

An attitude control of stabilizing system using indirect adaptive fuzzy control

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Abstract: The purpose of a tracking control system is to track a moving target and to find the exact information of the target. If the platform of the tracking control system is equipped on a moving vehicle such as a ship, the tracking control system will treat even the additional platform motion. In order to avoid the complexity comprising the tracking control system, a process to treat the platform motion, named stabilizing system, must be separated from the tracking control system. In this paper, a method to comprise an attitude control system for the platform stabilization is proposed using an adaptive fuzzy control which is applicable to the system with structural and parametric uncertainty. The suggested adaptive fuzzy control algorithm is the 2nd/1st-type indirect adaptive fuzzy control algorithm using the advantages of 1st-type and 2nd-type indirect adaptive fuzzy control algorithm. Several experiments using the implemented stabilizing system are executed for verifying the effectiveness of the suggested method.

Keywords: Active stabilization, Indirect adaptive fuzzy control, Structural and parameter uncertainty, 1st-type and 2nd-type.

1. Introduction

The purpose of a tracking system equipped on a platform is to track the moving target and to find the exact motional information of the target in view of the azimuth angle and the elevation angle.

When the tracking system is equipped on the moving platform such as a moving car, a moving ship, a running person or etc., the tracking system will need the additional information about the motion of the platform in order to compensate it. Naturally, it may not only cause the complexity to comprise the corresponding tracking control system but also cause the degradation of the tracking performance [1].

In order to solve the above problem, it needs to design a stabilizing system and the tracking system independently and separately. In this case, the stabilizing system has only a function to compensate the motion of the platform on which the tracking system is equipped, while the tracking system can be fully devoted into the function to track the target.

The applications of the platform stabilizing system can widely be found for equipment on board of ships [2], the sun tracking control system equipped on moving vehicles [3], a camera servo control system to take a stable image against the vibration of the camera [4], and etc.

In order to accomplish the above purpose, in this paper, a scheme to comprise the stabilizing system using an active control method is discussed and also a real system with two-degree-of-freedom (DOF) is

physic

ally implemented. Moreover, an adaptive fuzzy control algorithm as the active control method is suggested, which is applicable to systems with structural complexity and parameter uncertainty. A lot of researches [1][2][4]-[9] has been accomplished in order to control the linear or nonlinear system with the structural complexity and the unmatched uncertainty. The suggested control algorithm is the 2nd/1st-type indirect adaptive fuzzy control algorithm using advantages of 1st-type and 2nd-type adaptive control [8] and it is implemented as the controller based on CPU. Several experiments using the implemented stabilizing system are executed and then experimental results are analyzed in order to verify the performance and the effectiveness of the suggested stabilizing system.

2. Stabilizing System

A stabilizing system considered in this paper is shown in **Figure 1**. It has two DOF axes in order to control the attitude of the platform in the direction of x-axis and y-axis. The composition and functional explanation of the stabilizing system are as follows. A pair of a gyro, a motor and a potentiometer is installed at each axis. The gyro detects the angular velocity about the rotation axis, the motor drives the corresponding gimbal comprising the platform, and the potentiometer measures the rotation angle of the gimbal shaft driven by the motor. The

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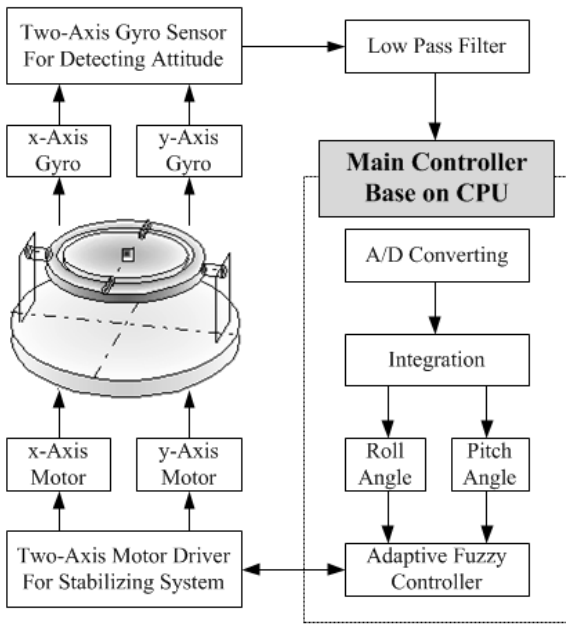


Figure 1: A stabilizing system considered in this paper.

gyro signals are transferred to A/D converter through low pass filters and a multiplexer. The velocity data from the A/D converter are integrated in CPU and thus the roll angle about x-axis and the pitch angle about y-axis are calculated. The calculated angles are used in adaptive fuzzy control algorithm to generate the control signals to drive axis motors. Then, each axis motor drives to stabilize the platform.

Figure 2 shows a stabilizing system physically implemented in this paper. It is used to execute several experiments to acquire results that are used to verify the effectiveness of the suggested stabilizing system.

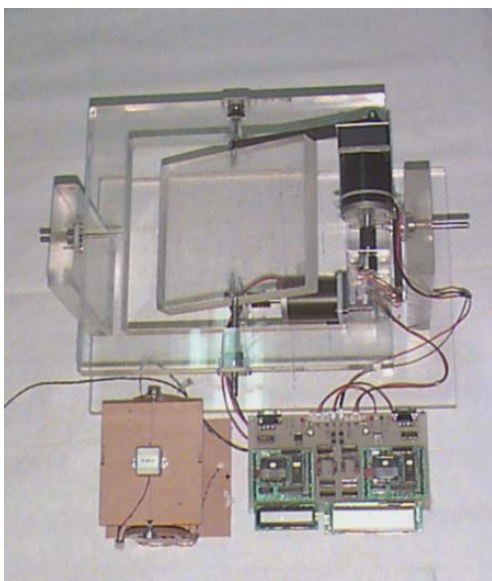


Figure 2: A stabilizing system physically implemented in this paper for experiments.

3. Indirect Adaptive Fuzzy Control

In this section, an indirect adaptive fuzzy control theory [3] is considered, which is an active control method used to generate control inputs of gimbal axes for stabilizing the platform. The reason for using adaptive fuzzy control is that it is so adequate to control the system, just as the stabilizing system, which cannot be exactly modeled by the mathematical equation owing to the structural complexity. Indirect adaptive control theory is classified into 1st-type and 2nd-type and each has advantages and disadvantages.

Figure 3 shows the general structure of the indirect adaptive fuzzy controller in [8]. The feature of the structure is that the control input for the unknown plant is generated using an identification model updated by the adaptive law and fuzzy basis function.

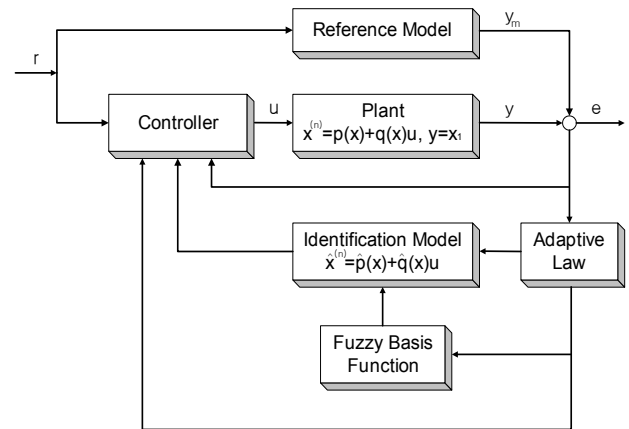


Figure 3: General structure of the indirect adaptive fuzzy controller

3.1 Identification Model

Consider the given nonlinear plant described by the n th-order differential equation shown in Equation (1) or Equation (2).

$$\begin{aligned} \dot{x}_1 &= x_2, \quad \dot{x}_2 = x_3, \dots, \quad \dot{x}_{n-1} = x_n, \\ \dot{x}_n &= p(x_1, x_2, \dots, x_n) + q(x_1, x_2, \dots, x_n)u, \quad y = x_1 \quad (1) \\ x^{(n)} &= p(x, \dot{x}, \dots, x^{(n-1)}) + q(x, \dot{x}, \dots, x^{(n-1)})u, \quad y = x \quad (2) \end{aligned}$$

where $p(\mathbf{x})$ and $q(\mathbf{x})$ are unknown plant functions, $u \in \mathbb{R}$ and $y \in \mathbb{R}$ are an input and an output of the plant respectively, and $\mathbf{x} = [x_1, x_2, \dots, x_n]^T = [x, \dot{x}, \dots, x^{(n-1)}]^T \in \mathbb{R}^n$ is a state vector of the plant. Then, the unknown functions are identified by the indirect control algorithm given as Equation (3).

$$\hat{p}(\mathbf{x} | \boldsymbol{\beta}_p) = \boldsymbol{\beta}_p^T \boldsymbol{\xi}_p(\mathbf{x}) \quad (3)$$

$$\hat{q}(\mathbf{x} | \boldsymbol{\beta}_q) = \boldsymbol{\beta}_q^T \boldsymbol{\xi}_q(\mathbf{x})$$

where $\boldsymbol{\beta}(\mathbf{x})$ is adaptation parameter vector and $\boldsymbol{\xi}(\mathbf{x})$ is fuzzy basis function vector defined as **Equation (4)**.

$$\boldsymbol{\beta} = [\beta_1, \dots, \beta_M]^T, \quad (4)$$

$$\boldsymbol{\xi}(\mathbf{x}) = [\xi_1(\mathbf{x}), \dots, \xi_M(\mathbf{x})]^T, \quad \xi_i(\mathbf{x}) = \frac{\prod_{l=1}^n \mu_{F_l^i}(x_l)}{\sum_{l=1}^M [\prod_{l=1}^n \mu_{F_l^l}(x_l)]}$$

3.2 Control Objective

The control objective of the indirect adaptive control is to determine the control input $u = u(\mathbf{x} | \boldsymbol{\beta})$ in order to satisfy **Equation (5)** based on fuzzy logic.

$$\lim_{t \rightarrow \infty} e(t) = \lim_{t \rightarrow \infty} [y_m(t) - y(t)] = 0 \quad (5)$$

In this case, an adaptive law for adjusting the parameter $\boldsymbol{\beta}$ can be achieved under the assumption that the given system should be globally stable and all variables should be uniformly bounded.

If the functions $p(\mathbf{x})$ and $q(\mathbf{x})$ are known, the control law given as **Equation (6)** results in **Equation (7)** which implies the main control objective $\lim_{t \rightarrow \infty} e(t) = 0$ **Equation (5)**.

$$u = \frac{1}{q(\mathbf{x})} [-p(\mathbf{x}) + y_m^{(n)} + \mathbf{k}^T \mathbf{e}] \quad (6)$$

$$e^{(n)} + k_1 e^{(n-1)} + \dots + k_{n-1} \dot{e} + k_n e = 0 \quad (7)$$

where, $\mathbf{e} = [e, \dot{e}, \dots, e^{(n-1)}]^T$ is the state error vector.

Unfortunately, the problem is that $p(\mathbf{x})$ and $q(\mathbf{x})$ are unknown, and so they must be identified using adaptive fuzzy control algorithm.

3.3 Certainty Equivalent Control

If unknown plant dynamics $p(\mathbf{x})$ and $q(\mathbf{x})$ are substituted by $\hat{p}(\mathbf{x} | \boldsymbol{\beta}_p)$ and $\hat{q}(\mathbf{x} | \boldsymbol{\beta}_q)$ respectively, the resultant control law can be given as **Equation (8)**.

$$u_c = \frac{1}{\hat{q}(\mathbf{x} | \boldsymbol{\beta}_q)} [-\hat{p}(\mathbf{x} | \boldsymbol{\beta}_p) + y_m^{(n)} + \mathbf{k}^T \mathbf{e}] \quad (8)$$

By applying **Equation (8)** to **Equation (2)**, the error differential equation can be obtained as shown in **Equation (9)**.

$$\dot{e}^{(n)} = -\mathbf{k}^T \mathbf{e} + [\hat{p}(\mathbf{x} | \boldsymbol{\beta}_p) - p(\mathbf{x})] + [\hat{q}(\mathbf{x} | \boldsymbol{\beta}_q) - q(\mathbf{x})] u_c \quad (9)$$

And **Equation (9)** can be transformed into error state equation shown as **Equation (10)**.

$$\dot{\mathbf{e}} = \Lambda_c \mathbf{e} + \mathbf{b}_c [\{\hat{p}(\mathbf{x} | \boldsymbol{\beta}_p) - p(\mathbf{x})\} + \{\hat{q}(\mathbf{x} | \boldsymbol{\beta}_q) - q(\mathbf{x})\} u_c] \quad (10)$$

where Λ_c and \mathbf{b}_c are given as **Equation (11)** as followings and they can be considered as system matrix and input matrix for the derived error dynamic system given as **Equation (10)**.

$$\Lambda_c = \begin{bmatrix} 0 & 1 & 0 \dots 0 & 0 \\ 0 & 0 & 1 \dots 0 & 0 \\ \dots & \dots & \dots & \dots \\ 0 & 0 & 0 \dots 0 & 1 \\ -k_n & -k_{n-1} & \dots & -k_1 \end{bmatrix}, \quad \mathbf{b}_c = \begin{bmatrix} 0 \\ 0 \\ \dots \\ 0 \\ 1 \end{bmatrix} \quad (11)$$

Since the control law **Equation (8)** was derived under the assumption that the output error should be bounded, Λ_c is a stable matrix, that is the roots of $\det(s\mathbf{I} - \Lambda_c) = 0$ are stable, there exists a positive definite matrix \mathbf{P} which satisfy **Equation (12)**.

$$\Lambda_c^T \mathbf{P} + \mathbf{P} \Lambda_c = -\mathbf{Q} \quad (12)$$

If a Lyapunov function candidate V_e is chosen as **Equation (13)** which is positive definite except that $\mathbf{e} \neq \mathbf{0}$, the time derivative \dot{V}_e can be derived as **Equation (13)**.

$$V_e = \frac{1}{2} \mathbf{e}^T \mathbf{e} \quad (13)$$

$$\dot{V}_e = -\frac{1}{2} \mathbf{e}^T \mathbf{Q} \mathbf{e} + \mathbf{e}^T \mathbf{P} \mathbf{b}_c [\{\hat{p}(\mathbf{x} | \boldsymbol{\beta}_p) - p(\mathbf{x})\} + \{\hat{q}(\mathbf{x} | \boldsymbol{\beta}_q) - q(\mathbf{x})\} u_c] \quad (14)$$

Thus, if the time derivative is less than or equal to 0, that is $\dot{V}_e \leq 0$, the control law **Equation (8)** is very sufficient to control the given

unknown plant. By the way, it is very difficult to find the control u_c which forces the last term of **Equation (14)** less than 0 such that $\dot{V}_e \leq 0$.

3.4 Supervisory Control

In order to control the given unknown plant by the indirect adaptive control, it is necessary to find the control input u which satisfy $\dot{V}_e \leq 0$. This problem can be solved by appending another control term u_s to u_c . It is called a supervisory control.

$$u = u_c + u_s \quad (15)$$

Substituting **Equation (15)** into **Equation (2)**, the new error equation can be derived as **Equation (16)**.

$$\begin{aligned} \dot{e} = & \Lambda_c e + b_c [\{ \hat{p}(x | \beta_p) - p(x) \} \\ & + \{ \hat{q}(x | \beta_q) - q(x) \} u_c - q(x) u_s] \end{aligned} \quad (16)$$

In this case, the time derivative of the Lyapunov function candidate is derived as **Equation (17)**.

$$\begin{aligned} \dot{V}_e = & -\frac{1}{2} e^T Q e + e^T P b_c [\{ \hat{p}(x | \beta_p) - p(x) \} \\ & + \{ \hat{q}(x | \beta_q) - q(x) \} u_c - q(x) u_s] \\ \leq & -\frac{1}{2} e^T Q e + | e^T P b_c | [| \hat{p}(x | \beta_p) - p(x) | \\ & + | \hat{q}(x | \beta_q) u_c | + | q(x) u_c |] - e^T P b_c q(x) u_s \end{aligned} \quad (17)$$

If it is assumed that p^U, q^U , and q_L are the plant function bounds such that $|p(x)| \leq p^U < \infty$ and $q_L \leq q(x) \leq q^U < \infty$, the supervisory control u_s which satisfy $\dot{V}_e \leq 0$ can be obtained as **Equation (18)**.

$$\begin{aligned} u_s = & I_1^* \operatorname{sgn}(e^T P b_c) \frac{1}{q_L(x)} [| \hat{p}(x | \beta_p) - p(x) | + p^U(x) \\ & + | \hat{q}(x | \beta_q) u_c | + | q(x) u_c |] \end{aligned} \quad (18)$$

where $I_1^* = 1$ if $V_e > \bar{V}$ and $I_1^* = 0$ if $V_e \leq \bar{V}$.

3.5 Derivation of the Adaptive Laws

It is necessary to derive the adequate adaptive law to find the adaption parameters β_p and β_q of the fuzzy logic system.

This problem can begin by defining the minimum approximation error ω shown in **Equation (19)**.

$$\omega = [\hat{p}(x | \beta_p^*) - p(x)] + [\hat{q}(x | \beta_q^*) - q(x)] u_c \quad (19)$$

where β_p^* and β_q^* are defined so as to satisfy **Equation (20)**.

$$\beta_p^* = \arg \min_{\beta_p \in \Omega_p} [\sup_{x \in U_c} | \hat{p}(x | \beta_p) - p(x) |] \quad (20)$$

$$\beta_q^* = \arg \min_{\beta_q \in \Omega_q} [\sup_{x \in U_c} | \hat{q}(x | \beta_q) - q(x) |]$$

If $\hat{p}(x | \beta_p)$ and $\hat{q}(x | \beta_q)$ are selected as fuzzy logic system according to **Equations (3)** and **(4)**, the error equation given as **Equation (16)** can be rewritten as **Equation (21)**.

$$\dot{e} = \Lambda_c e - b_c q(x) u_s + b_c \omega + b_c [\Phi_p^T \xi_p(x) + \Phi_q^T \xi_q(x) u_c] \quad (21)$$

where $\Phi_p = \beta_p - \beta_p^*$, $\Phi_q = \beta_q - \beta_q^*$, and $\xi(x)$ is the fuzzy basis function given as **Equation (4)**.

In order to derive the adaptive laws, consider the Lyapunov function candidate defined as **Equation (22)**, where v_1 and v_2 are positive constants.

$$V = \frac{1}{2} e^T P e + \frac{1}{2v_1} \Phi_p^T \Phi_p + \frac{1}{2v_2} \Phi_q^T \Phi_q \quad (22)$$

The time derivative of V along the trajectory given as **Equation (21)** is derived as **Equation (23)**.

$$\begin{aligned} \dot{V} = & -\frac{1}{2} e^T Q e - q(x) e^T P b_c u_s + e^T P b_c \omega \\ & + \frac{1}{v_1} \Phi_p^T [\dot{\beta}_p + v_1 e^T P b_c \xi_p(x)] \\ & + \frac{1}{v_2} \Phi_q^T [\dot{\beta}_q + v_2 e^T P b_c \xi_q(x)] \end{aligned} \quad (23)$$

Therefore, the adaptive laws for parameters β_p and β_q can be obtained as **Equation (24)** such that $\dot{V} = -\frac{1}{2} e^T Q e \leq 0$ when $\omega = 0$.

$$\dot{\beta}_p = -v_1 e^T P b_c \xi_p(x) \quad (24)$$

$$\dot{\beta}_q = -v_2 e^T P b_c \xi_q(x) u_c$$

3.6 Characteristics of 1st and 2nd-type Indirect Adaptive Fuzzy Controller

The structure of the indirect adaptive fuzzy controller is classified into the 1st and the 2nd-type whether the membership functions for calculating fuzzy basis functions $\xi(x)$ given as **Equation (4)** are fixed or not.

Figure 4 shows the structure of the 1st-type indirect adaptive controller. Since it uses the fixed membership functions, it has a low freedom in comprising the fuzzy logic system, it needs a large number of rules inevitably. In that aspect, it wastes much time to execute all rules for computing fuzzy basis functions. On the other hand, the adaptive laws which adjust the adaptation parameters are very simple.

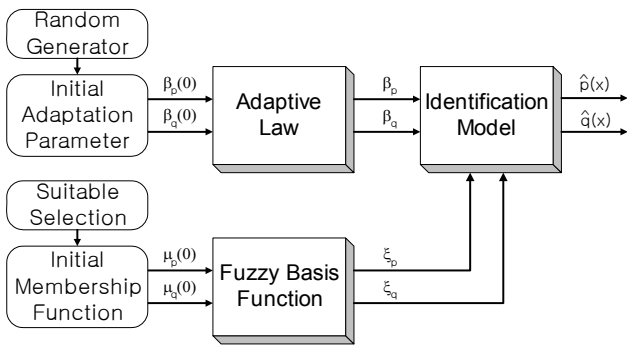


Figure 4: The structure of the 1st-type indirect adaptive fuzzy controller.

Figure 5 shows the structure of the 2nd-type indirect adaptive controller. Fuzzy basis functions are composed and calculated using the adjustable membership functions in the IF parts of the fuzzy rules. Thus fuzzy logic functions $\hat{p}(x | \beta_p)$ and $\hat{q}(x | \beta_q)$ are decided using rules smaller than those of 1st-type controller. Whereas, the adaptive laws which adjust the adaptation parameters are very complicated and the adaptive laws for adjusting membership functions must be required. For this reason, the pure 2nd-type indirect adaptive fuzzy controller is not preferable to the real-time control applications.

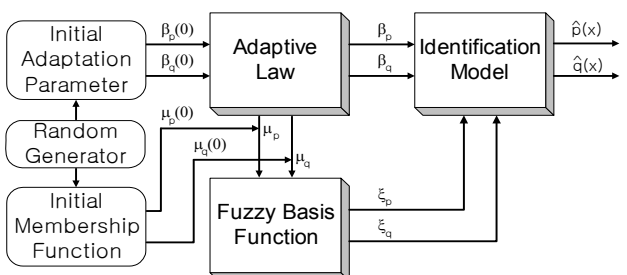


Figure 5: The structure of the 2nd-type indirect adaptive fuzzy controller.

3.7 Suggestion of a New 2nd/1st-type Indirect Adaptive Fuzzy Controller

In section 3.6, the structures, advantages, and disadvantages for the 1st-type and 2nd-type indirect adaptive fuzzy controller were investigated. The 1st-type has an advantage in the type of fuzzy basis functions in the viewpoint that all basis functions are fixed. And also it has another advantage in the adaptive laws because the adaptive laws are simple. On the other hand, the 2nd-type has an advantage that it uses much smaller fuzzy rules than 1st-type because it tuned initial adaptation parameters and initial membership functions.

In this section, a new 2nd/1st-type indirect adaptive fuzzy control structure is suggested. Figure 6 presents the suggested control structure. Its control algorithm is composed by adopting the advantages of 1st-type and initial adaptation parameters and initial membership functions indirect adaptive fuzzy control structure. As meaning of the name, initial fuzzy basis functions are tuned in a way that initial adaptation parameters and initial membership functions are decided by 2nd-type in order to reduce the number of fuzzy rules. It results in the same number of rules as those of 2nd-type structure. After then, all fuzzy basis functions are fixed during running adaption process as if it were the 1st-type case. It means that the adaptive laws are as simple as the case of 1st-type structure.

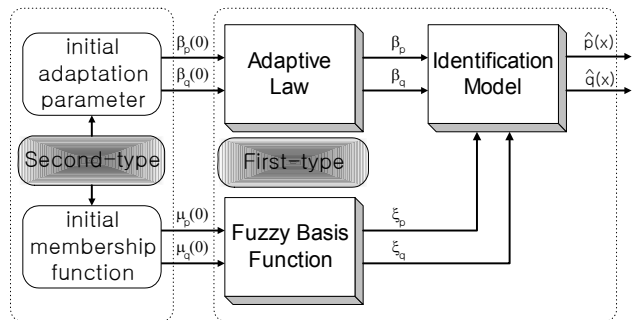


Figure 6: The structure of the 2nd/1st-type indirect adaptive fuzzy controller suggested in this paper.

The purpose to suggest the 2nd/1st-type indirect adaptive fuzzy control structure is not only to improve the control performance but also to implement a real-time control system in spite of using low-price CPU.

4. An Attitude Control for Stabilizing System

4.1 Mathematical Model of the Stabilizing System

This chapter deals with an attitude control for the stabilizing system implemented with two DOF, as shown in **Figure 2**.

The plant dynamic for the roll plant of the implemented stabilizing system can be modeled as a highly nonlinear 2nd-order differential equation with parametric uncertainties given as **Equation (25)**. The

$$\begin{aligned}
 |p(\mathbf{x})| &\leq |-3.625x_2| + |4.5 \sin(x_1) \cos(x_2)| \\
 &\quad + |a_1(t)x_1x_2| \leq p^U = 11.02 \\
 |q(\mathbf{x})| &\leq 6.25 + |a_2(t)| \leq q^U = 8.25 \\
 |q(\mathbf{x})| &\geq 6.25 - |a_2(t)| \geq q_L = 4.25
 \end{aligned}
 \tag{28}$$

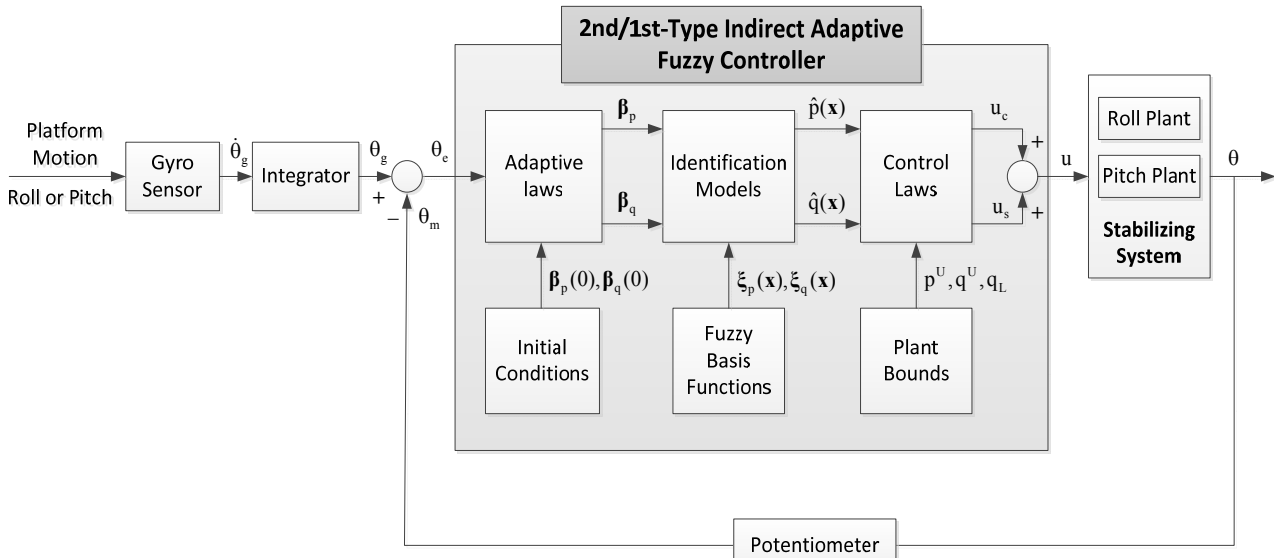


Figure 7: The control structure of the 2nd/1st-type indirect adaptive fuzzy control system for each roll and pitch plant.

plant dynamic for the pitch plant can also be modeled as the same nonlinear 2nd-order differential equation as **Equation (25)**. The only difference between the roll and pitch plant is the magnitudes of the least upper bounds for the uncertainties $a_1(t)$ and $a_2(t)$ in **Equation (25)**.

Unfortunately, the exact magnitude of the each least upper bound for the two plants cannot be known.

$$\begin{aligned}
 \ddot{x}(t) &= p(\mathbf{x}) + q(\mathbf{x})u \tag{25} \\
 p(\mathbf{x}) &= -3.625x_2 + 4.5 \sin(x_1) \cos(x_2) + a_1(t)x_1x_2 \\
 q(\mathbf{x}) &= 6.25 + a_2(t)
 \end{aligned}$$

The limits of the states x_1 and x_2 and the limit of the control input u were prescribed as **Equation (26)** and the least upper bounds for uncertainties $a_1(t)$ and $a_2(t)$ were supposed as **Equation (27)**.

$$-\frac{\pi}{6} \leq x_1 \leq \frac{\pi}{6}, \quad -\frac{4\pi}{9} \leq x_2 \leq \frac{4\pi}{9}, \quad 0 \leq u \leq 25 \tag{26}$$

$$|a_1(t)| \leq 5, \quad |a_2(t)| \leq 2 \tag{27}$$

In this case, plant constraint limits are calculated as **Equation (28)**.

4.2 Attitude Controller Design for the Stabilizing System Physically Implemented

As referred in section 4.1, the dynamic characteristic of the given stabilizing system with two DOF is highly nonlinear and its model uncertainties caused by the structural complexity are not known.

Figure 7: The control structure of the 2nd/1st-type indirect adaptive fuzzy control system for each roll and pitch plant.

For the control of the attitude of this system, the indirect adaptive fuzzy control, named 2nd/1st-type indirect adaptive fuzzy control algorithm developed in chapter 3, was applied to the roll and pitch plant, respectively. The controller structure of each plant including hardware and software are the same. In the design process of each control system, it was assumed that the plant dynamics having been modeled in section 4.1 should be unknown.

Figure 7 represents a block diagram of 2nd/1st-type indirect adaptive fuzzy control structure for each roll and pitch plant. And variables and functions described in the **Figure 7** are explained as followings:

θ_g : integrated value of the gyro sensor output

θ_m : motor output angle measured by potentiometer

θ_e : angle error signal

u_c : certainty equivalent control

u_s : supervisory control

$u = u_c + u_s$: control input for the plant

$\hat{p}(\mathbf{x}), \hat{q}(\mathbf{x})$: identified plant functions

$\beta_p(0), \beta_q(0)$: initial adaption parameters

β_p, β_q : adjustable parameters by adaptive laws

$\xi_p(\mathbf{x}), \xi_q(\mathbf{x})$: fuzzy basis functions

Two axis gyro sensors were used to measure the attitude of the platform motion, that is roll rate and pitch rate, of the stabilizing system. Therefore, the roll and pitch angle could be obtained by integrating the gyro sensor outputs. Two potentiometers were equipped on the rotating shafts of the roll gimbal and pitch gimbal for measuring the plant outputs. A digital controller was implemented based on CPU in view of hardware and software, in order to generate the control input for each roll and pitch plant. Naturally, the 2nd/1st-type indirect adaptive fuzzy control algorithm was implemented in CPU. By fully considering the computation time of the control algorithm, the sampling time for real time control could be selected as 0.05 second.

In order to identify the plant functions $\hat{p}(\mathbf{x})$ and $\hat{q}(\mathbf{x})$ in adaptive laws, the fuzzy basis functions $\xi_p(\mathbf{x})$ and $\xi_q(\mathbf{x})$ must be computed. To do this, fuzzy rules must be defined based on fuzzy membership functions.

Figure 8 shows a lookup table for generating fuzzy rules necessary to the roll plant control system design. Figure 9 shows membership functions for states x_1 and x_2 of the roll plant.

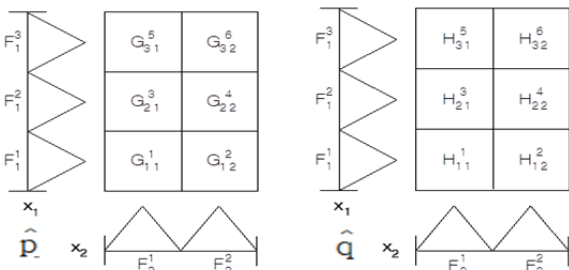


Figure 8: A lookup table for $\hat{p}(\mathbf{x})$ and $\hat{q}(\mathbf{x})$ of the roll plant

Figure 9 shows membership functions for states x_1 and x_2 of the roll plant, which are used in fuzzy rules.

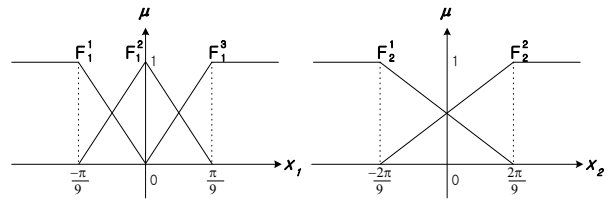


Figure 9: Fuzzy membership functions for states x_1 and x_2 of the roll plant.

By using Figures 8 and 9, the corresponding fuzzy rules for the roll plant can be arranged as follows:

- R_{roll}^1 : IF x_1 is F_1^1 and x_2 is F_2^1 THEN \hat{p} is G_{11}^1 and \hat{q} is H_{11}^1
- R_{roll}^2 : IF x_1 is F_1^1 and x_2 is F_2^2 THEN \hat{p} is G_{12}^2 and \hat{q} is H_{12}^2
- R_{roll}^3 : IF x_1 is F_1^2 and x_2 is F_2^1 THEN \hat{p} is G_{21}^3 and \hat{q} is H_{21}^3
- R_{roll}^4 : IF x_1 is F_1^2 and x_2 is F_2^2 THEN \hat{p} is G_{22}^4 and \hat{q} is H_{22}^4
- R_{roll}^5 : IF x_1 is F_1^3 and x_2 is F_2^1 THEN \hat{p} is G_{31}^5 and \hat{q} is H_{31}^5
- R_{roll}^6 : IF x_1 is F_1^3 and x_2 is F_2^2 THEN \hat{p} is G_{32}^6 and \hat{q} is H_{32}^6

In the similar manner, a lookup table and membership functions must be defined for generating fuzzy rules necessary to the pitch plant control system design. Figures 10 and 11 show them, respectively.

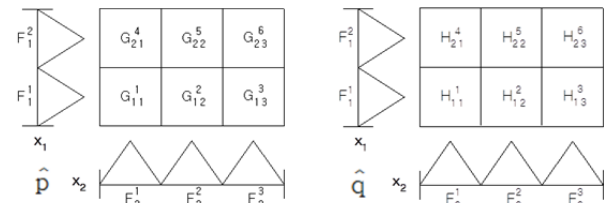


Figure 10: A lookup table for $\hat{p}(\mathbf{x})$ and $\hat{q}(\mathbf{x})$ of the pitch plant.

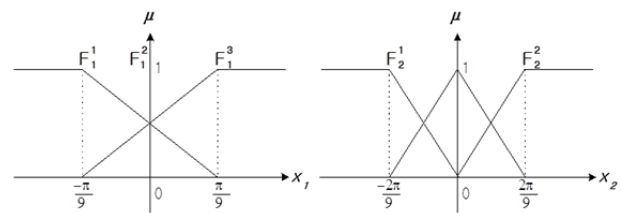


Figure 11: Fuzzy membership functions for states x_1 and x_2 of the pitch plant.

By using Figures 8 and 9, the corresponding fuzzy rules for the pitch plant can be arranged as follows:

- R_{pitch}^1 : IF x_1 is F_1^1 and x_2 is F_2^1 THEN \hat{p} is G_{11}^1 and \hat{q} is H_{11}^1
- R_{pitch}^2 : IF x_1 is F_1^1 and x_2 is F_2^2 THEN \hat{p} is G_{12}^2 and \hat{q} is H_{12}^2

$$R_{pitch}^3 : \text{IF } x_1 \text{ is } F_1^1 \text{ and } x_2 \text{ is } F_2^3 \text{ THEN } \hat{p} \text{ is } G_{13}^3 \text{ and } \hat{q} \text{ is } H_{13}^3$$

$$R_{pitch}^4 : \text{IF } x_1 \text{ is } F_1^2 \text{ and } x_2 \text{ is } F_2^1 \text{ THEN } \hat{p} \text{ is } G_{21}^4 \text{ and } \hat{q} \text{ is } H_{21}^4$$

$$R_{pitch}^5 : \text{IF } x_1 \text{ is } F_1^2 \text{ and } x_2 \text{ is } F_2^2 \text{ THEN } \hat{p} \text{ is } G_{22}^5 \text{ and } \hat{q} \text{ is } H_{22}^5$$

$$R_{pitch}^6 : \text{IF } x_1 \text{ is } F_1^2 \text{ and } x_2 \text{ is } F_2^3 \text{ THEN } \hat{p} \text{ is } G_{23}^6 \text{ and } \hat{q} \text{ is } H_{23}^6$$

4.3 Experiments and Discussion for Results

In order to test the possibility of the suggested control system, several experiments were executed using the stabilizing system shown in **Figure 2**. As a method to generate the platform motion of the stabilizing system, the platform on which the gyro sensors are installed was swung with the angle range about $-30^\circ \leq \theta_g \leq 30^\circ$ by using hands for each roll and pitch plant. The angular velocity of the gyro platform was measured about $\dot{\theta}_g = \pm 30^\circ / \text{s}$ and the swing frequency was about 1/6 Hz, which was similar to the rolling and pitching motion of ships.

Figure 12 shows the experimental results of the simple feedback system for the roll plant without controller. The integrated gyro sensor output is exerted on the feedback system as a reference signal and thus the potentiometer output is just the output of the system.

The upper figure in **Figure 12** is to compare the integrated gyro sensor output with the potentiometer output. The lower figure in **Figure 12** shows the output error between the integrated gyro sensor output and the potentiometer output. From the figure, it is known that the transient response of the simple feedback system for the roll plant reveals a considerable overshoot with the maximal error about $\pm 7^\circ$.

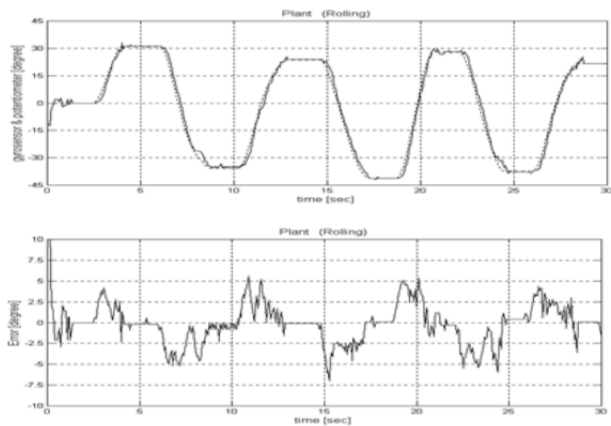


Figure 12: Angular position responses of the simple feedback system for the roll plant with time varying platform motion.

Figure 13 shows the experimental results of the 2nd/1st-type indirect adaptive fuzzy control system for the roll plant. From the figures, it is known that the transient response of the suggested control system for

the roll plant was improved in view of an overshoot. Although the transient response revealed a poor response similar to that of the simple feedback system during transient time, it was improved within the maximal error $\pm 2.0^\circ$ as time was passed to steady state.

Figure 14 shows the experimental results of the simple feedback system for the pitch plant without controller. The upper figure in **Figure 14** is to compare the platform motion as a reference input with the feedback system output for pitch plant. The lower figure in **Figure 14** shows the output error between the platform motion and the system output. From the figure, it is known that the transient response of the simple feedback system for the pitch plant reveals a overshoot with the maximal error with the range -1.0° to 6.0° . A distinguished feature of the error response is that the error was biased on positive side. The reason for this bias is just the influence of the mass unbalance caused by the geometrical complexity of the pitch plant.

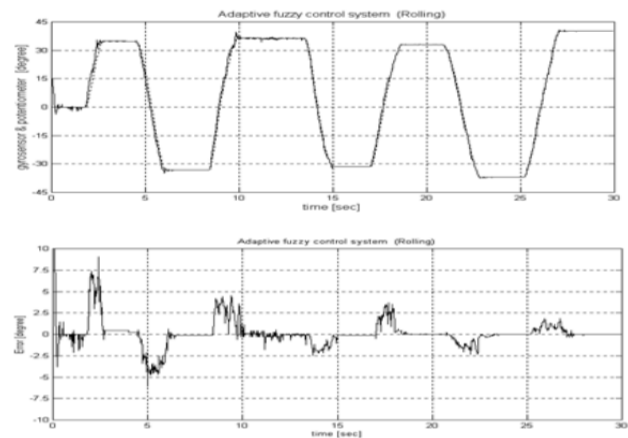


Figure 13: Angular position responses of the suggested control system for the roll plant with time varying platform motion.

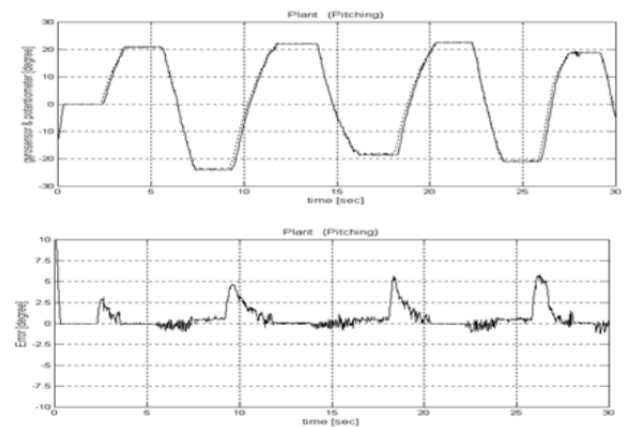


Figure 14: Angular position responses of the simple feedback system for the pitch plant with time varying platform motion.

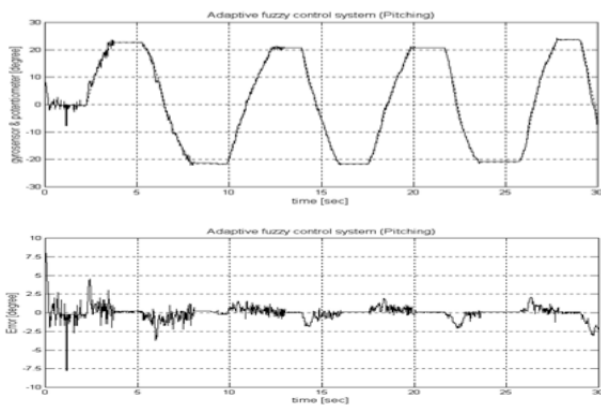


Figure 15: Angular position responses of the suggested control system for the pitch plant with time varying platform motion.

Figure 15 shows the experimental results of the 2nd/1st-type indirect adaptive fuzzy control system for the pitch plant.

From the figures, it is known that the transient response of the suggested control system was improved well in view of the overshoot and the output error. The steady-state response was also improved as time was passed within the maximal error $\pm 2.5^\circ$ and also the bias trend was disappeared.

In the conclusion, the possibility of the indirect adaptive fuzzy control system suggested in this paper for the stabilizing system, was convinced. However, the control performance in terms of the overshoot and the output error in steady-state could not be highly improved. It is noted that the only six fuzzy rules were used to compute the fuzzy basis functions. If the more numbers of fuzzy rules are used, the better performance of the fuzzy control system can be achieved.

5. Conclusions

In this paper, a method to comprise the control system for the stabilizing system with two DOF was suggested. The suggested method is the 2nd/1st-type indirect adaptive fuzzy control algorithm utilizing advantages of 1st-type and 2nd-type indirect adaptive control algorithm. And the control system for the roll and pitch plant of the stabilizing system was implemented in view of hardware and software. Several experiments using the implemented stabilizing system were executed and then results obtained from experiments were analyzed. Conclusively, the effectiveness of the suggested control algorithm was assured by analyzing the experimental results.

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