The Concept of Efficient Tool Path Generation Method for Industrial Robots

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***Abstract*—Growing interest in applying industrial robots for mechanical machining raises demand for intelligent and reliable methods able to generate comprehensively optimal tool paths. Currently, available tool path generation methods and tools typically have limited optimization capabilities, and the quality of created tool path strongly depends on the operator's experience. This paper covers the initial concept of the new path generation method for industrial robots. This method includes tool path interpolation using conventional offline programming tools, sensors data collection, and their data fusion for a machine learning-based path generation approach.**

Keywords—industrial robots, tool path, sensors fusion, machine learning

I. Introduction

The constant increase of industrial robots in the industry encourages their application to new tasks, including the growing interest in mechanical machining, painting, and similar cases that require precise positioning at the desired point and also a smooth movement trajectory. The smoothness of an industrial robot tool path is directly influenced by the dynamic characteristics of the robot, its motion generation algorithm, and its control system [1]. In order to achieve continuous and smooth movement, it is crucial to smooth the path that typically is made up of small linear segments. There are several types of research where to achieve smooth and even motion, the path is interpolated or smoothed in several ways, e.g. for industrial SCARA robots [2] or 6 degrees of freedom industrial robots [3], [4] by implementing computer-aided design (CAM) tools. This highlights the importance of path smoothing for industrial robots, as it can help to improve task performance and accuracy.

There are other influences affecting the quality of the machined workpiece, such as vibrations occurring from the machining process at the tool [5], [6] or for the whole robot [7], [8]. Another problem is the loss of position and orientation of the workpiece, which requires additional measures such as the workpiece [9] or tool end tracking [10]. This issue becomes critical dealing with unstable materials such as wood or plastics, which can significantly change their geometrical shape due to the impact of environmental factors.

Recently, machine learning (ML) techniques have been applied in industrial robotics manufacturing accuracy studies to improve machining performance [11]–[13]. Nevertheless, although ML helps improve the accuracy of the machining path, there are no significant evaluations on how it affects machining time. General tendencies of machine engineering lead to the hypothesis that achieving higher machining accuracy with ML will lead to a slower machining process, and whether it is possible to increase the speed of the machining process if required.

To explore this hypothesis, a robot path generation concept is proposed that involves ML-based interpolation of the path from measured sensor data. This paper hypothesizes that using ML, data about robot dynamic behavior, and real-time sensor data, it is possible to develop an individualized model for toll path generation, which will use higher-level trajectory interpolation features and will be able to optimize tool path concerning the accuracy, time, and motion smoothness.

II. Methodology

This section describes the concept of path generation for the industrial robotic tool, including path generation using an offline programming approach and an ML-based approach. In addition, it is described how sensor data fusion and the ML approach can be used to optimize tool paths, reduce machining time and improve the overall machining accuracy of robot machining.

As mentioned above, in most applications, the robotic machining tool path is linearly interpolated using CAM software tools. This means that a sequence of straight-line segments is created between predefined points or nodes, and the robot tool follows each segment at a constant velocity (Fig. 1). Running another segment and changing the direction of the tool movement introduces the potential for unwanted vibrations. Using linearly interpolated node coordinates from simulations and measured vibrations of the robot tool or all axes of the robot (Table 1: Case 1)) during the machining process, the ML model can be trained. This model can generate the continuous path with the reduced number of nodes by using higher-level interpolation, such as circular interpolation, spline interpolation, or polynomial interpolation in the path.

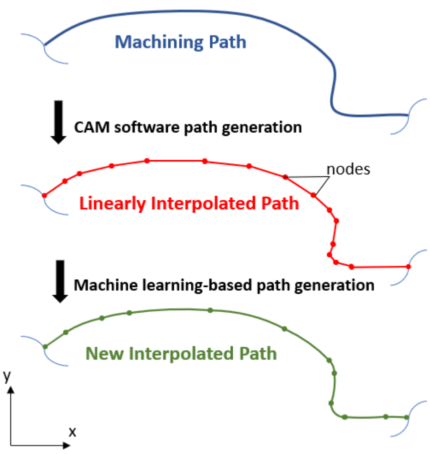

Fig. 1. Approach to robotic tool path generation.

For another case, to improve the machining accuracy more as an addition to the previous case, a camera-based path planning to identify the profile of a workpiece can be used (Table 1: Case 2)). Captured images from camera or video frames of the workpiece can be used to create a tool path that can exactly or approximately match the profile of the workpiece. Such an approach will be extremely useful when a robot should operate with already preprocessed parts whose real geometrical shapes have deviations from the initial 3D model. During machining, the camera can also help avoid abnormal movements of the initial ML-based generated paths.

TABLE I. DIFFERENT APPROACH CASES FOR THE USE OF SENSORS DATA

Case	**Different measurements**		
	Vibrations measurements in robot tool/ all axes	***Robotic machining time measurements***	***Machining profile identification by camera***
1)	+	-	-
2)	+	-	+
3)	+	+	-
4)	+	+	+

Alternatively, further evaluations are necessary regarding the hypothesis of increased machining time after accuracy optimization. (Table 1: Case 3)). Time measurements, as an additional variable to vibration measurements, can be used to train the ML model for a better accuracy/tool velocity ratio. For the final case (Table 1: Case 4)) all the above-mentioned different sensor measurements are used for the training. It is used to evaluate the overall influence of variables on the training and path generation quality. The developed model will be scalable to all types of industrial robots, but the data allowing to characterize the real state of individual robots will be required. Such data can be obtained by performing initial special tests or monitoring general robot operations for a longer time.

III. CONCLUSION

In this paper, an initial concept for an industrial robotic path generation method is presented. Combining CAM software, vibration and time measurements, and workpiece profile detection with a camera makes it possible to optimize the industrial robotic tool path generation process, resulting in improved machining accuracy and shorter processing time. The proposed approach has the potential to perform robotic machining for more complex trajectories with greater efficiency and precision.

In the future initial experiments will be performed to fully explore the capabilities and limitations of this approach. For the initial robotic machining performance and measurements, the use of ISO9283 performance testing standard for industrial robots is planned to use with already defined and known trajectories.

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