Adaptive Estimation of Human-Robot Interaction Force for Lower Limb Rehabilitation

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Abstract. Human-robot interaction force information is of great significance for realizing safe, compliant and efficient rehabilitation training. In order to accurately estimate the interaction force during human-robot interaction, an adaptive method for estimation of human-robot interaction force is proposed in this paper. Firstly, the dynamics of human-robot system are modeled, which allows to establish a state space equation. Then, the interaction force is described by a polynomial function of time, and is introduced into the state space equation as a system state. Meanwhile, the Kalman filter is adopted to estimate the extended state of system online. Moreover, in order to deal with the uncertainty of system noise covariance matrix, sage-husa adaptive Kalman filter is used to correct the covariance matrices of system noises online. Finally, experiments were carried out on a lower limb rehabilitation robot, and the results show that the proposed method can precisely estimate the interaction force and also has good real-time performance.

Keywords: Human-robot interaction · State estimation · Rehabilitation robot · Interaction force estimation

1 Introduction

Cerebral infarction, cerebral hemorrhage, brain trauma, acute myelitis and other neurological diseases can cause paralysis and limb weakness. Physical exercise is

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extremely important for the recovery of paralyzed patients. Rehabilitation robot can be applied in various periods of stroke rehabilitation, since it can be used to promote the functional compensation and reorganization of central nervous system through specific training and improve their daily living activities [1].

Studies have shown that rehabilitation training with patients' active participation can effectively promote neuroplasticity and motor function recovery [2]. Precise recognition of motion intention is the premise and one of the key issues of active rehabilitation training [3], and meanwhile, human-robot interaction force is an intuitive manifestation of human motion intention. Therefore, whether the interaction force between human and robot can be estimated in real time is of great significance for active rehabilitation training [4].

Human motion intention can be recognized by two types of methods. One is physiological signals based method. Physiological electrical signals mainly include muscle electrical signals and brain electrical signals. In [5], human motion intention was detected by surface electromyography (sEMG) signals, and then the robot motion is controlled according to human limb impedance. The physiological signals directly reflect the human motion intention, but they are susceptible to the surroundings. The collected EEG signals are weakly and difficult to recognize, and they are also susceptible to external interference [6].

The alternative is motion signals based method. The motion signal sensor has the characteristics of convenient wear, strong versatility and good environmental adaptability. For example, in [7], the force/position sensor based method was used to establish the moment mapping model between human limbs and robot joints, by detecting the generated force and motion of human limbs, to determine human motion intention. Huang placed a force sensor on the robot end effector to estimate the wearer's motion intention in real time [8].

Kalman filter method has higher estimation accuracy, and can also achieve estimation of robot state at the same time. Reasonable assumptions of interaction force model can improve the estimation accuracy of interaction force [9]. At present, most of the research work on human-robot interaction force uses the constant value hypothesis [10]. Hu adopted the interaction force model with polynomial and sinusoidal variation expression [9], which improved the effect of dynamic hypothesis to some extent. However, in actual process of human-robot interaction, the model of interaction force is usually time-varying, so the assumption of fixed order cannot meet the practical demand.

Based on the dynamic model of human-robot interaction system, an extended state space equation can be established by introducing the interaction force model using polynomial function of time. The improved sage-husa adaptive Kalman filter (SHAKF) is used to correct statistical characteristics of system state noise in real time to optimize the estimation of interaction force. Finally, the effectiveness of the proposed method is verified by experiments.

2 Human-Robot System Dynamic Model

During the rehabilitation exercise with robot, the patient's lower limbs are usually attached to the mechanical legs, as shown in Fig. 1. The hip and knee joints of mechanical leg can be respectively corresponding to the joints of human leg by adjusting the length of each link. Meanwhile, the lower limb of the human body can be fixed on the mechanical leg by using velcro fastener. Since the ankle joint contributes less to the end motion range, the above human-robot system can be treated as a two-bar linkage mechanism.

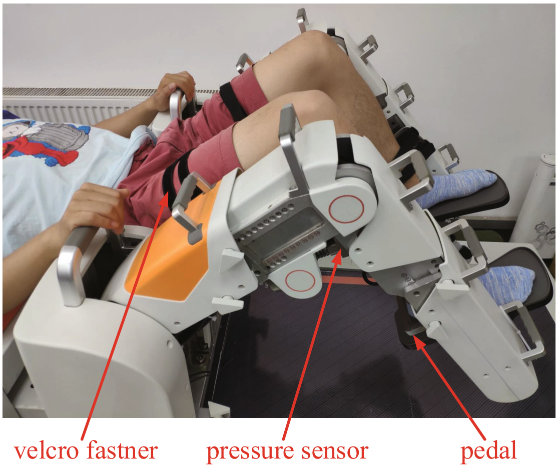

Fig. 1. Experiment platform for identification and validation of dynamics

The dynamic model of human-robot system can be obtained by Euler-Lagrange equation.

$$\frac{d}{dt}\left(\frac{\partial L}{\partial \dot{\theta}}\right) - \frac{\partial L}{\partial \theta} = \tau \tag{1}$$

where θ and $\dot{\theta}$ denote the joint angular and its velocity, τ denotes the joint moment, and L is Lagrangian equation of human-robot system.

$$L = \sum_{i=1}^{2} K_i - P_i \tag{2}$$

where K_i and P_i denote the human-robot system's kinetic and potential energy of linkage i respectively. In order to obtain the kinetic and potential energy of human-robot system, the two links are respectively considered to be composed of innumerable mass micro-elements. Firstly, the kinetic and potential energy are calculated for each micro-element, and then the integral operation is performed. As a result, the kinetic and potential energy of links 1 and 2 can be obtained as follows.

$$
\begin{cases}
K_1 = \int_{v_1} \frac{1}{2}\rho_v l_v^2 \dot{\theta}_1^2 dv \\
K_2 = \int_{v_2} \frac{1}{2}\rho_v l_1^2 \dot{\theta}_1^2 dv + \int_{v_2} \rho_v l_1 l_v \cos(\theta_2)\cos(\theta_v)\dot{\theta}_1(\dot{\theta}_1 + \dot{\theta}_2)dv \\
\quad + \int_{v_2} \frac{1}{2}\rho_v l_v^2 (\dot{\theta}_1 + \dot{\theta}_2)^2 dv - \int_{v_2} \rho_v l_1 l_v \sin(\theta_2)\sin(\theta_v)\dot{\theta}_1(\dot{\theta}_1 + \dot{\theta}_2)dv \\
P_1 = \int_{v_1} \rho_v g l_v \sin(\theta_1 + \theta_v)dv \\
P_2 = \int_{v_2} \rho_v g l_2 \sin(\theta_1)dv + \int_{v_2} \rho_v g l_v \sin(\theta_1 + \theta_2)\cos(\theta_v)dv \\
\quad + \int_{v_2} \rho_v g l_v \cos(\theta_1 + \theta_2)\sin(\theta_v)dv
\end{cases}
\tag{3}
$$

where $\dot{\theta}_i$ represents the angular velocity of joint i, dv represents the mass micro-element on the corresponding link, l_v represents the distance between dv and corresponding joint, θ_v represents the angle from the link's midline to connection between the joint and mass micro-element.

Combined with formulas one to three, the standard form of human-robot system dynamic equation can be derived.

$$D(\theta)\ddot{\theta} + C(\theta, \dot{\theta})\dot{\theta} + G(\theta) + \tau_f = \tau \tag{4}$$

where θ, $\dot{\theta}$ and $\ddot{\theta}$ denote the joint angular, its velocity and acceleration respectively. τ_f denotes the classical friction term, which consists of viscous friction and Coulomb friction. $D(\theta)$ is a symmetric positive definite matrix, $C(\theta, \dot{\theta})\dot{\theta}$ denotes the Coriolis and centripetal moment, $G(\theta)$ denotes the gravitational moment.

According to the linear characteristic of robot's dynamics, there is a parameter vector that makes them satisfy the following linear relationship.

$$D(\theta)\ddot{\theta} + C(\theta, \dot{\theta})\dot{\theta} + G(\theta) + \tau_f = Y\varphi \tag{5}$$

where Y is the regression matrix of joint variable, and φ is an unknown constant parameter vector.

3 Estimation of Human-Robot Interaction Force

3.1 Model of Human-Robot Interaction Force

In this paper, the joints of human lower limb are simplified into hip and knee joint, of which the interaction force models are similar to each other. Hence, the interaction force of hip joint is modeled below as an example.

Assuming that in the process of human-robot interaction, the change law of hip joint's interaction force, τ_a, is a polynomial function of time in a finite period. Then the dynamic expression of interaction force can be expressed as follows.

$$\begin{cases} \dot{\lambda} = \mathrm{L}\lambda \\ \tau_a = \mathrm{S}\lambda \end{cases} \tag{6}$$

where $\lambda = [\lambda_1 \ \cdots \ \lambda_{r+1}]$, r is the order of polynomial,

$$\begin{aligned} \mathrm{L} &= \begin{bmatrix} \mathbf{0}_{r\times 1} & diag(\partial_1, \cdots, \partial_r) \\ 0 & \mathbf{0}_{1\times r} \end{bmatrix} \\ \mathrm{S} &= \begin{bmatrix} 1 \ \mathbf{0}_{1\times r} \end{bmatrix} \end{aligned} \tag{7}$$

where $diag(\cdot)$ is a diagonal matrix, $\partial_1, \cdots, \partial_r$ is partial coefficients of polynomial.

3.2 Extended State Space Equation

We can get the following extended state space equation by introducing λ into state vector.

$$\begin{aligned} \dot{x} &= Ax + Bu + V \\ z &= Hx + N \end{aligned} \tag{8}$$

Therefore, the human-robot interaction force can be achieved by Eq. 9 under the extended state space model.

$$\tau_a = \begin{bmatrix} \mathbf{0}_{2\times 4} \ \mathbf{I}_{2\times 2} \ \mathbf{0}_{2\times r} \end{bmatrix} x \tag{9}$$

So, the estimation of state vector can be gained by using Kalman filter.

3.3 Sage-Husa Adaptive Kalman Filter

Kalman filtering is an autoregressive optimal estimation algorithm [11], which principle consists of two parts: state prediction process and update process. In the prediction step, the current state is estimated by previous state value, while in the update step, Q and R are calculated, based on which the confidence of the estimated and the measured value are weighted. The optimal estimation of current moment is performed according to the predicted value of previous moment, the measured value and the error covariance of the current moment, then the state value of next time is predicted, thereby forming an iterative loop.

$$\begin{aligned} &\hat{x}_{k|k-1} = A_k \hat{x}_{k-1|k-1} + B_k u_k \\ &\hat{P}_{k|k-1} = A_k \hat{P}_{k-1|k-1} A_k^T + Q_{k-1} \\ &V_k = Z_k - H_k \hat{x}_{k|k-1} \\ &K_k = \hat{P}_{k|k-1} H_k^T (H_k \hat{P}_{k|k-1} H_k^T)^{-1} \\ &Q_k = (1 - d_k) Q_{k-1} + d_k (K_k V_k V_k^T K_k^T + A_k \hat{P}_{k|k-1} A_k^T) \\ &\hat{x}_{k|k} = \hat{x}_{k|k-1} + K_k V_k \\ &\hat{P}_{k|k} = \hat{P}_{k|k-1} - K_k H_k \hat{P}_{k|k-1} \end{aligned} \tag{10}$$

4 Experiments and Discussion

In order to verify the effectiveness of the estimation method of human-robot interaction force, experiments are carried out on the lower limb rehabilitation robot, as shown in Fig. 1.

4.1 Identification and Validation of System Parameter

The parameters of human-robot system dynamic model need to be identified at first, so that the extended state space Eq. 8 can be obtained.

The samples used for parameter identification are collected during the motion process of performing excitation trajectory driven by motors in the human-robot interaction system, while the subject is required to passively follow the mechanical leg to move without applying any active torque. Unknown dynamic parameters are recognized by the Eq. 5 using the least squares method.

The parameters identification results are shown in Table 1.

Table 1. Identification results of system parameter

Parameter	IU	Number
φ_1	$Kg * m^2$	23.1118
φ_2	Nm	8.2613
φ_3	$Kg * m^2$	-2.4986
φ_4	$Kg * m^2$	-0.9827
φ_5	$Kg * m^2$	-0.4954
φ_6	Nm	-7.1493
φ_7	Nm	17.9843
φ_8	Nm	-0.5973
φ_9	Nm	26.2949
φ_{10}	Nm	-1.5535

After the parameters are recognized, a reference trajectory different from optimal excitation trajectory is carried out to verify the accuracy of identification parameters. The root mean square errors of hip and knee joints are 0.4417 Nm and 0.6937 Nm respectively, which indicates that the identification method used in this paper can effectively recognize the parameters of human-robot system dynamic model.

4.2 Estimation of Human-Robot Interaction Force

In this section, the experiment for estimation of human-robot interaction force is performed on the lower limb rehabilitation robot to verify the effectiveness of the proposed method.

In the experiment, the rehabilitation robot performs treadmill trajectory in the vertical sagittal plane. Treadmill exercise is a common rehabilitation training mode, which can slow the muscle atrophy, promote the recovery of limb motor function and improve blood circulation. For patients with central nervous system injury, it also has the effect of reducing muscle tension and improving muscle strength. During the treadmill exercise, the subject applies an interaction force to the pedal through foot, which can be collected by force sensor mounted on the pedal. To illustrate the effectiveness and versatility of the proposed method, the force applied to pedal by the subject is required to be a reciprocating force that varies in magnitude and direction over time. This force can be transformed by Jacobian matrix J into torque of robot's joint space.

By comparing the measured value of human's active joint torque with the calculated torque obtained by the proposed method, the feasibility for method of estimating the human-robot interaction force can be verified. The experimental results are illustrated in Fig. 2. The root mean square errors of the hip and knee joint measurements and estimation torques are 0.1379 Nm and 0.2413Nm respectively, which indicates that the improved sage-husa adaptive Kalman filter method based on the force model using polynomial function of time can precisely estimate the human-robot interaction force, thus verifying the effectiveness of the proposed method.

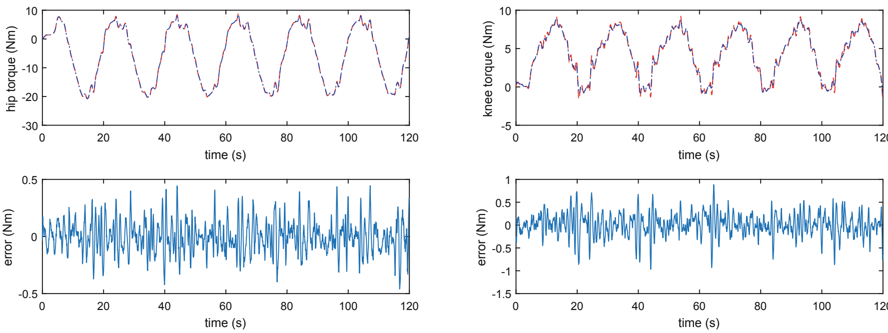

Fig. 2. Estimation of human-robot robot interaction force

5 Conclusion

In order to precisely estimate the interaction force during human-robot interaction, an adaptive method for estimation of human-robot interaction force is proposed in this paper. The interaction force is fitted by polynomial and then imported into the human-robot system dynamic model, in order to obtain the extended state space equation. To correct the time-varying covariance matrix of system noise, an improved sage-husa adaptive Kalman filter method is designed to estimate the state online. Experiments were carried out on the lower limb rehabilitation robot. The experimental results demonstrated that the proposed method can accurately estimate the human-robot interaction force and also has good real-time performance, which verifies the effectiveness of the proposed method. The experiments for paralyzed patients will be carried out in future research to test the clinical feasibility.

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