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Modified Model-Free Adaptive Control using Compact-Form Dynamic Linearization Technique

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Abstract: Model-free adaptive control has been used to design feedback in cases when accurate mathematical modeling of the system can not be realized. By using only input-output information, the control approach is attractive with respect to minimal design efforts. In this contribution an improved model-free control program is proposed and applied to flexible systems. The main control idea is based on the compact-form dynamic linearization technique. A linearized controller structure which contains a matrix of unknown time-varying parameters namely pseudo-partial derivative can be designed. First, an equivalent linearized data-based model of the original system is established and corrected locally by using the recursive least-squares estimation algorithm. Then a modified objective function with respect to the controller parameter matrix considering minimization of the current tracking errors and its variations is proposed for control performance improvement. Finally, the required control inputs are calculated to fulfill control requirements. For illustration and as example, the newly introduced method is applied to reduce vibrations of an elastic crane representing a multivariable system. The control effectiveness is verified nummerically and compared with conventional model-free and PI controllers.

Keywords: Model-free adaptive control, Dynamic linearization, Recursive least-squares, Estimation parameters, Vibration control

1. INTRODUCTION

In recent years, model-free control (MFC) has been received increasing attention, particularly in control design of unknown multi-input multi-output (MIMO) nonlinear systems. Because of less complexities in dynamical analysis and control design, MFC could be an alternative solution beside model-based control (MBC). Model-free controllers only require input-output (I/O) information which are directly measured or calculated from the closed-loop system without any requirements about the system model (Hou (2013)). Up to now, different MFC strategies are introduced in literature enhancing robustness against unknown inputs and disturbances as well as improving tracking control abilities. Based on controller structure design, MFC can be divided into two groups (Hou (2013)). In the first group the controller structure is assumed to be known. The control task is based on the identification of unknown time-varying parameters. Typical methods include intelligent PID control (Fliess (2008)) and virtual reference feedback tuning control (Guardabassi (2000)). However, other MFC approaches such as iterative learning control (Bristow et al. (2006)) and model-free adaptive control (Hou (2011)) can also be classified.

As a typical MFC, model-free adaptive control (MFAC) was firstly proposed by Hou et al. (Hou (2013)) for a class of single-input single-output (SISO) nonlinear systems. The core idea of MFAC is establishment of a local linearized data-based model which contains time-varying parameters at every step of the system operation. These parameters can be estimated and updated recursively. Several dynamic linearization techniques are introduced to obtain the linearized model including compact-form dynamic linearization (CFDL) (Hou (2013)), partial-form dynamic linearization (PFDL) (Hou (2011)), and full-form dynamic linearization (FFDL) (Li (2011)). Compared to MBC, MFAC possesses several advantages. First, no information about model description is utilized in MFAC design. Second, MFAC does not require any external testing signals or training processes. Furthermore, MFAC approaches are characterized by low computational load. Finally, the convergence and stability of a model-free-based control system can be guaranteed under some reasonable assumptions (Hou (2013)).

Different MFAC strategies are developed and applied to SISO and MIMO nonlinear systems. By combination of MFAC and sliding mode control, a novel model-free adaptive controller is designed by Liu (2018) for discrete-time systems with tracking error constraints. To improve tracking error convergence, another modified MFAC strategy is developed by combination of MFAC with a single output tracking differentiator (Ma (2009)). Furthermore, Zhen et al. (Zhen (2017)) proposed a novel MFAC program based on dynamic linearization techniques and predictive control ideas. As result, the robustness of the control algorithm can be improved. Other MFAC methods are discussed such as combinations of MFC and MBC including model-free adaptive predictive control (Yu-Chang (2012)) or model-free adaptive iterative learning control (Madadi et al. (2018)).

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In this study an improved MFAC program using the CFDL technique is proposed for a class of MIMO systems. The designed controller is applied to reduce vibrations of a crane represented as a typical example of mechanical flexible systems. Motion-induced vibrations can become dangerous so needed to be reduced or suppressed. Many vibration control techniques have been presented and applied to flexible structures which can be separated in three categories namely active, passive, and hybrid control (Rahman (2015)). He et al. (He (2015)) introduced a vibration control method for an Euler-Bernoulli beam with a boundary output constraint in which the system model has to be derived. In addition, active vibration control is decribed in Rahman (2017) to suppress unexpected oscillations of a flexible beam structure using chaotic fractal search algorithm. However, most of the above methods require a precise mathematical model of the system which could be difficult to obtain due to nonlinearities, unmodeled dynamics, or uncertainties of the system.

In this contribution a modified MFAC strategy is proposed by using the CFDL concept not only for the original system but also for the unknown controller. The linearized data-based models of the system and the controller are established which contain unknown time-varying parameters. To estimate these parameters, instead of using traditional projection algorithms as discussed in Hou (2013) and Hou (2011) recursive least-squares (RLS) estimation algorithm (Aström (1995)) is applied for estimation accuracy improvement. Furthermore, to reduce tracking errors a modification of minimizing the output errors and its variations is discussed. This idea was already introduced in Madadi et al. (2018) and applied successfully to an inverted elastic cantilever beam as a SISO example. In this paper the control performance is verified by applying the proposed method to control of an elastic crane as MIMO system. The rest of the paper is organized as follows. Theory of MFAC using the CFDL technique will be introduced in the next section. Recursive least-squares estimation method applied to the CFDL model as well as a CFDL-based controller structure are also discussed in detail. In Section 3 a modified estimation algorithm of the controller parameters is presented. Simulation results and discussion are illustrated in Section 4. Finally, conclusion is given in the last section.

2. MODEL-FREE ADAPTIVE CONTROL USING CFDL TECHNIQUE

2.1 CFDL-based RLS estimation algorithm

For a class of unknown MIMO nonlinear systems, a general I/O representation can be described in discrete-time as (Hou (2013))

$$\mathbf{y}(k+1) = f(\mathbf{y}(k), \dots, \mathbf{y}(k-m_y), \mathbf{u}(k), \dots, \mathbf{u}(k-m_u)), \tag{1}$$

where $\mathbf{y}(k) \in R^r, \mathbf{u}(k) \in R^m$ denote the system outputs and inputs at step k, respectively. The unknown system orders are m_y and m_u, while m and r indicate the known number of inputs and outputs, correspondingly. The unknown nonlinear function $f(\dots)$ consists of the previous system outputs and control inputs.

As discussed in Hou (2013), two assumptions should be satisfied for system (1) as follows:

Assumption 1: The partial derivatives of $f(\dots)$ with respect to $\mathbf{u}(k)$ exist and are considered as smooth.

Assumption 2: The system (1) satisfies the general Lipschitz condition $\|\mathbf{y}(k+1) - \mathbf{y}(k)\| \le b\,\|\mathbf{u}(k) - \mathbf{u}(k-1)\|$ at each time instant k with $\|\mathbf{u}(k) - \mathbf{u}(k-1)\| \neq 0$, and b is a small positive constant. Assumption 2 defines an upper limitation on the change rates of the outputs driven by the change rates of the control inputs.

Based on the above assumptions, the original system (1) can be linearized locally as a CFDL data-based model

$$\Delta\mathbf{y}(k+1) = \Phi(k)\Delta\mathbf{u}(k), \tag{2}$$

in which the unknown time-varying parameters $\Phi(k)$ called pseudo-jacobian matrix (PJM) can be estimated recursively. The matrix PJM appears as

$$\Phi(k) = \begin{bmatrix} \phi_{11}(k) & \phi_{12}(k) & \phi_{13}(k) & \dots & \phi_{1m}(k) \\ \phi_{21}(k) & \phi_{22}(k) & \phi_{23}(k) & \dots & \phi_{2m}(k) \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ \phi_{r1}(k) & \phi_{r2}(k) & \phi_{r3}(k) & \dots & \phi_{rm}(k) \end{bmatrix}_{r\times m}, \tag{3}$$

assuming $\|\Phi(k)\| \le b$ according to assumption 2.

The RLS estimation method as introduced in Aström (1995) is applied to the virtual CFDL model (2) to update the PJM parameters continuously. As result, the CFDL-RLS algorithm is obtained as

$$\hat{\Phi}(k) = \hat{\Phi}(k-1) + \mathbf{K}(k)\left[\Delta\mathbf{y}(k) - \hat{\Phi}(k-1)\Delta\mathbf{u}(k-1)\right], \tag{4}$$

$$\mathbf{K}(k) = \mathbf{P}(k)\Delta\mathbf{u}(k-1) = \mathbf{P}(k-1)\Delta\mathbf{u}(k-1) \cdot \left[I + \Delta\mathbf{u}^T(k-1)\mathbf{P}(k-1)\Delta\mathbf{u}(k-1)\right]^{-1}, \tag{5}$$

$$\mathbf{P}(k) = \mathbf{P}(k-1) - \mathbf{P}(k-1)\Delta\mathbf{u}(k-1) \cdot \left[I + \Delta\mathbf{u}^T(k-1)\mathbf{P}(k-1)\Delta\mathbf{u}(k-1)\right]^{-1} \cdot \Delta\mathbf{u}^T(k-1)\mathbf{P}(k-1), \tag{6}$$

where $\mathbf{P}_0 = \mathbf{P}(0) > 0$ is the initial parameter matrix.

2.2 CFDL applied to an assumed nonlinear controller

As introduced in Hou (2013), it is assumed that an I/O data-based controller description in discrete-time which can stabilize the original system (1) is written as

$$\mathbf{u}(k) = g(\mathbf{u}(k-1), \dots, \mathbf{u}(k-n_c), \mathbf{e}(k+1), \dots, \mathbf{e}(k-n_e)), \tag{7}$$

where $g(\dots)$ is a smooth unknown nonlinear function; $\mathbf{e}(k) = \mathbf{y}^d(k) - \mathbf{y}(k)$ denotes the current tracking errors, while $\mathbf{y}^d(k)$ and $\mathbf{y}(k)$ are the desired and actual outputs, respectively. Here n_c and n_e are two positive integers indicated as the unknown orders of the controller (7).

To obtain the CFDL-based controller structure, the following conditions (Hou (2013)) have to be satisfied:

Assumption 3: The controller (7) is a smooth nonlinear function, and the partial derivatives $\partial g(\mathbf{e})/\partial\mathbf{e}$ are continuous.

Assumption 4: The generalized Lipschitz condition is fulfilled for the controller (7), that is $\|\mathbf{u}(k) - \mathbf{u}(k-1)\| \le c\,\|\mathbf{e}(k+1) - \mathbf{e}(k)\|$; $c > 0$. This assumption imposes an upper bound on the change rates of the controller outputs driven by the change rates of the tracking errors. With these assumptions, a CFDL-based controller structure is described as (Hou (2013))

$$\Delta\mathbf{u}(k) = \Psi(k)\Delta\mathbf{e}(k+1), \tag{8}$$

$$\mathbf{u}(k) = \mathbf{u}(k-1) + \Psi(k)\left[\mathbf{e}(k+1) - \mathbf{e}(k)\right], \tag{9}$$

where $\Psi(k)$ is an unknown time-varying parameter matrix of the controller called pseudo-partial derivative (PPD), and $\|\Psi(k)\| \leq c$ for any step k. Theoretically, it is assumed that the controller (7) can generate perfect control input signals to acquire perfect control performance (Hou (2013)), so that the upcoming output tracking errors are $\mathbf{e}(k+1) = [0]$. However, from a practical point of view the tracking errors $\mathbf{e}(k+1)$ will not vanish completely because of uncertainties or estimation errors. Therefore, the redefined actual errors in practice are rewritten as follows

$$\varepsilon(k+1) = \mathbf{y}^d(k+1) - \mathbf{y}(k+1), \tag{10}$$

$$\varepsilon(k) = \mathbf{y}^d(k) - \mathbf{y}(k). \tag{11}$$

Hence, the practical control law based on the CFDL concept is described as

$$\mathbf{u}(k) = \mathbf{u}(k-1) - \Psi(k)\varepsilon(k). \tag{12}$$

Based on the system CFDL model (2), assuming $\mathbf{y}^d(k+1) = \mathbf{y}^d(k) = const$, the error dynamic equations are

$$\mathbf{y}^d(k+1) - \mathbf{y}(k+1) = \mathbf{y}^d(k) - \mathbf{y}(k) - \Phi(k)\Delta\mathbf{u}(k), \tag{13}$$

$$\varepsilon(k+1) = \varepsilon(k) - \Phi(k)\Delta\mathbf{u}(k), \tag{14}$$

$$\varepsilon(k+1) = \varepsilon(k) + \Phi(k)\Psi(k)\varepsilon(k), \tag{15}$$

$$\varepsilon(k+1) = \left[I + \Phi(k)\Psi(k)\right]\varepsilon(k), \tag{16}$$

where $\Phi(k)$ and $\Psi(k)$ are the unknown PJM and PPD parameter matrices of the system (1) and the controller (7), respectively.

To estimate the matrix $\Psi(k)$, the following objective function is considered

$$J(\Psi(k)) = \left\|\mathbf{y}^d(k+1) - \mathbf{y}(k+1)\right\|^2 + \lambda_k\|\Psi(k) - \Psi(k-1)\|^2, \tag{17}$$

where $\lambda_k > 0$ is a weighting factor which is added to limit the change rates of $\Psi(k)$. By using the CFDL model of the plant

$$\mathbf{y}(k+1) = \mathbf{y}(k) + \Phi(k)\Delta\mathbf{u}(k), \tag{18}$$

$$\mathbf{y}(k+1) = \mathbf{y}(k) - \Phi(k)\Psi(k)\varepsilon(k), \tag{19}$$

the cost function (17) can be rewritten as

$$J(\Psi(k)) = \left\|\mathbf{y}^d(k+1) - \mathbf{y}(k) + \Phi(k)\Psi(k)\varepsilon(k)\right\|^2 + \lambda_k\|\Delta\Psi(k)\|^2. \tag{20}$$

By minimizing (20) with respect to $\Psi(k)$, the final estimation algorithm of the PPD matrix

$$\hat{\Psi}(k) = \hat{\Psi}(k-1) - \frac{\rho_k\left[\mathbf{y}^d(k+1) - \mathbf{y}(k) + \hat{\Phi}(k)\varepsilon(k)\hat{\Psi}(k-1)\right]\hat{\Phi}^T(k)\varepsilon^T(k)}{\lambda_k + \left\|\hat{\Phi}(k)\varepsilon(k)\right\|^2}, \tag{21}$$

where $\rho_k > 0$ denoting a step-size constant is obtained. The matrix PJM $\hat{\Phi}(k)$ in (21) could be estimated by using the CFDL-RLS algorithm (4), (5), and (6). Finally, the required control input vector $\mathbf{u}(k)$ is updated via (12) based on the actual tracking errors (11) and the estimated PPD parameters (21).

3. MODIFIED CFDL-BASED MODEL-FREE ADAPTIVE CONTROL

In this section a modified estimation algorithm of the PPD matrix $\hat{\Psi}(k)$ is proposed by minimization of the actual tracking errors $\varepsilon(k+1)$ and the error variations $\Delta\varepsilon(k+1)$ within a specified length of sampling instants $N > 0$ to improve control performance. The modified control approach has been implemented successfully to an inverted elastic cantilever beam as an example of SISO nonlinear systems (Madadi et al. (2018)). In this study a modified objective function of the PPD matrix $\Psi(k)$ is proposed. As result, a novel parameter estimation algorithm of the design controller is developed. Based on the updated parameters and the current output tracking errors, the required control inputs $\mathbf{u}(k)$ are computed. Explanation of how to apply the proposed method to control of a class of MIMO systems is discussed in detail.

3.1 Modified parameter estimation algorithm

Based on the existing objective function of $\Psi(k)$ as given in (17), a modified function is proposed as

$$J(\Psi(k)) = \left\|\mathbf{y}^d(k+1) - \mathbf{y}(k+1)\right\|^2 + \tau\left\|\Delta\mathbf{y}^d(k+1) - \Delta\mathbf{y}(k+1)\right\|^2 + \lambda_k\|\Psi(k) - \Psi(k-1)\|^2, \tag{22}$$

where $\tau > 0$ denotes a constant design parameter. To minimize the tracking error variations, the term of $\left\|\Delta\mathbf{y}^d(k+1) - \Delta\mathbf{y}(k+1)\right\|$ is added. Substituting the system output increment equation (19) into (22) results to

$$J(\Psi(k)) = \left[\mathbf{y}^d(k+1) - \mathbf{y}(k) + \Phi(k)\Psi(k)\varepsilon(k)\right]^2 + \tau\left[\Delta\mathbf{y}^d(k+1) + \Phi(k)\Psi(k)\varepsilon(k)\right]^2 + \lambda_k(\Delta\Psi(k))^2. \tag{23}$$

Differentiating (23) in term of $\Psi(k)$ and letting it zero, the following equations

$$\begin{aligned}&\left[\mathbf{y}^d(k+1) - \mathbf{y}(k) + \Phi(k)\Psi(k)\varepsilon(k)\right]\left[\Phi^T(k)\varepsilon^T(k)\right]\\ &+ \tau\left[\Delta\mathbf{y}^d(k+1) + \Phi(k)\Psi(k)\varepsilon(k)\right]\left[\Phi^T(k)\varepsilon^T(k)\right]\\ &+ \lambda_k\Delta\Psi(k) = 0,\end{aligned} \tag{24}$$

$$\begin{aligned}\hat{\Psi}(k) = \hat{\Psi}(k-1) &- \frac{\rho_k\left[\mathbf{y}^d(k+1) - \mathbf{y}(k)\right]\hat{\Phi}^T(k)\varepsilon^T(k)}{\lambda_k + (1+\tau)\left\|\hat{\Phi}(k)\varepsilon(k)\right\|^2}\\ &- \frac{\rho_k(1+\tau)\hat{\Phi}(k)\varepsilon(k)\hat{\Psi}(k-1)\hat{\Phi}^T(k)\varepsilon^T(k)}{\lambda_k + (1+\tau)\left\|\hat{\Phi}(k)\varepsilon(k)\right\|^2}\\ &- \frac{\tau\left[\mathbf{y}^d(k+1) - \mathbf{y}(k) - \left(\mathbf{y}^d(k) - \mathbf{y}(k-1)\right)\right]\hat{\Phi}^T(k)\varepsilon^T(k)}{\lambda_k + (1+\tau)\left\|\hat{\Phi}(k)\varepsilon(k)\right\|^2},\end{aligned} \tag{25}$$

can be derived. The estimation algorithm (25) is different from the standard algorithm (21). As discussed in Madadi et al. (2018), the output error differences which are defined as

$$\left[\mathbf{y}^d(k+1) - \mathbf{y}^d(k) - (\mathbf{y}(k) - \mathbf{y}(k-1))\right], \tag{26}$$

in (25) only consider minimizing one step of the tracking errors from previous steps with relatively small amplitudes. Therefore, the extended error variations within a length of $N > 0$ sampling instants are considered as

$$\left[\mathbf{y}^d(k+1) - \mathbf{y}(k) - \left(\mathbf{y}^d(k-N+1) - \mathbf{y}(k-N)\right)\right], \tag{27}$$

resulting to the modified estimation equation

$$\hat{\Psi}(k) = \hat{\Psi}(k-1) - \frac{\rho_k \left[\mathbf{y}^d(k+1) - \mathbf{y}(k)\right] \hat{\Phi}^T(k)\varepsilon^T(k)}{\lambda_k + (1+\tau)\left\|\hat{\Phi}(k)\varepsilon(k)\right\|^2} \tag{28}$$
$$- \frac{\rho_k (1+\tau)\hat{\Phi}(k)\varepsilon(k)\hat{\Psi}(k-1)\hat{\Phi}^T(k)\varepsilon^T(k)}{\lambda_k + (1+\tau)\left\|\hat{\Phi}(k)\varepsilon(k)\right\|^2}$$
$$- \frac{\tau\left[\varepsilon(k) - \varepsilon(k-N)\right]\hat{\Phi}^T(k)\varepsilon^T(k)}{\lambda_k + (1+\tau)\left\|\hat{\Phi}(k)\varepsilon(k)\right\|^2},$$

where $\varepsilon(k) = \mathbf{y}^d(k+1) - \mathbf{y}(k); \varepsilon(k-N) = \mathbf{y}^d(k-N+1) - \mathbf{y}(k-N)$ denote the actual output tracking errors at step k and $k-N$, respectively. Here $\rho_k > 0$ is a step-size constant. The PJM matrix $\hat{\Phi}(k)$ can be estimated by using the CFDL-RLS algorithm (4), (5), and (6).

3.2 Control scheme for application to MIMO systems

The proposed control method can be applied to a class of MIMO systems. The modified control scheme is shown in Fig. 1. To design the modified CFDL-MFAC, the following steps have to be implemented:

(1) Based on the CFDL data model and the available I/O data from the system, the unknown PJM parameters are estimated and updated recursively using the RLS estimation algorithm. According to Hou (2013), to improve the ability in tracking time-varying parameters a reset condition is defined as

$$\hat{\Phi}(k) = \hat{\Phi}(1) \;\; if \;\; \left\|\hat{\Phi}(k)\right\| \leq \gamma \;\; or \;\; \|\Delta\mathbf{u}(k)\| \leq \gamma, \tag{29}$$

where γ is a small positive constant, and $\hat{\Phi}(1)$ denotes the initial PJM values.

(2) By using the updated PJM $\hat{\Phi}(k)$ and the current tracking errors $\varepsilon(k)$, the controller parameters $\hat{\Psi}(k)$ are estimated. To increase the tracking ability of the matrix PPD, another reset condition should be considered (Hou (2013))

$$\left\|\hat{\Psi}(k)\right\| = -b_1 \;\; if \;\; \left\|\hat{\Psi}(k)\right\| > b_1, \tag{30}$$

where $b_1 > 0$ is a small constant. Matrix $\hat{\Psi}(k)$ is always negative, whereas matrix $\hat{\Phi}(k)$ is positive (according to the reset conditions (29) and (30)), that means the future errors $\varepsilon(k+1)$ will converge to zero regarding (16).

(3) Based on the corrected PPD $\hat{\Psi}(k)$ and the actual tracking errors $\varepsilon(k)$, the control input vector $\mathbf{u}(k)$ is calculated via (12). Then the next output values $\mathbf{y}(k+1)$ are computed or measured and the given process is implemented repeatedly.

4. SIMULATION RESULTS AND DISCUSSION

4.1 Introduction to an elastic ship-mounted crane

An elastic crane with the "Maryland Rigging" equipped in large ships in open sea was considered as a MIMO example in Al-Sweiti (2007). During the system operation, due to the effects of wave motions and wind forces represented as unknown disturbances the crane normally becomes unstable. In Fig. 2 the crane configuration with an elastic part of the boom (part AB) is described. In addition, because of non-zero initial conditions of the system states large oscillations of the payload and the elastic boom occur and they might lead to suspension of the system operation. Three control input variables are defined for control implementation namely the displacements of the luff angle $\Delta\rho$, the upper cable length ΔL, and the lower suspension point ΔD which are written as

$$\mathbf{u}(k) = [\Delta\rho(k) \;\; \Delta L(k) \;\; \Delta D(k)]^T. \tag{31}$$

The system output vector consists of the angular displacements of the elastic boom $\Delta\theta_6$ (at node 6), and the cables of the payload m_2 denoted as

$$\mathbf{y}(k) = [\Delta\theta_6(k) \;\; \Delta\alpha_2(k) \;\; \Delta\phi_2(k)]^T. \tag{32}$$

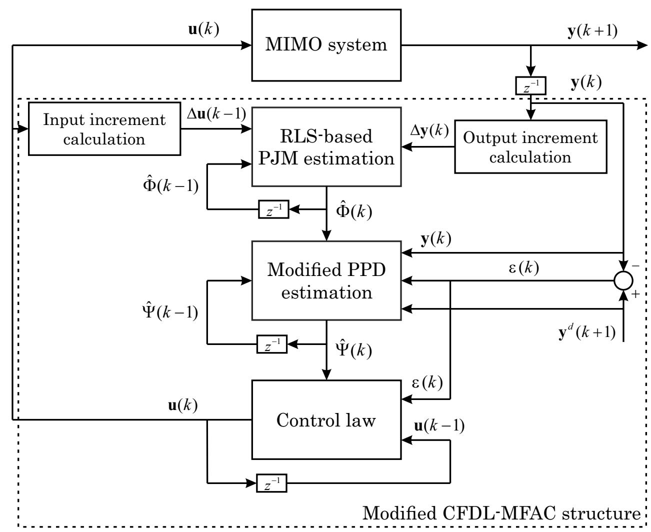

Fig. 1. Modified CFDL-MFAC scheme for MIMO systems

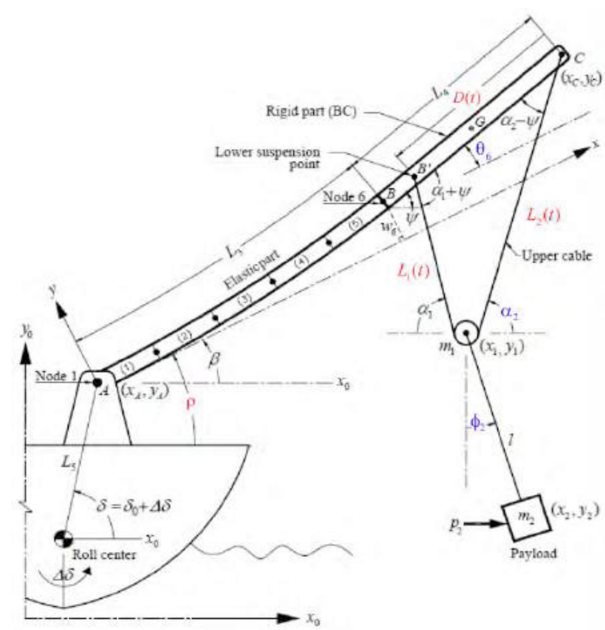

Fig. 2. Configuration of an elastic ship-mounted crane with the "Maryland Rigging" (Al-Sweiti (2007))

To estimate the system parameters PJM, the available I/O data from the simulation of the crane are used. Therefore, the state-space model as developed in Al-Sweiti (2007) is applied which can be rewritten in discrete-time as

$$\begin{aligned}\mathbf{z}(k+1) &= \mathbf{G}\mathbf{z}(k) + \mathbf{H}\mathbf{u}(k) + \mathbf{J}\Delta\delta(k) + \mathbf{Q}p_2(k), \\ \mathbf{y}(k) &= \mathbf{C}\mathbf{z}(k) + \mathbf{D}\mathbf{u}(k) + \mathbf{F}\Delta\delta(k),\end{aligned} \tag{33}$$

where $\mathbf{z}$ denotes the state vector. Here $\mathbf{G}, \mathbf{H}$ are the system and input matrices, respectively; meanwhile the system output and the input direct transmission matrices are represented as $\mathbf{C}$ and $\mathbf{D}$, correspondingly. The external disturbance matrices are indicated as $\mathbf{J}$ due to ship rolling ($\Delta\delta$), and $\mathbf{Q}$ due to wind force (p_2). The disturbance direct transmission matrix $\mathbf{F}$ is resulted by sea motion. In Table 1 initial parameters of the crane and the modified CFDL-based model-free adaptive controller (modified CFDLc-MFAC) are given.

Table 1. Initial parameters of the crane and the modified CFDLc-MFAC

Parameter	Meaning	Value [Unit]
β_0	Orientation of the boom axis	$\pi/4$ [rad]
D_0	Low-point suspension cable	0.55 [m]
L_0	Upper cable length	1.60 [m]
m_2	Mass of the payload	5.0 [kg]
$\dot{\phi}_{20}$	Initial angular velocity of the payload	5.0 [rad/s]
ρ_k	Step-size constant	0.01 [-]
λ_k	Constant weighting factor	4.0 [-]
τ	Constant design parameter	0.02 [-]
γ	Small positive constant	10^{-5} [-]
b_1	Small positive constant	0.009 [-]

4.2 Simulation results and discussion

In this contribution simulation results are obtained in the case of without considering external disturbance effects ($\Delta\delta(k) = p_2(k) = 0$). As mentioned before, the unexpected in-plane vibrations in the crane need to be reduced by control. The modified CFDLc-MFAC is compared with the normal MFAC which uses traditional projection algorithm for online parameter estimation (Hou (2011)) and PI control.

In Fig. 3 the vibration control results of the payload displacement in x- and y-direction are shown. Compared to the normal MFAC (red line) and the PI control (blue-dot line), the proposed controller (green line) has better control performance with respect to smaller tracking errors. The controllers are activated from $t = 30$ [s]. To obtain the system dynamic behavior due to non-zero initial condition of the payload ($\dot{\phi}_{20}$), the uncontrolled case results (pink-dash line) are also presented. In addition, comparison of vibration control regarding the angular displacements of the upper and payload cables ($\Delta\alpha_2$ and $\Delta\phi_2$) is illustrated in Fig. 4. It can be seen that these angular oscillations are reduced considerably from around 30 [deg] and 50 [deg] to nearly zero at the end of the simulation by all approaches, but faster by the proposed controller (green line).

To evaluate control performance of the discussed methods by varying controller parameters, the relationship between the control input energy $\int_{t_1}^{t_2} \mathbf{u}^2(t)dt$ and the output tracking

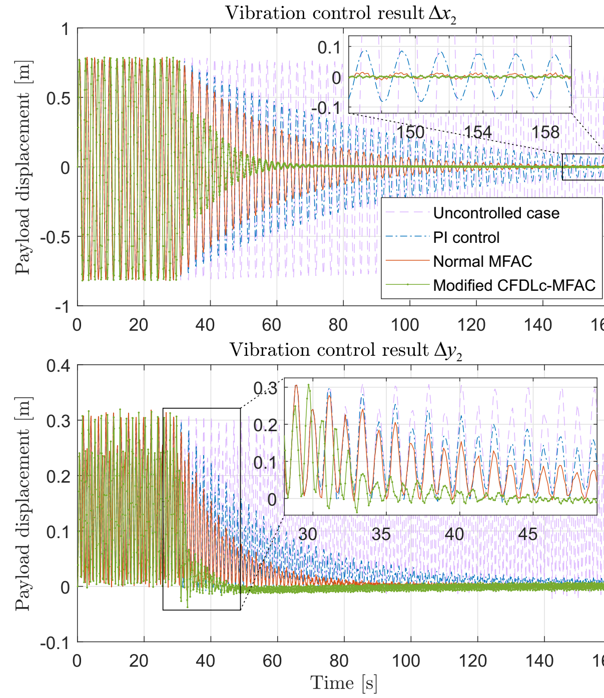

Fig. 3. Vibration control comparison with respect to the payload position Δx_2 and Δy_2

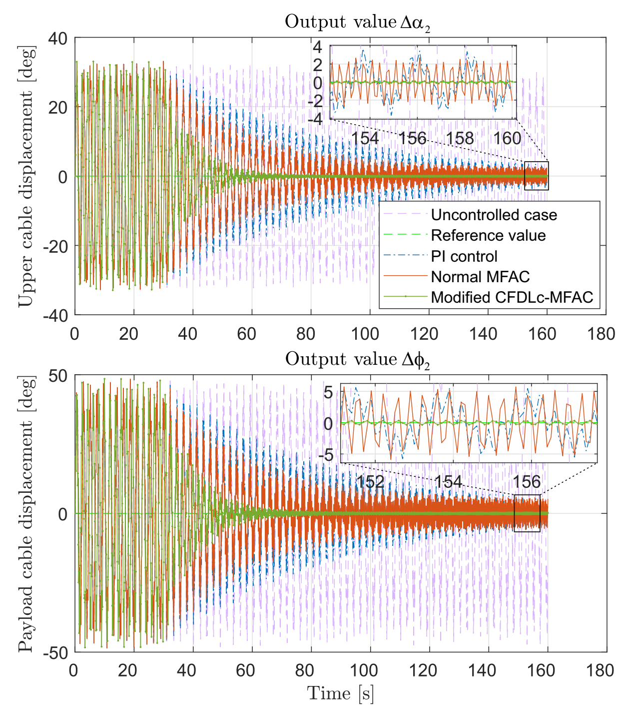

Fig. 4. Vibration control comparison with respect to the output values $\Delta\alpha_2$ and $\Delta\phi_2$

error $\int_{t_1}^{t_2} \mathbf{e}^2(t)dt$ within a specified length of time $T = [t_1\ t_2]$ [s] (Liu and Söffker (2012)) is applied as follow

$$P_K = \left[\int_{t_1}^{t_2} \mathbf{u}^2(t)dt, \int_{t_1}^{t_2} \mathbf{e}^2(t)dt\right]_K, \tag{34}$$

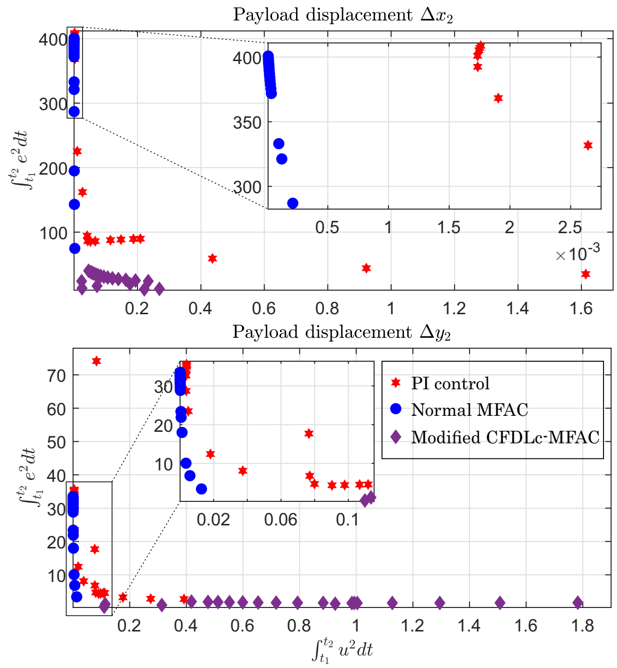

Fig. 5. Control performance evaluation regarding the criteria (34)

where $K = [K_p, K_i, \lambda, \lambda_k]$ is a set of control parameters of the PI control, normal MFAC, and modified CFDLc-MFAC, respectively. Here λ and λ_k are the important parameters which can improve the model-free control performance. The trajectory of the control input energy with $\mathbf{u} = [\Delta L, \Delta D]$ as well as the control errors $\mathbf{e} = [\Delta x_2, \Delta y_2]$ is denoted as P_K. In Fig. 5 control performance evaluation with respect to the criteria (34) within the sampling interval $T = [30\ 160]$ [s] is shown. The trajectory P_K of the modified CFDLc-MFAC (violet dot) is closer to the origin (upper figure) when varying parameters K than that of the normal MFAC (blue dot) and the PI control (red dot). However, the modified model-free controller still requires more input energy (lower figure) to obtain smaller control errors compared with other approaches.

5. CONCLUSION

This contribution discusses a modified MFAC which uses the CFDL technique not only for the unknown system, but for the unknown controller. To estimate the time-varying parameters of the linearized system model, the RLS algorithm is applied instead of using traditional projection-based method. Finally, an improved model-free controller is designed and implemented to reduce vibrations of an elastic crane representing a MIMO system. Simulation results illustrate the advantages of the modified approach in comparison with the conventional methods.

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