euspen's 23rd International Conference & Exhibition, Copenhagen, DK, June 2023
www.euspen.eu

Data-driven learning methods for industrial robot stiffness model identification

Tae Hwa Hong[1], Kyeongeun Song[1], Jungsu Nam[1], Tae-Gon Kim[1], Seok-Woo Lee[1], and Seong Hyeon Kim[1#]

[1]*Smart Manufacturing System R&D Department, Korea Institute of Industrial Technology (KITECH), Republic of Korea*

#Corresponding Author / E-mail: shkim@kitech.re.kr

Abstract
The demand for robotic machining systems is on the rise due to various advantages such as wide workspace, flexibility, repeatability, and cost-effectiveness. In particular, the aerospace industry, which manufactures large-size components, has shown a high interest in robotic machining systems. However, the low stiffness of the robot manipulator restricts the application of robotic machining, leading to low machining accuracy. To solve the problem, various compliance error compensation algorithms were proposed that predict compliance errors using the stiffness model and compensate for the estimated errors. The accuracy of prediction of compliance error is critical for the effectiveness of the error compensation algorithms. For simplicity and acceptable accuracy, the virtual joint approach (VJA) is widely used to model robot manipulator stiffness. However, the VJA considers the stiffness of manipulator links as infinite and assumes all compliance error sources are concentrated in the joint, which results in modelling error. Thus, a data-driven learning method was proposed to identify the robot stiffness more precisely. In the study, a novel experimental setup was proposed to generate sufficient data for the data-driven learning method. A motor is connected to the robot end-effector using a wire and various force is applied to the robot manipulator by controlling the wire tension in multiple manipulator postures. The acquired data was then used to train a machine learning algorithm to develop the stiffness model. To verify the effectiveness of the developed stiffness model, a comparison with the previous stiffness model was performed.

Keywords: Industrial robot, Machine learning, Compliance model, Robotic machining

1. Introduction

The demand for robotic machining systems is on the rise due to various advantages such as wide workspace, flexibility, repeatability, and cost-effectiveness. However, robotic machining systems face limitations due to the low machining accuracy caused by the low stiffness of robot manipulators [1]. Thus, precise stiffness models are crucial for enhancing the performance of robotic machining.

The VJA (Virtual Joint Approach) method is the most widely used approach for determining the rigidity of industrial robots [2,3]. This method involves adding virtual elastic joints between two adjacent links to create a multi-rigid model. The VJA model assumes that the links are rigid and that the joints are compliant and considered virtual springs, which combine all types of compliance sources into a single entity. However, due to this simplification, the accuracy of the VJA model is only about 80%. To improve the prediction accuracy of the stiffness model, data-driven methods have been proposed [4].

The data-driven approach has the advantage of developing a more accurate stiffness model by training a machine-learning model with a vast amount of data. However, due to the significant time and cost required to generate data for training, there have been no cases of the data-driven approach being applied yet [5]. Thus, this study proposes a new experimental setup to generate adequate data for training the robot stiffness model. To verify the effectiveness of the developed stiffness model, a comparison with the previous stiffness model was performed.

2. Data-driven stiffness identification method

Stiffness identification involves comparing the load applied to the robot with the corresponding amount of deflection. A common experimental method suspends a dead weight from the robot end-effector and measures the deflection using a laser tracker. However, this method is time-consuming since all variable values must be measured in equilibrium states. The existing experimental method has limitations when applying it to the data-driven stiffness model. Therefore, in this study, a novel experimental setup was proposed to generate sufficient data for the data-driven learning method. The experimental setup consists of a servo motor, a wire, a Force/Torque sensor (FT sensor), a laser tracker, and a robot manipulator as shown in Figure 1.

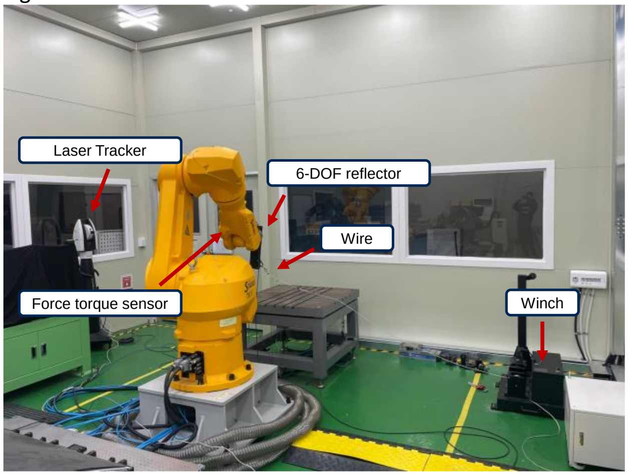

Figure 1. Data-driven stiffness identification experiment setup

The servo motor was utilized to pull the wire attached to the end-effector, thereby imposing a load on the robot manipulator. Concurrently, the FT sensor measured the external force imposed on the robot manipulator, while a laser tracker system measured the corresponding deflection of the end-effector. By adjusting the tension of the wire using the servo motor, various forces were applied to the robot end-effector in multiple postures. The experimental data obtained in one robot posture is presented in Figure 2. The proposed method can efficiently produce training data by collecting data in a non-equilibrium state. Experiment was performed in 10 different postures. The robot posture that used in experiment are indicated in Table 1. The machine learning algorithm used for robot stiffness identification in this study is a random forest model. Random forests are a combination of tree predictors such that each tree depends on the values of a random vector sampled independently and with the same distribution for all trees in the forest [6].

The training dataset for the machine learning model comprised six joint angles, force-torque data, and deflection data. In the machine learning model, joint angle and force-torque data were utilized as inputs, while deflection data was used as an output. The sampling time was 1kHz, and down sampling was performed at 400Hz to prevent overfitting. A moving average filter was used to remove noise from the FT sensor. To train and test the machine learning model, 80% of the data was used for training and 20% for testing.

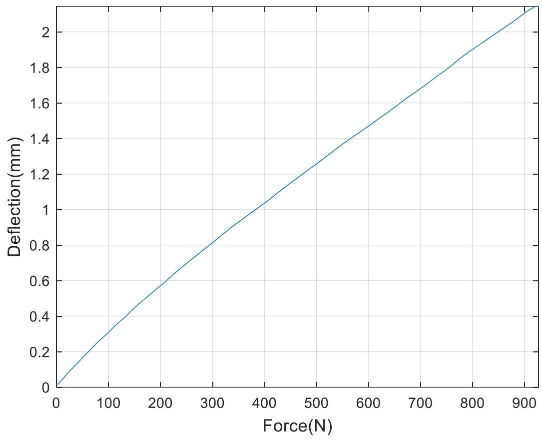

Figure 2. Force-deflection experiment result

Table 1. Robot posture used for data acquisition

Joint 1	Joint 2	Joint 3	Joint 4	Joint 5	Joint 6
97.28	5.6	89.02	-3.2	-72.25	-162.33
101.34	4.01	99.68	-3.21	-72.25	-162.33
109.7	-11.51	99.68	-3.21	-72.25	-162.33
107.89	6.76	69.13	4.71	-57.02	-168.64
102.89	9.76	65.13	4.71	-57.02	-168.64
95.4	88.07	-53.94	12.55	63.25	1.45
71.57	46.17	43.5	7.14	-42.76	1.75
95.71	-32.14	-75.32	2.04	62.77	1.75
88.43	32.15	61.93	7.14	-42.77	1.75
1.75	75.49	53.58	37	-27.78	-206.41

3. Results

To evaluate the performance of the machine learning model, the predicted deflection values obtained using the VJA and machine learning algorithms were compared with the actual deflection values. The comparison results are presented in Figure 3. When 800 N of force was applied to the robot end-effector, the prediction accuracy of the VJA algorithm and the machine learning algorithm was 81.9% and 92.8%, respectively.

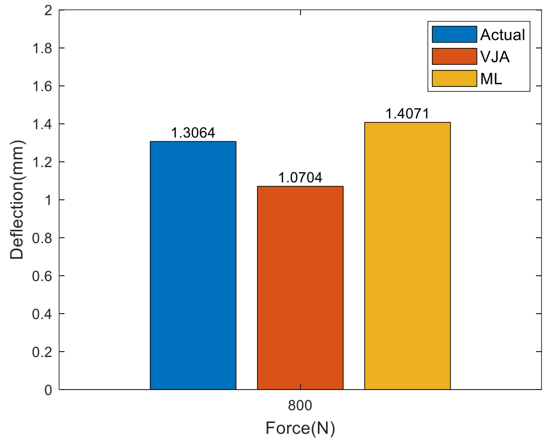

Figure 3. Prediction of deflection using VJA method and machine learning

4. Conclusion

The accurate prediction of the deflection of a robot end-effector is crucial in robotic machining. To predict the deflection of a robot, a data-driven approach using a machine learning model has been proposed. However, the previous experimental method for stiffness identification cannot provide sufficient data for training a machine learning model. To address this issue, this study proposed a novel experimental method. By adjusting the tension of the wire attached to the servo motor, various forces were applied to the robot end-effector in multiple postures. By comparing the deflections predicted by the existing VJA method with those predicted by the proposed machine learning algorithm, it was confirmed that the proposed method offers an improvement of approximately 10% in performance.

Acknowledgment

This work was supported by the Korea/Czech International Joint Technology Development Project (P0019623, Development robot manufacturing system for milling/routing/trimming using smart workpiece holder and smart gripper) funded by the Ministry of Trade, Industry & Energy (MOTIE), Korea.

This study has been conducted with the support of the Korea Institute of Industrial Technology as "Development of holonic manufacturing system for future industrial environment (KITECH EO-23-0006)".

References

[1] Wei J, Wang L. Industrial robotic machining: a review. Int J Adv Manuf Technol 2019;103(1–4):1239–55.

[2] Klimchik A, Pashkevich A. Serial vs. quasi-serial manipulators: comparison analysis of elasto-static behaviors. Mech Mach Theory 2017;107:46–70.

[3] Pashkevich A, Klimchik A, Chablat D. Enhanced stiffness modeling of manipulators with passive joints. Mech Mach Theory 2011;46(5):662–79.

[4] Nguyen V, Cvitanic T, Melkote S. Data-driven modeling of themodal properties of a six-degrees-of-freedom industrial robot andits application to robotic milling. J Manuf Sci Eng-Trans ASME2019;141(12) 121006.105.

[5] C. Ye, J. Yang, H. Ding, High-accuracy prediction and compensation of industrial robot stiffness deformation, Int. J. Mech. Sci. (2022), 107638.

[6] Breiman L. Random forests. Mach Learn. 2001;45(1):5–32.