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ESTIMATION METHOD OF KINEMATIC PARAMETERS CONSIDERING POSTURE OF ARTICULATED ARM TYPE COORDINATE MEASURING MACHINE BY MACHINE LEARNING

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Abstract: *The stylus coordinates of an arm type CMM are determined by the kinematic parameters and joint angles. When the arm type CMM measures in different postures, the kinematic parameters change due to deformation caused by the arm's dead weight and other factors. In this study, we attempted to estimate the changes in the kinematic parameters due to the posture of the arm type CMM using machine learning.*

Key words: *Articulated Arm Coordinate Measuring Machine, Machine Learning, Kinematic Parameters, Artifact, Coordinate Measurement*

1. INTRODUCTION

Research on calibration and inspection methods for coordinate measuring machines has been conducted mainly on Cartesian coordinate systems[1-6]. On the other hand, there is an articulated-type coordinate measuring machine with six or more joints. These are referred to as arm type CMMs in this paper. As the measurement accuracy of articulated coordinate measuring machines improves and they are widely used in production, calibration and inspection methods for arm type CMMs have been studied[7-9]. Since Cartesian coordinate measuring machines have a motion mechanism based on an inherently Cartesian coordinate system, it is simple to obtain three-dimensional Cartesian coordinate values from input from a sensor based on a Cartesian coordinate system. However, since the kinematic model of the arm type CMM is based on more than six joint motions, obtaining the input from the sensor as three-dimensional Cartesian coordinate values is complicated. Calibration of the arm type CMM was achieved by constructing a kinematic model to obtain three-dimensional coordinate values from the sensor of the arm type CMM and obtaining its kinematic parameters.

However, due to the complexity of the kinematic mechanism and the flexibility of the kinematic mechanism, the arm type CMM can measure the same coordinate point in different arm postures. When the arms are in different postures, the deflection of the arm due to the effect of gravity is different. Therefore, different mechanism parameters or different mechanism models are required for different arm postures to achieve high accuracy of the arm type CMM[10].

In [1], a calibration method that introduced a physical model of the main arm posture was proposed, but it was not sufficiently effective.

Therefore, machine learning was utilized to estimate the mechanism model and mechanism parameters of the arm type CMM. In this paper, we constructed the mechanism model and estimated the mechanism parameters by using deep learning, Kernel method, Random Fourier Features method, and the combination of deep learning and DH notation. The results are reported.

2. LEARNING BY MACHINE LEARNING

2.1 Machine Learning with Supervised Data

In order to estimate the coordinates of stylus of an arm type CMM by machine learning, a combination of the joint angles of the arm type

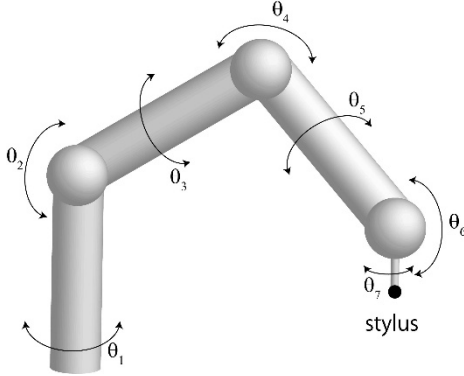


Fig.1. The kinematic model of Articulating arm CMM.

CMM and the known coordinates are required. These data are called the training dataset. The training dataset is created by measuring the known points with the arm type CMM and recording the joint angle and known point coordinates.

In this study, the arm type CMM with 7 angular joints as shown in Fig. 1 was used. In machine learning, x is used as the vector of joint angles, y is used as the known point coordinates. In the training dataset, the mean value of the known point coordinates is set to zero.

In the machine learning of this paper, our goal is to find a function that relates joint angles to stylus coordinates.

2.2 Deep Learning

An NN consists of an input layer that takes in data, an output layer that outputs estimation results, and an intermediate layer that connects the input and output layers. Each layer has multiple nodes.

In general, any function can be represented by an NN. Therefore, it is possible to construct a function that estimates the coordinates of the stylus from the input data.

2.3 Kernel Method

In general, the function $f(x)$ is expressed as Eq.(1).

$$y = f(x) = \sum \alpha_n k(x, x_n) \quad (1)$$

Choosing a Gaussian kernel as in Eq.(2), α is obtained as in Eq.(3) using the dataset for training[11].

$$k(x, x_n) = \exp(-\gamma|x - x_n|^2) \quad (2)$$

$$\alpha = (K + \lambda I)^{-1}y \quad (3)$$

,where γ and λ are hyperparameters to adjust the learning.

The coordinates of stylus is estimated as Eq.(4).

$$f(x) = k(x, x_n)^t (K + \lambda I)^{-1}y \quad (4)$$

2.4 Random Fourier Feature Method

In the Kernel process, As shown in Eq.(5), the Gaussian kernel can be thought of as the inverse Fourier transform of a Gaussian function.

$$\begin{aligned} & \exp(-\gamma|x - x_n|^2) \\ &= \frac{1}{2\pi\sqrt{\gamma}} \int_{-\infty}^{\infty} \exp\left(-\frac{\eta^2}{4\gamma}\right) \exp(-i\eta(x - x_n)) d\eta \end{aligned} \quad (5)$$

From a different perspective, this equation can be viewed as calculating the expected value of a complex function.

Therefore, the Gaussian kernel can be determined using the Monte Carlo method.

Using the random number η , the kernel function can be determined.

2.5 Combination of Deep Learning and DH Notation

We have described a method for estimating the coordinates of stylus by machine learning using deep learning, the Kernel method, and the random Fourier feature method. These methods determine a function that estimates the coordinates of stylus from the joint angles of the arm type CMM. However, they only show the function to estimate the coordinates of stylus from the joint angles of the arm type CMM as a result of machine learning, and do not show how they relate to the kinematic mechanism of the arm type CMM.

In order to determine the relation of the kinematic model of the arm type CMM, the kinematic model of the arm type CMM is expressed in DH notation as shown in Eq.(7).

$${}^{i-1}A_i = \begin{pmatrix} \cos\theta_i & -\sin\theta_i \cos\alpha_i & \sin\theta_i \sin\alpha_i & a_i \cos\theta_i \\ \sin\theta_i & \cos\theta_i \cos\alpha_i & -\cos\theta_i \sin\alpha_i & a_i \sin\theta_i \\ 0 & \sin\alpha_i & \cos\alpha_i & d_i \\ 0 & 0 & 0 & 1 \end{pmatrix} \quad (6)$$

$$T = {}^0A_1 {}^1A_2 {}^2A_3 {}^3A_4 {}^4A_5 {}^5A_6 {}^6A_7 \quad (7)$$

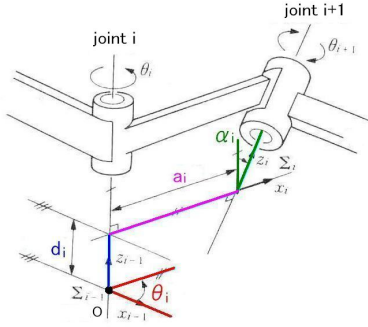


Fig.2. Expression of kinematic parameters in DH notation.

The kinematic parameters necessary for DH notation as shown in Fig.2 are estimated by deep learning.

3.EXPERIMENTAL SETUP AND DATASET FOR MACHINE LEARNING

The Vectoron, manufactured by Kosaka Laboratory, was used as the arm type CMM. This arm type CMM has seven rotational joints as shown in Fig. 1.

Fig. 3 shows the artifacts used in this research. The artifact has eight pillars, each of which has a conical indentation on its upper surface. When the stylus of the arm type CMM touches the conical indentations, the 3D coordinates of the contact point and the amounts of the seven angular joints are determined. These amounts of seven angular joints and the 3D coordinates were used as the data for training and verification in the dataset. The coordinates of the conical indentations of the artifacts were measured by a Cartesian coordinate measuring machine and used as the calibration values for the training dataset.

The conical indentations on the eight pillars were measured 2000 times each while changing the posture of the arm type CMM. As a result, the training dataset consists of 16,000 combinations of joint angles and 3D coordinates.

4.EXPERIMENT

From the training dataset, seven pillars of data were used for training, and the remaining pillar was used for validation.

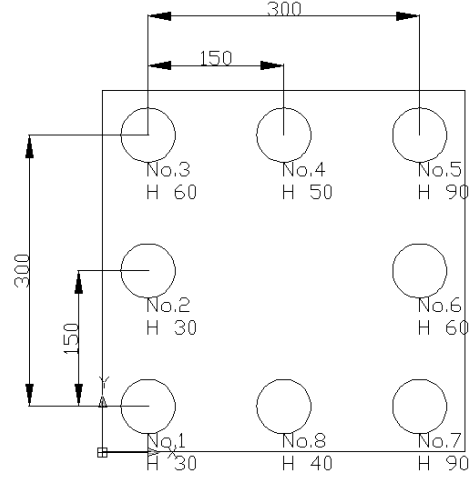


Fig.3. Artifact has 8 pillars, which has the conical indentation on the top.

The deep learning, Kernel method, and random Fourier feature method are performed well on the training data.

Using the training results to estimate the data for the remaining pillar, we found that the mean of 2000 points was well estimated.

With the combination of deep learning and DH notation method, the training data was estimated well. Using the training results to estimate the data for the remaining pillar, the mean value of 2000 points was also estimated well.

5. CONCLUSIONS AND FUTURE WORK

In order to estimate the difference of mechanism parameters depending on the posture of the arm CMM, we applied some machine learning methods: deep learning, Kernel process method, random Fourier feature method, and the combination of deep learning and DH notation method.

The results showed that the combination of deep learning and DH notation method gave better results.

Although the deep learning, Gaussian process method, and random Fourier feature methods provided an estimation function for the stylus coordinates based on the training dataset, the function could not be explained. In contrast, with the combination of deep learning and DH notation method, the kinematic mechanism of the arm type CMM can be explained by the DH notation method, making the result of machine learning possible to be explained.

In the future, it will be necessary to study the necessary training dataset to obtain learning results that cover the entire wide measurement space. To determine the function based on the mechanism of the arm type CMM, the kinematic mechanism of the arm type CMM is expressed in DH notation, and the mechanism parameters necessary for DH notation are estimated by deep learning.

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Title and abstract in Romanian (10 pt)

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