Developing a High-Speed Working Motion of the Multi Robot in DENSO

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Abstract

The number of labor force is expected to decrease due to the declining birthrate and aging population. Although many efforts to solve this social issue using automation technology by robots around the world have been implemented, most of the current applications of robots are still repetitive works such as picking and placing in mass production lines in factories, and small progress of the application of robots for high-mix low-volume production lines where the operations are is frequently changed. In this paper, we discuss the reasons and the potential solutions for autonomous control technologies including the AI and deep learning. Moreover, the high-speed working motion of the multi robot developed by DENSO will be presented in this paper.

Keywords: Unmanned Manufacturing, Motion Planning, Deep Neural Networks (DNN), Intelligent robotics

1. Introduction

The decline in the working-age population due to aging is progressing worldwide, becoming a serious social issue. In particularly Japan, we have been facing on a severe decrease in the working-age population, with estimates suggesting a decrease to 52.75 million people (a 29.2% decrease from 2021) by 2050 [1]. To address this issue, DENSO is actively intensifying its research and development efforts in automation technology utilizing robots. At DENSO's factories, we aim to achieve fully unmanned manufacturing and significantly reduce production lead times through the utilization of AI in process design for automation by 2035. We are also advancing the development of robots for automated harvesting of crops in agriculture field and automated disassembling of vehicles in the field of circular economy. As the utilization of robots advances in various sectors of society, such as production and agriculture, our group company DENSO WAVE has developed the human-collaborative robot COBOTTA PRO. COBOTTA PRO is a human-collaborative robot that combines the speed (2,500mm/s) and precision (repeatability ±0.04mm) comparable to industrial robots. It maximizes its operation speed when there are no workers nearby and minimizes the distance required for deceleration and stoppage when a worker approaches, achieving a good balance between productivity and safety aspect.

However, there are still several important issues that need to be addressed for further utilization of robots. Firstly, one of these issues is related to the design of robot movements. The work of teaching and programming for robot motion design requires specialized technicians to physically operate the robot and refine its movements, resulting in significant time and effort when introducing robots. Although the cost of the robot itself is becoming affordable in the market, it cannot be ignored due to its motion design cost when frequent motion changes are made in low-volume, high-mix production. The same issue arises in scenes such as agriculture field or vehicle disassembling outside of factory, where it is difficult to fix the motion of robots due to their variability.

The second issue is related to adapting to changes and variations in the workpieces. In the teaching playback method commonly used in repetitive tasks in factories, it is difficult to manage changes and variations in the workpieces, making it challenging to accommodate misalignment or stacking of the workpieces. Efforts to address these issues have progressed at a practical level by utilizing vision systems. The vision system uses 2D or 3D sensor cameras and recognition algorithms to recognize the position and posture of the workpiece and the surrounding environment, and the robot system as a whole uses this information to generate robot movements according to the situation. However, the range of workpieces that can be handled is still limited, and the recognition capabilities for complex shapes, reflective properties, transparent objects, and even indefinite shapes are still insufficient. Furthermore, the construction of these vision systems requires the actual objects of the workpieces for adjustment, which involves significant time and effort.

Additionally, tasks that involve handling flexible materials are particularly challenging for robots. The tasks such as handling wire harnesses and arranging components that undergo significant shape changes due to interactions with the robot and the environment are difficult for robots to predict and respond to, making them one of the tasks where automation has not yet advanced in factories.

2. Literature Survey

Efforts to automate teaching are primarily progressing through the development of motion planning techniques. Motion planning is the technology that automatically generates a path connecting the start and end points of robot motion. Traditional manual teaching requires significant effort to create robot paths that are collision-free and have the shortest possible motion time. Motion planning techniques are predominantly based on the sampling-based methods, with Rapidly-exploring Random Trees (RRT [2]) being devised and subsequently improved upon [3], [4], [5]. Currently, these techniques have reached a practical stage where they are implemented within robot simulators and used for pre-verification of motion in simulation environments. However, there are issues related to the trade-off between computation time and the quality of generated paths, as well as the variability in the computation time required for path generation. Further technological advancements are expected to enable real-time motion generation, particularly in complex environments with narrow spaces or multiple robots sharing the workspace, where computation time significantly increases. One promising approach for generating high-quality paths with fast and constant computation time is to utilize Deep Neural Networks (DNN) as an alternative to traditional computation methods. For example, Chi, C., et al. have employed diffusion models to acquire DNN models for generating robot motion paths, which have demonstrated superior performance in terms of discreteness and multimodality compared to conventional imitation learning [6]. As improvements in learning stability and environmental robustness progress, expectations for practical implementation are increasing.

One example of addressing changes and variations in work pieces is the utilization of AI in vision systems. The Dex-Net (The Dexterity Network [7]) project has constructed a large-scale database for object grasping and developed models that predict the gropability of given objects by training DNN using the database as training data. This project utilizes not only real-world data but also synthetic point clouds generated from 3D models, significantly reducing the cost of creating training data. The scalability of both DNN models and training data is expected to enhance generalization, leading to improved performance for unknown objects.

In the Dactyl project by OpenAI, they demonstrate an example of acquiring dexterous manipulation skills using deep reinforcement learning, where a robot with five human-like fingers adeptly manipulates a cube [8]. The Deep Learning techniques often require a large amount of training data to achieve high performance, which presents a challenge for real-world applications. However, Dactyl addresses this issue by employing a technique called domain randomization, which diversifies the physical behavior in the simulation environment. By training solely in the simulated space with varied physics, it is able to acquire movements that can be applied Denso's in the real world. While the current examples in the Dactyl project primarily focus on manipulating rigid objects, it is anticipated that similar techniques will be explored to extend the acquisition of movements for flexible objects in the future.

3. Research in Denso

In order to replace robots with more advanced tasks in the future, it is essential to have coordination among multiple robot arms as a single robot arm has its limitations. However, when trying to apply RRT-based motion planning to multiple robots, as mentioned earlier, the search space expands exponentially with the increase in the number of robots, resulting in a significant increase in computation time. To address this challenge, we incorporated the expertise of skilled teaching engineers into the exploration algorithm and effectively constrained the search range, significantly reducing computation time while maintaining path optimality. Fig. 1 illustrates the relationship between the number of controlled robots and the computation time required to output the initial solutions for the generated paths. With the conventional RRT-based method, the computation time exceeded 31 seconds for two robots, over 32 minutes for three robots, and reached more than 87 hours for four robots (estimated computation time for four robots). However, with the method we developed, the computation time was reduced to approximately 0.4 seconds for two robots, 0.7 seconds for three robots, and 1.6 seconds for four robots.

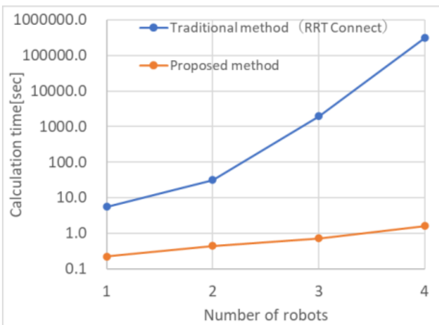
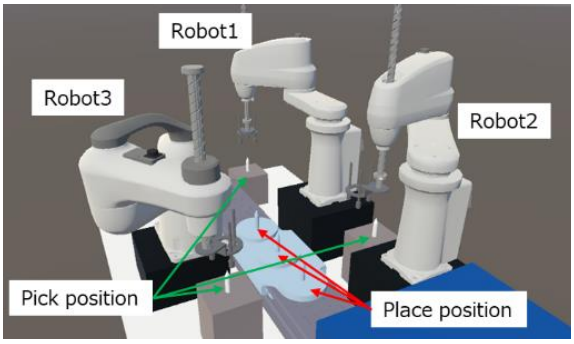


Fig. 1. Relationship between computation time and number of robots in route generation

Furthermore, by adding post-processing for path optimization, we reduced the robot motion time. Through practical verification in actual pick-and-place operations (In the environment shown in Fig. 2, we conducted a demonstration of placing 75 CDs to three designated locations using three robots.), we confirmed a 23.8% reduction in robot operation time compared to the results of skilled teaching engineers (The results of skilled teaching engineers: 48.9 seconds, Automatic Generation by Motion Planning: 37.2 seconds).

2-1. View of the actual machine environment



2-2. Overview of the demonstration environment

Fig. 2. The demonstration of pick-and-place operations with multiple robots

Table 1 shows a more detailed comparison. In a multi-robot operation, the amount of movement (joint movement) as well as the degree to which the robot is able to operate simultaneously greatly affect its working time. When we compared these results, we found that there was no significant difference in joint movement between the teaching result and the auto-generated result (The auto-generated result showed approximately 3.7% less movement compared to the teaching result.), but the auto-generated result showed a greater improvement of over 30% in the simultaneous movement rate compared to the teaching result.

In this development case study, we have shown that we can automate advanced teaching tasks that handle multiple robots and generate highly optimal paths compared to skilled teaching engineers. In the future, we intend to make it possible to automatically generate placement of robots and peripheral equipment, and operation procedures, leading to fully automated start-up of equipment.

Table. 1. Comparison of the results of motion generation by teaching and automatic generation algorithms

1-1. Comparison of joint movement

	Joint movement [rad]		Reduction rate [%]
	(a) Teaching method	(b) Proposed method (Automatic generation)	Reduction rate from (a) to (b)
Robot 1	6363.3	6268.7	1.49
Robot 2	5835.7	5352.7	8.28
Robot 3	4209.9	4176.7	0.79
Total	16408.9	15798.1	3.72

1-2. Comparison of simultaneous operation rates of multiple robots

	(a) Teaching method	(b) Proposed method (Automatic generation)	Improvement value from (a) to (b)
Total operation time [sec]	48.9	31.7	-
Maximum possible concurrent operation time [sec]	46.6	29.3	-
Actual Concurrent Operation Time [sec]	28.2	26.8	-
Rate of concurrent operation [%]	60.6	91.4	30.8

4. Conclusion

To expand the applications of robots, the development of technology that automatically generates their movements is desired. Motion planning is an effective technique for automatically generating optimal paths for robots to reach their work points. In this paper, we introduced examples of automatically generating movements, specifically for cases where multiple robots operate simultaneously with high motion speed, to demonstrate the effectiveness of motion planning. The technology for accurately recognizing and manipulating the position and orientation of target objects is still under active research. We are confident that the advancement of deep learning-based techniques will contribute to solving these challenges. Unlike language and images, the cost of generating large amounts of training data is an issue in robot motion. However, by utilizing synthetic point clouds generated from 3D models and physical simulations, successful examples of robot motion generation applicable to real space are emerging, and further performance improvements can be expected.

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Authors Introduction

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He is the Chief of Intelligent Robotics R & I Section in AI R & I Division at DENSO CORPORATION. He graduated from the Graduate School of Information Technology, Kyushu Institute of Technology in 2001. He is currently working on research and development related to the application of AI in factory automation, with a specific focus on autonomous control of robot arms.