Generation of synthetic Force-Torque data for learning-based control of robots with Sim2Real transfer in industrial assembly processes

Divishad R. Londhe[1 *], Navya Prakash[1], and Markus G. R. Sause[1]
[1]*Institute for Materials Resource Management (MRM),*
University of Augsburg, Augsburg, Germany.
*corresponding author: divishad.londhe@uni-a.de

I. Introduction

Robots are widely used in industrial assembly processes for various applications. However, conventional control algorithms that rely on static programming are not adaptable for facilitating human-robot collaborations and interactions with an unknown environment. In applications such as these, force and torque feedback become vital, and the potential of this control strategy can be fully leveraged by training a supervised learning algorithm with force-torque data. However, collecting training data for learning-based force-torque control can be time-consuming and inefficient. Hence, simulations can generate abundant data for interactions between the robot and its environment. This paper proposes a synthetic force-torque data generation method for hassle-free robot training when interacting with rigid and deformable materials in industrial assembly tasks by leveraging transfer learning techniques. Additionally, it discusses how the simulation model of the environment can be validated to obtain the most accurate estimates of the real forces in the physical world with Sim2Real transformation of the industrial assembly setup.

Since the inception of the usage of robots in assembly lines, control strategies have primarily focused on ensuring the positional accuracy of the robot's end effector to execute tasks effectively. However, this emphasis on positional precision often encounters difficulties over time due to the wear and tear of various robot parts. As these components degrade, they can cause slips in drives and provide false encoder values, resulting in deviations of the tool centre point (TCP) position from the desired location. These deviations pose significant risks, particularly in scenarios requiring human-robot collaboration, where even minor discrepancies in positioning can lead to potentially fatal accidents [1]. Moreover, in tasks involving the handling of softer materials, the slightest deviation from the intended path may damage the handled workpiece, leading to the wastage of valuable resources. Therefore, there is a need to evolve control strategies beyond conventional positional accuracy to address such challenges and enhance safety and efficiency in assembly processes. Incorporating force adaptability into control systems can mitigate the impact of wear and tear on robot components, reducing the likelihood of positioning errors. Thus, using state-of-the-art sensing technologies, such as force-torque sensors, can better estimate interactions between the robot and its environment.

By integrating this feedback into control algorithms, the robot can dynamically adjust its movements to account for variations in material properties or unexpected obstacles, thus minimizing the risk of damages or accidents. Additionally, adopting learning-based control approaches, such as reinforcement learning (RL) or neural network-based methods, can facilitate the development of more adaptive and resilient control policies. These algorithms can continuously learn from interactions with the environment, allowing the robot to autonomously optimize its behaviour over time and counter the evolving conditions, including wear-induced degradation. Training robots for these data-driven, learning-based force-torque control approaches needs substantial physical data with accurate force and torque estimates, which can be challenging to obtain with real robot systems. Hence, adopting synthetic data generation methods becomes vital for efficiently acquiring ample and diverse data [2]. By leveraging state-of-the-art simulation platforms, one can generate synthetic data that closely mimic real-world scenarios while offering several advantages [3]. Synthetic data generation allows for rapidly accumulating large datasets within a fraction of the time required for real-world data collection. This accelerated data acquisition process significantly paces the training of learning-based control algorithms.

Moreover, simulation environments enable the inclusion of diverse environmental variations, introducing a wide range of forces and torques acting on the robot's end effectors. Hence, by utilizing these advantages in the selected simulation environment, the method is proposed where the data generated using the robot's interaction with a metallic peg-in-hole test bench is used to train the suitable machine learning (ML) model and this pre-trained model to be incorporated directly on an actual metallic industrial assembly workpiece used in a similar peg-in-hole assembly setup by transfer learning. Furthermore, the Sim2Real transfer can also be validated by comparing the results obtained from the synthetic data in the simulation with the data from the real robot for a particular material.

II. Proposed Method

The setup to generate synthetic force and torque data for a robotic industrial assembly process is modelled in a simulation environment Isaac Sim by NVIDIA, as shown in Fig.1. The robot used in this context is a 7-axis collaborative robot, Franka Panda from Franka Robotics. As the paper focuses on force and torque control, one of the standard use cases to be set up and tested is a peg-in-hole assembly, which has been formally tested in various previous research works [4]. Thus, for training the robot on a chosen material, a cylindrical peg of length 40 mm and diameter 6 mm is designed and is provided with a cubical top so that the two-finger gripper can conveniently hold the peg from both sides. Moreover, a cubical block is designed with various holes with varying diameters and shapes. Three circular holes were of varying diameters, 6.05 mm, 6.10 mm, and 6.30 mm, respectively. A fourth hexagonal hole is tested to get some non-uniform behaviour in the X and Y-axis forces exerted on the robot end effector during the task. After a depth of 10 mm, this slot also consists of a 6.30 mm circular hole. The real robot is provided with an inbuilt force torque sensor at its end effector with force and torque resolution of 0.05 N and 0.02 Nm, respectively. Hence, a similar virtual sensor is also made available in the model used in the simulation.

Fig. 1 Simulation model of the robot peg-in-hole test bench setup with metallic peg and hole

The peg and block are metallic and are used to set up a physical test bench with the real robot system; thus, in the simulation, the block and peg are assigned the same material to mimic the properties, reaction forces, and deformability behaviour in our real-world setup. The real-time position and force-torque data in 6-axes are gathered from the simulation environment for the end effector. The recorded data is plotted against time as a time series of the events of placing the peg in the hole. As an example, the plot shown in Fig. 2 is generated for the action of placing the peg in the hexagonal hole of the block.

This data generated using metal is now suitable as training data for a learning-based algorithm of choice, as explained in [4][5], where both position and forces at the end effector are used for the adaptive control. These models can apply to a broader set of materials and use cases. The proposed method involves first generating synthetic data in varying environmental settings, randomized via a Python API in Isaac Sim. To validate the correctness of the proposed generated synthetic data and the parameters of the simulation environment, the forces and torques from the real robot system are also recorded along with the corresponding positions for the processes in the peg-in-hole test bench setup with peg and block. Comparing the real force-torque data with the generated synthetic dataset gives us an estimate of the parameters in the simulation environment that are ideal for creating a reliable and robust pipeline for training dataset generation.

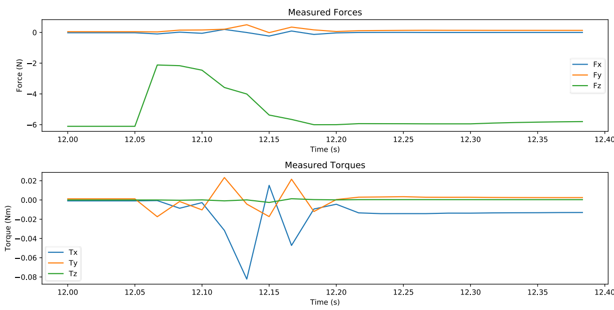

Fig. 2 Generated force and torque data plot for the proposed test bench setup in the simulation of metallic peg-in-hole assembly.

The data produced and validated through this pipeline is reliable as labelled training data and, after feature extraction for forces and torques in the peg-in-hole action, will be ready for training an ML algorithm to predict the position of the tool centre point (TCP) based on six features: three forces and three torques. Given the variety in the range of values for the forces and torques, the data needs to be normalized to a scale. Moreover, as the generated time series data comprises the whole process from picking the peg to inserting it into the hole, the valuable time series can be extracted according to the use case. As seen in Fig. 2, the deviation in forces is negligible until the insertion of the peg, and only when it is being inserted do the forces fluctuate. Thus, one can use only the data excerpt where this fluctuation occurs. After training an ML model with this data, it can later be tested for accuracy on other holes of the block, which vary in size and shape and require the TCP to adjust the position accordingly. Also, if needed, data from the insertion of the peg into different holes can be combined to create a training dataset with differing hole sizes, thus avoiding overfitting to a particular shape and size of the hole.

III. Conclusion

The proposed approach could replace the monotonous and time-consuming process of physical data generation with a synthetic alternative that considers various materials. Additionally, in supervised learning algorithms where force and torque feature vectors need to be labelled with the respective positions, this approach will save significant labelling time and resources. Finally, by leveraging the transfer learning capabilities, a robust pre-trained model can be created and used for a wide range of materials for the specific use case.

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