RH20T: A Robotic Dataset for Learning Diverse Skills in One-Shot

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***Abstract*—A key challenge in learning task and motion planning in open domains is how to acquire diverse and generalizable skills for robots. Recent research in one-shot imitation learning has shown promise in transferring trained policies to new tasks based on demonstrations. This feature is attractive for enabling robots to acquire new skills and improving task and motion planning. However, due to limitations in the training dataset, the current focus of the community has mainly been on simple cases, such as push or pick-place tasks, relying solely on visual guidance. In reality, there are many complex skills, some of which may even require both visual and tactile perception to solve.This paper aims to unlock the potential for an agent to generalize to hundreds of real-world skills with multi-modal perception. To achieve this, we have collected a dataset comprising over 110,000 *contact-rich* robot manipulation sequences across diverse skills, contexts, robots, and camera viewpoints, all collected *in the real world*. Each sequence in the dataset includes visual, force, audio, and action information, along with a corresponding human demonstration video. We have invested significant efforts in calibrating all the sensors and ensuring a high-quality dataset. The dataset will be made publicly available.**

I. Introduction

Enabling robots to learn new skills with minimal effort is one of the ultimate goals of the robot learning community, as it can significantly advance task and motion planning in unstructured environments. Recent research in one-shot imitation learning [9, 12] and emerging foundation models [2, 4] paints an exciting picture of skill transfer to new tasks based on task descriptions. This paper shares the same aspiration.

While the future is promising, most research in robotics only demonstrates the effectiveness of their algorithms on simple cases, such as pushing, picking, and placing objects in the real world. Two main factors hinder the exploration of more complex tasks in this direction. Firstly, there is a lack of large and diverse robotic manipulation datasets in this field [2], despite the community's long-standing eagerness for such datasets. This suggests the existence of systematic problems in our data collection paradigm that impede the collection of complex manipulation tasks. Secondly, most methods focus solely on visual guidance control, yet it has been observed in physiology that humans with impaired digital sensibility struggle to accomplish many daily manipulations with visual guidance alone [19]. This indicates that more sensory information should be considered in order to learn various manipulations in open environments.

To address these problems, we revisit the data collection process for robotic manipulation. In most imitation learning literature, expert robot trajectories are manually collected using simplified user interfaces like 3D mice, keyboards, or VR remotes. However, these control methods are inefficient and pose safety risks when the robot engages in rich-contact interactions with the environment. The main reasons are the unintuitive nature of controlling with a 3D mouse or keyboard, and the inaccuracies resulting from motion drifting when using a VR remote. Additionally, tele-operation without force feedback degrades manipulation efficiency for humans. In this paper, we equipped the robot with a force-torque sensor and employed a haptic device with force rendering for precise and efficient data collection. With the goal that the dataset should be representative, generalized, diverse and close to reality, we collect around 150 skills with complicated actions other than simple pick-place. These skills were either selected from RLBench [17] and MetaWorld [37], or proposed by ourselves. Many skills require the robot to engage in contact-rich interactions with the environment, such as cutting, plugging, slicing, pouring, folding, rotating, etc. We have used multiple different robot arms commonly found in labs worldwide to collect our dataset. The diversity in robot configurations can also aid algorithms in generalizing to other robots. So far, we have collected around 110,000 sequences of robotic manipulation and 110,000 corresponding human demonstration videos for the same skills. This amounts to over 40 million frames of images for the robotic manipulation sequences and over 10 million frames for the human demonstrations. Each robot sequence contains abundant visual, tactile, audio, and proprioception information from multiple sensors. The dataset is carefully organized, and *we believe that a dataset with such diversity and scale is crucial for the future emergence of foundation models in general skill learning,* as promising progress has been witnessed in the NLP and CV communities [5, 30, 21].

II. Related Works

We briefly review related works in zero/one-shot imitation learning, robotic manipulation datasets, and vision-force learning methods.

a) Dataset: Our community has been striving to create a large-scale and representative dataset for a significant period of time. Previous research in one-shot imitation learning has either collected robot manipulation data in the real world [12] or in simulation [25]. However, their datasets are usually small and the tasks are simple. Some attempts have been made to create large-scale real robot manipulation datasets [13, 26, 32,

Fig. 1: Sampled RBG images from RH20T. Our dataset contains diverse skills, robots, viewpoints, objects, backgrounds, etc. Note that these images are center-cropped for better visualization.

8, 20, 18]. For example, RoboTurk [26] developed a crowd-sourcing platform and collected data on three tasks using mobile phone-based tele-operation. MIME [32] collected 20 types of manipulations using Baxter with kinesthetic teaching, but they were limited to a single robot and simple environments. RoboNet [8] gathered a significant amount of robot trajectories with various robots, grippers, and environments. However, it mainly consists of random walking episodes due to the challenges of performing meaningful skills. BC-Z [18] presents a manipulation collection of 100 "tasks", but as pointed out in [25], they are combinations of 9 verbs and 6-15 objects. Similarly, RT-1 [4] also collects a large-scale manipulation dataset but focuses on a limited set of skills. These datasets lack diversity in skill settings and, more importantly, they do not include the crucial force modality during manipulation. Our goal is to address these gaps and provide a dataset with a wider range of skills and more comprehensive information, including the force modality.

b) Zero/One-shot imitation learning: The objective of training policies that can transfer to new tasks based on robot/human demonstrations is not new. Early works [31, 27, 13] focused on imitation learning using high-level states such as trajectories. Recently, researchers [12, 9, 38, 16, 36, 29, 28, 39, 14, 33, 3, 35, 7, 24, 18, 25] have started exploring raw-pixel inputs with the advancement of deep neural networks. Additionally, the requirement of demonstrations has been reduced by eliminating the need for actions. Recent approaches have explored various one-shot task descriptors, including images [16, 3], language [33, 24], robot video [12, 7, 25], or human video [36, 18]. These methods can be broadly classified into three categories: model-agnostic meta-learning [12, 36, 16, 3, 39], conditional behavior cloning [9, 7, 18, 25], and task graph construction [14, 15]. While significant progress has been made in this direction, these approaches only consider visual observations and primarily focus on simple robotic manipulations such as reach, pick, push, or place. Our dataset offers the opportunity to take a step further by enabling the learning of *hundreds* of skills that require *multi-modal perception* within a single imitation learning model.

c) Multi-Modal Learning of Vision and Force: Force perception plays a crucial role in manipulation tasks, providing valuable and complementary information when visual perception is occluded. The joint modeling of vision and force in robotic manipulation has recently garnered interest within the research community [10, 23, 11, 22, 1, 6, 34]. However, most of these studies overlook the asynchronous nature of different modalities and simply concatenate the signals before or after the neural network. Moreover, the existing research primarily focuses on designing multi-modal learning algorithms for specific tasks, such as grasping [6], insertion [22], twisting [10], or playing Jenga [11]. The question of how to effectively handle multi-modal perception at different frequencies for various skills in a coherent manner remains open in robotics. Our dataset presents an opportunity for exploring multi-sensory learning across diverse real-world skills.

III. RH20T Dataset

We introduce our robotic manipulation dataset, Robot-Human demonstration in 20TB (RH20T), to the community. Fig. 1 shows an overview of our dataset.

A. Properties of RH20T

RH20T is designed with the objective of enabling general robotic manipulation, which means that the robot can perform various skills based on a task description, typically a human demonstration video, while minimizing the notion of rigid tasks. The following properties are emphasized to fulfill this objective.

a) Diversity: The diversity of RH20T encompasses multiple aspects. To ensure task diversity, we selected 48 tasks from RLBench [17], 29 tasks from MetaWorld [37], and introduced 70 self-proposed tasks that are frequently encountered and achievable by robots. Hundreds of objects were

Fig. 2: On the left side are the multi-view images. On the right side, we display the point cloud generated by fusing the RGBD data from these multi-view cameras. The red pyramids indicate the camera poses. Additionally, the robot model is rendered in the scene based on the joint angles recorded in our dataset. In the right image, it is evident that all the cameras are calibrated with respect to the robot's base frame, and all the recorded data are synchronized in the temporal domain.

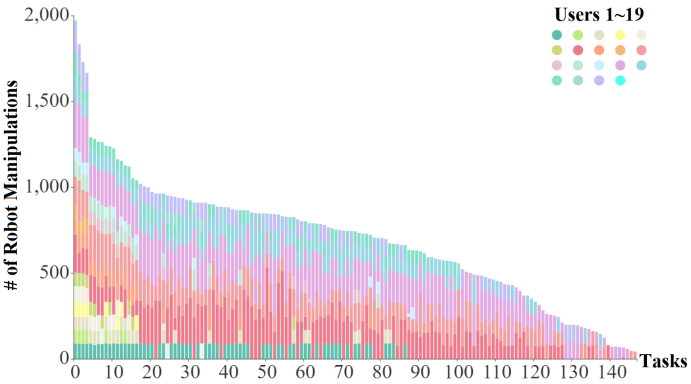

Fig. 3: Statistics on the amount of robotic manipulation for different tasks.

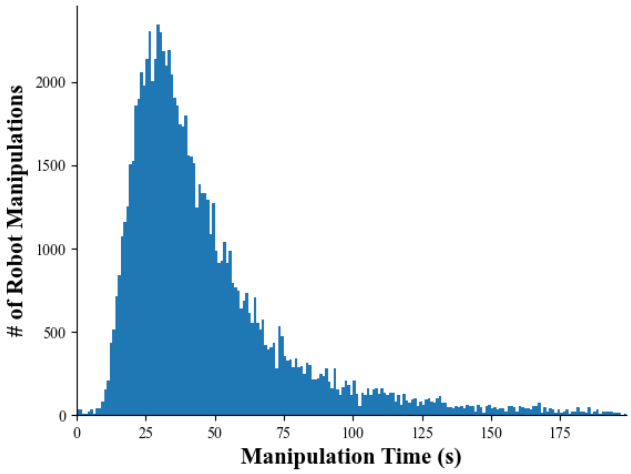

Fig. 4: Statistics on the execution time of different robotic manipulations in our dataset.

collected to accomplish these tasks. To ensure applicability across different robot configurations, we used 4 popular robot arms, 4 different robotic grippers, and 3 types of force-torque sensors, resulting in 7 robot configurations. More details about the robot configurations can be found in Appendix A.

To enhance environment diversity, we frequently replaced over 50 table covers with different textures and materials, and introduced irrelevant objects to create distractions. Manipulations were performed by tens of volunteers, ensuring diverse trajectories. To increase state diversity, for each skill, volunteers were asked to change the environmental conditions and repeat the manipulation 10 times, including variations in object instances, locations, and more. Additionally, we conducted robotic manipulation experiments involving human interference, both in adversarial and cooperative settings. Further details about each task are provided in Appendix B.

b) Multi-Modal: We believe that the future of robotic manipulation lies in multi-modal approaches, particularly in open environments, where data from different sensors will become increasingly accessible with advancements in technology. In the current version of RH20T, we provide visual, tactile, audio, and proprioception information. Visual perception includes RGB, depth, and binocular IR images from three types of cameras. Tactile perception includes 6 DoF force-torque measurements at the robot's wrist, and some sequences also include fingertip tactile information. Audio data includes recordings from both in-hand and global sources. Proprioception encompasses joint angles/torques, end-effector Cartesian pose, gripper states, and more. All information is collected at the highest frequency supported by our workstation and saved with corresponding timestamps. An example sampled from our dataset is shown in Fig. 2.

c) Scale: Our dataset consists of over 110,000 robot sequences and an equal number of human sequences, with more than 50 million images collected in total. On average, each skill contains approximately 750 robot manipulations. Fig.3 provides a detailed breakdown of the number of manipulations across different tasks in the dataset, showing a relatively uniform distribution. Fig.4 presents statistics on the manipulation time for each sequence in our dataset. Most sequences have durations ranging from 10 to 100 seconds. With its substantial volume of data, our dataset stands as the largest in our community at present.

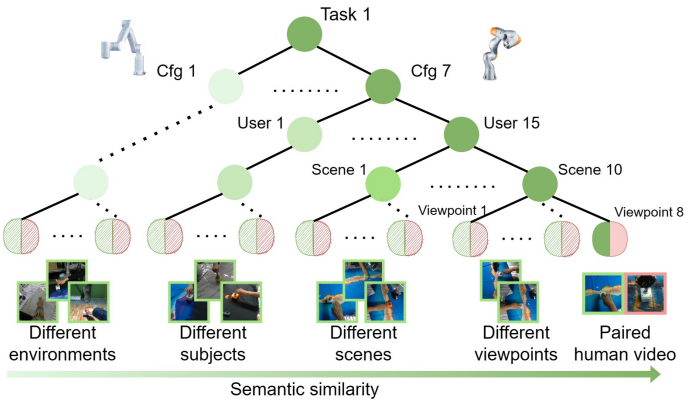

Fig. 5: Example of data hierarchy: The leaf nodes in the hierarchy consist of human demonstrations (highlighted in green) and robot manipulations (highlighted in red). We can pair a robot manipulation sequence with human demonstration videos captured from different viewpoints, scenes, human subjects, and environments. Zoom in to explore the details of various human demonstrations.

d) Data Hierarchy: Humans can accurately understand the semantics of a task based on visual observations, regardless of the viewpoint, background, manipulation subject, or object. We aim to provide a dataset that offers dense <human demonstration, robot manipulation> pairs, enabling models to learn this property. To achieve this, we organize the dataset in a tree hierarchy based on intra-task similarity. Fig. 5 illustrates an example tree structure and the criteria at different levels. Leaf nodes with a more recent common ancestor are more closely related. For each task, millions of <human demonstration, robot manipulation> pairs can be constructed by pairing leaf nodes with a common ancestor at different levels.

e) Compositionality: RH20T includes not only short sequences that perform single manipulations but also long manipulation sequences that combine multiple short tasks. For example, a sequence of actions such as grabbing the plug, plugging it into the socket, turning on the socket switch, and turning on the lamp can be considered as a single task, with each step also being a task. This task composition allows us to investigate whether mastering short sequences improves the acquisition of long sequence tasks.

B. Data Collection and Processing

Unlike previous methods that simplify the tele-operation interface using 3D mice, VR remotes, or mobile phones, we place emphasis on the importance of intuitive and accurate tele-operation in collecting contact-rich robot manipulation data. Without proper tele-operation, the robot could easily collide with the environment and generate significant forces, triggering emergency stops. Consequently, previous works either avoid contact [18] or operate at reduced speeds to mitigate these risks.

a) Collection: Figure 6 shows an example of our data collection platform. Each platform contains a robot arm with force-torque sensor, gripper and 1-2 inhand cameras, 8-10 global cameras, 2 microphones, a haptic device, a pedal and a data collection workstation. All the cameras are extrinsically calibrated before conducting the manipulation. The human demonstration video is collected on the same platform by human with an extra ego-centric camera. Tens of volunteers conducted the robotic manipulation according to our task lists and text description. We make our tele-operation pretty intuitive and the average training time is less than 2 hours. The volunteers are also required to specify ending time of the task and give a rating from 0 to 9 after finishing each manipulation. 0 denotes the robot enters the emergency state (e.g., hard collision), 1 denotes the task fails and 2-9 denotes their evaluation of the manipulation quality. The success and failure cases have a ratio of around 10:1 in our dataset.

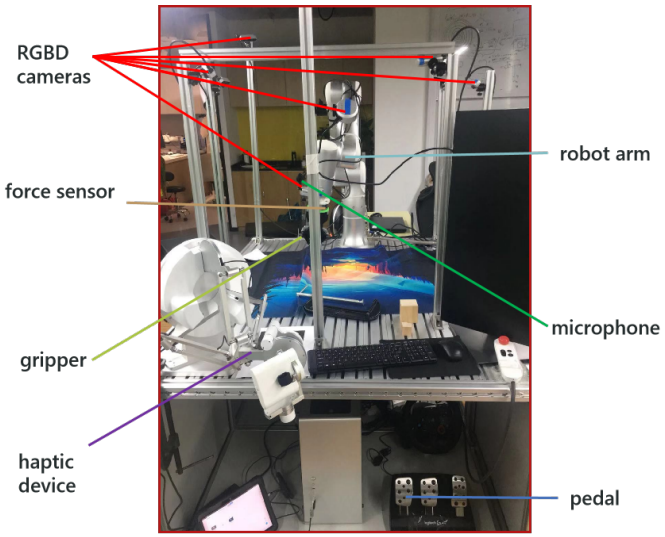

Fig. 6: Illustration of our data collection platform

b) Processing: We preprocess the dataset to provide a coherent data interface. The coordinate frame of all robots and force-torque sensors are aligned. Different force-torque sensors are tared carefully. The end-effector Cartesian pose and the force-torque data are transformed into the coordination system of each camera. Manual validation is performed for each scene to ensure the camera calibration quality.

IV. Discussion and Conclusion

In this paper we present the RH20T dataset for diverse robotic skill learning. We believe it can facilitate many areas in robotics including learning for task and motion planning. The current limitations of this paper are that (i) the cost of data collection is expensive and (ii) the potential of robotic foundation models is not evaluated on our dataseet. We have tried to duplicate the results of some recent robotic foundation models but haven't succeeded yet due the limit of computing resources. Thus, we decide to open source the dataset at this stage and hope to promote the development of this area together with our community. In the future, we hope to extend our dataset to broader robotic manipulation, including dual-arm and multi-finger dexterous manipulation.

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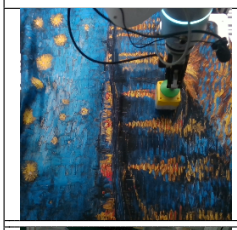
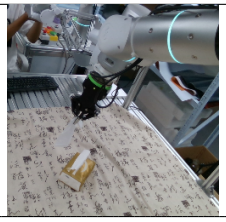
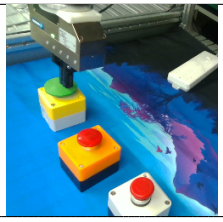
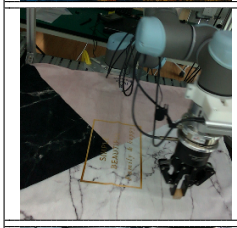
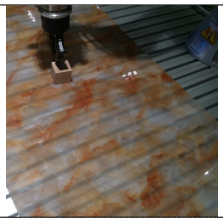
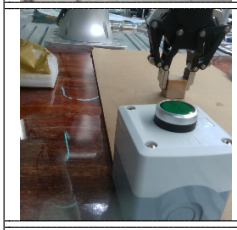
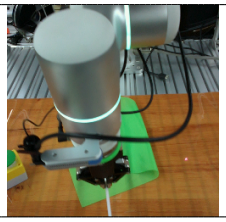
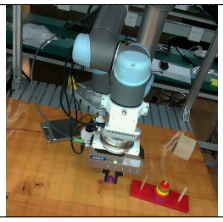
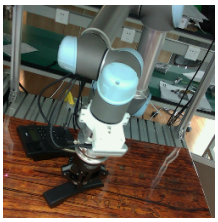
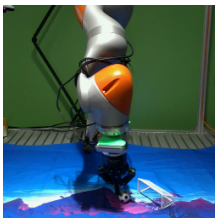
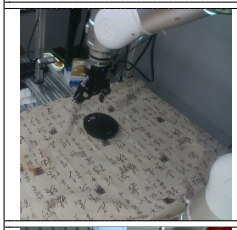
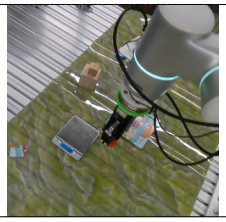
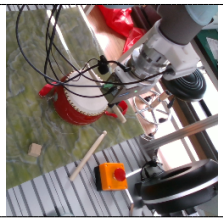
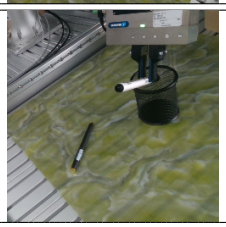
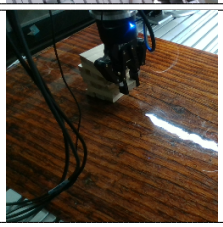
Appendix A Hardware configuration used in our dataset

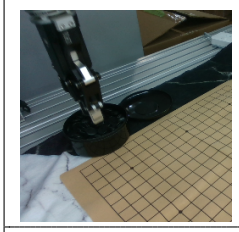
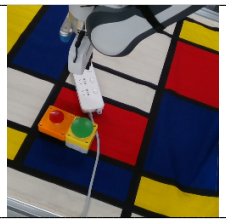
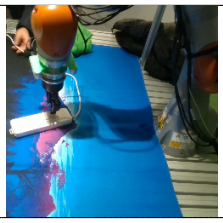
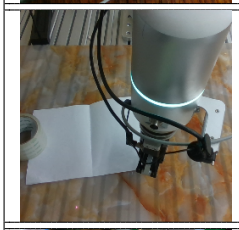
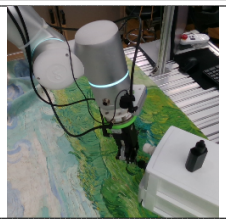
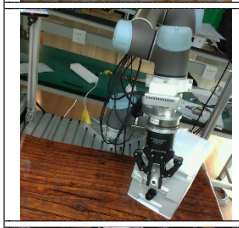
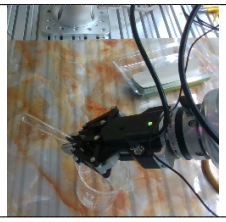
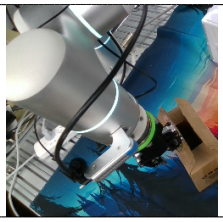
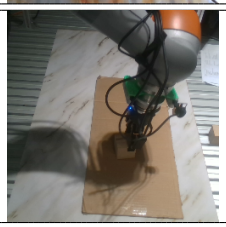
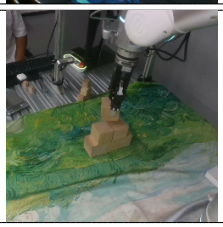
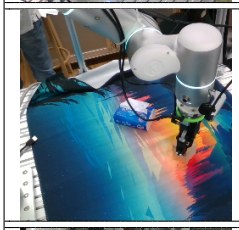
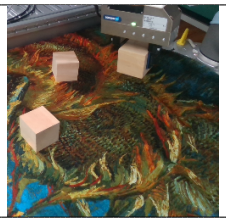
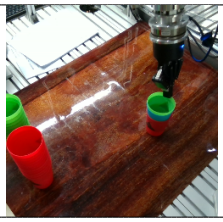
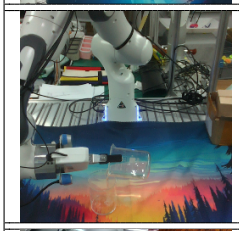
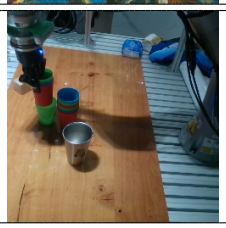
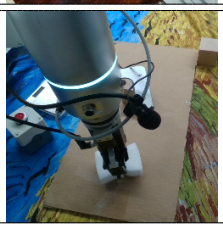
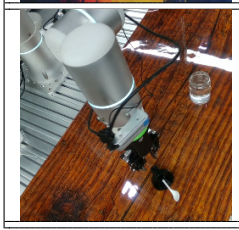
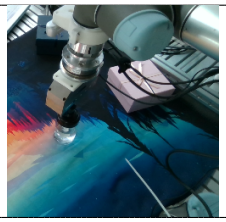
Configuration	Robot	Gripper	F/T Sensor	Tactile Sensor	Camera
cfg 1	Flexiv	Dahuan AG95	OptoForce	None	RealSense D435, D415
cfg 2	Flexiv	Dahuan AG95	ATI Axia80-M20	None	D435, D415, L515
cfg 3	UR5	WSG50	ATI Axia80-M20	None	D435, D415, L515
cfg 4	UR5	Robotiq-85	ATI Axia80-M20	None	D435, D415, L515
cfg 5	Franka	Franka	Franka	None	D435, D415, L515
cfg 6	Kuka	Robotiq-85	ATI Axia80-M20	None	D435, D415, L515
cfg 7	Kuka	Robotiq-85	ATI Axia80-M20	USkin	D435, D415, L515

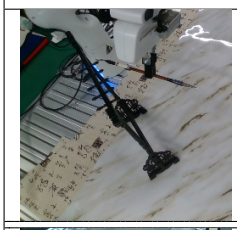
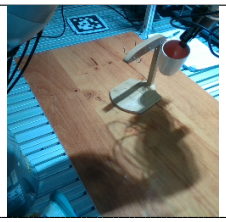
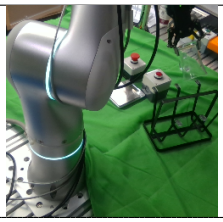
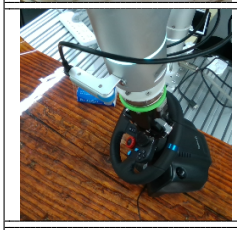
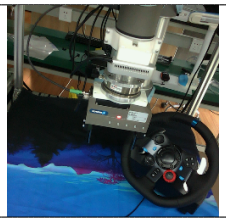
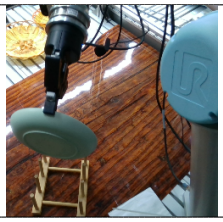
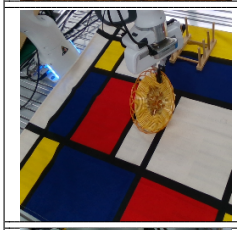
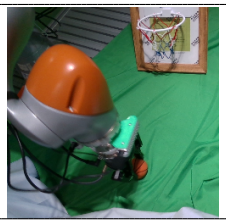
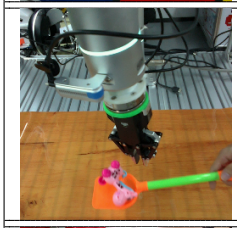
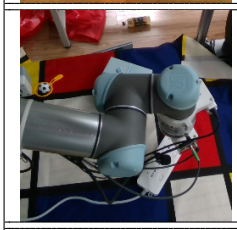
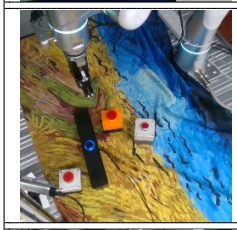
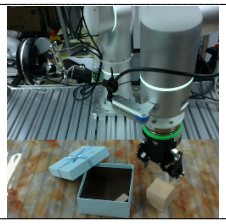
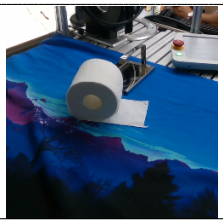
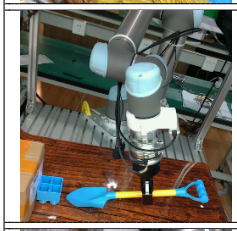
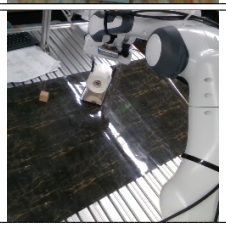
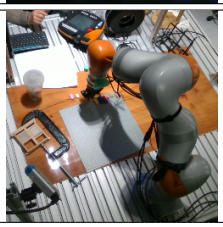
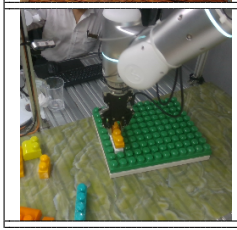
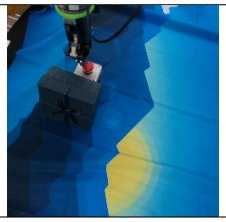
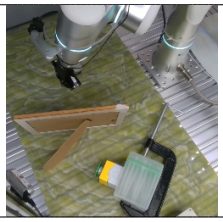
Table 1: Hardware specification of different configurations.

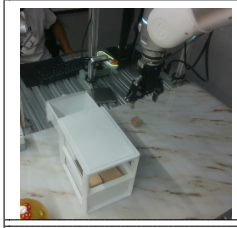
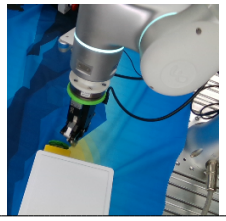
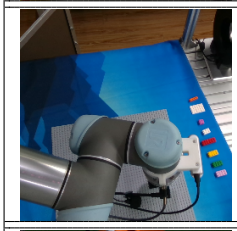
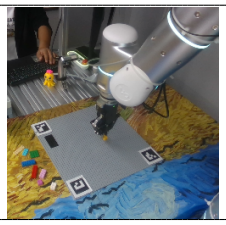
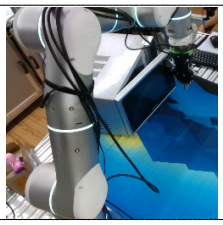
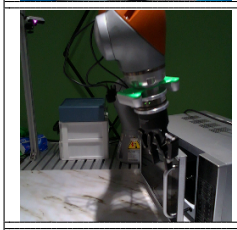
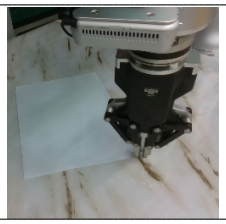
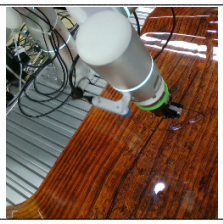
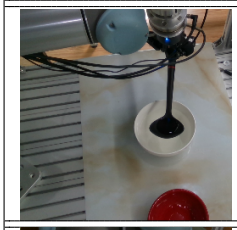
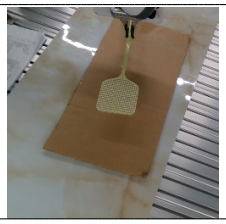
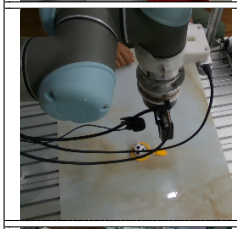
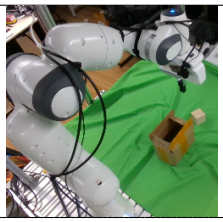
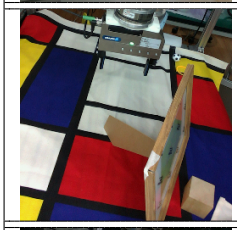
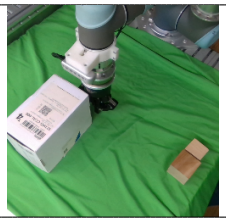
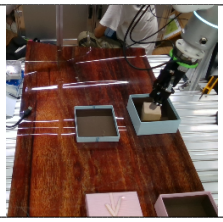
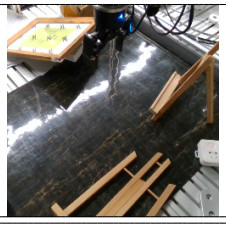
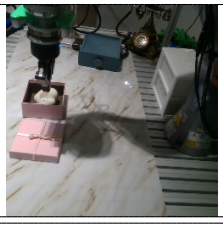
Appendix B Task Specification of RH20T

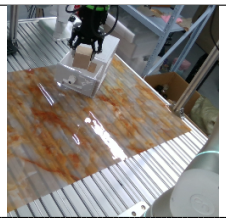
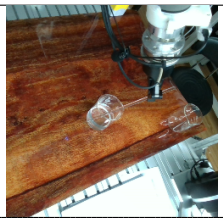
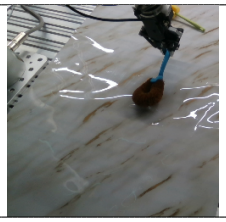
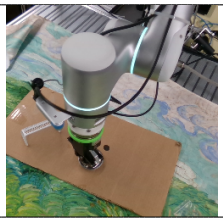
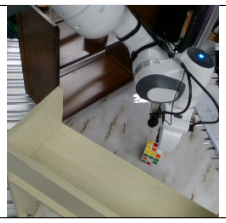
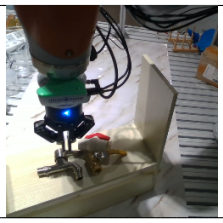
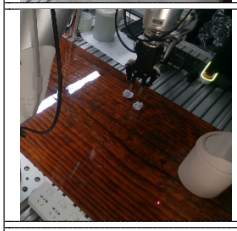
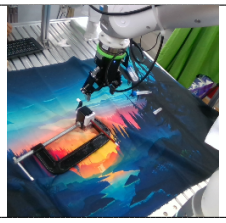
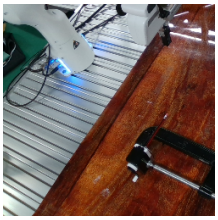
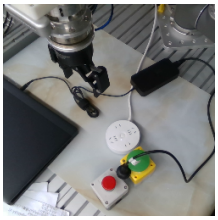
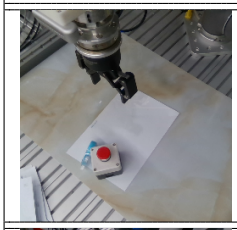
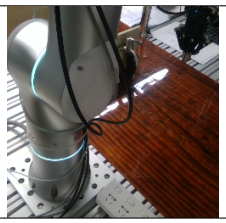
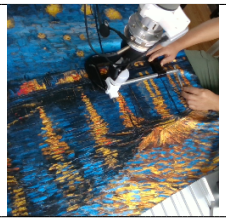
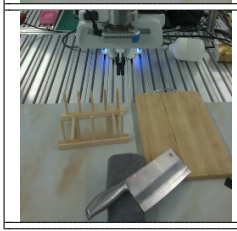
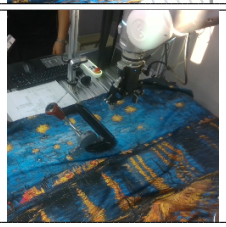
Table 2: Task description for our dataset. “Src.” denotes the source of the task.

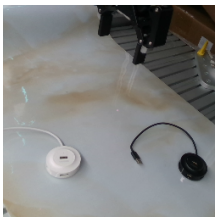
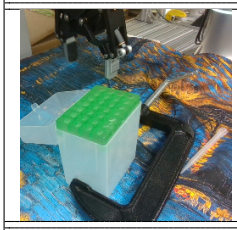
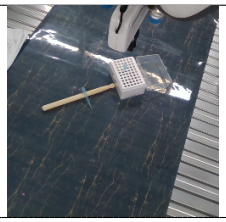
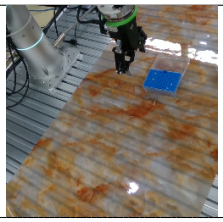
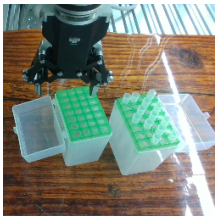
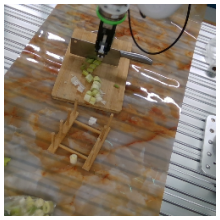
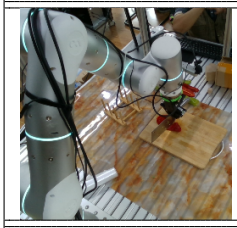
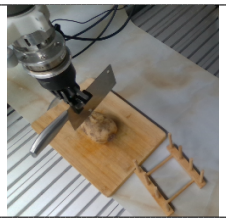
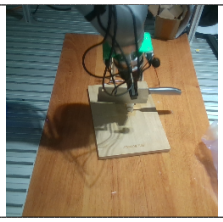
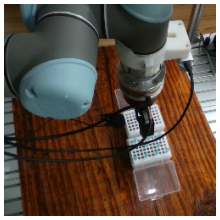
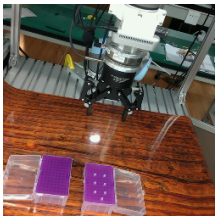
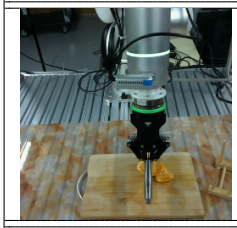
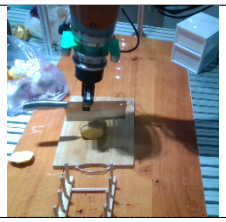
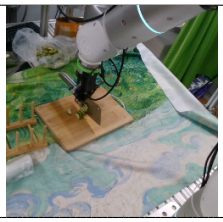
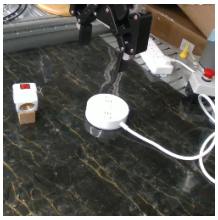
Items	Task Desc.	Src.	Items	Task Desc.	Src.	Items	Task Desc.	Src.
	1. Press the button from top to bottom	Meta-World		2. Pull out a napkin	Self-Proposed		3. Press three buttons from left to right in sequence	RLBench
	4. Pick up a block on the left and move it to the right	Meta-World		5. Approach and touch the side of a block	Meta-World		6. Use the gripper to push a block from left to right	Meta-World
	7. Hold a block with the gripper and sweep it from left to right on the table	Meta-World		8. Grab a block and place it at the designated location	RLBench		9. Take out one Hanoi block and throw it aside	RLBench
	10. Place the handset of the telephone on the corresponding phone cradle	RLBench		11. Water the plant	RLBench		12. Push the soccer ball into the goal	Meta-World
	13. Place the block on the scale	RLBench		14. Remove the object from the scale	RLBench		15. Play the drum	Self-Proposed
	16. Hit the pool ball	RLBench		17. Put the pen into the pen holder	RLBench		18. Play Jenga	RLBench

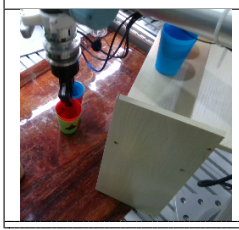
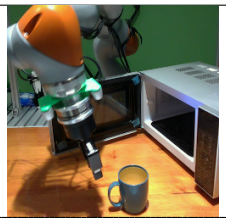
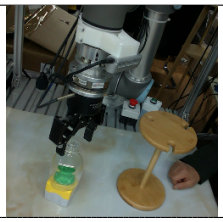
Items	Task Desc.	Src.	Items	Task Desc.	Src.	Items	Task Desc.	Src.
	19. Play the first move as black in the upper right corner of the Go board	Self-Proposed		20. Turn on the desk lamp by pressing the button	RLBench		21. Turn off the desk lamp by pressing the button	RLBench
	22. Wave the flag	Self-Proposed		23. Turn on the power strip by pressing the button	Self-Proposed		24. Turn off the power strip by pressing the button	Self-Proposed
	25. Unfold a piece of paper	Self-Proposed		26. Use the gripper to push and close the drawer	Meta-World		28. Grasp the handle and close the drawer	RLBench
	29. Grasp the handle and open the drawer	RLBench		30. Pour out the test tube	Self-Proposed		31. Cover the box	Meta-World
	32. Slide the outer casing onto the gift box	Self-Proposed		33. Grasp one block to sweep the other block onto the mark	Meta-World		34. Stack the squares into a pyramid shape	RLBench
	35. Pick up one small block	RLBench		37. Stack the blocks in a vertical line of five	RLBench		38. Pick up the cup	RLBench
	39. Pour the water from one cup into another empty cup	blabla		40. Stack the cups	RLBench		41. Clean the tabletop with a sponge	RLBench
	42. Screw the lid onto the jar	RLBench		43. Unscrew the lid from the jar	RLBench		44. Pick up a bag of things	Self-Proposed

Items	Task Desc.	Src.	Items	Task Desc.	Src.	Items	Task Desc.	Src.
	45. Place the brush on the pen rack	Self-Proposed		46. Put the cup on the cup rack	RLBench		47. Take the cup off the cup rack	RLBench
	48. Rotate the steering wheel 90 degrees clockwise	Self-Proposed		49. Rotate the steering wheel 90 degrees counter-clockwise	Self-Proposed		50. Put the dish on the dish rack	Self-Proposed
	51. Take the dish off the dish rack	Self-Proposed		52. Grab a basketball, release it and shoot it into the basket	Meta-World		53. Use a clamp	Meta-World
	54. Catch the moving object	Self-Proposed		55. Transfer liquid using a dropper	Self-Proposed		56. Receive something handed over by a human	Self-Proposed
	57. Turn on the four buttons on the power strip	Self-Proposed		58. Turn off the four buttons on the power strip	Self-Proposed		59. Turn the knob to increase the volume of a speaker	Self-Proposed
	60. Turn the knob to decrease the volume of the speaker	Self-Proposed		61. Take everything out of the gift box	Self-Proposed		62. Put the toilet paper on its holder	Self-Proposed
	63. Use a shovel to scoop up an object	Self-Proposed		64. Take the toilet paper off its holder	Self-Proposed		65. Build with small Lego blocks	Self-Proposed
	66. Build with large Megabloks	Self-Proposed		67. Press a button from top to bottom with obstacles	Meta-World		68. Press a button horizontally with obstacles	Meta-World

Items	Task Desc.	Src.	Items	Task Desc.	Src.	Items	Task Desc.	Src.
	69. Assemble one piece of a puzzle	RLBench		70. Open a sliding window	Meta-World		72. Drop coins into a piggy bank	Self-Proposed
	73. Put things in the drawer	RLBench		74. Press the button horizontally	Meta-World		75. Finish setting up the starting position of a chessboard that is almost arranged	Self-Proposed
	76. Stack blocks (small Lego) one on top of the other every time	Self-Proposed		77. Stack blocks (small Lego) randomly one at a time	Self-Proposed		78. Close the microwave door	RLBench
	79. Open the microwave door	RLBench		80. Flip over and spread out the paper that is laid flat on the table	Self-Proposed		81. Unfold the leg of the glasses (with one hand)	Self-Proposed
	82. Scoop water with a large spoon from one bowl to another	Self-Proposed		83. Swat with a fly-swatter	Self-Proposed		84. Assemble: Attach the bubble ring to the ball	Meta-World
	85. Remove the bubble ring from the assembled bubble ring and ball	Meta-World		86. Dial a number on an old rotary phone	Meta-World		88. Pick up and place an object with obstacles	Meta-World
	89. Push an object with obstacles	Meta-World		90. Approach and touch an object with obstacles	Meta-World		91. Move an object from one box to another	Meta-World
	92. Turn the hands of a clock	RLBench		93. Put the photo frame on the bracket	RLBench		94. Open a box	RLBench

Items	Task Desc.	Src.	Items	Task Desc.	Src.	Items	Task Desc.	Src.
	95. Take the photo frame down from the bracket	RLBench		96. Take something out of a drawer	RLBench		100. Stir the beaker with a glass rod	Self-Proposed
	101. Clean the table with a cloth	Self-Proposed		102. Scrub the table with a brush	Self-Proposed		103. Drag the plate to the goal post after holding it down	Meta-World
	104. Drag the plate back after holding it down	Meta-World		105. Put the object on the shelf	Meta-World		106. Take the object down from the shelf	Meta-World
	107. Put the garbage in the trash can	RLBench		108. Sharpen the pencil with a pencil sharpener	Self-Proposed		109. Insert the pencil into the pencil sharpener	Self-Proposed
	110. Take the pencil out from the pencil sharpener	Self-Proposed		111. Put the object with the corresponding shape into the corresponding hole	RLBench		112. Plug in the charger to the socket	Self-Proposed
	116. Use the correction tape on paper	Self-Proposed		118. Turn on the water tap	Meta-World		119. Turn off the water tap	Meta-World
	120. Install the light bulb by rotating it	RLBench		121. Take out the light bulb by rotating it	RLBench		122. Put the knife on the cutting board	RLBench
	123. Put the knife on the knife rack	RLBench		124. Push down the lever	Meta-World		125. Pull up the lever	Meta-World

Items	Task Desc.	Src.	Items	Task Desc.	Src.	Items	Task Desc.	Src.
	126. Plug in the power cord to the socket	Self-Proposed		127. Plug in the power cord of the desk lamp, turn on the socket, and light up the desk lamp	Self-Proposed		128. Plug in the USB drive to the docking station	RLBench
	200. Insert the tip of a large pipette into the holder for large pipette tips	Self-Proposed		201. Insert the tip of a medium pipette into the holder for medium pipette tips	Self-Proposed		202. Insert the tip of a small pipette into the holder for small pipette tips	Self-Proposed
	204. Transfer all large pipette tips from one holder to another holder for large pipette tips	Self-Proposed		205. Chop the scallions	Self-Proposed		206. Chop the green garlic	Self-Proposed
	207. Chop the chili peppers	Self-Proposed		208. Slice the lotus root	Self-Proposed		209. Slice the carrots	Self-Proposed
	210. Chop the onions	Self-Proposed		211. Transfer all medium pipette tips from one rack to another holder for medium pipette tips	Self-Proposed		212. Transfer all small pipette tips from one rack to another holder for small pipette tips	Self-Proposed
	213. Chop the orange	Self-Proposed		215. Chop the potatoes	Self-Proposed		216. Chop the cucumber into shreds	Self-Proposed
	217. Plug in the bulb holder to the socket	Self-Proposed		218. Plug in the bulb holder to the socket, install the bulb, turn on the socket to light up the bulb	Self-Proposed		222. Cover the pot with the lid	RLBench

Items	Task Desc.	Src.	Items	Task Desc.	Src.	Items	Task Desc.	Src.
	223. Take the cups off the shelf and stack them together	Self-Proposed		225. Put the bowl into the microwave	Self-Proposed		329. Put the glass cup onto the shelf	Self-Proposed