Neurocomputing 151 (2015) 996–1005

Contents lists available at ScienceDirect

Neurocomputing

journal homepage: www.elsevier.com/locate/neucom

A calibration method for enhancing robot accuracy through integration of an extended Kalman filter algorithm and an artificial neural network

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ARTICLE INFO

Article history:
Received 21 November 2013
Received in revised form
4 March 2014
Accepted 28 March 2014
Available online 23 October 2014

Keywords:
Extended Kalman filter
Artificial neural network
Robot calibration
Geometric parameter
Non-geometric parameter
Kinematic identification.

ABSTRACT

Robot position accuracy plays an important role in advanced industrial applications. In this paper, a new calibration method for enhancing robot position accuracy is proposed. In order to improve robot accuracy, the method first models and identifies its geometric parameters using an extended Kalman filtering (EKF) algorithm. Because the non-geometric error sources (such as the link deflection errors, joint compliance errors, gear backlash, and so on) are either difficult or impossible to model correctly and completely, an artificial neural network (ANN) will be applied to compensate for these un-modeled errors. The combination of model-based identification of the robot geometric errors using EKF and a compensation technique using the ANN could be an effective solution for the correction of all robot error sources. In order to demonstrate the effectiveness and correctness of the proposed method, simulated and experimental studies are carried out on serial PUMA and HH800 manipulators, respectively. The enhanced position accuracy of the robots after calibration confirms the practical effectiveness and correctness of the method.

1. Introduction

Recently, robotic manipulators have been widely used for applications that require high accuracy, such as off-line programming, robot-based machining, robot-aided surgery, and so on. For various reasons such as machining tolerance, assembly tolerance, structural deformation of robots, etc., the physical robot and its nominal kinematic model are different. This difference significantly reduces the robot position accuracy. Therefore, before being use, the robots should undergo a necessary calibration procedure to enhance their position accuracy.

Many works have addressed the modeling of the error sources of robots for calibration [1–12]. These error sources can be classified into two categories: geometric parameter errors such as link length and link twist errors and non-geometric errors such as gear backlash, link and joint compliance, etc. Some studies have focused on the modeling and identification of the geometric parameter errors and have ignored the non-geometric errors [1–3,6–8]. These studies assumed that the effect of the non-geometric errors on the robot position errors is small. The identified kinematic parameters are therefore inaccurate [4,6,9]. Because these non-geometric errors still affect the robot accuracy, non-geometric error parameters cannot be ignored. Other researchers [4,10–14] developed the robot kinematic model including geometric and joint compliance errors. The joint compliance error is caused by the robot weight and the carried payload. Judd and Knasinski [4] examined experimentally many error sources of a physical robot such as geometric errors, gear errors, servo error, structural deformation errors, thermal change errors, gear wear errors and base misalignment. In addition, the authors proposed to use a homogeneous transformation matrix at the robot end plate to improve robot accuracy. However, these error sources are specific to individual physical robots, so the method is not general. Earlier, Dulen and Schröer [15] applied the elastic beam theory to investigate the robot link effects as represented by the changes of six differential elements (three for translation changes and three for rotation changes). Hudgens et al. [16] used a method for the identification of general robot compliance characteristics under applied torques and forces. However these methods had to resort to the use of special tools to identify the compliance error elements. Both studies [15,16] did not include sufficient non-geometric errors for accurate robot calibration.

In the above research [1–12], the least squares algorithm is used for parameter identification [17]. There are many other studies using various algorithms for parameter identification such as non-linear optimization procedure [18,19], iterative linearization [20], extended Kalman filter [5,20–22]. The effectiveness of the identification algorithms was compared in the calibration study for SCARA robot by Omodei et al. [20]. Omodei et al. concluded that EKF is the

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http://dx.doi.org/10.1016/j.neucom.2014.03.085
0925-2312/

best among the above algorithms due to the advantages such as fast convergence, reliability and estimation of identification result uncertainty [20]. Park and Kim [21] conclude the same remark that EKF converges faster than Least Squares Estimation [21]. Some algorithms also used for parameter identification for examples maximum likelihood [23], Levenberg–Marquardt [11,24] although their convergence speeds are fairly slow.

Besides, to increase robot accuracy, its kinematic properties are identified based on robot signature [5,25–27]. Stone et al. developed an identification method to estimate S model parameters based on joint features such as rotation plane, rotation center and rotation radius [25,26]. Afterward, D-H parameters can be extracted from the parameters of S model. Abderrahim and Whittaker [27] identify directly D–H parameters by adopting the method of Stone et al. [25,26] without utilizing the S model. These studies, however, only found out robot geometric parameters. Another calibration method applied genetic programming for calibrating manipulators [28]. The advantage of the method is that it makes a correcting model automatically by genetic programming (or symbolic regression) and therefore avoiding the involvement of human in building robot calibration models. However, this method does not supply knowledge of error sources in robot structure and has slow convergence speed due to the nature of the method.

In addition to the model-based calibration methods mentioned above, alternative approaches such as the so-called model-free calibration have been developed for robot calibration [29–36]. These approaches are based on an approximation of robot kinematic relationships, such as the relationship between the robot joint readings and its position errors or between the robot positions and its position errors. In order to approximate these relationships, some researchers have used radial basis function networks (RBFN) [29], fuzzy logic algorithms [30], and artificial neural networks (ANN) [31,32]. Some other researchers have utilized polynomials such as Fourier polynomials, ordinary polynomials, and the polynomials of Jacobi, Laguerre and Hermeite, and Bessel. Other works [33,34] have used Fourier and ordinary polynomials to predict the robot position errors at its configurations or end-effector positions. However, these techniques are limited due to their low accuracy and complicated polynomials. Among those approximation techniques, the ANN-based functional approximation is the most effective due to its ability to generalize high adaptation, flexibility, and learning ability. In some studies [35,36], a functional relationship between the robot joint angle and its corresponding joint errors are formulated based on an ANN. However, the ANN training data that are obtained by the robot's nominal inverse kinematics are inaccurate. In one study [29], the robot workspace is divided into sub-workspaces, the kinematic parameters are identified in these sub-workspaces, and finally the functions of each identified parameter are formulated. Some studies [31,32] have utilized ANNs to represent the functional relationship of the robot position errors in terms of its Cartesian positions. So, these robots only can work accurately for the task frames used in the calibration process. However, Meggiolaro et al. [37] and Zhong and Lewis [38] showed that a robot can come to the same Cartesian position with multiple configurations (multiple joint angle sets), and therefore the position errors at individual robot configurations are completely different. Therefore, the developed relationships and training data in [31,32] are not appropriate. Generally, the methods of approximation for robot kinematics are limited with regard to understanding the essence of the robot error sources, even the errors that can be modeled easily, such as the link geometric parameters.

Model-based calibration has many advantages due to its lower cost computation, fast convergence, and insights into error sources. Because not all of the errors (especially the non-geometric errors) can be modeled correctly and completely, therefore the portion of the robot position error that is caused by these un-modeled error sources should be compensated by using an ANN. The combination of both model-based calibration and ANN-based error compensation methods can be an effective solution for enhancing robot position accuracy.

In this paper, a new calibration method is proposed to enhance the robot position accuracy. This method is based on a combination of model-based calibration and ANN-based error compensation. First, the robot geometric parameters are modeled and identified using an EKF, and then the robot non-geometric errors are compensated using the ANN. The EKF algorithm has advantages because it identifies the robot geometric parameters from the given noisy measurements and the process noise (due to the un-modeled non-geometric errors [6,9]). The residual robot positions after model correction will be compensated using the ANN. Our proposed method is different from the one in [31]. Instead of compensation for non-geometric errors based on a specific net of Cartesian coordinate points in a specific task frame [31] (a cubic net of points), we approximate the actually appropriate non-linear relationship between the robot input (robot joint angle position) and the robot output (residual position errors after robot geometric parameter compensation by EKF), therefore the robot after calibration (by EKF and ANN) can operate in any task frames. Moreover, as mentioned above, the developed relationships and training data for ANN in [31,32] are not appropriate. Simulated and experimental studies on the PUMA 560 and Hyundai HH800 serial robots, respectively, are performed to demonstrate the effectiveness and correctness of the method. We also accomplish a comparison between the proposed method and other methods modeling both geometric and non-geometric parameters [10,12]. The calibration results show the better robot performance when compared with the other works [10,12].

The rest of the paper is organized as follows: Section 2 develops a kinematic model of the PUMA serial robot. Section 3 derives a formulation for the identification of the robot geometric parameters. Section 4 applies the EKF algorithm for determining the robot geometric errors. Section 5 constructs and trains the ANN and shows its application for robot calibration. Section 6 presents the simulation study and the results for the PUMA robot. Section 7 performs an experimental calibration and presents the results for the HH800 robot. Finally, Section 8 presents some conclusions.

2. Kinematic model of the PUMA 560 robot

The kinematic model of a PUMA serial robot (Fig. 1) is developed based on the material in [40], which used the Denavit–Hartenberg (D–H) convention [39]. The coordinate frames are fixed on the links from the robot base to the end-effector as shown in Fig. 1. The nominal D–H parameters are given in Table 1. A homogenous transformation of two consecutive link frames, $\{i-1\}$ and $\{i\}$, is described by the following matrix:

$$ {}^{i-1}_{\;\;i}\boldsymbol{T} = Rot(x_{i-1},\alpha_{i-1})Tr(x_{i-1},a_{i-1})Tr(z_i,d_i)Rot(z_i,\theta_i), \quad (1)$$

where the parameters of link $i-1$ include the link twist angle α_{i-1}, link length a_{i-1}, and link offset d_i, and the parameter of link i is the

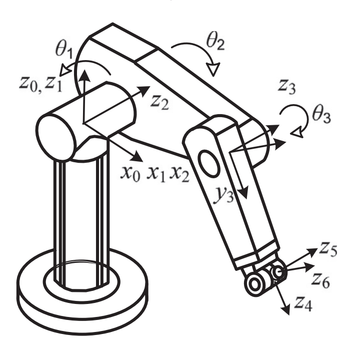

Fig. 1. PUMA 560 robot and its link frames.