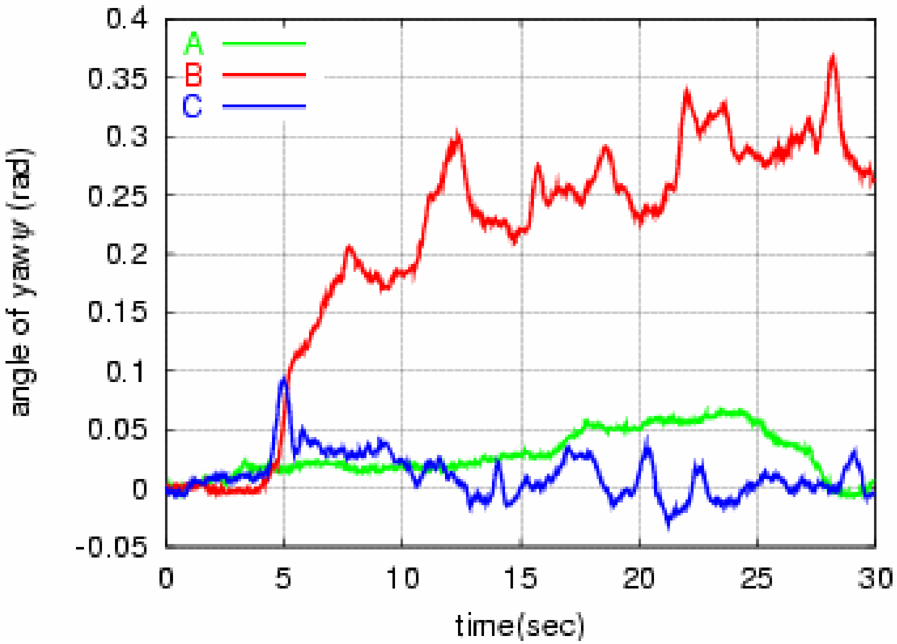
Use together with on-line training

On-line Training of Neural Network

Indoor Experiment using a small helicopter(electrically powered)

Case1.

Under disturbance



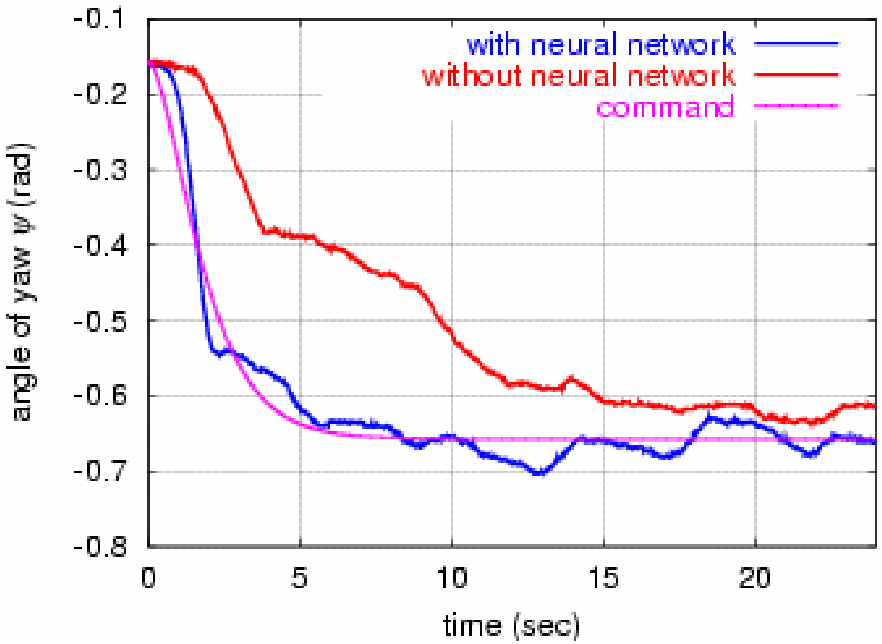
A: without network(no disturbance)

B: without network(with disturbance)

C: with network(with disturbance)

Case2.

Efficiency of the control is reduced



A:with network

B:without network

For the reliability of the autonomous flight

Robust Controllers against Stochastic Uncertainties

Performance index = Stochastic

Statistical value should be used as an index for training

Index for training robust control systems

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

Sample Performance index J

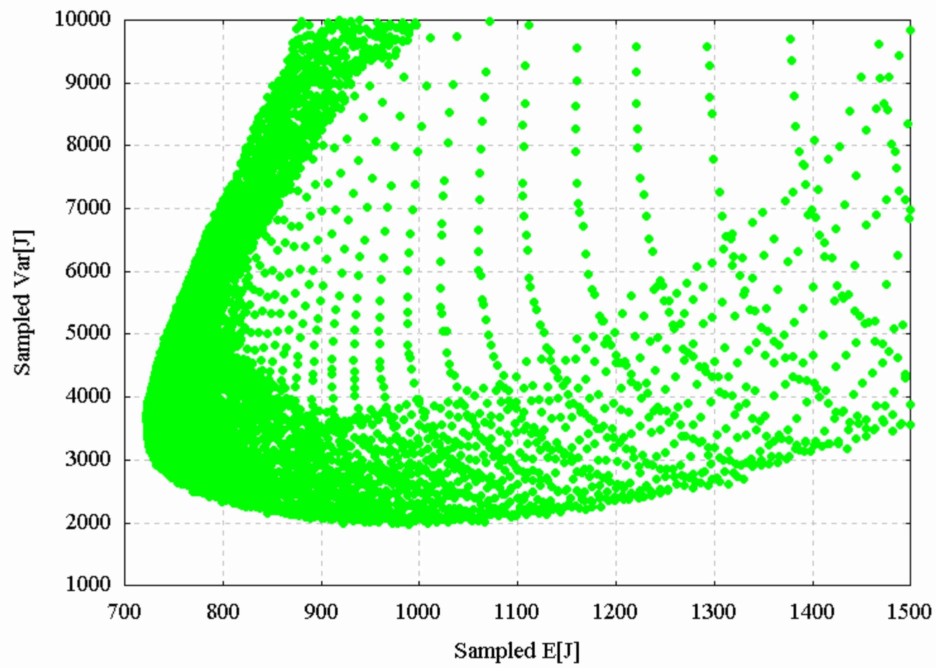
Scalar Parameter γ

$|\gamma| << 1$

$$J_{\gamma} = E\left[J\right] + \gamma \cdot Var\left[J\right]$$

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

$$J_\gamma = E\left[J\right] + \gamma \cdot Var\left[J\right]$$



$\gamma < 0$ Making
the variance of the index big

$\gamma = 0$ $J_\gamma = E\left[J\right]$

$\gamma > 0$ Making
the variance of the index small

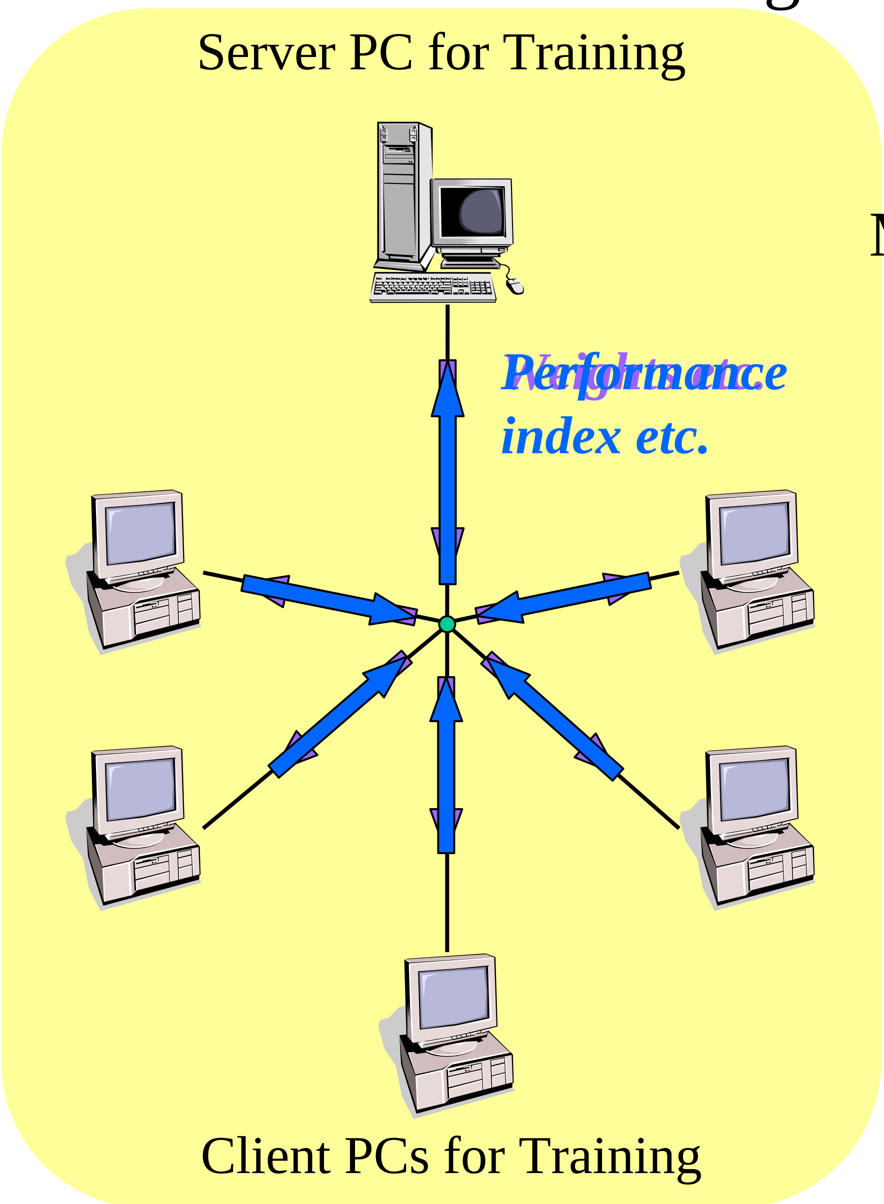
$\gamma \geqq 0$ In Training

γ *is L_2* gain from stochastic disturbance to outputs

Computing on PC Cluster System

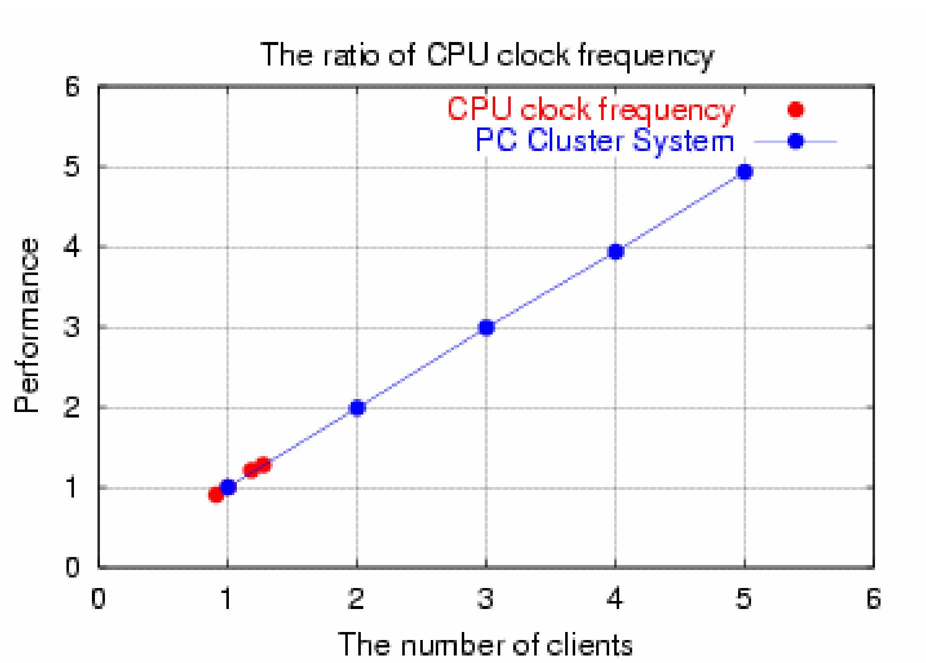
Calculation the large-scale number of samples

Time-consuming

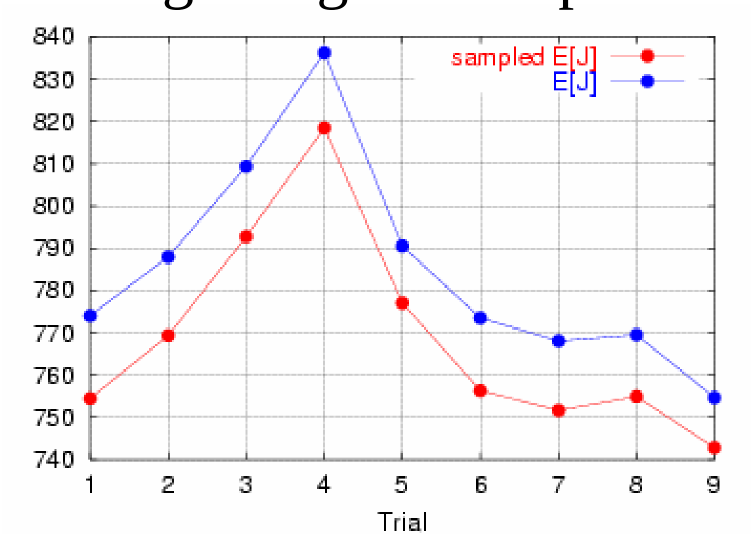


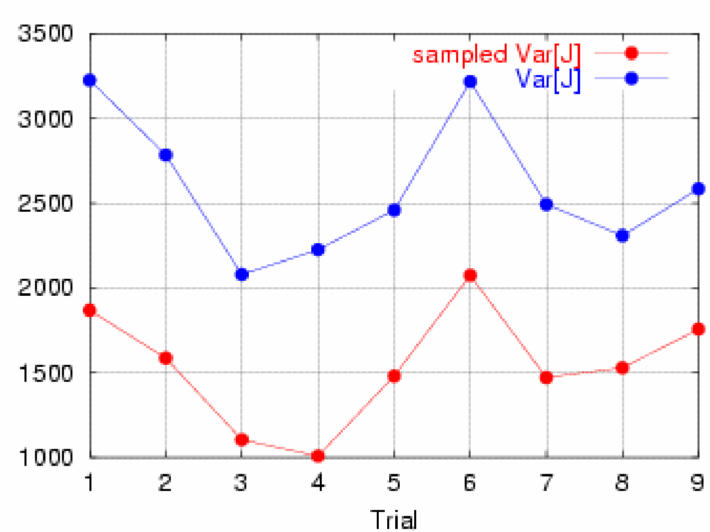
Many PCs are connected by Ethernet

for distributed and parallel computing

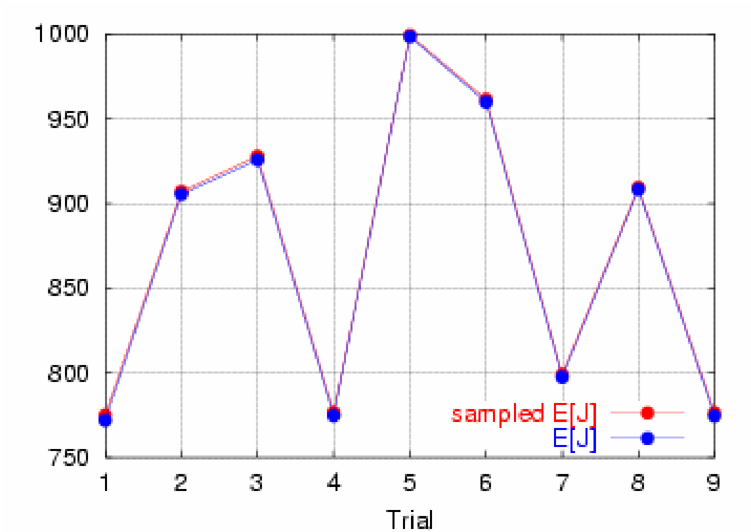


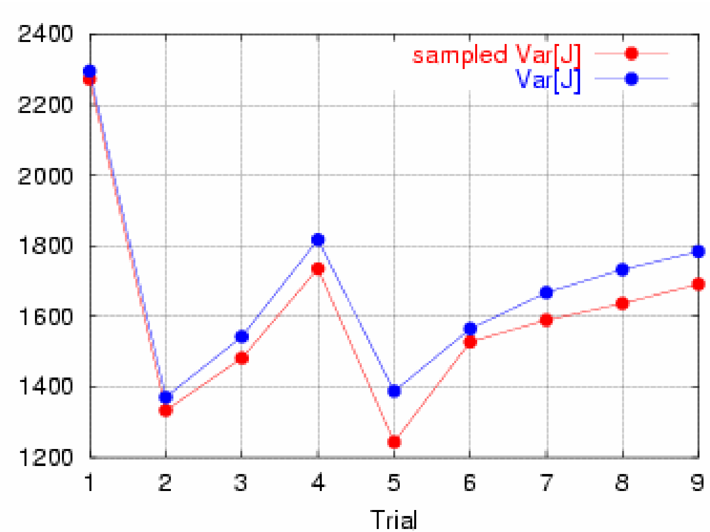
Training using 40 Samples





Training using 450 Samples





Numerical Simulations

Altitude Control

- Inputs of a neural network

  Altitude z velocity v_z

- Output of a neural network

  Collective control $\delta_{collective}$

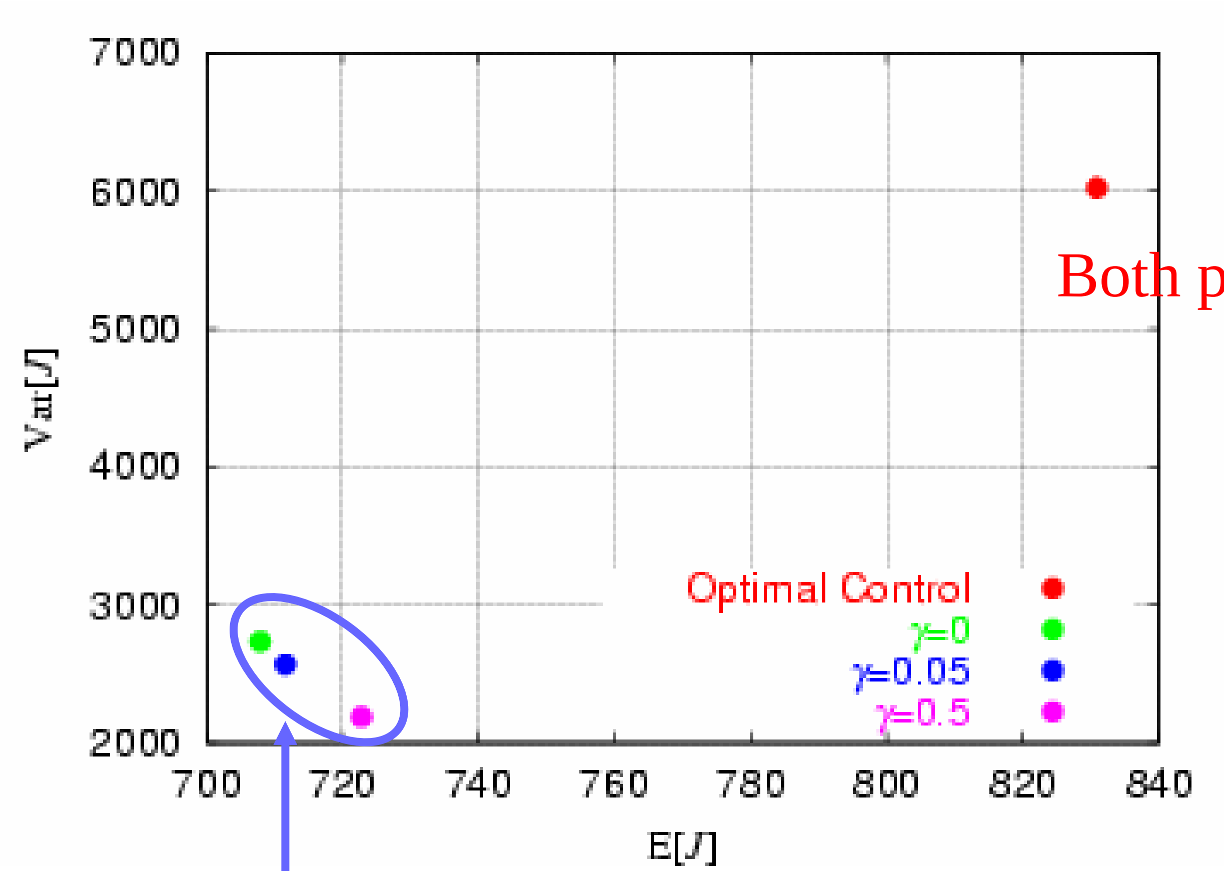
- Performance index

$$J_{\gamma} = \sum_{t=0}^{T=40\,\mathrm{sec}} (z(t)-d(t))^2 + v_z^2(t)$$

Assumptions

- Other controllers (pitch, roll, and yaw) are proper PD Controllers
- Only vertical wind exists(No horizontal wind)
- 20 samples are used to calculate statistical values

Designing Controllers by Proposed Method using J_γ



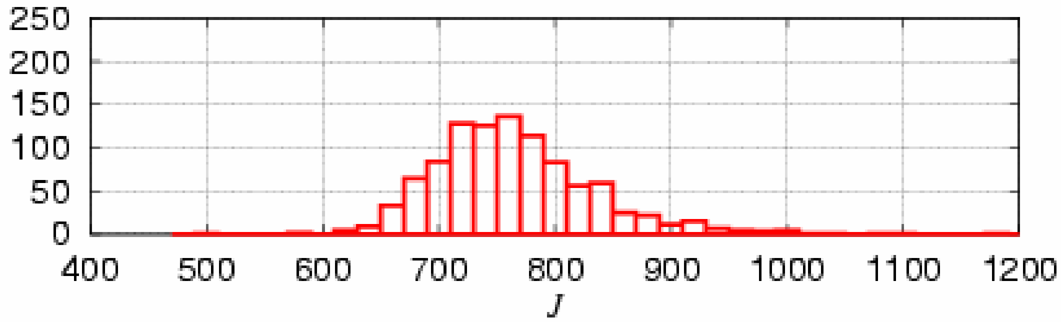
Optimal Control
A neural network trained without considering wind

Both performance and robustness
Not Good

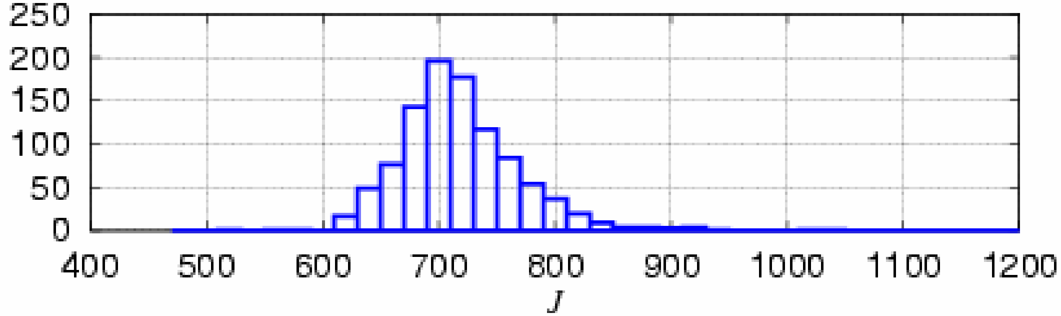
Both average and variance are small

Effectiveness of the proposed method

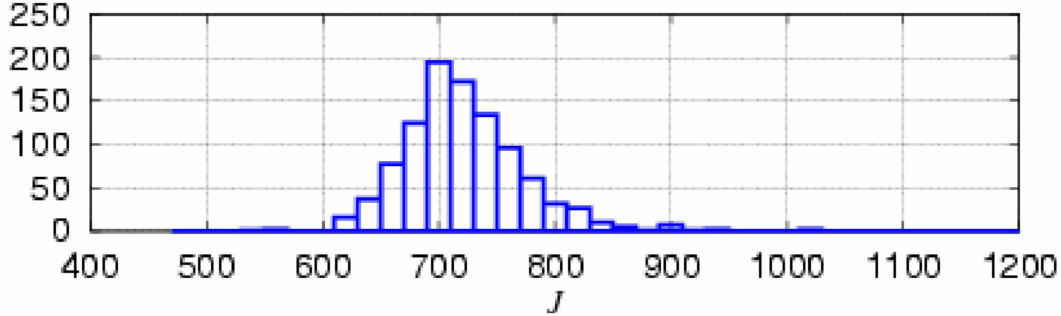
Optimal Control



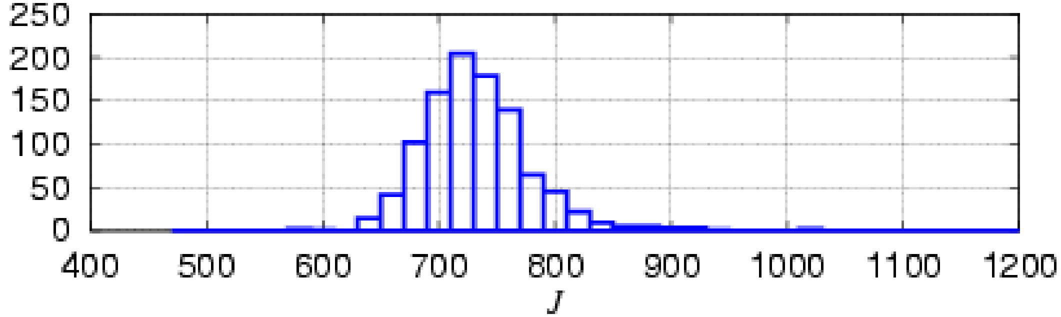
γ =0



γ =0.05



γ =0.5



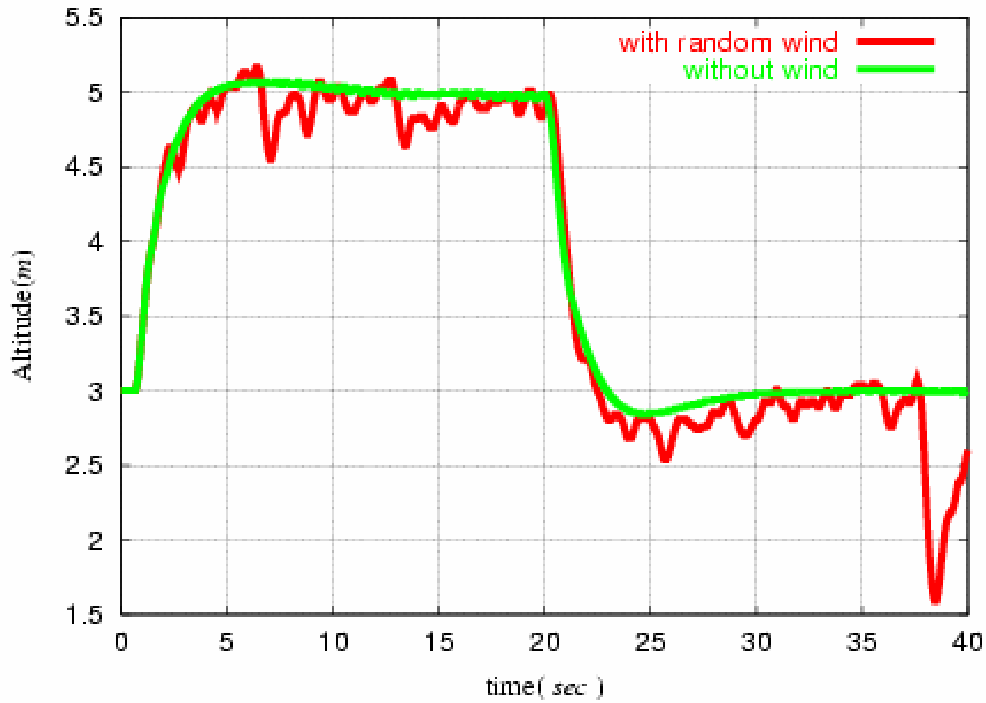
Improvement of Robustness → Reduction of the Performance

Optimal Controllers

Response in Climbing

||

Response in Descending

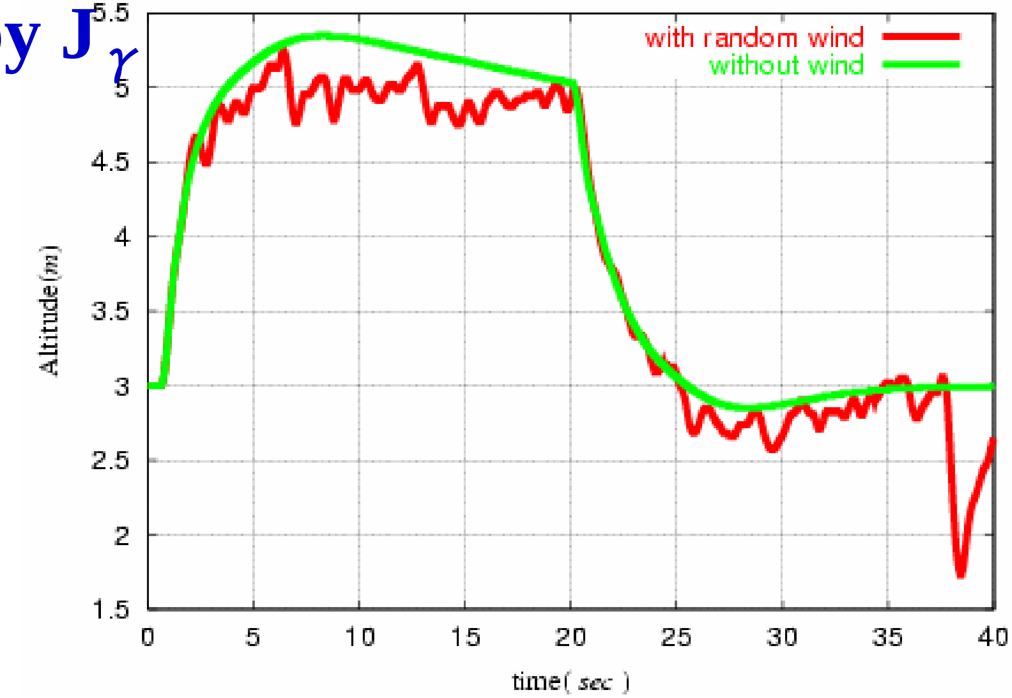


Neural Network trained by J_γ

Response in Climbing

∦

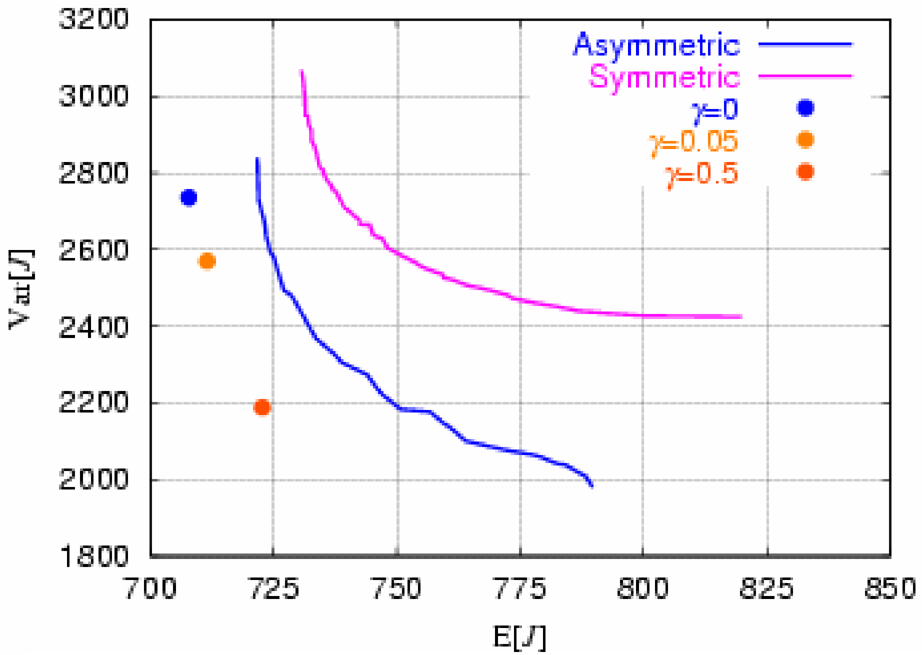
Response in Descending

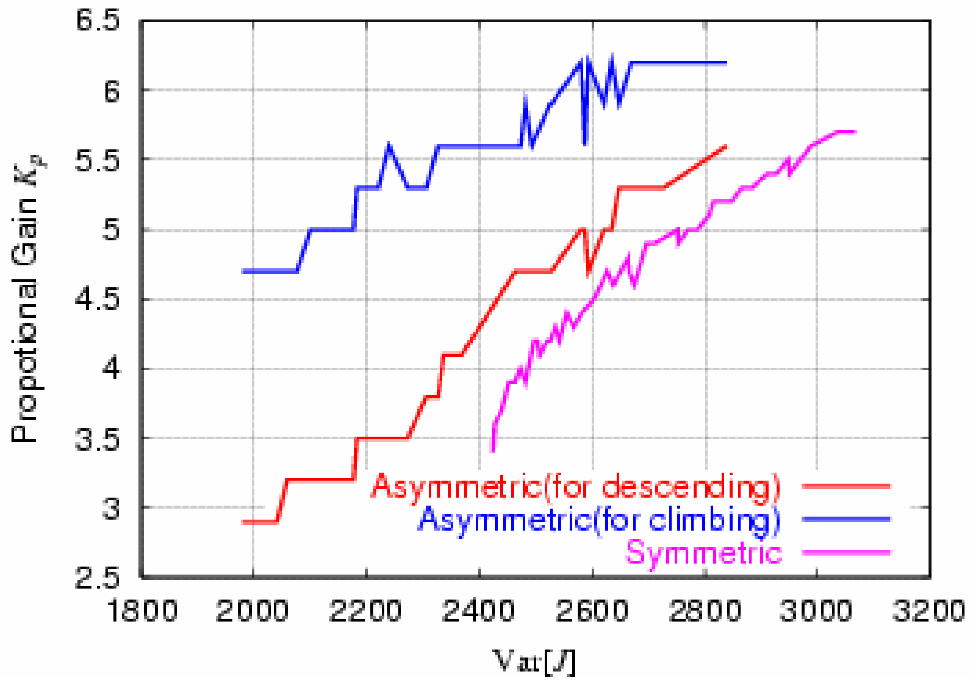


Designing Robust Controllers

Robust Controller ⇔Pareto-Optima

- PD Controllers
  (Symmetric Controllers)
- Gain Scheduling Controllers
  (Asymmetric Controllers)





- Performance
- Robustness

are both improved
by our design method

Environments of Flight Experiments

Data modem

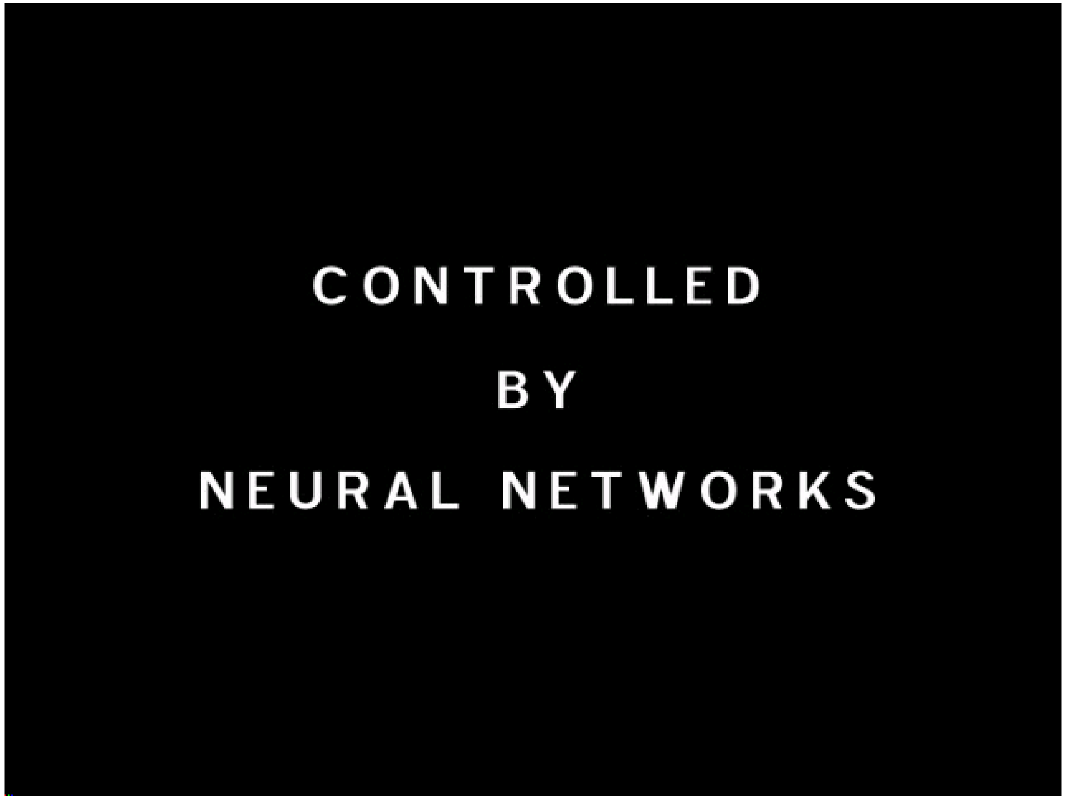
Controller
Note PC
Pentium3 650Mz
OS RT-Linux

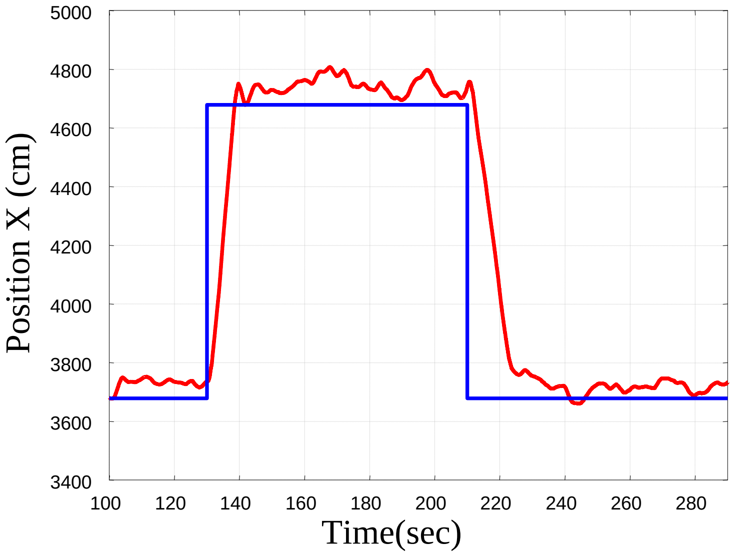
Inertial Sensor(3 axis Platform)
- Accelerometers
- Gyroscopes

D-GPS

Magnetic Azimuth Compass

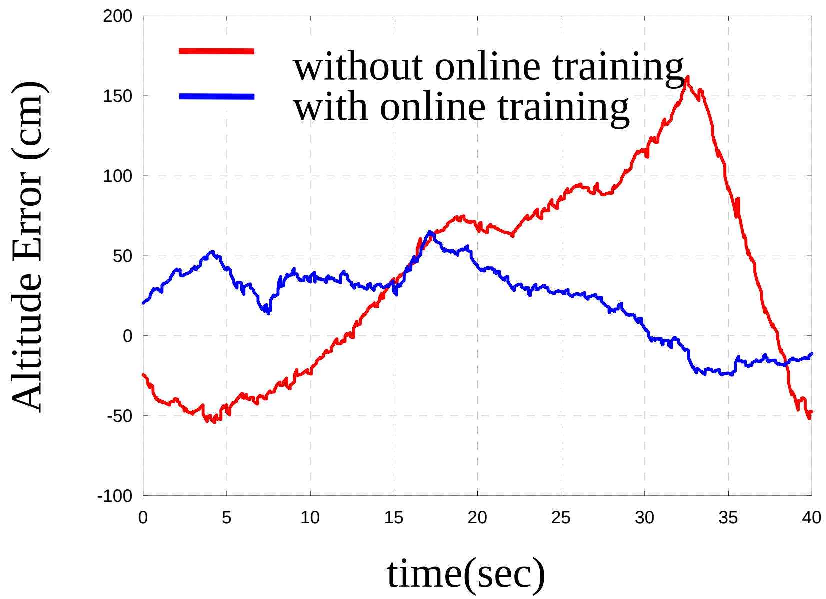
Flight Experiment
(Controlled by Trained Neural Network)





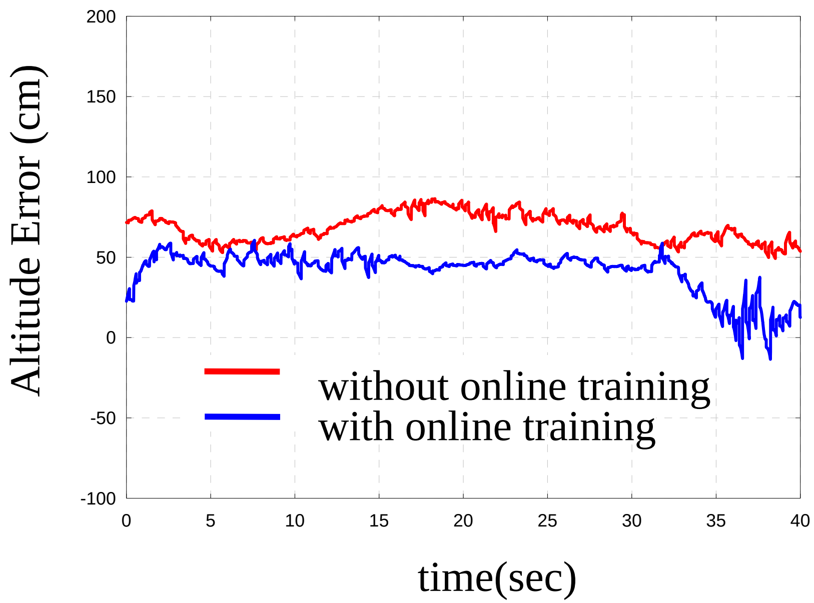
Results of Flight Experiments

- Hovering by PD Controller



	E[err] (cm)	Var[err] (cm^2)
without online training	37.8	3832.4
with online training	22.3	554.4

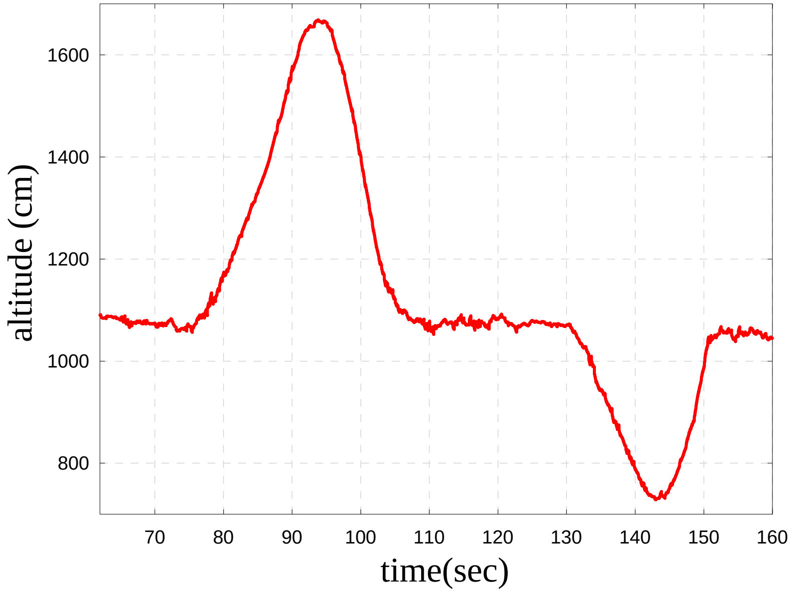
- Hovering by Neural Networks

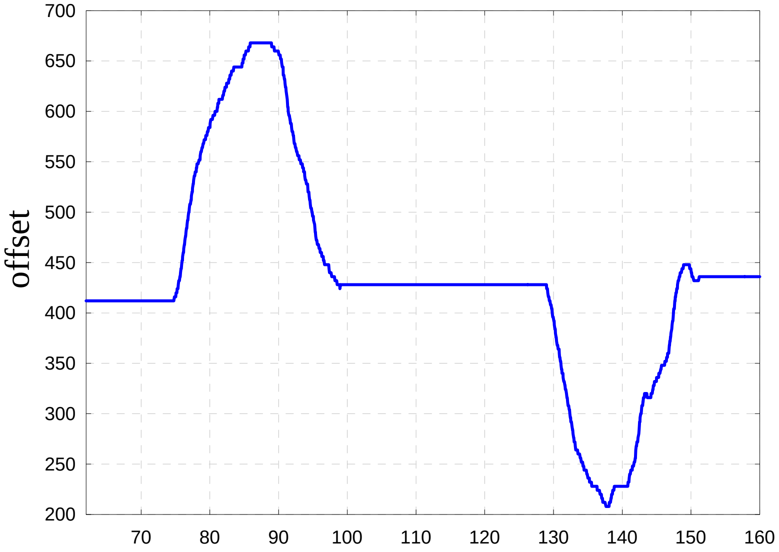


	E[err] (cm)	Var[err] (cm^2)
without online training	68.5	77.9
with online training	41.6	174.5

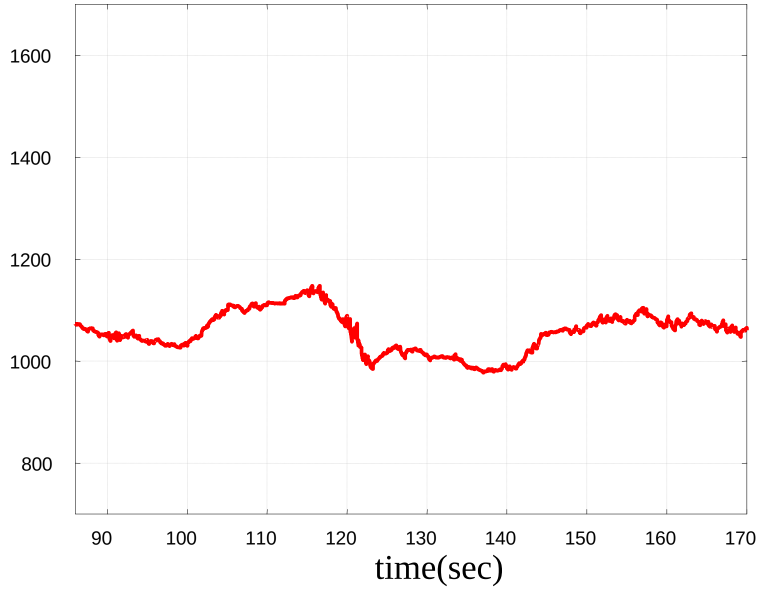
Gust Responses (Emulated Experiments)

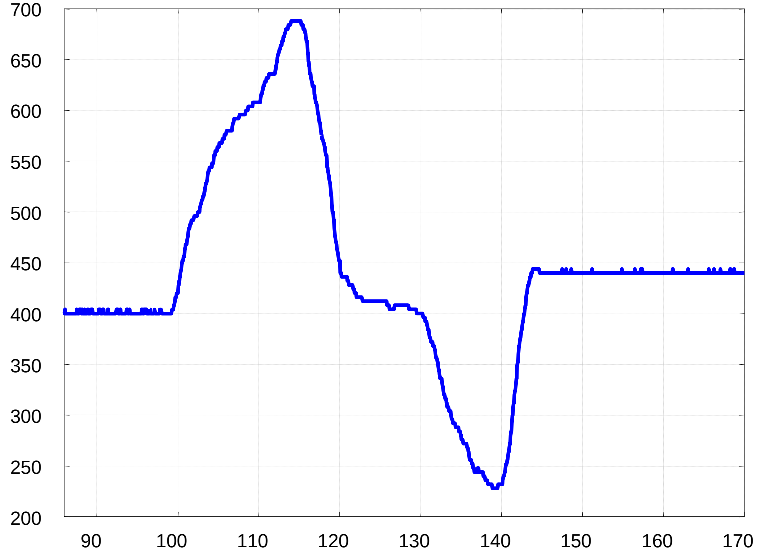
without online training





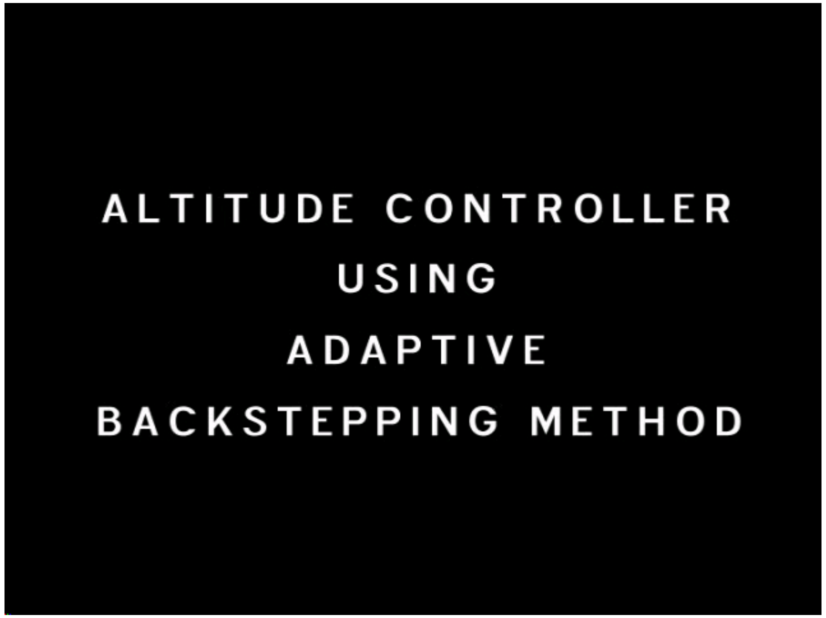
with online training

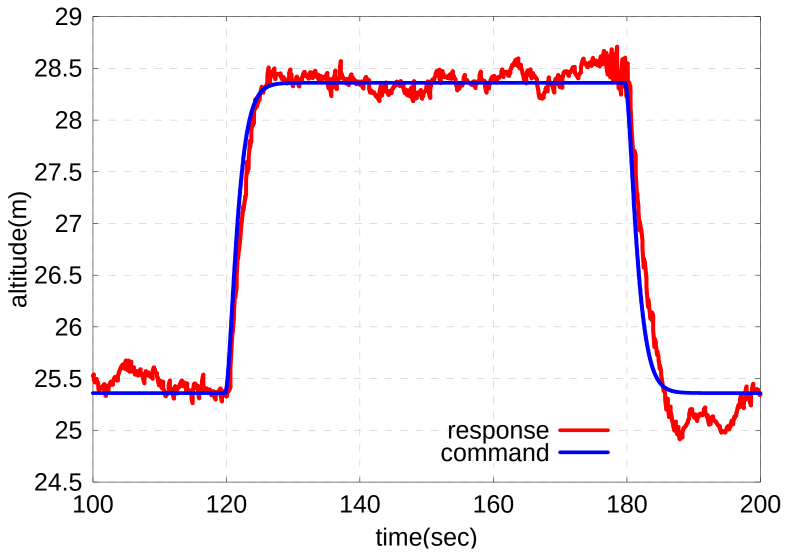


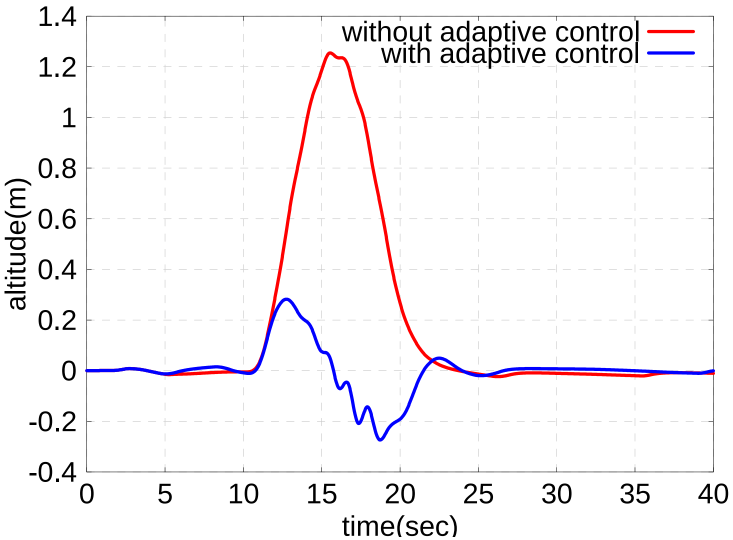


Adaptive Flight Control

Towards Reconfigurable Controllers







Effective in reducing the effect of the gust.

Applications of Autonomous Unmanned Helicopter

Trial Experiment made by a Team of Yamaha Motor:

Observation of Damages caused by Eruption of Mt. Usu in Hokkaido, Japan, April, 2000

Promising Area of Applications launched by the Ministry of Education, Culture, Sports, Science and Technology

(1) Project "Research Revolution 2002"

- Life Science
- Information and Communication
- Environment
- Nanotechnology
- Disaster Prevention

Disaster Prevention

(Special Project on Prevention and Reduction of Losses caused by Earthquake in Megalopolises)

1. Prediction of strong seismic wave
2. Development of anti-earthquake structures
3. **Rescue of earthquake victims**

   Information gathering robots, Intelligent sensors, etc.
4. Development of anti-earthquake procedures

\3,100,000,000JPY ($25,800,000USD) will be funded only in the first year, 2002.

(2) Research Project on "Technology of Humanitarian Detection and Removal of Anti-personnel Mines"

Technology to be developed:

1) Advanced sensor technology that can detect 100% of anti-personnel mines

2) Access and control technology that can carry the above sensors into minefield and can detect and remove mines safely and effectively

More than \5,000,000,000JPY ($41,700,000USD) will be funded in each year, starting in 2002.

We are intending to make proposals based on our Autonomous Unmanned Helicopter to both of the Projects.

We do hope that our proposals attract reviewers attention and some \200,000,000JPY ($1,700,000USD) will be funded to our two research projects

Peace on earth, no mines and no disasters on earth!!!

Thank you very much for your kind attention!!!