Robot Dynamic Parameter Identification based on BBO Algorithm

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Abstract. In this paper, a linearized robot dynamics model is first established. The DH parameters and physical constraints of the robot are given. The joint motion trajectory based on Fourier series is designed then. By setting the conditional number of the observation matrix as the objective function, an Biogeography-based optimization algorithm is applied to identify the dynamic parameters of the robot. The physical constraint calibration and predictive torque results are compared with the traditional genetic algorithm to verify the advanced nature of our method.

1. Background
With the advent of the Industrial 4.0 era, industrial robots have been widely used. The design of motion controller based on robot dynamics model has become an effective method to acquire highly precise motion control. Since the design of motion controllers require the dynamic parameters of the robot, it is necessary to design specific identification methods for different kinds of robots. The identification of robot dynamic parameters generally includes the following 5 steps: Robot dynamics modeling, excitation trajectory designing, sampling and processing data, parameter estimation and model verification. It is worth noting that the accuracy of identification depends on the method of parameter estimation to a large extent.

Many methods of robot dynamic parameter identification are put forward by scholars at home and abroad. Gauter determined the minimum set of tree-structure robots’ inertial parameters by giving complete information[1]. The excitation trajectory of Fourier series based on finite item was put forward by Swevers[2]. Least squares was modified by Park, but this method can only identify linear models, and the Coulomb-viscous friction model used is not accurate in describing the friction characteristics[3].

A scheme of sequential identification was proposed, where the parameters to be identified need to take the identified parameters as the priori value causing a large cumulative error[4]. The classical Striebeck, Dahl and Lugre models do not work well when describing the friction between the joints of the robot[5,6].

2. Robot Dynamics Linearization Model
The dynamic model of robot with N-DOF rotating joint series should be described as:

\[ M(q)\ddot{q} + C(q, \dot{q})\dot{q} + G(q) + \tau_f = \tau \]  

(1)

Where \( q \in R^n \) refers to the joint angular vector, \( M(q) \in R^{n\times n} \) refers to the positive definite symmetric inertial matrix, \( C(q, \dot{q}) \in R^{n\times n} \) is the matrix of centrifugal force and the gothic force, \( G(q) \in R^n \) is the gravity vector, \( \tau_f \in R^n \) is the joint friction moment vector and \( \tau \in R^n \) is the torque control input vector.
In order to solve the problem that the traditional friction model is discontinuous at a speed of 0, a continuous function is used to approximate the traditional friction model. Thus the static continuous friction model can be expressed as:

$$\tau_f = AF(\dot{q}_i) + f\dot{q}_i$$  \hspace{1cm} (2)

Where \(F(\dot{q}_i)\) is continuous nonlinear function which is already acquired, the selection of \(F(\dot{q}_i)\) should be able to reflect the friction characteristics of the joints, which can also be achieved by the motor and other driving elements. \(A\) is the amplitude of the unknown parameter to be identified.

As the friction torque can be linearized, the dynamic model can be further expressed as:

$$\tau = \Phi(q, \dot{q}, \ddot{q}) \beta$$  \hspace{1cm} (3)

Where \(\beta = [P_b, A_{1f}, f_{s1}, \cdots, A_{nf}, f_{sn}]^T \in R^{(p+2n)\times 1}\) is a vector containing dynamic parameters, which includes the basic parameter set and friction parameters, and \(\Phi(q, \dot{q}, \ddot{q}) \in R^{(p+2n)\times 1}\) is the corresponding regression matrix.

To summarize, the goal of robot dynamic parameter identification is to make the robot track the specific excitation trajectory and estimate the value of the dynamic parameter vector \(\beta\) by measuring the joint angles and torques.

3. Excitation Trajectory Design and Optimization

3.1. Excitation Trajectory Design

On account that Fourier series have strong ability to reduce noise, it is utilized to generate excitation trajectory. In order to satisfy the requirement that the robot can return to the starting position at the end of a period, the constant coefficients in the Fourier series are replaced by five times polynomial. Therefore, the Fourier series related with joint \(i\) can be expressed as:

$$q_i(t) = \sum_{l=0}^{n_i} \left( m_{l,i} \sin(\omega_{l,i} t) \right) + \sum_{l=0}^{n_i} \left( n_{l,i} \cos(\omega_{l,i} t) \right) + \sum_{k=1}^{5} h_{k,i} \left( t - (j - 1) t_f \right)^k$$

$$t_f = \frac{2 \pi }{\omega_f}$$

$$j = \left[ \frac{t}{t_f} \right]$$  \hspace{1cm} (4)

Unknown coefficients \(m_{l,i}\) and \(n_{l,i}\) will be determined in the following excitation trajectory optimization.

3.2. Excitation Trajectory Optimization

Adopting the observation matrix condition number as the optimization criterion, the excitation trajectory optimization problem based on the conditional number criterion can be described as:

$$\min_{m_{l,i}, n_{l,i}} \text{cond}(W)$$

$$q(0) = q_{\text{start}}, \dot{q}(0) = \ddot{q}(0) = 0$$

$$q(t_f) = q_{\text{start}}, \dot{q}(t_f) = \ddot{q}(t_f) = 0$$

$$-q_{\text{M, max}} \leq q(t) \leq q_{\text{M, max}}, -\dot{q}_{\text{M, max}} \leq \dot{q}(t) \leq \dot{q}_{\text{M, max}}$$

$$-\ddot{q}_{\text{M, max}} \leq \dddot{q}(t) \leq \dddot{q}_{\text{M, max}}$$  \hspace{1cm} (5)

Where \(q_{\text{M, max}}, \dot{q}_{\text{M, max}}, \ddot{q}_{\text{M, max}}, \dddot{q}_{\text{M, max}}\) are the constraint vectors for joint angle, angular velocity, and angular acceleration. This is a nonlinear constraint optimization problem, which can be processed by the following Biogeography-based optimization algorithm.
4. Biogeography-based Optimization Algorithm

The Biogeography-based optimization algorithm\cite{7,8} is a simulation of the population migration behavior. The algorithm takes the condition number of the dynamic parameter observation matrix as the objective function and obtains the optimal parameters based on the migration and mutation principles. Data of the input excitation trajectory and the output joint moment and angular displacement are collected as the experimental samples. The specific process of the algorithm is shown in figure 1.

![Flowchart of the Biogeography-based optimization algorithm.](image)

We define $Options.pmodify$ represents the correction probability of the habitat, mutation probability is expressed as the initial mutation rate, and $N$ represents the number of iterations. The values of these parameters are of some empirical nature and need to be adjusted based on specific objects. In short, the identification uses the conditional number of the robot dynamic parameter observation matrix as the objective function. Then the initial population is obtained through the population initialization and migration with mutation are undergone by each iteration to record the according fitness value. At the end of the iteration, the optimal individual in the current iterative loop is the global optimal solution of the algorithm.

5. Experimental Results and Analysis

The DH parameters of the robot for experiment is first given in below.

| joint | theta | d      | alpha | a       |
|-------|-------|--------|-------|---------|
| 1     | 0     | 0.1    | 0     | 0       |
| 2     | -1.5708 | 0.1355 | 1.5708 | 0       |
| 3     | 0     | 0      | 0     | 0.4250  |
| 4     | -2.5708 | 0.019  | 0     | 0.1     |
| 5     | 3.1416 | 0.0978 | -1.5708 | 0       |
| 6     | 0.6283 | 0.0828 | -1.5708 | 0       |

Then we set $N=100$, $Options.pmodify=0.7$, $Options.pmutate=0.005$ in the Biogeography-based optimization algorithm. After about 100 iterations, the algorithm converges gradually to the global optimal, and the condition number of observed matrix finally converges to the global optimal value. The main indicators of the algorithm are shown in table 2.
### Table 2. Main result of the BBO algorithm

| Overall Iterations | The optimum condition number from BBO |
|--------------------|---------------------------------------|
| 150                | 25                                    |

In order to verify the dynamic parameters calculated by the algorithm proposed in this paper can describe the dynamic characteristics of the robot more effectively, the traditional genetic algorithm [9,10] is also used to optimize the condition number. The result from the traditional genetic algorithm is 32. However, the condition number obtained by the Biogeography-based optimization algorithm is 25. It can be seen that based on the method described in this paper, the accuracy of the conditional number is increased by about 21.88%.

We also draw the acceleration diagram of the joints in figure 2 to illustrate that the results of the optimization algorithm can meet the physical constraints very well. Each acceleration of robot joints reach zero both at the start and the end of the test time.

![Joint Acceleration vs Time](image)

**Figure 2. Joint acceleration results**

Therefore, compared with the traditional genetic algorithm, the identification accuracy of the method described in this paper has been improved.

![Torque Prediction Results](image)

**Figure 3. Torque prediction results**
On the other hand, in order to display the superiority of the identification model more vividly, the torque prediction results are plotted in figure 3. It can be found that the prediction moment based on the method described in this paper has a high fitting degree. At the same time, there is no jumping and other phenomena in the joint prediction moment, which effectively inhibits the peak error.

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