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Research Article

Information Fusion Based Decoupling Control for Multivariable Nonlinear System

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A decoupling control method based on information fusion estimation for a nonlinear system is presented in the paper. For each main channel and its coupled channels of the system, according to the information fusion theorem, the estimation of the system future state is obtained by fusing the information of the desired output trajectory of the system. Furthermore, approximate optimal control rule is obtained by fusing the system future state information and the control energy soft constraint information. Then an information fusion based decoupling control (IFBDC) system is established for the nonlinear coupled multiple-input multiple-output systems. This system cannot only control every channel to track reference signals, but also control any channel to be decoupled with other channels. Finally, a robot manipulator system is given to investigate the effectiveness of the decoupling control strategy, analyze its key parameters, and analyze the computational cost. The simulation results show that the IFBDC method is characterized by adjustable decoupling degree and high control quality.

1. Introduction

For many multiple-input and multiple-output (MIMO) systems, one channel often has coupling influence on other channels, so designs of the decoupling control structure and the control law are necessary for satisfying the high control performance requirement. Tao et al. proposed an optimal decoupling control scheme for the multivariable nonlinear systems with sandwiched backlash [1]. Huijberts et al. gave necessary and sufficient conditions for solvability of the strong input-output decoupling problem by static measurement feedback for nonlinear control systems [2]. Lian and Lin designed a traditional fuzzy controller from the viewpoint of a single-input single-output (SISO) system for controlling each degree of freedom of a MIMO system and then designed an appropriate coupling fuzzy controller to compensate for coupling effects between the degree of freedom [3]. Liu et al. proposed a decoupling control scheme based on an internal model control structure [4] and later proposed an analytical decoupling control method by using a unity feedback control structure [5]. Wang et al. presented a generalized predictive control algorithm based on quantitative feedback theory for controlling the highly uncertain and cross-coupling plants [6]. Liu et al. presented a new control methodology based on active disturbance rejection control (ADRC) for designing the tension decoupling controller of the unwinding system in a gravure printing machine [7]. However, there is a high frequency flutter problem for ADRC. A tracking control scheme combined with a nonlinear decoupling control was proposed to compensate for the effect of the interactions between axes and track the reference trajectory for *XY* micropositioning stages [8]. However, the proposed control strategy is complex with high computation cost. In all, there are few references published on the topic of the nonlinear system decoupling control problem.

Information fusion estimation, which is a basic fusion mode of the original data, is an important fundamental theory of information fusion. The definitions of information fusion were first presented in [9, 10]. In the field of information fusion estimation, Carlson proposed the linear minimum variance estimation as the optimal fusion estimation, under the condition of uncorrelated estimation error [11]. Kim presented the maximum likelihood estimation as the optimal fusion estimation in the situation of correlated

estimation error with joint normal distribution [12]. Mutambara derived an information based estimation algorithm for both linear and nonlinear systems [13]. Li et al. established the framework for three estimation fusion architectures: centralized, distributed, and hybrid, and then a unified linear model based on best linear unbiased estimation. Furthermore, the weighted least squares and their generalized versions are presented for cases with complete, incomplete, or no prior information. These rules are more general and flexible and have wider applicability than previous results [14]. Zhu et al. developed a general multisensor unbiased linearly weighted estimation fusion, which essentially is the linear minimum variance estimation with the linear equality constraint [15]. Sun and Deng presented a new multisensor optimal information fusion criterion weighted by matrices in the linear minimum variance sense, which is equivalent to the maximum likelihood fusion criterion under the assumption of normal distribution [16].

It should be mentioned that Zhou et al. adopted the linear minimum variance as the optimal rule of fusion estimation and presented the concept of information weight which represents the contribution of the information to the estimated variable. Moreover, Zhou et al. proved that the estimation accuracy will be higher when more measurements are used, even if a sensor with bad accuracy is used [17]. For the latter proof, Wang et al. proposed a preview control method for nonlinear systems, by fusing the system preview trajectory information and the soft constrained information of the control energy. This work originally applied the information fusion estimation theory into the control field. Therefore the control problem and the estimation problem are unified as a decision making problem [18]. Moreover, Zhen et al. applied the information fusion estimation to the optimal control of the linear and nonlinear systems [19–21]. Notice that some identification methods can be utilized when applying information fusion estimation based control methods in the systems with unknown parameters [22, 23].

This paper investigates the decoupling control problem of the multivariable nonlinear system by using the information fusion estimation method. Actually, for the real systems, the coupling effects between subchannels in multivariable system are nonlinear and dynamic behaviours. Therefore, a nonlinear and dynamic decoupling method will be more applicable to this situation. The paper presents an information fusion based decoupling control (IFBDC) method and is organized as follows. Section 2 describes the linear and nonlinear information fusion estimation theorems. Section 3 derives an information fusion estimation based decoupling control algorithm for the nonlinear time-delayed system. Section 4 shows the experimental results and analysis. Finally, conclusions are given in Section 5.

2. Information Fusion Estimation Theory

2.1. Linear Information Fusion Model. References [14–16] proposed the unified linear models of information fusion estimation under the information rule of linear minimum variance estimation. However, [17] proposed a linear information model from an aspect of information weight. This is more convenient to use with respect to controller design.

Suppose the ith measurement information of the state $x \in R^n$ is given by

$$z_i = H_i x + v_i, \quad i = 1, 2, \ldots, N, \tag{1}$$

where N is the measurement information number of the state x, $z_i \in R^{m_i}$ is the measurement vector, $H_i \in R^{m_i \times n}$ is the measurement information mapping matrix, $v_i \in R^{m_i}$ is measurement error, and

$$E\left[v_i\right] = 0, \qquad E\left[v_i v_j^T\right] = \begin{cases} R_i, & i = j, \\ 0, & i \neq j. \end{cases} \tag{2}$$

Then an optimal fusion estimation of the state x is equal to

$$\begin{aligned} \widehat{x} &= \arg\min_{\widehat{x}} E\left[(x - \widehat{x})(x - \widehat{x})^T\right] \\ &= \arg\min_{\widehat{x}} \sum_{i=1}^{N} \left\| z_i - H_i \widehat{x} \right\|_{R_i^{-1}}^2 . \end{aligned} \tag{3}$$

Theorem 1 (see [17]). *For the above linear information fusion estimation problem, if $\sum_{i=1}^{N} H_i^T R_i^{-1} H_i$ is nonsingular, then the optimal fusion estimation of the state can be expressed as*

$$\widehat{x} = \left(\sum_{i=1}^{N} H_i^T R_i^{-1} H_i \right)^{-1} \sum_{i=1}^{N} H_i^T R_i^{-1} z_i, \tag{4}$$

where $I[z_i] = R_i^{-1}$ is defined as the information weight of the measurement $\widehat{y}_i$ on itself, and $I[z_i \mid x] = H_i^T R_i^{-1} H_i$ is defined as the information weight of the measurement z_i on the state x; then the information weight of the optimal fusion estimation $\widehat{x}$ on itself can be expressed as

$$I[\widehat{x}] = \sum_{i=1}^{N} I\left[z_i \mid x\right] = \sum_{i=1}^{N} H_i^T I\left[z_i\right] H_i = \sum_{i=1}^{N} H_i^T R_i^{-1} H_i. \tag{5}$$

Several properties of the information weight can be concluded from (4), as shown in the following.

(i) The information weight of the information on itself is equal to the variance of the information. The larger the information weight, the higher the estimation accuracy.

(ii) The sum of the information weight of all the state measurements is equal to the information weight of the optimal fusion estimation on itself.

(iii) When the information weight is zero, the measurement information is not useful to the state. When the information weight is infinite, the measurement information is certain.

2.2. Nonlinear Information Fusion Model

Theorem 2. *Suppose the ith measurement information of the state $x \in R^n$ is given by*

$$z_i = h_i(x) + v_i, \tag{6}$$

where $h_i(\cdot) : R^n \rightarrow R^{m_i}$ is a nonlinear mapping, v_i is described in Theorem 1, and $i = 1 \sim N$. If $\sum_{i=1}^{N} H_i^T R_i^{-1} H_i$ is nonsingular, then a closed analytic expression of the nonlinear information fusion estimation can be represented as

$$\sum_{i=1}^{N} H_i^T R_i^{-1} h_i(\hat{x}) = \sum_{i=1}^{N} H_i^T R_i^{-1} z_i, \tag{7}$$

where $H_i = (\partial h_i/\partial x)|_{x=\hat{x}}$, $\hat{x}$ is the fusion estimation of the state x, and the information weight of the fusion estimation $\hat{x}$ is given by $I[\hat{x}] = \sum_{i=1}^{N} H_i^T R_i^{-1} H_i$ [18].

Theorem 2 is a unified nonlinear model of the information fusion estimation. Obviously, (2) is a special result of (7) when all the information of the state is linear. In Theorem 1, the expression of the fusion estimation $\hat{x}$ contains its information weight $I[\hat{x}]$, while the information weight $I[\hat{x}]$ does not contain the fusion estimation $\hat{x}$. However, for the nonlinear information fusion problem, the expression of the fusion estimation $\hat{x}$ does not contain its information weight $I[\hat{x}]$, and the information weight $I[\hat{x}]$ is related with the fusion estimation $\hat{x}$, as can be seen from Theorem 2.

Therefore, the nonlinear information fusion problem is equal to the minimum problem, as given by

$$\hat{x} = \arg\min \sum_{i=1}^{N} \left\| z_i - h_i(\hat{x}) \right\|_{R_i^{-1}}^2. \tag{8}$$

For the convenient calculation of the fusion estimation $\hat{x}$ hiding in (7), two cases as follows are considered.

Case 1. If there is a unit mapping $h_j(\cdot)$ in all the nonlinear mappings (i.e., $z_j = x + v_j$) according to (7), the fusion estimation $\hat{x}$ can be recursively calculated according to the following explicit expression:

$$\hat{x} = z_j + R_j \sum_{i=1, i\neq j}^{N} H_i^T R_i^{-1} \left[z_i - h_i(\hat{x}) \right]. \tag{9}$$

Case 2. Let $\tilde{x}$ be prior information or calculated presumption of the state x; then we can get a linearized expression of (6),

$$z_i - h_i(\tilde{x}) = H_i (x - \tilde{x}) + v_i, \tag{10}$$

where $H_i = (\partial h_i/\partial x)|_{x=\tilde{x}}$, $i = 1 \sim N$. Then, according to Theorem 1, we get

$$\hat{x} = \tilde{x} + \left(\sum_{i=1}^{N} H_i^T R_i^{-1} H_i \right)^{-1} \sum_{i=1}^{N} H_i^T R_i^{-1} \left[z_i - h_i(\tilde{x}) \right]. \tag{11}$$

By iteration of (11), an estimation with higher accuracy can be achieved.

The solving problem of the fusion estimation is in fact the linear quadratic optimization problem (3). Therefore, the linear quadratic optimal control problems can also be solved by fusion estimation, where the control sequence needs to be estimated. Hence, the linear quadratic control problem and the linear quadratic estimation problem are unified according to the optimization process.

3. Information Fusion Estimation Method for Solving Nonlinear Decoupling Control Problem

3.1. Problem Description. Consider the following nonlinear multivariable controlled object:

$$\begin{aligned} x(k+1) &= f[x(k), u(k)], \\ y(k) &= h[x(k)], \end{aligned} \tag{12}$$

where $x(k) = [x_1(k), \ldots, x_n(k)]^T \in R^n$ is the system state vector, $u(k) = [u_1(k), \ldots, u_p(k)]^T \in R^p$ is the system control vector, $f(\cdot,\cdot) : R^n \times R^p \rightarrow R^n$ and $h[\cdot] : R^n \rightarrow R^p$ are the monotone and continuously differentiable functions, and k is the time index.

Suppose the channels of the nonlinear system (12) exit the coupling effect. For solving the decoupling control problem of the nonlinear system, we need to find an appropriate control structure and control law in order to decrease or eliminate the intercoupling influence of the system channels. As a decoupled system, the system input has a one-to-one correspondence relation with the system output.

The decoupling control law is designed in the situation that the ith channel is the main channel and the other channels are the coupled channels, $i = 1 \sim n$.

For the ith channel, we consider the following quadratic performance index:

$$J_i = \sum_{j=k+1}^{k+T} \left\| y^*(j) - y(j) \right\|_{Q(j)}^2 + \sum_{j=k}^{k+T-1} \left\| u^*(j) - u(j) \right\|_{R(j)}^2, \tag{13}$$

where $y^*(j) = [y_1^*(j), \ldots, y_p^*(j)]^T \in R^p$ is the desired output vector, $u^*(j) = [u_1^*(t), \ldots, u_p^*(t)]^T \in R^p$ is the desired control vector, $Q(j) \in R^{p\times p}$ and $R(j) \in R^{p\times p}$ are two symmetric positive definite matrixes, and T is the preview step number.

For the coupled nonlinear multivariable system, the output $y(j)$ tracking to the desired output $y^*(j)$ is expected, and the smallest control energy is also expected, so the desired output vector and the desired control vector of the ith channel are, respectively, given by

$$\begin{aligned} y_i^*(j) &= \begin{cases} y_0, & \text{except } i\text{th channel}, \\ r_i(j), & i\text{th channel}, \end{cases} \\ u^*(j) &= 0, \end{aligned} \tag{14}$$

where $r_i(j)$ is the desired tracking output vector of the ith channel and y_0 is the original output.

The outputs of the coupled channels are expected to be zero, while the output of the current ith channel is expected to track the desired output. However, for many systems, the future output trajectory is unknown in advance. For this situation, the current input of the ith channel is regarded as the future desired outputs, so we have

$$r_i(j) = r_i(k), \quad j = k+1 \sim k+T, \tag{15}$$

where $r_i(k)$ is the current reference input of the ith channel of the system.

The decoupling control law of the ith channel can be obtained by minimizing the quadratic performance index (13). The remaining subsections will investigate the solution to this problem.

3.2. Information Fusion Estimation of System Controller Sequence. For reducing the computational cost, we only need to obtain the current control vector $u(k)$. There are two types of information of the current control vector $u(k)$, shown as follows.

(i) The soft constraint information of the control vector $u(k)$ from the quadratic performance index (13) is

$$u^*(k) = u(k) + n(k), \tag{16}$$

where $n(k)$ is a white noise with zero mean and covariance of $R^{-1}(k)$. Thus, the information weight of the control vector $u(k)$ from the desired control vector $u^*(k)$ can be given by

$$I[u^*(k)] = R(k). \tag{17}$$

(ii) Suppose that the state fusion estimation $\hat{x}(k+1)$ and its information weight $P^{-1}(k+1)$ have been obtained; then we get the information equation

$$\begin{aligned}\hat{x}(k+1) &= x(k+1) + w(k+1)\\ &= f[x(k), u(k)] + w(k+1),\end{aligned} \tag{18}$$

where $w(k+1)$ is a white noise with zero mean and covariance of $P(k+1)$.

Therefore, according to Theorem 2, a fusion estimation of the control vector $u(k)$ can be derived by fusing the two information equations shown in (16) and (18), described as

$$\begin{aligned}&R(k)\hat{u}(k) + B^T(k)P^{-1}(k+1)f[x(k), \hat{u}(k)]\\ &\quad = R(k)u^*(k) + B^T(k)P^{-1}(k+1)\hat{x}(k+1),\end{aligned} \tag{19}$$

where $\hat{u}(k)$ is implicated.

According to Case 1, information equation (16) is linear; then we get

$$\begin{aligned}\hat{u}(k) &= u^*(k) + R^{-1}(k)B^T(k)P^{-1}(k+1)\\ &\quad\cdot\{\hat{x}(k+1) - f[x(k), \hat{u}(k)]\}\\ &= u^*(k) + R^{-1}(k)B^T(k)P^{-1}(k+1)\\ &\quad\cdot\{\hat{x}(k+1) - B(k)[\hat{u}(k) - u^*(k)] - f[x(k), u^*(k)]\}.\end{aligned} \tag{20}$$

It can be further deduced to be

$$\begin{aligned}\hat{u}(k) &= u^*(k) + \left[R(k) + B^T(k)P^{-1}(k+1)B(k)\right]^{-1}\\ &\quad\cdot B^T(k)P^{-1}(k+1)\{\hat{x}(k+1) - f[x(k), u^*(k)]\},\end{aligned} \tag{21}$$

where $B(k) = (\partial f_0/\partial u(k))|_{u(k)=u^*(k)}$.

According to Case 2, take $u^*(k)$ as a prior information; then we can get

$$\begin{aligned}\hat{u}(k) &= u^*(k) + \left[R(k) + B^T(k)P^{-1}(k+1)B(k)\right]^{-1}\\ &\quad\cdot B^T(k)P^{-1}(k+1)\{\hat{x}(k+1) - f[x(k), u^*(k)]\}.\end{aligned} \tag{22}$$

Equation (22) is the same as (21), which means that Case 1 is actually equal to Case 2.

As shown above, in order to obtain the control vector estimation $\hat{u}(t)$, the system future state estimation $\hat{x}(k+1)$ and its information weight $P^{-1}(k+1)$ need to be solved first.

3.3. Information Fusion Filtering of System Future State. There are two types of information of the system future state $x(j)$, $j = k+T \sim k+1$, which is described as follows.

(i) Derived by the quadratic performance index (13), the desired output information of the tracking requirement can be given by

$$y^*(j) = y(j) + m(j) = h[x(j)] + m(j), \tag{23}$$

where $m(j)$ is a white noise with zero mean and covariance of $Q^{-1}(j)$. Therefore, according to Theorem 1, the information weight of the system desired output $y^*(j)$ on the state $x(j)$ can be expressed as

$$I[y^*(j) \mid x(j)] = C^T(j)Q(j)C(j), \tag{24}$$

where $C(j) = (\partial h[x(j)]/\partial x(j))|_{x(j)=x^*(j)}$, $x^*(j)$ is a prior information of $x(j)$, and

$$\begin{aligned}x^*(k+1) &= f(x(k), 0)\\ &\vdots\\ x^*(k+T) &= f(x^*(k+T-1), 0).\end{aligned} \tag{25}$$

(ii) Suppose that the state fusion estimation $\hat{x}(j+1)$ and its information weight $P^{-1}(j+1)$ have been obtained; then we have

$$\begin{aligned}\hat{x}(j+1) &= x(j+1) + w(j+1)\\ &= f[x(j), u(j)] + w(j+1),\end{aligned} \tag{26}$$

where $w(j+1)$ is a white noise with zero mean and covariance of $P(j+1)$. From the quadratic performance index (13), we get an information equation of the future control vector $u(j-1)$ as

$$u^*(j) = u(j) + n(j). \tag{27}$$

Substituting (27) into (26), we get

$$\hat{x}(j+1) = f[x(j), u^*(j) - n(j)] + w(j+1). \tag{28}$$

Then, according to Theorem 2, we get an estimation of $x(j)$ that satisfies

$$\begin{aligned} & C^T(j)Q(j)h[\hat{x}(j)] \\ & \quad + A^T(j)\left[B(j)R^{-1}(j)B^T(j)+P(j+1)\right]^{-1} \\ & \quad \cdot f[\hat{x}(j),u^*(j)] \\ & = C^T(j)Q(j)y^*(j)+A^T(j) \\ & \quad \cdot \left[B(j)R^{-1}(j)B^T(j)+P(j+1)\right]^{-1}\hat{x}(j+1), \end{aligned} \tag{29}$$

which can be further transferred to be

$$\begin{aligned} \hat{x}(j) &= x^*(j)+P(j)C^T(j)Q(j)[y^*(j)-h[x^*(j)]] \\ & \quad + P(j)A^T(j)\left[B(j)R^{-1}(j)B^T(j)+P(j+1)\right]^{-1} \\ & \quad \cdot \{\hat{x}(j+1)-f[x^*(j),u^*(j)]\}, \end{aligned} \tag{30}$$

and its information weight is

$$\begin{aligned} P^{-1}(j) &= C^T(j)Q(j)C(j)+A^T(j) \\ & \quad \cdot \left[B(j)R^{-1}(j)B^T(j)+P(j+1)\right]^{-1}A(j), \end{aligned} \tag{31}$$

where $A(j) = (\partial f/\partial x(j))|_{x(j)=x^*(j),u(j)=u^*(j)}$, $B(j) = (\partial f/\partial u(j))|_{x(j)=x^*(j),u(j)=u^*(j)}$, and $x^*(j)$ is prior information of $x(j)$.

4. Information Fusion Based Decoupling Control System

Based on the above derivation, a scheme of decoupling a control system for a nonlinear system is designed as shown in Figure 1.

In Figure 1, the future state filter equations are shown in (29) and (30), where the inverse time sequence of the total information weight $\{P^{-1}(j),\ j = k+T \sim k+1\}$ and the inverse time sequence of the system future state fusion estimation $\{\hat{x}(j),\ j = k+T \sim k+1\}$ are calculated. The initial values of these sequences are given by

$$\begin{aligned} P^{-1(i)}(k+T) &= C^T Q^{(i)}(k+T)C+\lambda I, \\ \hat{x}^{(i)}(k+T) &= h^{-1(i)}\left[y^*(k+T)\right] \text{or} 0. \end{aligned} \tag{32}$$

And λ is a small constant, which makes $P^{(i)}(j)$ nonsingular.

The control estimator equations are shown in (22), where i is a channel number, $i = 1 \sim p$. It should be mentioned that $\hat{x}^{(i)}(j) = [\hat{x}_1^{(i)}(j), \hat{x}_2^{(i)}(j), \ldots, \hat{x}_n^{(i)}(j)]$ represents the system future state vector estimation in the design of the ith channel control estimator; $\hat{u}^{(i)}(k) = [\hat{u}_1^{(i)}(k), \hat{u}_2^{(i)}(k), \ldots, \hat{u}_p^{(i)}(k)]^T$ is the control input vector obtained in designing the control estimator of the ith channel, not the control variable of the ith channel.

Thus, the total controller output is the sum of all control estimator outputs:

$$\hat{u}(k) = \hat{u}^{(1)}(k) + \hat{u}^{(2)}(k) + \cdots + \hat{u}^{(p)}(k). \tag{33}$$

Notice in (33) only if the ith channel output is desired to track the nonzero reference input, and also desired to be decoupled with other channels, then it needs to compute the control input $\hat{u}^{(i)}(k)$, $i = 1, 2, \ldots, p$.

5. Simulation Research

In this section, the information fusion based decoupling control method is used to control a two-degree robot manipulator. The controlled object is a four-rank nonlinear system, the mathematical model of which can be given by [18]

$$\begin{aligned} x(k+1) &= \begin{pmatrix} x_1(k)+t_s x_2(k) \\ x_2(t) - \dfrac{4t_s x_2(k)x_4(k)\left[x_3(k)+0.5\right]}{1+2\left[x_3(k)+0.5\right]} \\ x_3(k)+t_s x_4(k) \\ x_4(k)+t_s x_2^2(k)\left[x_3(k)+0.5\right] \end{pmatrix} \\ & \quad + \begin{bmatrix} 0 & 0 \\ \dfrac{t_s}{1+2\left[x_3(k)+0.5\right]} & 0 \\ 0 & 0 \\ 0 & 0.5t_s \end{bmatrix} u(k), \\ y(k) &= \begin{bmatrix} 1 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 \end{bmatrix} x(k), \end{aligned} \tag{34}$$

where $x_1(k)$ and $x_2(k)$ represent the position and the speed of one joint, denoted as joint 1, $x_3(k)$ and $x_4(k)$ represent the position and speed of the other joint, denoted as joint 2, t_s is the sampling period, and $t_s = 0.02$ s, initial output $y_0 = [4, 2]^T$, and the reference inputs of the two joints are

$$y^*(k) = \begin{bmatrix} 4-\sin(k\cdot t_s) \\ 2+\sin(k\cdot t_s) \end{bmatrix}. \tag{35}$$

5.1. Comparisons Analysis of Different Controller or Parameters. In order to verify the advantage of the information fusion based decoupling control method, the PID control is used to be compared with it. Moreover, for studying the influence of the key parameters in the proposed control algorithm, including the preview step number T and the weight matrixes Q and R, three combinations of parameters settings are selected in the simulation, as given by

(a) $T = 2$, $Q = \begin{bmatrix} 4\times10^6 & 0 \\ 0 & 4\times10^5 \end{bmatrix}$, $R = \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix}$;

(b) $T = 2$, $Q = \begin{bmatrix} 5\times10^6 & 0 \\ 0 & 5\times10^5 \end{bmatrix}$, $R = \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix}$;

(c) $T = 4$, $Q = \begin{bmatrix} 5\times10^6 & 0 \\ 0 & 5\times10^5 \end{bmatrix}$, $R = \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix}$.

Figure 2 shows the position outputs and control inputs curves of joint 1 and joint 2, respectively. r_1 and r_2 are the desired position outputs of joint 1 and joint 2, respectively.

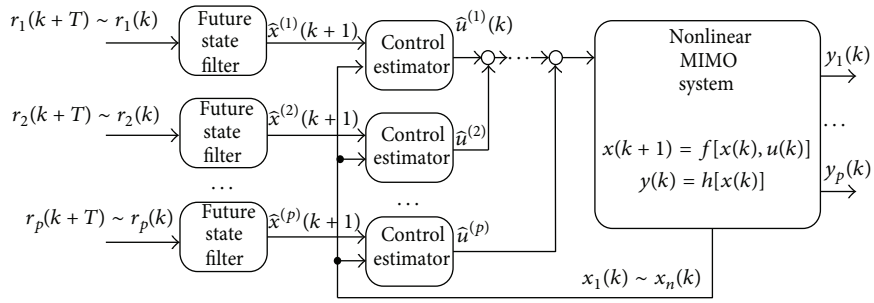

Figure 1: Information fusion based decoupling control system.

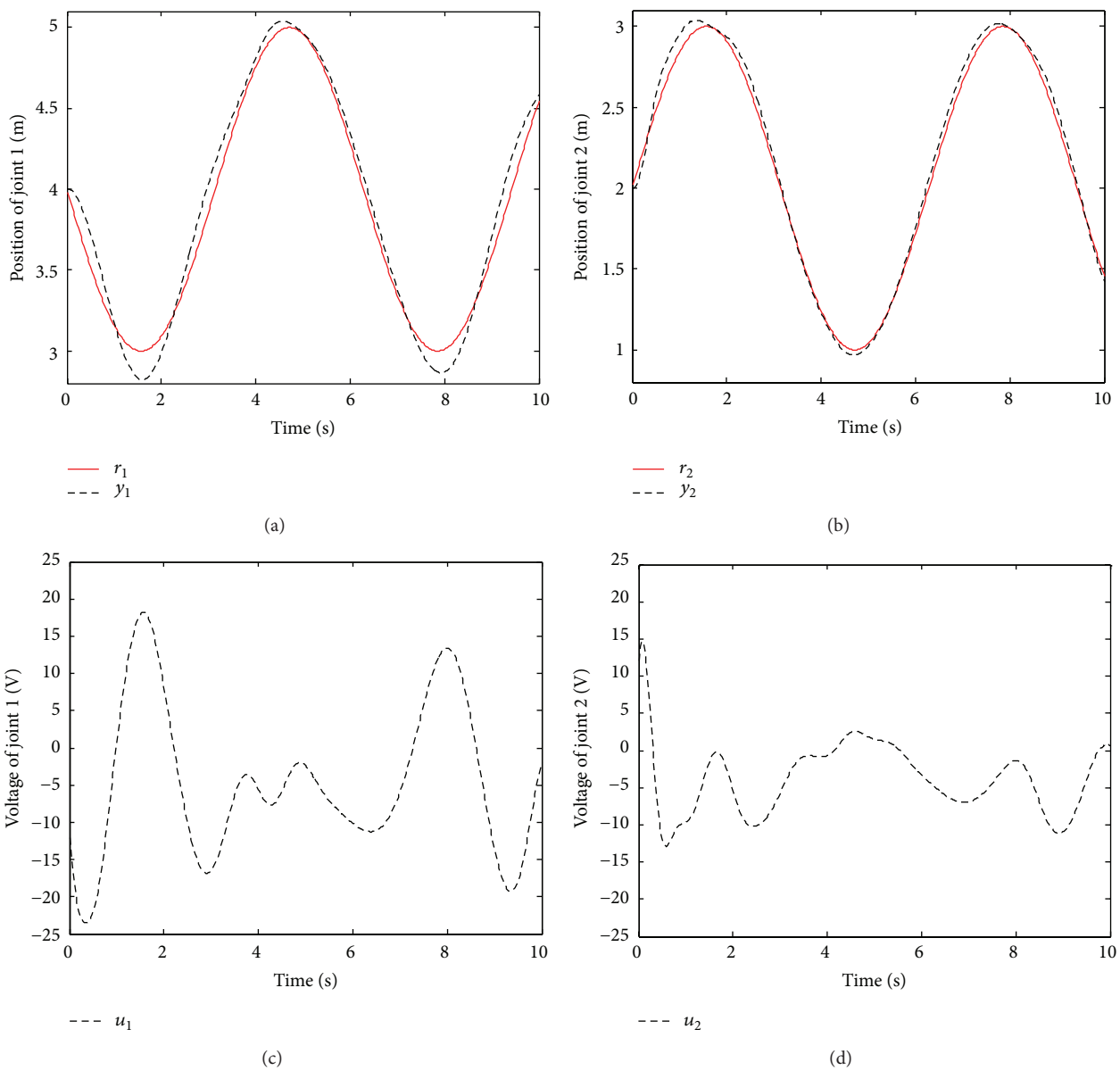

Figure 2: Responses of system positions by PID control.

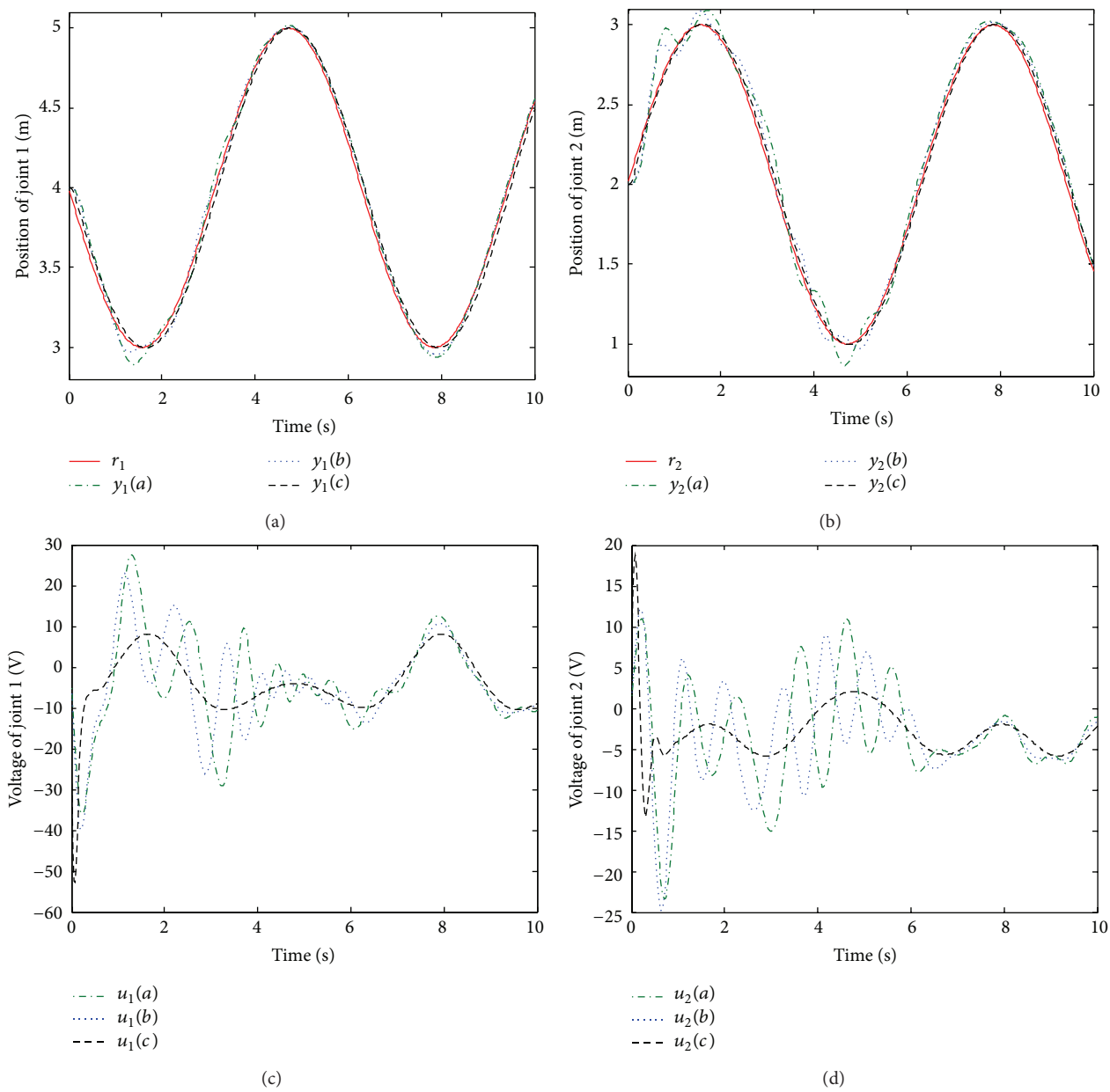

Figure 3: Responses of system positions by IFBDC.

y_1 and y_2 are the real position outputs of joint 1 and joint 2, respectively. u_1 and u_2 are the control inputs of joint 1 and joint 2, respectively. The above results are the responses of the PID controller. The control gains for joint 1 and joint 2 are as follows:

$$k_{p1} = k_{p2} = 100, \qquad k_{i1} = k_{i2} = 5, \qquad k_{d1} = k_{d2} = 10. \tag{36}$$

Correspondingly, Figure 3 also shows the position outputs and control inputs curves of joint 1 and joint 2, respectively. The above results are the responses of the proposed IFBDC method.

Based on the above simulation results, several points can be summarized as follows.

(i) The IFBDC is designed under the constraint of a performance index function and is a state feedback control method, which fuses more information than the traditional PID control. Therefore, when the system precise model is obtained, the IFBDC method can achieves better response performance than the traditional PID control, as shown in Figures 2 and 3.

(ii) Along with the increase of the preview step number, more and more future information of the system is utilized, which contributes towards the system achieving higher control accuracy, shown in Figure 3.

(iii) When the matrix R is set as a unit matrix and larger weight values in the matrix Q are chosen, the control performance of the nonlinear system will be better.

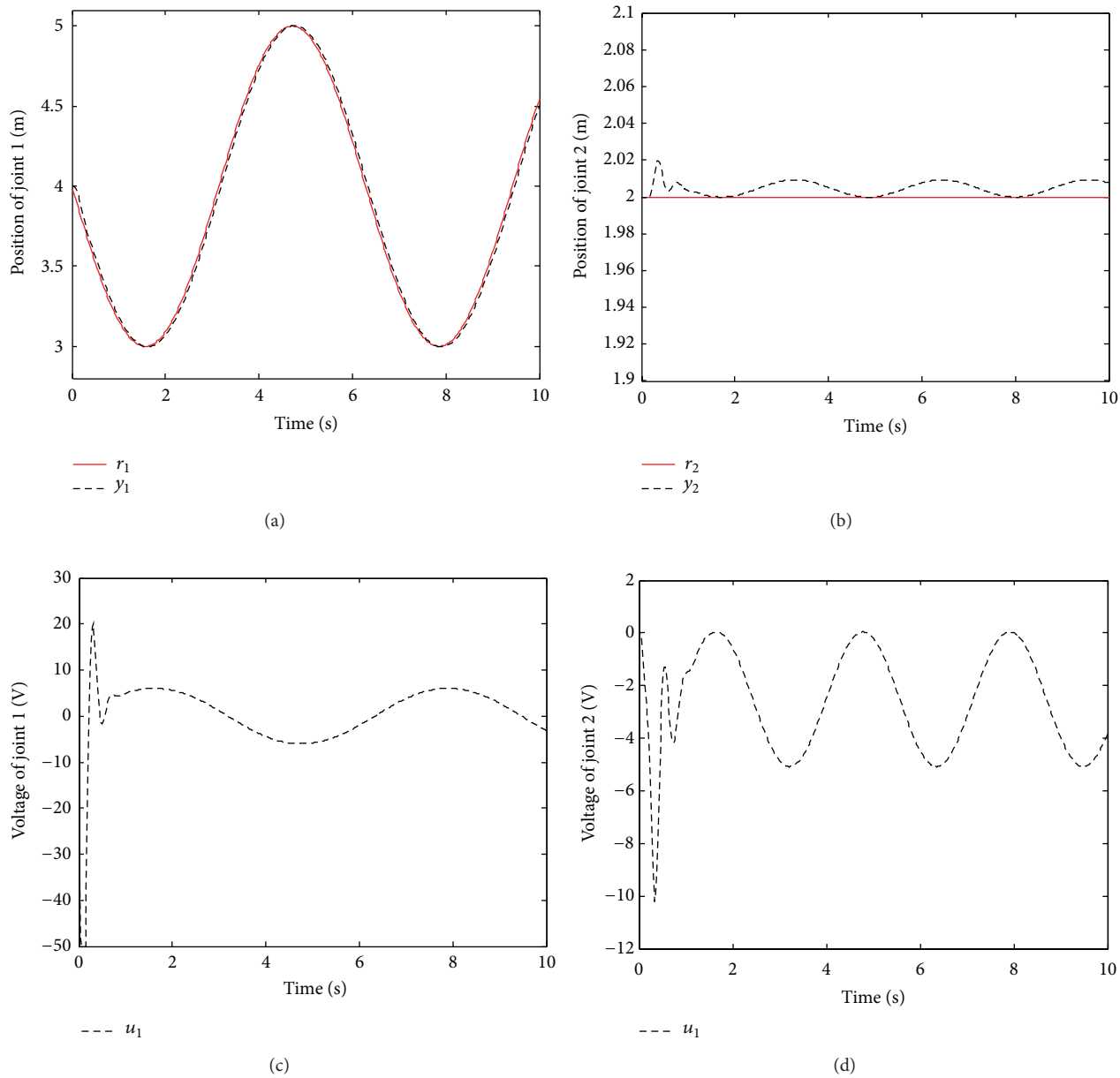

FIGURE 4: Decoupling responses of system positions.

5.2. Decoupling Effect Analysis. In order to see the decoupling performance of the IFBDC method, we only connect $\hat{u}^{(1)}$ to the system and break $\hat{u}^{(2)}$, set $r_1 = y_1^*(k) = 4 - \sin(k \cdot t_s)$, and set $r_2 = y_0(2) = 2\,\text{m}$. Then we get the position responses of joint 1 and joint 2 in Figure 4. The parameters of the decoupling control algorithm are same as (c) in Section 5.1.

From the simulation results, we find the position output of joint 1 tracks reference signal with high precision, while the position output of joint 2 keeps nearly unchanged, which realizes the decoupling control for the manipulator system. Furthermore, the decoupling degree of the system can be regulated through the selection of the weight matrixes. However, this will increase the control energy correspondingly.

5.3. Computational Cost Analysis. As shown in above simulation, IFBDC method is effective in tracking a control problem and also effective in decoupling a control problem. It can transfer the decoupling control problem into the tracking control problem. However, IFBDC is a type of modern control methods which feedback the full states and have many matrices operations.

In the simulation condition of Intel Core (TM) i3 CPU (3.2 GHz) and MATLAB R2009a, the computation time of PID control is 0.0332 s, while the computation time of IFBDC is 0.3340 s with the parameters selection (a) in Section 5.1. Furthermore, the computational cost of IFBDC will increase when the more preview pieces of information are fused.

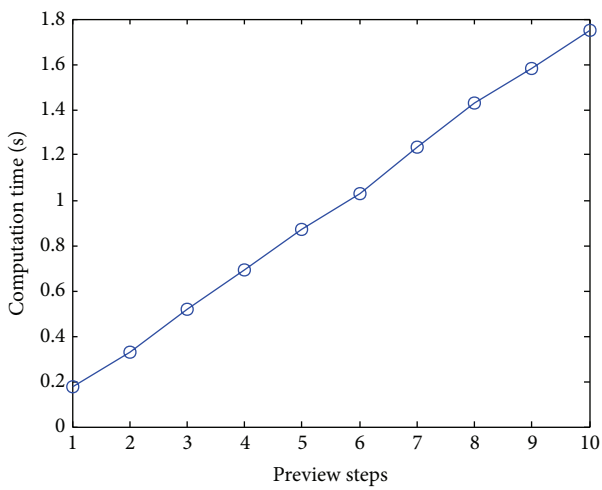

Figure 5: Relationship between computation time and the preview steps for IFBDC.

Figure 5 shows the relationship between the computation time of IFBDC and the preview steps.

We find that the computation time of IFBDC grows approximate linearly with the preview steps. Fortunately, a few preview steps are generally enough for IFBDC to realize tracking control with satisfied performance. Therefore, similar with the model predictive control methods, the IFBDC is applicable in the real systems.

6. Conclusion

This paper investigates the decoupling control problem of nonlinear multivariable systems based on the theory of information fusion estimation. The decoupling control law of each main channel and its coupled channels is singly designed, and the control law of the system is the sum of these control laws. According to the information fusion theorems, the current control variable is obtained by fusing the system future output information, the system desired trajectory information, and the control energy soft constraint information. The simulation results show the effectiveness and advantages of the control strategy when comparing with the PID control and verify the importance of the appropriate large preview step number and large weight values of the quadratic performance index, for improving the decoupling control performance of the nonlinear system.

Conflict of Interests

The authors declare that there is no conflict of interests regarding the publication of this paper.

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