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A Fuzzy Compensation Technique for Cooperative Control between Two Actuations of an One-wheel Robot

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Abstract: In this paper, a fuzzy compensation (FC) technique along with the on-line system identification of two actuator systems of a one-wheel robot. Recursive least square (RLS) algorithm is used to identify the system with FIR-typed moving average filters for both a gimbal and a body system. To compensate for uncertainties in the modeling process, a fuzzy compensator is designed. Experimental studies of balancing a one-wheel robot are conducted. Performances by different control schemes, FC without RLS and FC with RLS are compared.

Keywords: fuzzy compensator, one-wheel robot, on-line system identification, recursive least square.

1. INTRODUCTION

One-wheel robot system is quite a challenging system in aspects of design and control. Typically for the balancing control of one-wheel system, an indirect actuation induced from a gimbal system by a gyroscopic principle is required. For the driving, a direct actuator is used to rotate the body.

Therefore, cooperation between the gimbal system and the body system can be a main goal for the balancing control of one-wheel robot system. In other words, a roll angle of the body and a tilt angle of the gimbal must be considered simultaneously in control action. The actuator controls both the roll of the body and the tilt of itself simultaneously [1].

Nonholonomic and underactuated properties of the one-wheel system lead us to investigate a more intelligent control method. An indirect adaptive fuzzy control method was proposed for a nonholonomic and underactuated inverted pendulum problem in [2]. An adaptive fuzzy control method was proposed for wheeled mobile robot control [3]. Takagi-Sugeno fuzzy control scheme was proposed for real-time control of an underactuated robot [4]. With a stability viewpoint, the fuzzy stability has been also presented [5]. Unknown or uncertain parameters in the nonlinear control systems were considered in the fuzzy control method [6]. Hardware realization of fuzzy control was implemented [7].

System identification methods have been intensively proposed in the signal processing area. A recursive least square (RLS) method for a nonlinear system based on the model decomposition was proposed [8]. System parameters such as inertia and friction were estimated using a position measurement [9]. A kernel recursive least squares algorithm was proposed [10]. An online parameter estimation method was explored where forgetting factor was considered [11]. A data filtering method was proposed for moving average model [12]. Consequently, LS or RLS has been intensively used for the model identification of unknown or uncertain systems.

In this paper, two actuating systems are identified by the RLS method. Input-output data are respectively used to estimate the system models of gimbal system and body system. Based on the identified model, next step outputs of given systems are estimated and the differences with the real outputs are extracted. Those errors can be used directly via the inverse models of given systems. However, the error in the identified models and a coupled effect between two systems degrade performance.

Therefore, in this paper, the fuzzy compensator is designed along with a RLS method to tackle the aforementioned problem. Experimental studies of balancing a one-wheel robot are conducted to confirm the proposition of the proposed control scheme. Experimental performances by FC and RLS-FC are compared

2. SYSTEM IDENTIFICATION

2.1 RLS algorithm

Unknown or uncertain systems can be identified as a time series in the recursive least squares (RLS) algorithm. When the input and consequent output can be overserved, the coefficients of RLS are estimated. For the time-series system identification, autoregressive (AR), moving average (MA), and autoregressive moving average (ARMA) can be used as a system identification method.

An MA model can be realized as a FIR-filter where stability can be guaranteed. However, the accuracy is poor compared with an AR or an ARMA model at the same order. Considering the control point of view, stability is more important so that MA model is preferred in this paper.

Three taps of FIR filters of two systems are used as simplified models. A system model can be depicted as follows.

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$$y(t) = \mathbf{x}^T \boldsymbol{\psi}(t) \tag{1}$$

$$\mathbf{x}^T = [x(t), x(t-1), \cdots, x(t-n)] \tag{2}$$

$$\boldsymbol{\psi}^T = [a(t), a(t-1), \cdots, a(0)] \tag{3}$$

where, y is the system output, $\mathbf{x}$ is the system input vector, and $\boldsymbol{\psi}$ is the coefficient vector. As an estimation equation of (1), (4) can be considered.

$$y(t) = \mathbf{x}^T \hat{\boldsymbol{\psi}}(t) + \hat{e}(t) \tag{4}$$

$$\hat{e}(t) = y(t) - \mathbf{x}^T \hat{\boldsymbol{\psi}}(t) \tag{5}$$

where, $\hat{e}$ is the estimation error at time t.

Least squares algorithm is the solution for finding out the $\hat{\boldsymbol{\psi}}$ vector considering the criterion function as followings.

$$J = \sum_{t=1}^{N} \hat{e}^2 = \hat{\mathbf{e}}^T \hat{\mathbf{e}} \tag{6}$$

An optimal solution can be found as

$$\frac{\partial}{\partial \hat{\boldsymbol{\psi}}} J = 0 \tag{7}$$

The solution of (7) can be written as follow.

$$\hat{\boldsymbol{\psi}}(t) = [\mathbf{x}^T(t)\mathbf{x}(t)]^{-1}[\mathbf{x}^T(t)\mathbf{y}(t)] \tag{8}$$

Covariance vector is defined as follow.

$$\mathbf{P}(t) = [\mathbf{x}^T(t)\mathbf{x}(t)]^{-1} \tag{9}$$

Based on the Matrix Inversion Lemma, the estimated covariance vector and the estimated coefficient vector can be written as follows.

$$\mathbf{P}(t+1) = \mathbf{P}(t)(\mathbf{I} - \frac{x(t+1)x^T(t+1)\mathbf{P}(t)}{1 + x^T(t+1)\mathbf{P}(t)x(t+1)}) \tag{10}$$

$$\hat{\boldsymbol{\psi}}(t+1) = \hat{\boldsymbol{\psi}}(t) + \mathbf{P}(t+1)\mathbf{x}(t+1)(y(t+1) - \mathbf{x}^T(t+1)\hat{\boldsymbol{\psi}}(t)) \tag{11}$$

$$\hat{y}(t) = \mathbf{x}^T(t)\hat{\boldsymbol{\psi}}(t) \tag{12}$$

$$\hat{y}(t+1) = \hat{y}(t) + x^T(t+1)\hat{\psi}(t+1) \tag{13}$$

As a next step estimation, we have

$$\hat{y}(t+1) = \mathbf{x}^T(t+1)\hat{\boldsymbol{\psi}}(t+1) \approx \mathbf{x}^T(t+1)\hat{\boldsymbol{\psi}}(t) \tag{14}$$

Considering the forgetting factor, the equations can be extended. The forgetting factor λ can be considered to find out the memory index of FIR filter as follow.

$$\text{M.I.} = \frac{1}{1-\lambda} \tag{15}$$

When λ is zero, the memory index becomes 1. This means that the filter considers current states only and neglects all historical data of input. Therefore, the output shows a rapid response property to the current input or states of the system.

However, the detection of the system trend is not easy to find out. As the value λ approaches to one, the memory effect of the filter is increased. This means that many input data are considered in the process. Therefore, the system can be estimated more stably. However, the current accuracy of the estimated output is relatively poor. Therefore, there is the trade-off relation between the accuracy and the stability.

Considering the design factor λ, (10) can be rewritten as

$$\mathbf{P}(t+1) = \frac{1}{\lambda}\left(\mathbf{P}(t)(\mathbf{I} - \frac{x(t+1)x^T(t+1)\mathbf{P}(t)}{\lambda + x^T(t+1)\mathbf{P}(t)x(t+1)})\right) \tag{16}$$

The initial values of the algorithm can be considered as follows.

$$\boldsymbol{\theta}(0) = 0, \mathbf{P}(0) = \delta\mathbf{I} \tag{17}$$

The value of δ is chosen as 10000 and the value of λ is chosen as 0.995.

Considering the RLS algorithm, system outputs can be estimated as Fig. 1.

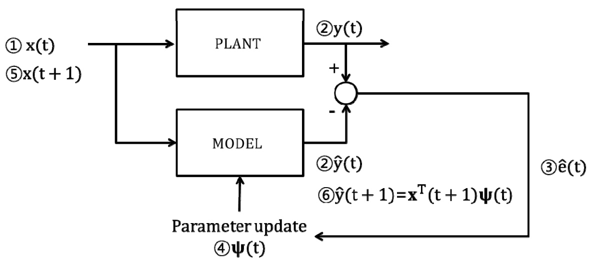
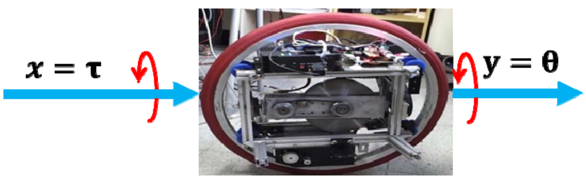


Fig. 1 Proposed RLS algorithm

2.2 RLS-based system identification

Given two systems can be described by input-output data as shown in Fig. 2.

(a) Gimbal system



(b) Body system

Fig. 2 System models for identification

After applying RLS algorithm in both systems, output differences between the estimated output and the actual output are shown in Fig. 3. The transfer function of the identified gimbal system is considered as $G_1(s)$ and the body system as $G(s)$.

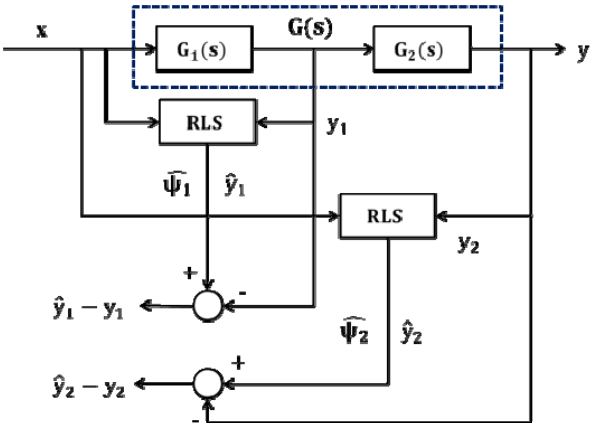


Fig. 3 Proposed RLS application

3. FUZZY COMPENSATOR DESIGN

The overall control block diagram is shown in Fig. 4. A fuzzy compensator is added to the system for merging the influences of two systems of the gimbal system and the body system. Two fuzzy inputs are updated by the on-line RLS algorithm.

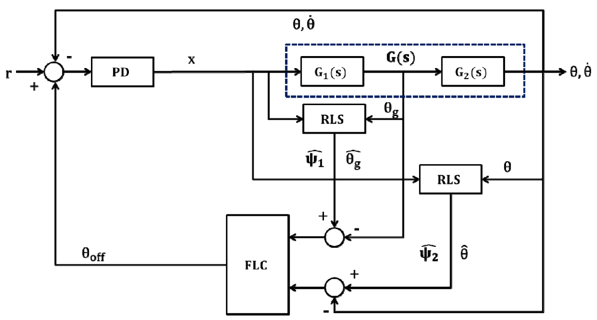


Fig. 4 Proposed control architecture

In the fuzzification process, a real scalar value of RLS estimation results can be translated into fuzzy values. In the error fuzzy set, NB is negative big, NM is negative medium, NS is negative small, ZO is zero, PS is positive small, and PB is positive big.

Fuzzy rules are listed in Table 1.

Table 1. Fuzzy rules

		Error 1				
		NB	NS	ZO	PS	PB
Error 2	NB	N	N	N	ZO	ZO
	NS	N	N	ZO	ZO	P
	ZO	N	N	ZO	P	P
	PS	N	ZO	ZO	P	P
	PB	ZO	ZO	P	P	P

Through the gain adjustments on the output of the designed FC, the fuzzy output is fed back to the main controller added to the reference input so that the fuzzy output adjusts the roll angle as an offset.

4. EXPERIMENTAL STUDY

4.1 Experimental setup

Experimental setup is shown in Fig. 5. Through the data communication cable, control states of the robot are monitored. As an electronic element for algorithm realization, TMS320F28335 is placed on the top of the robot and the control is operated every 10ms.

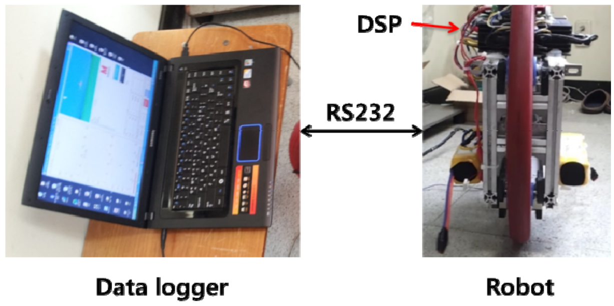
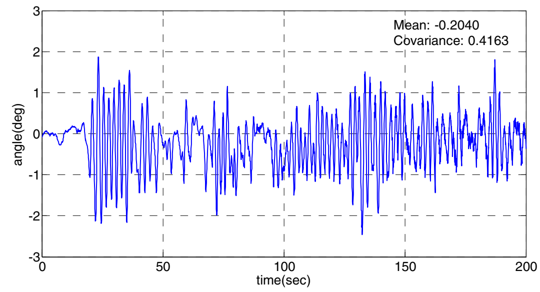


Fig. 5 Experimental setup

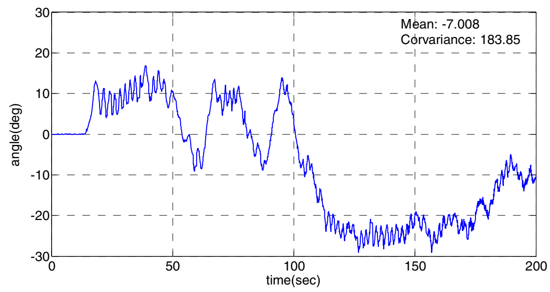
4.2 Experimental result

1) Scheme 1 : Fuzzy compensator scheme

Firstly, the PD+FC scheme without identifying models is investigated. The system outputs of two systems are directly connected to the FC. The results in both the roll angle and the tilt angle are shown in Fig. 6. Although the balancing task has been successfully performed, the deviation of the tilt angle becomes large. The roll angle is maintained within ± 2 degrees.



(a) Roll angle



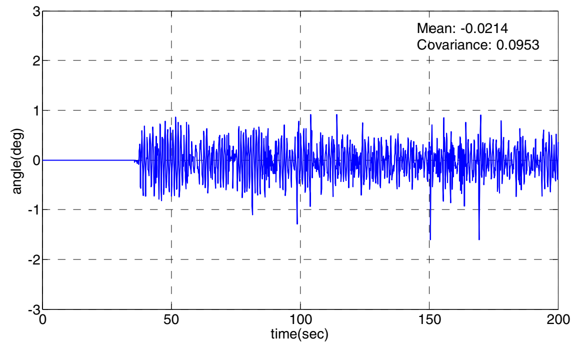
(b) Tilt angle

Fig. 6 FC balancing performances

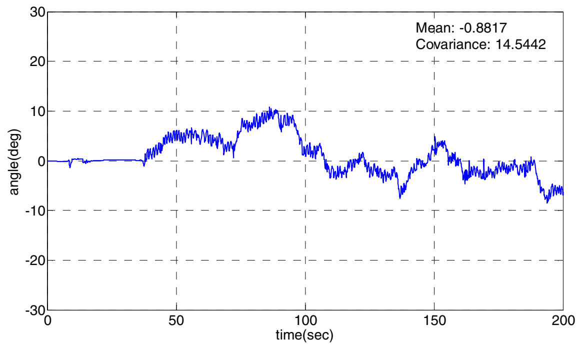
2) Scheme 2: Fuzzy compensator scheme with RLS

The same balancing experiment by the control scheme 2 was conducted. In Fig. 7, the results of two angles by the proposed control method are plotted. The roll angle shown in Fig. 7 (a) is maintained within ± 1 degree which is smaller than that of Fig. 6 (a). The deviation of the tilt angle shown in Fig. 7 (b) is kept within ± 10 degrees, which is much smaller than that of Fig. 6 (b).

We clearly see that Scheme 2 performs better than Scheme1.



(a) Roll angle



(b) Tilt angle

Fig. 7 RLS-FC balancing performances

5. CONCLUSION

In the paper, a novel control method of combining recursive least square method and fuzzy logic for the cooperative control between two systems of one-wheel robot was proposed. To estimate the respective system's influence on the other system, RLS algorithm-based estimation method was used in association with the fuzzy logic. The proposed control method was realized by experimental studies of balancing a one-wheel robot and their control performances have been compared. As expected, FC with RLS outperforms.

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