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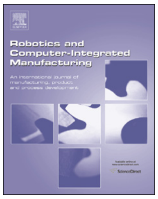

Online robot calibration based on hybrid sensors using Kalman Filters

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ABSTRACT

This paper presents an online robot self-calibration method based on an inertial measurement unit (IMU) and a position sensor. In this method, a position marker and an IMU are required to rigidly attach to the robot tool, which makes it possible to obtain the position of the manipulator from the position sensor and the orientation from the IMU in real time. An efficient approach which incorporates Kalman Filters (KFs) to estimate the position and the orientation of the manipulator is proposed in this paper. Using these pose (orientation and position) estimation methods will result in improving the reliability and accuracy of pose measurements. Finally, an Extended Kalman Filter (EKF) is used to estimate kinematic parameter errors. Compared with the existing self-calibration methods, the greatest advantage of this method is that it does not need any complex steps, such as camera calibration, corner detection and laser tracking, which makes the proposed robot calibration procedure more autonomy in a dynamic manufacturing environment. What's more, reduction in complex steps leads to improving the accuracy of calibration. Experimental studies on a GOOGOL GRB3016 robot show that this proposed method has better accuracy, convenience and effectiveness.

1. Introduction

Because of the manufacturing and assembly tolerance, the actual kinematic parameters of a robot deviate from their nominal values, which is referred to as kinematic errors. The kinematic errors would result in the robot tool's errors if the nominal kinematics were used to estimate the poses of the robot. With the restriction of cost, the kinematic calibration is an effective way to improve the absolute accuracy of robots. Nowadays, calibration tasks use a lot of measurement techniques like coordinate measuring machines, laser tracking interferometer systems, and inexpensive customized fixtures [1]. These systems are not only very expensive, but also not friendly to use or with small working volume. A system which is used in a dynamic environment is expected to perform calibration without any external expensive calibration apparatus and elaborate setups, which means self-calibration.

Self-calibration techniques can be classified into two kinds: (1) redundant sensor approach and (2) motion constraint approach.

There is a self-calibration method for parallel mechanism with a case study on the Stewart platform which is proposed by Zhuang in [2]. He used the forward and inverse kinematics with six rotary encoders for three objective functions of parameter identification. Khalil and Besnard [3] installed two orthogonally allocated inclinometers to the tool to calibrate the Stewart platform except the redundant sensors which are mentioned above. However, there are some limitations of these methods. One of them is that some kinematic parameters orthogonally are not independent of the error models and the position and/or orientation of the tool on the platform cannot be calibrated.

For the other approach, that is the motion constraint approach, the mobility of the resultant system will be lower than its inherent degrees-of-sensing by fixing one or more passive joints or constraining partial DOF of the manipulator so that the calibration algorithm can be performed [4]. Park et al. [5] lowered the mobility of the tool of a serial manipulator and performed self-calibration by using only the inherent joint sensors in the manipulator. And this idea was used and extended to calibrate a robot system with a hand-mounted instrumented stereo camera [6]. However, the position and/or orientation of the tool on the platform cannot be calibrated, and some parameter errors related to the locked passive joints may become unobservable in the calibration algorithm because of the mobility constraints.

To solve these limitations, advances in robot calibration allow the researchers to use a hand-mounted camera to calibrate a robot instead of using measurements from passive joints or imposing mechanical constraints. Compared to those mechanical measuring devices, this camera system costs less and it is easier to use and more accurate. The traditional vision-based methods [7] to calibrate a robot require the precise 3D fixtures measured in a

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reference coordinate system and the procedure is inconvenient, time consuming and it may not be feasible for some applications. The self-calibration methods [8,9] assume that the camera is rigidly attached to the robot tool. Closed-loop method “Virtual closed kinematic chain”, which is proposed in [10], uses the joint angle measurements already in the robot can be considered self-calibrating. A method uses laser to capture robot position data to model the stiffness of the manipulator [11] and predict kinematic parameters [12]. O'Brien et al. [13] used a magnetic motion to capture robot data to estimate the kinematic parameters. Du et al. [14] used two pose sensors to calibrate the parameters. However, particle filter is inefficiency. Rauf et al. [15] used a vision-based measuring device and a pose measurement device for kinematic calibration, respectively. Du et al. [16] employed a continuous data capture method by using a camera to estimate the kinematic parameters. However, these approaches have a limitation, i.e., the calibration is completed off-line. The optimization technique was based on the measured positions of the tool. The parameter error was minimized in the measured positions, but the error increased in positions that are very different. Moreover, the parameter error increased while the robot withstood different loads. When the robot is used in high-temperature or high-pressure environment, such as deep sea or outer space, the shape of the robot links are easy to change. Therefore, online calibration is an indispensable method to rectify the kinematic parameters.

In this paper, we propose an original approach of online robot calibration by using an IMU and a position sensor to measure the robot poses. In our method, an IMU and a position marker are required to rigidly attach to the robot tool (Fig. 1) to measure the robot poses in real time. Fig. 2 shows the outline of the proposed method. The key steps of kinematic parameter calibration are kinematic modeling, pose measurement, parameter identification. Standard Denavit–Hartenberg (D–H) [17] is used as kinematic modeling because it has a minimal representation for the common normal between two revolute links [4]. For measuring the pose, an IMU and a position marker are attached to the robot tool to measure the orientation and the position of the tool. By using a set of measured poses, KFs are used to estimate the accurate poses. A Jacobian matrix, which represents how each kinematic parameter error influences the variance deviation between the theoretical and measured pose is formulated for parameter identification. EKF is iterated to estimate parameter errors by using the estimated poses. Then, parameter errors are used to correct the kinematic parameters. Unlike some existing self-calibration methods, the described method does not require special complex steps such as camera calibration or laser tracking. Moreover, this method does not require the robot to make the motion for obtaining the measurements, which makes our method more efficient.

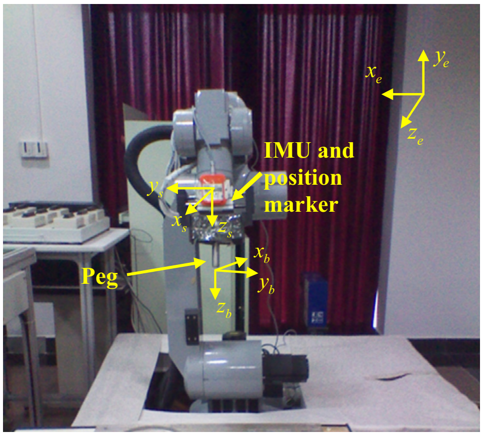

Fig. 1. Structure of the system.

The remainder of the paper is organized as follows. Section 2 provides kinematic modeling for the serial robot. In Section 3, a method of the pose measurement is detailed. Parameters identification algorithm based on EKF is proposed in Section 4. Finally, the experimental results are shown in Section 5 and we conclude the paper in Section 6.

2. Kinematic modeling

A robot kinematic model relates the robot joint coordinate with the pose of the robot tool. A robot kinematic model should meet the following rules for the kinematic-parameter identification [18].

1) Completeness: the robot kinematic model should have enough parameters to define any possible deviation from the nominal values.
2) Continuity: any small changes in the structure of the robot must correspond to small changes in kinematic parameters [18].
3) Minimality: the kinematic model must include only a minimal number of parameters [2].

Many researchers have found suitable kinematic models for robot since 1980s, such as the Hayati et al. models [19], the Veitschegger and Wu's model [20], the Stone and Sanderson's S-model [21], and the Zhuang et al. model [22]. Standard Denavit–Hartenberg (D–H) convention is the most widely used to describe the robot kinematics. The error models of D–H are not continuous for robots that possess parallel joint axes (Fig. 2). To avoid the singularity of D–H convention, D–H modeling or Hayati modeling convention were used, respectively. The singularity-free calibration model prevents the use of a single minimal modeling convention which can be used to identify all possible robot parameters.

The robot tool position and the orientation are defined according to the controller conventions. Through consecutive homogeneous transformations from the base coordinate to the robot tool coordinate, the kinematic equation can be defined as

$$T_N^0 = T_N^0(\boldsymbol{v}) = T_1^0 T_2^1 \ldots T_N^{N-1} = \prod_{i=1}^{N} T_i^{i-1} \tag{1}$$

where T_i^{i-1} is the translation matrix from $i-1$ coordinate to i coordinate, N is the number of joints (Fig. 3). $\boldsymbol{v} = \left[v_1^{\mathrm{T}} v_2^{\mathrm{T}} \ldots v_N^{\mathrm{T}}\right]^{\mathrm{T}}$ is the parameter vector for the robot, and v_i^{T} is the link parameter

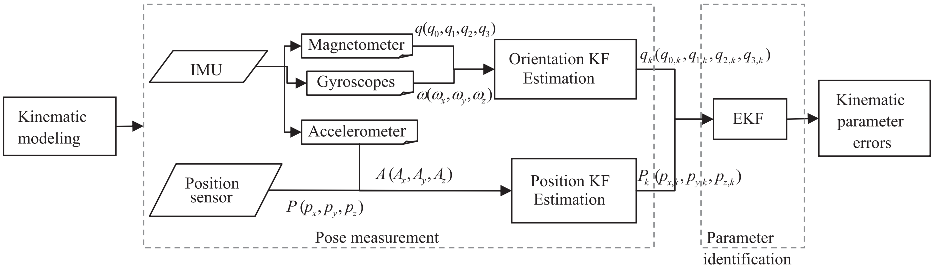

Fig. 2. Outline of the proposed method.