

RoboTwin: Dual-Arm Robot Benchmark with Generative Digital Twins (early version)

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<https://robotwin-benchmark.github.io/early-version>

Abstract. Effective collaboration of dual-arm robots and their tool use capabilities are increasingly important areas in the advancement of robotics. These skills play a significant role in expanding robots' ability to operate in diverse real-world environments. However, progress is impeded by the scarcity of specialized training data. This paper introduces RoboTwin, a novel benchmark dataset combining real-world teleoperated data with synthetic data from digital twins, designed for dual-arm robotic scenarios. Using the COBOT Magic platform, we have collected diverse data on tool usage and human-robot interaction. We present an innovative approach to creating digital twins using AI-generated content, transforming 2D images into detailed 3D models. Furthermore, we utilize large language models to generate expert-level training data and task-specific pose sequences oriented toward functionality. Our key contributions are: 1) the RoboTwin benchmark dataset, 2) an efficient real-to-simulation pipeline, and 3) the use of language models for automatic expert-level data generation. These advancements are designed to address the shortage of robotic training data, potentially accelerating the development of more capable and versatile robotic systems for a wide range of real-world applications.

Keywords: Dual-arm robotic benchmark · Digital twin simulation

1 Introduction

In the fast-evolving robotics field, the integration of dual-arm coordination and advanced tool use is crucial for developing sophisticated autonomous systems.

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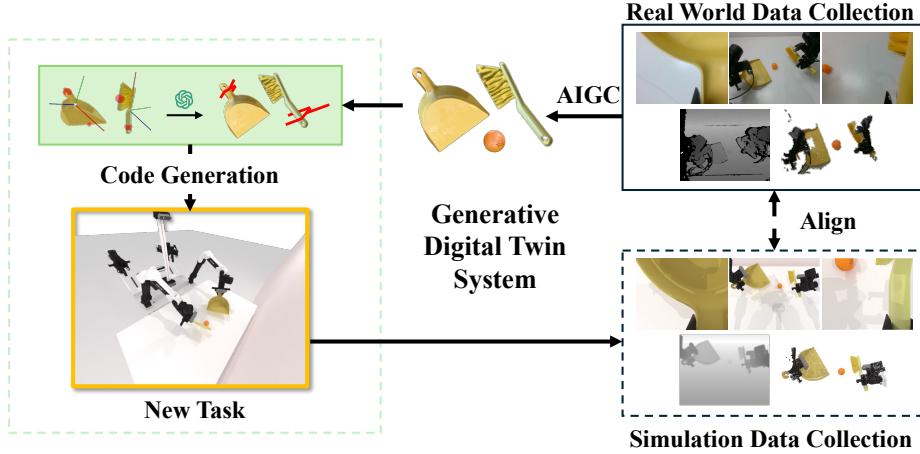


Fig. 1: RoboTwin Benchmark.

These capabilities are essential for enabling robots to function effectively in diverse real-world settings such as manufacturing plants, healthcare centers, and homes. By using tools, robots can significantly expand their operational scope, adapting to a variety of tasks and challenges with greater flexibility. However, the advancement in these areas is substantially hindered by the lack of specialized, high-quality training data. These activities, which often require tailored solutions, are difficult to standardize and are typically not well-represented in conventional datasets.

Addressing this critical gap, we introduce "RoboTwin", a comprehensive benchmark that includes both real-world teleoperated data and corresponding synthetic data generated by a digital twin. Specifically designed for scenarios involving dual-arm robotic tool use and human-robot interactions. RoboTwin features high-quality annotations and diversity of examples to ensure robust training and evaluation. To collect real-world data, we employ the open-source COBOT Magic platform developed by AgileX Robotics. This platform is outfitted with four AgileX Arms and four Intel Realsense D-435 RGBD cameras, mounted on a robust Tracer chassis. The data encompasses a variety of typical tasks, including tool usage and human-robot interaction.

Transforming from the collection of real-world data to its virtual replication, the challenge is to create accurate and cost-effective digital twins. Traditional methodologies often rely on expensive, high-fidelity sensors, limiting their widespread adoption. To circumvent these limitations, we have developed a novel, cost-effective approach using Artificial Intelligence Generated Content (AIGC) to construct 3D models from a single 2D RGB image. This method significantly reduces costs while providing lifelike visual representations and supporting physical simulations. Our process begins with converting a 2D image into a detailed 3D model, featuring complex geometry, surface textures, and accurate details,

which are crucial for realistic visualizations and simulations. We further enhance the model by defining functional coordinate axes on the object parts, enabling the automated computation of grasp poses essential for robotic manipulations. To enhance the utility and relevance of our dataset, we have also established an innovative pipeline leveraging large language models (LLMs) for the automatic generation of expert-level training data. This methodology not only enriches the dataset with high-quality, scenario-specific examples but also integrates the versatility of LLMs in synthesizing complex interactive sequences. Integrating the reasoning capabilities of GPT4-V [1], we automate the generation of task-specific pose sequences, thereby increasing the precision of task executions. Moreover, we employ GPT4-generated scripts to activate trajectory planning tools, which streamline the programming efforts and expedite the deployment of robotic systems in various environments.

The core contributions of this work are: 1) The development of "RoboTwin", a benchmark that includes both real-world teleoperated data and high-fidelity synthetic data generated for corresponding scenarios. 2) The establishment of a convenient real-to-simulation pipeline that requires only a single RGB image from the real world to generate the 3D models of target objects and corresponding scenes. 3) The utilization of large language models (LLMs) combined with simulation environment information to generate code that automatically creates expert-level data. These advancements collectively aim to bridge the gap in robotic training data, significantly enhancing the potential for robots to learn and operate using tools in a manner that mimics human dexterity and interaction finesse.

2 Related Work

2.1 Datasets and Benchmarks for Robotics

To enhance the collection of effective demonstrations for robotic tasks, human teleoperation has traditionally been employed. In this method, a human operator manually guides a robot through various tasks [10, 14, 22, 25, 26, 34]. Recent advancements have extended this methodology by employing teams of human operators over prolonged periods to assemble substantial real-world datasets [3, 5, 10, 14]. An alternative method involves the use of algorithmic trajectory generators within simulations [9, 11, 13, 16, 33], which, while efficient, often depend on privileged information and hand-designed heuristics, making them labor-intensive for arbitrary tasks. However, current systems often fail to produce high-fidelity expert simulation data that accurately mimics data from actual machine operations. Although initiatives like MimicGen [23] and RoboCaca [27] strive to generate simulated expert data using limited human demonstrations, they still heavily rely on predefined scenes and interactive objects. To overcome these limitations, we introduce RoboTwin. This innovative system not only generates expert data and simulation scenes derived from real-world scenarios but also utilizes large language models (LLMs) to generate demonstration codes and expert data for similar tasks involving the same class of objects. This strategy

significantly reduces the dependence on continuous human intervention, thereby streamlining the generation of reliable training data for robotic tasks.

2.2 Robot Manipulation Learning Methods

The adoption of human demonstrations to instruct robots in manipulation skills is a prevalent method in Robot Manipulation Learning [4, 6, 15, 21, 29]. Among the techniques, Behavioral Cloning stands out for learning policies offline from these demonstrations. It replicates observed actions from a curated dataset [5, 9, 10, 14, 16, 24, 28, 34]. Conversely, Offline Reinforcement Learning enhances policy learning by optimizing actions based on a predefined reward function and exploiting large datasets [7, 12, 17–20]. The Action Chunking with Transformers (ACT) technique integrates a Transformer-based visuomotor policy with a conditional variational autoencoder to structure the learning of action sequences [30, 31, 35]. Recently, the Diffusion Policy method has gained prominence. It employs a conditional denoising diffusion process for visuomotor policy representation, effectively reducing the accumulative error in trajectory generation that is often observed in Transformer-based visuomotor policies [8]. The 3D Diffusion Policy [32] uses point clouds for environmental observations, enhancing spatial information utilization and managing various robotic tasks in both simulated and real environments with only a small number of demonstrations.

3 Real-to-sim transfer of the scene

3.1 Generative Digital Twin System

To synthesize high-fidelity data through simulation, a major challenge is the creation of accurate and cost-effective digital twins. Traditional methods often depend on costly high-precision sensors, which can hinder widespread adoption. In response, we have developed a more economical approach using Artificial Intelligence Generated Content (AIGC) to construct 3D models from simple 2D RGB images powered by Deemos’s Rodin platform⁶. This technique significantly reduces the reliance on expensive sensors while achieving realistic visual effects and supporting physical simulations. Our innovative pipeline commences with generating a detailed 3D mesh and texture of the target object involved in a robot’s task, created from a single real-world image. This capability ensures a high-fidelity recreation of real-world scenarios within a simulated environment. The process begins by transforming a single 2D image into a 3D model that encompasses detailed geometry, surface normals, wireframes, and textures. These features enhance the visual realism and ensure compatibility with physics engines for simulations. Once the 3D model is ready, we assign specific coordinate axes to functional parts of objects within the model. For instance, as shown in Fig. 3,

⁶ We use Deemos’s 3D digital asset Generation Model (from text or image) Rodin: <https://hyperhuman.deemos.com/rodin>

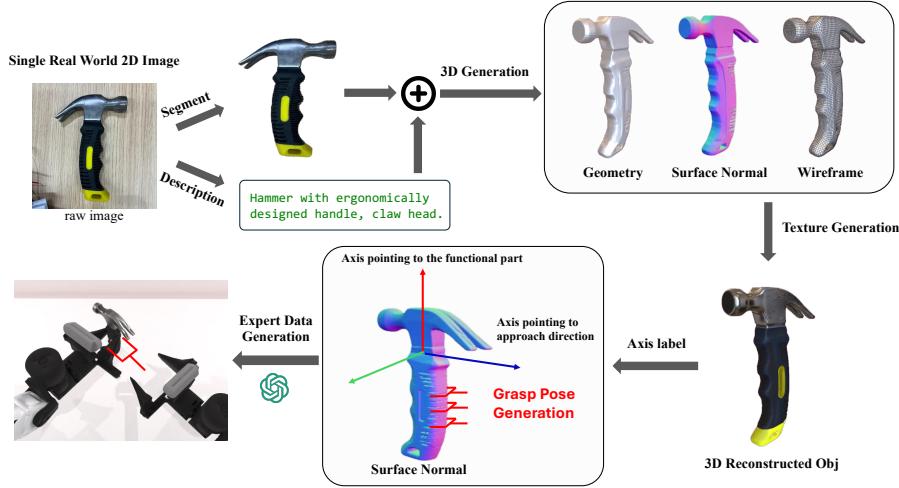


Fig. 2: AIGC & Expert Data Generation pipeline. Automatic extraction of object segmentation and textual description from a single RGB photo, followed by the generation of 3D geometry, surface normals, Wireframe, and texture maps to create a high-fidelity simulation object. With the object’s surface normal and pose information, we can decompose and generate grasping postures, and leverage the large model’s capabilities to zero-shot generate expert data for tasks.

for a hammer, one axis is aligned with the hammerhead—identifying the functional part—while another axis indicates the approach direction. This strategic alignment is crucial for automating the calculation of grasp poses, which are essential for robotic manipulation and tool usage. Grasp poses are computed perpendicular to the surface normal of the functional part along the designated approach direction axis, facilitating correct and efficient tool use with minimal manual intervention.

3.2 Expert Data Generation

We leverage the reasoning capabilities of GPT4-V [1] to write code that calculates the relationships between key poses and the functional coordinate axes of objects. GPT4-V analyzes task requirements and generates a sequence of poses that align with these requirements, ensuring precise task execution. We also generate code via GPT4 [2] to invoke trajectory planning tools based on the computed poses. This automation substantially decreases the time and labor associated with manual programming, facilitating the swift deployment of robotic systems across diverse applications. It also offers a scalable approach for generating high-quality data essential for robotic learning.

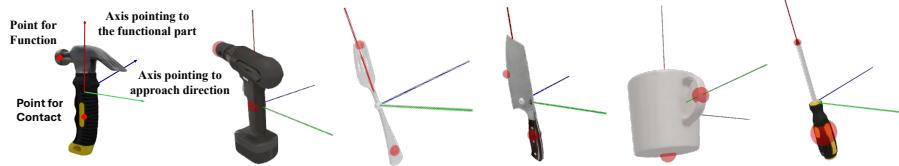


Fig. 3: Point for Function and Contact, Axis pointing to the functional part and approach direction

4 Benchmark

To further research and development in this area, as shown in Fig. 4, we introduce a comprehensive benchmark specifically designed to assess dual-arm robots in a variety of scenarios. This benchmark encompasses a diverse set of tasks, each presenting unique challenges that are critical for assessing the dexterity, coordination, and operational efficiency of robotic arms in a simulated environment. The tasks range from simple object manipulation to complex, coordinated actions requiring synchronized movements of both arms. Appendix A.2 outlines the specific tasks and their descriptions, providing a clear framework for comparative analysis and further development of advanced robotic capabilities. For each task, we provide a robust API that supports the generation of expert data across infinitely variable scenarios, such as different object placements and environmental conditions. This feature allows researchers to extensively test and refine the adaptability and precision of robotic systems under controlled yet varied conditions. Additionally, an offline dataset is available for each task, offering pre-generated expert data to facilitate offline training and benchmarking of algorithms. This benchmark aims to bridge the gap between theoretical robotic control models and their practical implementation, ensuring that the robotic systems can perform reliably in dynamic, real-world environments.

5 Real-world Dataset

For the acquisition of real-world data, we employed the open-source Cobot Magic⁷ platform from AgileX Robotics, which is equipped with four AgileX Arms and four Intel Realsense D-435 RGBD cameras and is built on the Tracer chassis. These cameras are strategically positioned: one on the high part of the stand for an expansive field of view, two on the wrists of the robot's arms, and one on the low part of the stand which is optional for use. The front, left, and right cameras capture data simultaneously at a frequency of 30Hz, as depicted in Figure 5. The data collection and alignment are facilitated by tools provided by the ARIOData Alliance, available at our GitHub repository⁸. Each captured frame consists of

⁷ Platform Introduction: <https://global.agilex.ai/products/cobot-magic>

⁸ Tool for data alignment: <https://github.com/ario-dataset/ario-tools>

Table 1: The testing results for DP3 on various tasks, trained with varying amounts of expert data.

Task	10 demo.	20 demo.	50 demo.
Block Hammer Beat	24%	56%	80%
Empty Cup Place	10%	60%	96%
Dual-Bottles Pick	10%	42%	74%
Block Sweep	28%	70%	86%
Apple Cabinet Storage	30%	57%	64%
Block Handover	50%	90%	98%

three images from the cameras, each providing an RGB and depth image at a resolution of 640×480 pixels. Additionally, the data includes the poses of the robotic arms' joints and end-effectors for both master and slave configurations, encompassing both left and right arms. All data storage and formatting adhere to the unified standards established by the ARIES Data Alliance.

Our dataset task design features two major highlights: a focus on human-robot interaction and tool usage. As shown in Appendix A.3, we have designed 17 tasks, 9 of which emphasize tool usage, 5 involve interpersonal interactions and 6 tasks are dual-arm. We collected 30 trajectories for each task. During trajectory collection, we broke down the tasks into multiple stages and conducted slower data collection for key sub-trajectories that required precise operations, enhancing the detail of the trajectories for better model learning.

6 Experiment

Our experimental aim is not to delve into the design choices of different strategy networks but to explore the correctness and effectiveness of our Benchmark expert data. Our experiments are intended to verify: a) the rationality of the COBOT Magic platform settings, and b) the effectiveness of the automatically generated expert data.

We utilized the 3D Diffusion Policy (DP3) [32] to test six tasks within the benchmark, with each task being tested using strategies trained from 10 sets, 20 sets, and 50 sets of expert data, respectively, to obtain the success rates. For the success criteria of each task, please refer to the appendix. The experimental results, as summarized in Table 1, demonstrate the performance of the 3D Diffusion Policy (DP3) across six tasks, each trained with varying quantities of expert demonstration data (10, 20, and 50 sets). Notably, for the "Block Hammer Beat" task, the success rate improved from 24% with 10 demonstrations to 80% with 50 demonstrations. The "Empty Cup Place" task saw success rates soar from 10% to 96% with increased demonstrations. The "Dual-Bottles Pick" task success rates climbed from 10% to 74% as demonstrations increased. The "Block Sweep" task success improved steadily from 28% to 86%, while the "Apple Cabinet Storage" task showed more modest gains, from 30% to 64%.

The "Block Handover" task achieved the most significant improvement, reaching 98% success with 50 demonstrations, up from 50%. These results suggest a strong correlation between the number of expert demonstrations and task success, highlighting the effectiveness of the automatically generated expert data in enhancing task performance on the COBOT Magic platform. The data further underscores the importance of ample training examples in the development of robust strategies for complex tasks.

7 Conclusion

In this study, we introduce RoboTwin, a benchmark integrating real-world and synthetic data to evaluate dual-arm robots, addressing the significant shortage of specialized training data in robotics. Our dataset, developed using the AgileX Robotics platform and enhanced through generative digital twins powered by Deemos's Rodin platform, effectively accelerates the training of robotic systems, enabling performance improvements across diverse tasks. Our results demonstrate the potential of this hybrid data approach to refine robotic dexterity and efficiency, providing a scalable tool that could revolutionize robotic research and applications.

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**Fig. 4:** Task Execution of RoboTwin Benchmark.**Fig. 5:** Illustration of our robot platform, with the capabilities for teleoperation, mobility, and data acquisition.

A Appendix

A.1 Licensing

RoboTwin is released under the open-source MIT license.

A.2 Benchmark Task Descriptions

In this subsection, we present a comprehensive overview of six carefully designed simulation tasks aimed at evaluating the capabilities of robotic systems in various manipulation scenarios. These tasks are crafted to challenge different aspects of dexterous control, coordination between multiple limbs, and the ability to perform complex sequences of actions. Each task is intended to simulate real-world challenges that a robotic system might encounter, thus providing a robust benchmark for assessing the effectiveness of various robotic algorithms. Detailed descriptions of these tasks are provided in Table 2, which outlines the specific objectives and required actions for each scenario.

Table 2: Detailed descriptions of 6 simulation tasks we propose.

Task	Description
<i>Block Hammer Beat</i>	A hammer and a red block are on the table. The right arm uses the hammer to strike the block.
<i>Empty Cup Place</i>	A cup (without liquid) is on the table. The right arm picks up the cup from above downwards and places it on a cup mat.
<i>Dual-Bottles Pick</i>	The left arm grasps a cola can, while the right arm simultaneously picks up a sprite can.
<i>Block Sweep</i>	There is a red block on the table. The left arm of the robotic arm holds the dustpan and the right arm holds the brush. The two arms work together to sweep the block in.
<i>Apple Cabinet Storage</i>	On the table, there's a cabinet and an apple. The left arm opens the cabinet, and the right arm picks up the apple, placing it inside.
<i>Block Handover</i>	The left arm picks up the red cuboid on the left side of the desk and hands it over to the right arm, which will then place the cuboid in the blue target area on the right side.

A.3 Dataset Task Descriptions

Our dataset comprises 17 distinct, real-world robotic tasks designed to evaluate the dexterity, coordination, and contextual understanding of robotic systems in

a controlled environment. Each task is uniquely structured to challenge various aspects of robotic manipulation, from simple object transfers to complex, dual-arm coordination tasks. Table 3 provides detailed descriptions of each task, outlining the specific actions, objects, and expected interactions. These descriptions are pivotal for replicating the tasks in different research settings, ensuring consistency in performance benchmarks across various robotic platforms. The diverse nature of these tasks enables comprehensive testing of the robots' abilities to handle real-world scenarios, thereby advancing our understanding and development of more adaptive and capable robotic assistants.

Table 3: Detailed descriptions of 17 real-world tasks we propose.

Task	Description
<i>Paddle Sweep</i>	On the table, there is a dustpan, a brush, and a ping pong ball. Using the left arm to grasp the dustpan and the right arm to grasp the brush, the two arms work together to sweep the ping pong ball into the dustpan.
<i>Mark Hammer Beat</i>	A hammer and a red mark are on the table. The right arm picks up the hammer and strikes the mark.
<i>Flour Scoop</i>	On the table, there is a bowl full of flour and an empty plate. The right arm initially holds a spoon, scoops a spoonful of flour from the bowl, and then pours it into the empty plate.
<i>Brush Adjust</i>	A brush is on the table. The left arm first picks up the brush, and the right arm adjusts the brush's position.
<i>Plate Scrub</i>	A dishrag and a plate are on the table. The left arm picks up the plate, and the right arm picks up the dishrag. The two arms work together to scrub the plate with the dishrag for three circles.
<i>Pot Wire Scrub</i>	A stainless steel pot and a steel wool pad are on the table. The left arm adjusts the position of the pot, and the right arm picks up the steel wool pad.
<i>Cake Fork</i>	A small plate with a piece of cake is on the table. Initially, the right arm holds a fork, and it uses the fork to pierce the cake and lift it.
<i>Stain Clean</i>	There is a juice stain on the table with a rag. The right arm picks up the rag and wipes away the juice.

Continued on next page

Table 3 – continued from previous page

Task	Description
<i>Scissors Take</i>	A human is holding the head of the scissors. The right arm grabs the handle of the scissors and takes them over.
<i>Pot Handover</i>	A human is holding the pot with both hands. The robot arms work together to grab the pot's handles and transfer the pot to the table.
<i>Empty Cup Place</i>	A cup (without liquid) is on the table. The right arm picks up the cup from above downwards and places it on a cup mat.
<i>Empty Cup Handover</i>	A water cup (without liquid) is on the table. The right arm grasps the cup from above downwards and hands it over to a human.
<i>Empty Cup Transfer</i>	A human is holding a cup (without liquid). The right arm picks up the cup from above downwards and transfers it to a cup mat.
<i>Water Cup Place</i>	A cup with water is on the table. The right arm picks up the cup from the side and places it on a cup mat.
<i>Juice Cup Transfer</i>	A human is holding a cup with juice. The right arm picks up the cup from the side and transfers it to a cup mat.
<i>Juice Cup Place</i>	A cup with juice is on the table. The right arm picks up the cup from the side and places it on a cup mat.
<i>Dual-Bottles Pick</i>	The left arm grasps a cola can, while the right arm simultaneously picks up a sprite can.