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Digital twin of dynamic error in a robotic machining system

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Abstract

This paper presents a newly developed digital twin (DT) of dynamic errors of a robotic machining system in real time. A dynamic error test was performed to obtain acceleration data near the tool centre position (TCP) of the robot DT by using accelerometers (PCB 356B18) and ground truth dynamic errors at the TCP measured by a laser interferometer (Renishaw ML10). An ensembled bagged tree machine learning algorithm was used to develop the dynamic error prediction model as a function of eight features of accelerations at the TCP. The machine learning prediction model forms the core part of the DT of dynamic errors. The accuracy of DT prediction was evaluated by future dynamic tests. The evaluation results show that the DT can accurately model the dynamic errors with a mean absolute error of 11µm. This DT approach lays down a solid foundation for developing a DT-driven error compensation approach for dynamic errors in robotic manufacturing.

Robotic machining, Digital twin, Dynamic error, Positioning error

1. Introduction

Due to the advantages of high flexibility, adaptability and relatively low cost, industrial robots have been adopted in many factories for material handling, assembly, manufacturing, quality inspection, packing, and palletisation to improve productivity [1-4]. However, robotic machining has a low exposure due to its limited accuracy and material removal rate [1]. This is because the robot's encoders used in feedback control cannot detect the positional error caused by deformations beyond the flange in links and gears due to forces such as machining forces, gravity and inertia. Machining forces were found to contribute 8-10% of pose errors at the robot's tool centre position (TCP) [5, 6], while the frequent acceleration and deceleration of robots and change of loading result in time-dependent dynamic errors significantly affected the robot's positional accuracy [7]. It is important to model these dynamic errors to enhance machining accuracy.
Digital twin (DT) is a digital representation of physical systems incorporating real-time communication between the physical and cyber domains using sensor data. It has already been used to predict tracking errors in machining [9]. DT technology provides a potential solution for modelling dynamic errors.

In robotic machining, dynamic errors depend on structural characteristics like component stiffness and factors such as gravity and inertia [8]. Developing a generic approach to accurately model dynamics error in real-time is challenging. Addressing this problem was a key motivation for this work. This paper presented an initial feasibility study of a generic approach of establishing DT of dynamic errors in a robotic machining system by using low-cost industrial viable accelerometers and machine learning. The work will lay down a solid foundation for a DT-driven error compensation approach in the near future.

2. Methodology

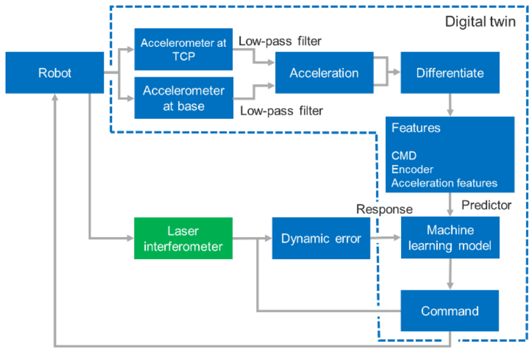

Figure 1 DT block diagram.

The methodology to establish a DT of dynamic error of a robotic machining system is illustrated in Figure 1. It is realised by measuring accelerations near the TCP and at the base of the robotic machining system by two accelerometers. By dividing the two accelerations data, the background noise will be removed. Acceleration data is split into different features, which will be utilised as inputs to a machine-learning precision model for dynamic error.

A laser interferometer will be used to measure the linear displacement of the TCP. This is the ground truth data, and subtracting the command data from the ground truth is considered as dynamic errors in this paper. The data of measured dynamic errors and features of accelerations near the TCP will be used to train a machine learning prediction model in which the dynamic error is presented as a function of features of accelerations.
Once the machine learning prediction model is calibrated by further experimental data, it will be used in the DT, which will take live acceleration input data to predict dynamic errors at the TCP. The prediction results will be used to update the command

sent back to the robot to mitigate dynamic errors before they take effect.

3. Experimental setup and procedure for dynamic test

As shown in Figure 2, a UR10e collaborative robot with a spindle mounted at its arm as an end effector was used in this study. The UR10e robot has repeatability of 50 µm. Two PCB triaxial accelerometers (356B18) are mounted on the spindle and robot's base respectively. A Renishaw laser interferometer (ML10) was used to measure the displacement of the TCP as the ground truth data to obtain dynamic errors by subtracting the command data. A National Instruments data acquisition device (DAQ-9174) was used to collect the accelerometer and displacement signals simultaneously. The synchronisation of data collection was controlled by a MATLAB program.

In the dynamic test, the robot arm moved in a straight line with a displacement of 200mm and a velocity of 10mm/s along the X direction. The test was repeated 15 times to obtain sufficient data for machine learning training.

All acceleration signals were filtered through a low pass filter set at 50Hz to remove the low-frequency noise. The differentiation of acceleration was turned into features using various functions such as mean, skewness, kurtosis, dominant frequency, spectral Bandwidth and more. These extracted acceleration features and the corresponding dynamic errors will form a training dataset to develop prediction models using a MATLAB regression learner toolbox. The prediction accuracy of the established dynamic error prediction model was validated by further dynamic tests.

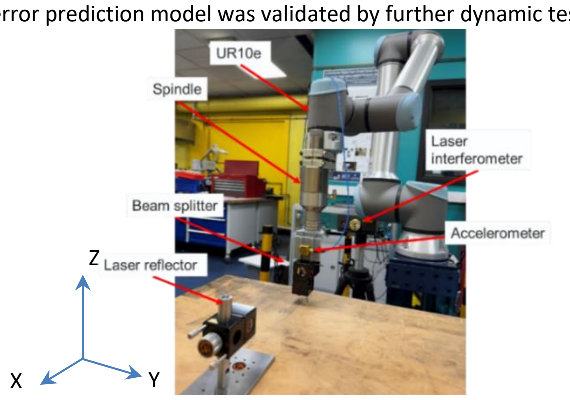

Figure 2 Dynamic test setup.

4. Results and discussions

In this study, raw acceleration data was filtered and directly fed through different functions to characterise the features of acceleration signals. This allows different system dynamics to be understood using one data source. Eight of the most effective features were selected for modelling dynamic errors in this study, including mean in X and Y, median of X, sum of the absolute in Z, peak-2-peak X, root mean square X, Skewness Z and command position. These features give a root mean square error of 0.014 on test data using the best ML model tested, an ensembled bagged tree in this study.

A maximum displacement at the TCP measured by laser interferometer was 200.05mm, meaning a dynamic error of 50 µm, while the encoder only recorded a displacement of 199.68mm. This indicates that 82 um of dynamic errors cannot be measured by the encoder and therefore, will be missed in the feedback control loop. It can be seen from Figure 3 that the DT predicted a maximum dynamic error of 235 µm while the true maximum dynamic error was 257 µm measured by the laser interferometer. The presence of prediction errors is because the selected acceleration features cannot capture all machine dynamics, i.e., unknowing dynamics are encountered by the machined learning prediction error model. Further improvement of the prediction accuracy of the model should be focused on the accuracy and comprehensiveness of extracting features of acceleration signals to allow the magnitude of these errors to be reduced. As shown in Figure 3, the DT can accurately predict dynamic errors with a mean absolute prediction error of the DT is 11 µm. This performance is better than that of the encoder, which provides an average error from the command path of 32 µm and a further 50 µm from the laser interferometer readings.

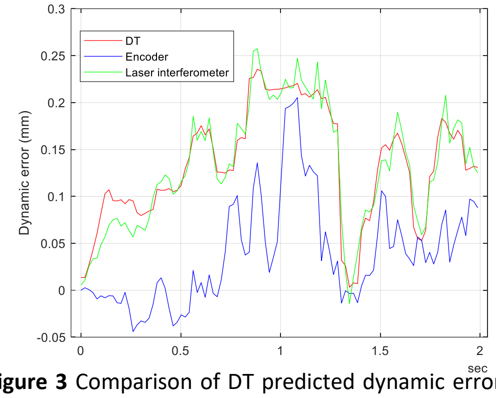

Figure 3 Comparison of DT predicted dynamic error and measured by robot encoder and laser interferometer.

Limitations of this DT approach are as follows: 1) Due to the nonlinear dynamics of the robot system, training would be recommended for multiple locations. 2) Accelerometers have low-frequency noise, leading to signalled vibrations on lower frequencies that result in incorrect vibrations and inaccuracies within the control system and dynamic error model. 3) Collecting data using an NI datalogger and controlling the robot while calculating the errors and updating positioning is computationally challenging. This limits the sampling rate at the frequency of corrections.

5. Conclusions

This paper presented a DT of a dynamic error. It uses acceleration measured by triaxial accelerometers as inputs to predict and compensate for dynamic errors caused by acceleration, deceleration and vibration within a robotic machining system. A prediction error of 11 µm was achieved in this study. Future work will concentrate on improving the accuracy and robustness of the approach to obtain more data at a broader range of accelerations and velocities, including circular movements that can be predicted during machining, using a similar methodology to train the prediction model.

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