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Review

An overview of dynamic parameter identification of robots

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ABSTRACT

Due to the importance to model-based control, dynamic parameter identification has attracted much attention. However, until now, there is still much work for the identification of dynamic parameters to be done. In this paper, an overview is given of the existing work on dynamic parameter identification of serial and parallel robots. The methods for estimating the dynamic parameters are summarized, and the advantages and disadvantages of each method are discussed. The model to be identified and the trajectory optimization are reviewed. Further, the methods for validating the estimated model are summarized and the application of dynamic parameter identification is mentioned. The results of this review are useful for manufacturers of robots in selecting proper identification method and also for researchers in determining further research areas.

Contents

1. Introduction

The dynamic parameters that describe the dynamic model are important for the advanced model-based control algorithms, the validation of the simulation results and the accurate path planning algorithms [1]. Especially in the special mechatronics area of robotics, model-based control is crucial for the increase of the system's precision and reliability. However, the dynamic model of the robot contains uncertainties in many parameters and many control methods are sensitive to their values. Sensitivity to parameter uncertainty is especially severe in high speed operations. Dynamic parameter identification methods have gained importance for developing model based controllers. In general, a standard robot identification procedure consists of modeling, experiment design, data acquisition, signal processing, parameter estimation and model validation [2]. The last step of the identification procedure is model validation, where the user verifies that the model satisfies the accuracy specifications. If the obtained model does not pass the validation tests, one or several steps of the procedure are repeated and some of the choices are reconsidered. The identification of dynamic parameters has attracted considerable attention from numerous researchers. Atkeson et al. [3] proposed the estimation of inertial parameters. Gautier et al. [4] proposed a dynamic identification method from

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only the torque data. Grotjahn et al. [5] used the two-step approach to perform the friction and rigid body identification of robot dynamics.

In contrast to the vast amount of literature concerning the identification of serial robots, there are only a few publications dealing with experimental identification of the dynamics of fully parallel mechanisms. Most of these publications apply no real-time identification approaches but adaptive control algorithms. Further, the parameter determination is restricted to very simple models. There are different reasons for this lack of identification algorithms for the dynamics of complex parallel mechanisms. In comparison to serial robots, the workspace constraints strongly restrict the experimental possibilities. Furthermore, an independent investigation of local influences like joint friction is impossible since single joint motions cannot be carried out.

This paper reviews the work on dynamic parameter identification of serial and parallel robots. Due to the lack of identification algorithms for the dynamics of complex parallel mechanisms, dynamic parameter identification of parallel robot is emphasized. Identification method, linear model, trajectory optimization, validation and application are discussed, and the relevant research work is reviewed. The results of this review are useful for manufacturers of robots and researchers.

2. Methods of dynamic parameter identification

The accuracy of dynamic model depends on the geometrical parameters and dynamic parameters. High-precision geometrical parameters can be obtained by kinematic calibration, and the dynamic parameters should be estimated by identification methods. Many different methods, which can be categorized as on-line identification and off-line identification methods, are proposed to determine the dynamic parameter values. In the off-line procedure, all the input–output data can be collected prior to analysis and do not impose any limits on the computation time. In contrast, the on-line procedure deals with real-time updates of the parameters to be identified during robot operations.

2.1. Off-line identification

There are three main off-line methods for estimating the dynamic parameters of a robot.

(1) Physical experiments: the robot is disassembled to isolate each link, some inertial parameters can be obtained by experiments. For example, the mass could be evaluated directly, the coordinates of the center-of-mass could be obtained by determining counterbalanced points of the link and the diagonal elements of the inertia tensor could be obtained by pendular motions [6]. Based on physical experiments, some other methods are developed [7–11]:

(a) Frequency response function: the vibration response of the links is used to determine the inertial parameters.
(b) Modal model method: the modal model of the link is utilized to determine the inertial parameters.
(c) Inertia restricted method: the method is developed based on the residual inertia of the rigid body, which is computed from the measuring value of frequency response experiment.
(d) Direct system identified method: the inertial parameters are identified to minimize the error between the measuring value and the theoretic value of frequency response.

In physical experiments, the special measuring devices are necessary and the joint characteristic is neglected. The identification accuracy depends on the accuracy of measuring devices. Further, physical experiments are very tedious and should be realized by the manufacturer before assembling the robot.

(2) Computer aided design (CAD) techniques: these approaches find the required dynamic parameters of a link by using its geometric and material characteristics. All robotics CAD/CAM packages provide tools to calculate the inertia parameters from 3-dimensional models. It is easy to obtain the independent parameter value. In the design phase of a robot, the dynamic performance and model-based control performance of the robot can be investigated based on the estimated dynamic parameters, and the performance analysis can be used further to improve the design. However, the precision of the link model in CAD system determines the accuracy of the estimated parameter. Due to the manufacturing error of the link, the CAD model is not identical with the real part and the accuracy of the estimated parameter values is effected. Moreover, estimates of friction parameters are not provided by the manufacturers and are not predictable from CAD drawing.

(3) Identification: this approach is based on the analysis of the "input/output" behavior of the robot on some planned motion and on estimating the parameter values by minimizing the difference between a function of the real variables and its mathematical model. This method has been used extensively and was found to be the best in terms of ease of experimentation and precision of the obtained values [12]. Using this method, Guegan et al. [13] identified the 43 base dynamic parameters of Orthoglide parallel kinematic machine. Vivas et al. [14] identified the base dynamic parameters of H4 parallel robot, which are necessary for the dynamic model, and pointed out the use of the accelerometer and rotation sensor was not very necessary. Compared to the above two methods, identification approach can obtain good accuracy of identification, and the measurement is relatively easy. This method gives better results than the physical experiment and CAD technique.

2.2. On-line identification

On-line identification is a classical and well studied problem: finding values of the parameters in the mathematical model of a system from on-line measured data such that the predicted dynamic response coincides with that of the real system [15]:

(1) Adaptive control algorithms: the method has been investigated extensively as an interesting approach to estimate or adjust on-line the dynamic parameter values used in the control. For parallel robots, the workspace constraints and the complexity of the dynamic equations make an independent excitation of different parameters extremely difficult. If also friction in passive joints of the structure is taken into account, the parameter space will be much larger. These problems are reduced with adaptive control algorithms, since a sufficient excitation is not as crucial as for identification approaches. Based on the Jacobian matrix, Burdet and Codourey [16] projected the force and torque of each moving part onto the Cartesian space. This is the base for the nonlinear adaptive control algorithm to be used for the identification of dynamic parameters. Honegger et al. [17] used a nonlinear adaptive control algorithm to identify the base dynamic parameters of the Hexaglide parallel kinematic machine. In this algorithm, however, parameter convergence cannot be guaranteed.

(2) On-line approach based on neural network: neural networks have received considerable attention in the control and identification fields. It has been demonstrated that neural networks can be used effectively for the identification of nonlinear systems [18]. The identified parameters are regarded as the weights of the network, and the weights approach the actual

values of the identified parameters by training the weights. Neural network can realize the on-line identification since the sampled real-time data are input to the network to obtain the real-time parameter value. Jiang et al. [19] proposed an identification approach with neural network based compensation of uncertain dynamics, and the dynamic parameter identification process is divided into two steps.

Although dynamic parameter values of a robot can be obtained by off-line and on-line methods, all of them involve approximations and errors. This means that the dynamic parameters are only known with some uncertainties. In these parameters, static moments and diagonal terms of the inertia matrices should be estimated with a good accuracy, and the other terms are not so important and could be estimated with a lower accuracy.

3. Model and identification algorithm

3.1. Identification model

The identification of dynamic parameters of robot is based on the use of the inverse dynamic model, which is linear with respect to the dynamic parameters. Not all the inertial parameters have an effect on the dynamic model, while others appear to have an effect in linear combinations. The dynamic parameters of a robot can be classified into three groups: fully identifiable, identifiable in linear combinations only and unidentifiable [20], and it is impossible to estimate all the link dynamic parameter values from the data of link motions and joint torques or forces since the link dynamic parameters are redundant to determine the manipulator dynamic model uniquely. The non-redundant and identifiable dynamic parameters can be termed a minimum set of dynamic parameters whose values can determine the dynamic model uniquely. Such a set of dynamic parameters is called base dynamic parameters or minimum dynamic parameters, which is sufficient to describe the dynamic behavior of the mechanical system along with the reduced observation matrix [21,22].

After the base dynamic parameters are determined, the model to be identified should be derived with different methods such as Newton–Euler method, Lagrangian equation and virtual work principle. The dynamic model can be easily derived and expressed from Lagrange equation as follows:

$$\boldsymbol{M}(\boldsymbol{\theta})\ddot{\boldsymbol{\theta}}+\boldsymbol{H}(\boldsymbol{\theta},\dot{\boldsymbol{\theta}})+\boldsymbol{g}(\boldsymbol{\theta})=\boldsymbol{\tau} \tag{1}$$

where $\boldsymbol{\theta}$ and $\boldsymbol{\tau}$ are joint variable and torque, respectively, $\boldsymbol{M}(\boldsymbol{\theta})$ is inertia matrix, $\boldsymbol{H}(\boldsymbol{\theta},\dot{\boldsymbol{\theta}})$ contains Coriolis and centrifugal force, and $\boldsymbol{g}(\boldsymbol{\theta})$ denotes gravitational force.

The dynamic model can be written into a set of linear equations of the unknown parameters as follows:

$$\boldsymbol{y}(\boldsymbol{\tau},\dot{\boldsymbol{\theta}})=\boldsymbol{\varphi}(\boldsymbol{\theta},\dot{\boldsymbol{\theta}},\ddot{\boldsymbol{\theta}})\boldsymbol{p} \tag{2}$$

where $\boldsymbol{p}$ is the dynamic parameters.

The model to be identified can be classified into three forms: explicit dynamic model, implicit dynamic model and energy model. Gautier [24] and Gautier and Khalil [23] compared the 3 models and the results show that the 3 models give close estimations and accuracy, and the filtered power model is very attractive for its simplicity and accuracy. The other two dynamic models give the same results, then there is no advantage in using the dynamic model with implicit acceleration because its expression is more complicated than that of the dynamic model with explicit acceleration.

Although many methods have been used to derive the dynamic model, much work has been concentrated on serial robots. Due to the complex and coupled dynamics, the task for parallel robots still remains challenging. In fact, dynamic modeling of parallel robots has been studied extensively by using general approaches, however, it is difficult to rewrite the dynamic model into the linear form. Most applications for dynamic parameter identification use very simplified models. Some other approaches are presented to derive the linear dynamic model. Khalil and Guegan [25] derived the inverse and direct dynamics modeling of Gough–Stewart robots. Grotjahn et al. [26] used Newton–Euler equation in combination with Jourdain's principle to derive the linear dynamic model of a Gough–Stewart platform. Using the virtual work principle, Wu et al. [27] presented a method to derive the dynamic formulation of redundant and non-redundant parallel manipulators for dynamic parameter identification.

For the identification of dynamic parameter, the parameters crucial for accurate position control are to be modeled. Modeling the nonlinear dynamic effects of friction, actuator characteristics or closed kinematic chains pose challenges in modeling for identification and are examples of areas where further research and development work are needed.

3.2. Identification algorithm

The input/output signals of the robot are sampled while the robot is tracking trajectories that excite the system dynamics in order to get an overdetermined linear system. Then it is solved to estimate the base parameters using numerical optimization methods such as weighted least squares estimation method, Kalman filtering method and maximum-likelihood estimation. The selection of a parameter estimation algorithm is a compromise between accuracy and complexity of implementation.

In the class of estimation algorithms, the weighted least squares estimation method takes a particular place for robot manipulator identification [28]. Based on the use of the inverse model linear in relation to the parameters, it allows to estimate the base inertial parameters providing measurement or estimation of the joint torques and the joint positions. The weighted least square method, which is a noniterative method that finds the parameter estimates in a single step using the singular value decomposition, optimizes the root-mean square residual error of the model under the assumption that the measurement errors are negligible. However, one problem for the parameter estimates of the weighted least square method is the sensitivity to measurement noise [29]. Noise will limit the accuracy of parameters obtained by the least squares, and will limit the convergence rate of the recursive least squares algorithm. To overcome this problem, one can generate the so-called exciting trajectories and/or use data filtering. By using such "input data improvement", a lot of excellent parameter estimations using the least squares method have been obtained [30,31].

Applying the identification model (2) at a sufficient number of points on some trajectories, the following overdetermined linear system of equations in p is obtained:

$$\boldsymbol{Y}(\boldsymbol{\tau},\dot{\boldsymbol{\theta}})=\boldsymbol{\Phi}(\boldsymbol{\theta},\dot{\boldsymbol{\theta}},\ddot{\boldsymbol{\theta}})\boldsymbol{p}+\boldsymbol{\rho} \tag{3}$$

where $\boldsymbol{\Phi}$ is an observation matrix and $\boldsymbol{\rho}$ is the residual error vector.

The estimated values $\hat{p}$ can be obtained as

$$\hat{\boldsymbol{p}}=\min_{p}\|\boldsymbol{\rho}\|^{2} \tag{4}$$

Namely

$$\hat{\boldsymbol{p}}=(\boldsymbol{\Phi}^{\boldsymbol{T}}\boldsymbol{\Phi})^{-1}\boldsymbol{\Phi}^{\boldsymbol{T}}\boldsymbol{\tau} \tag{5}$$

An alternative method, more common in the automatic control community, is the use of Kalman filtering algorithm. Based on the direct dynamic model, which is nonlinear in relation to the state and the parameters, an extended state containing the physical parameters is considered. Gautier and Poignet [32,33] presented an experimental comparison on a two degrees-of-freedom robot using weighted least squares estimation and extended Kalman filtering approach. The comparison shows that estimations of the parameters are very close for both methods, but extended Kalman filtering algorithm is very sensitive to the initial conditions and the convergence speed is slower. Thus, the weighted least squares method with the inverse dynamic model appears to be better than the extended Kalman filtering approach for off-line identification.

In addition, Swevers et al. [34] presented a new approach toward the design of optimal robot excitation trajectories, and formulated the maximum-likelihood estimation of dynamic model parameters. But the models used often encompass significant deterministic structural errors that cannot be accounted for by random variables [35]. Olsen et al. [36] pointed out that the use of the maximum-likelihood method should only be considered in cases where both the measured positions and torques are noisy. In the practical case, they are considered additive noise that leads to a weighted least squares estimation. Besides, Calafiore and Indri [37] used linear matrix inequalities to account for the uncertainties in the observation matrix due to modeling error or measurement noise.

4. Optimal trajectory

In order to improve the convergence rate and the noise immunity of the least squares estimation, the trajectory used in the identification must be carefully selected. Such a trajectory is known as a persistently exciting trajectory [38]. To obtain an exciting trajectory, two schemes are generally used: (1) calculation of a trajectory satisfying some optimization criteria and (2) use of sequential sets of special test motions, where each motion will excite some dynamic parameters.

4.1. Trajectory optimization

When designing an identification experiment for a system, it is necessary to consider the sufficiency of excitation [39]. It is shown that the convergence rate and noise immunity of a parameter identification experiment depend directly upon the condition number of the persistent excitation matrix computed from the inverse dynamic model. It is important to emphasize that the configurations for which measurements are taken must correspond to a well-conditioned reduced observation matrix since the condition number represents an upper limit for input/output error transmissibility [40]. In the literature, other criteria have also been used to define the exciting condition [41]:

(1) the sum of the condition number of observation matrix with a parameter equilibrating the values of the elements of observation matrix:

$$C = \mathrm{cond}(\boldsymbol{\Phi}) + \frac{\max\left|\phi_{ij}\right|}{\min\left|\phi_{ij}\right|}, \quad \min\left|\phi_{ij}\right| \neq 0, \tag{6}$$

where ϕ_{ij} is the (i,j) element of $\boldsymbol{\Phi}$.

(2) The sum of the condition number of observation matrix and the inverse of the smallest singular value of observation matrix:

$$C = cond(\boldsymbol{\Phi}) + k_1 \frac{1}{\sigma_{\min}} \tag{7}$$

where $k_1 > 0$ is a weighting scalar parameter and $\sigma_{\min}$ is the minimum singular value of $\boldsymbol{\Phi}$.

(3) The condition number of a weighted observation matrix:

$$C = \mathrm{cond}(\boldsymbol{\Phi}\ \ \mathrm{diag}(\boldsymbol{Z})) \tag{8}$$

where $\boldsymbol{Z}$ is a weighting vector.

The use of the condition number of the observation matrix is subject to statistical assumptions as was pointed out by Presse and Gautier [42]. It is known that such a condition ensures that the parameters to be identified are well-excited and have a balanced effect on the external forces. Consequently, Armstrong [43] and Presse and Gautier [42] dealt with these configurations directly, at the generalized accelerations level in the first and the generalized velocities and positions in the second, proposing the use of an optimization process with the aim of minimizing the condition number of the observation matrix. However, this process has some disadvantages. To overcome these disadvantages, Swevers et al. [44] suggested considering the configurations governed by a single global trajectory. This trajectory is parameterized using a finite Fourier series function to guarantee periodic excitation. Periodic excitation enables time-domain data averaging and estimation of the characteristics of the measurement noise, which is useful for maximum-likelihood parameter estimation. This method has received more attention [45]. Park [46] has proposed the use of parameterization based on a combined Fourier series and polynomial functions to overcome the disadvantages of the Fourier series parameterization.

Based on the determination of a sequence of optimal joint position velocity couples, Caccavale and Chiacchio [47] proposed a method to determine the optimal trajectory where a continuous smooth “optimal” trajectory is found by interpolating optimal joint position velocity couples via fixed order polynomials. The number of decision variables and the computational effort in this case are dependent on the number of samples along the trajectory. An alternative solution to the above-described methods, which are gradient based, where a random search approach is used to determine the set of optimal points to be interpolated, is proposed by Van and Can [48]. Based on the parameterization of the class of joint position time functions, Calafiore et al. [49] proposed a method and the key idea underlying this method is to restrict attention to some parameterized family of possible trajectories, thus reducing the original infinite-dimensional problem to a more tractable finitely parameterized optimization problem.

In particular, a new method is developed for the determination of optimal joint trajectories for the identification experiment, which is based on evolutionary optimization techniques. A genetic algorithm is used to determine excitation trajectories that minimize either the condition number of the regression matrix or the algorithmic determinant of the Fisher information matrix.

4.2. Sequential identification

Sequential identification is proposed to use a set of different trajectories where each trajectory excites some parameters. For example, we can move some joints while locking some others. This technique simplifies the identification equations. However, an accumulation of errors may occur since the values of some estimated parameters will be assumed to be known in subsequent identification. In serial robots, some joints can be locked to estimate the dynamic parameters of certain links. However, this approach is not suitable for parallel robots since the motion of a single joint cannot be realized due to the structural limit. Vandanjon et al. [50] has proposed to avoid this drawback by generating four different trajectories to excite four different

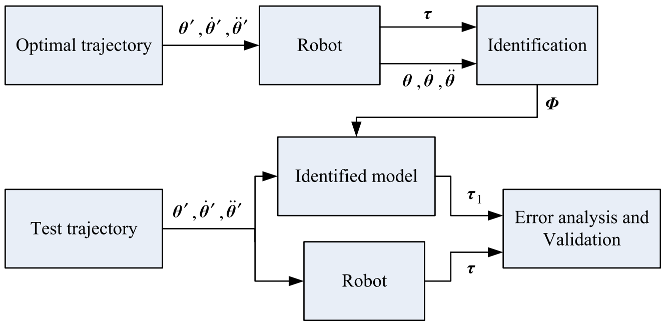

Fig. 1. Identification and validation scheme.

physical phenomena, which are: inertial effect, centrifugal coupling, inertial coupling and gravity effect. The trajectories are periodic between two points (except for gravity). The experiments are designed in order to ensure optimal condition number of the observation matrix. These trajectories are then combined in a global identification system of equations.

Based on the above discussion, it can be concluded that excitation trajectories are generally obtained by means of nonlinear optimization with motion constraints. The mathematical description of the motion is crucial for success and computational efficiency of the optimization, because the trajectory parameters are the degrees-of-freedom of the problem. For serial robots, several approaches have been presented, which use different trajectory parameterizations. Due to the compliance with strong workspace constraints, the optimization problem in the case of parallel robot is generally very challenging.

5. Validation and application

The aim of the model validation is to obtain confidence in the estimated robot model in view of its intended application. Obviously, the most appropriate validation test is to use the model in the application and evaluate its success. The validation scheme is shown in Fig. 1. The validation of the estimated values can be carried out using the following methods: (1) carrying out another experiment with a different validation trajectory by comparing the measured torques and an estimate of these torques based on the model and the measured position data; (2) carrying out the identification process using the energy model and then by using the dynamic model and comparing the obtained values; (3) direct validation on the identification trajectory by calculating the error vector and (4) reidentify the parameters of the robot while it is loaded by a known load. In this case the values of some base parameters will be changed as a function of the load parameters. The values calculated from the base parameters identified without load plus the load effect are the same as those of the identified values with the load. For example, Gautier et al. [51] used two methods to verify the identification results: (1) carrying out the identification process using the energy model and then by using the dynamic model and comparing the obtained values and (2) reidentify the parameters of the robot while it is loaded by a known load. All these tests show very good results.

It is known that accurate modeling and precise parameterization and identification are very important for the improvement of robot control. Thus, the identified dynamic model should be used in a robotic system to improve the motion performance of the robot. Honegger et al. [52] identified the dynamic parameters on-line and then the identified parameters were used in the dynamic feedforward control system of Hexaglide parallel kinematic machine. A good tracking performance is obtained. Kakizaki et al. [53] presented an experimental study on the dynamic parameter identification of a typical industrial robotic manipulator, and the effectiveness of dynamic control based on the identified parameters was demonstrated through high speed trajectory control experiments. Abdellatif et al. [54] used the identified parameters to the feedforward control system of PaLiDA machine tool, and the control performance was improved. Wu et al. [55,56] added the identified and unidentified dynamic parameters to the position/force switching control system of a redundant machine tool and the same experiments were performed. The results that the tracking errors are reduced by using the identified dynamic parameters show that the identified results are more accurate.

6. Conclusions

In this paper, the existing work on dynamic parameter identification of serial and parallel robots has been reviewed. The methods for the identification of dynamic parameters are classified as off-line identification methods and on-line identification methods. The identification model and trajectory optimization are discussed. Further, we have pointed out that the validation of the estimated values can be carried out using a few different methods. Since the identification algorithms for the dynamics of complex parallel mechanisms are few, the dynamic parameter identification of parallel robot is emphasized. The results of this review are useful for manufacturers of robots and researchers.

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