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Implementation and Optimization of Grasping Learning with Dual-modal Soft Gripper

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Abstract— **Robust and efficient grasping of different objects is still an open problem due to the difficulty of integrating multidisciplinary knowledge such as gripper ontology design, perception, control, and learning. In recent years, learning-based methods have achieved excellent results in grasping various novel objects. However, current methods are usually limited to a single grasping mode or rely on different end effectors to grasp objects of different shapes. For human beings, our hands are capable of grasping various objects with changes in grasping methods and form of hands. In light of this, developing a gripper with similar performance could possibly improve the robot's gripping ability. In this paper, we design a dual-modal soft gripper (DSG) and propose a deep reinforcement learning (DRL) framework to implement the operations. Both of our grasping modes, namely enveloping and pinching, are achieved through the tendon drive system and the deformation of the spring steel plate, which enables the gripper to switch between the two grasping modes in real time. We also combined the cutting-edge achievements of deep learning and reinforcement learning to design an autonomous grasping algorithm based on Q-learning and a deep Q network. Moreover, to fully utilize the visual input from the sensor, we added semantic embeddings of target objects to facilitate the learning, which is especially useful in deciding the grasping method for objects previously unseen. We also evaluate our DRL framework in different scenarios, offering a detailed comparison of each grasping mode and the mixed method (with or without semantic information). Our design has proved efficient in reducing the number of failing grasping actions and improving the success rate when facing novel and tricky objects.**

I. INTRODUCTION

Designing grippers and realizing flexible grasping are important and challenging tasks in object manipulation. Typically, a traditional rigid gripper realizes grasping through rigid contact, which may easily cause damage to the target object and even the gripper itself. Apart from this, such grippers also requires external (and often expensive) sensing equipment, and complex closed-loop control algorithms to achieve smooth grasping for tricky objects. By contrast, owing to the adaptability of the material and flexibility in its overall structure, the soft gripper proved to have a natural protective effect on the object. Yet what equally happens to the widely used unimodal grippers is the grasping efficiency loss brought about by its repetitive and onefold action.

Current grasping methods can be roughly divided into two categories: model-based and learning based. Model-based methods conduct operations in a fixed routine, which relies on the depth perception system and 3D geometric information of objects. However, what still bothers is its vulnerability when facing various novel objects especially in changing environments. Learning-based methods employ a trained model to predict probabilities and guide the robotic grasping. Such methods can deal with some novel objects, but require the access to large-scale training data. Furthermore, existing algorithms mainly focus on a single grasping mode trained in an isolated ensemble manner. Thus, the mixed grasping problem is still calling for robust and systematical solutions.

In this paper, we develop and design a hybrid grasping system that realizes robotic envelope-pinch operations, including gripper design, grasping modeling, policy training, and real robotic experiments, as shown in Fig. 1. The contributions of this paper can be concluded as follows: (1) We designed a dual-modal soft gripper, which can grasp objects with knowledge of both geometric and physical properties of objects, manifesting the its advantages in terms of precise and strong grasping, showing high adaptability and robustness. (2) We propose a deep reinforcement learning (DRL) based model to describe hybrid grasping skills. In addition, we also innovatively add the semantic information of the target object in the network to facilitate the selection of grasping method especially on novel objects (please refer to the experiment section for details). (3) To overcome the limitation of collecting real-world data, we train the DRL model in the simulated environment of CoppeliaSim. A theoretical model is established in the simulation and trained with physics engine, which can accurately simulate the grasping process of the designed gripper in the real scene. Our design stands out as a novel attempt in robotic envelope-pinch hybrid grasping achieved by combining a dual-modal soft gripper and a DRL-based machine learning model. (4) We conduct multiple experiments in simulated and real environments to evaluate the performance of our proposed method. The results show that our model exhibits high performance in terms of grasping efficiency in scenes with different types of objects, and can be well generalized in novel conditions.

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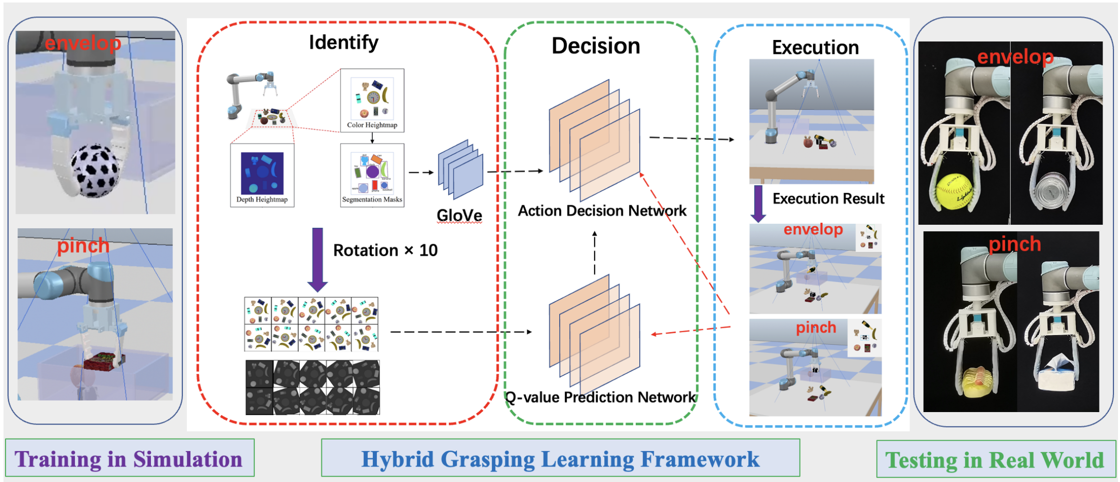

Fig. 1. System overview. The soft gripper has both pinching and enveloping methods, and it can switch between two different models for objects of various shapes. The hybrid grasp learning model takes an RGB-D image (captured by an overhead camera) as input and outputs a matrix of Q values. The robot performs the action with the highest value. DRL algorithms are trained in simulations and then transferred to real-world robots.

II. RELATED WORKS

A. Soft gripper

The multi-modal operation capability of today's soft grippers has become an important indicator of the capabilities of a gripper [1]. T Feix, IM Bullock, AM Dollar summarized a variety of crawling methods from object classification and the characteristics of the object attributes specified by seven categories [2]. Soft robot claw gradually developed to multi-model grasp, so as to combine various hand simulation operations to improve the ability to grasp. A two-finger flexible robotic claw with envelope and clamping dual modes is proposed [3]. This soft robot is based on a two-finger design and consists of two two-module variable chamber height air mesh actuators. A soft gripper made of silicone rubber is proposed, which can be applied to the robot soft body gripper [4]. At the same time, the soft gripper can be divided into two grasping methods: adsorption and clamping. A new variable stiffness flexible robot claw composed of three layers of thin sheet extrusion blocking structure is proposed, which adopts the principle of wire drive based on the motor [5]. The change in stiffness allows it to change modes. [6]Proposes a soft robotic claw for three-dimensional surface grabbing using a gecko-inspired fiber binder which demonstrates bond control in multi-modal gripping.

B. Learning-Based Robotic Grasping

Based on autonomous learning, robot grasping method has been widely studied and applied in robot technology. In this process, machine vision can provide comprehensive information obtained from RGB, or RGB-D images on the target object and environment, so that the robot can achieve more robust grasping [7]-[9]. Only using RGB or using RGB and depth information at the same time, can effectively improve the capture performance, thus making pixel level capture detection possible in the field of robot grasping [10]-[13]. However the poor judgment and adaptability to novel objects have also become the defects of this method. To solve these, some designs detect and recognize objects only based on depth images or only RGB images that are invariant to the object color [14]-[17].

Whether we have large-scale data sets largely determines whether the learning-based grasping algorithm can be successfully trained. To solve related problems, some research uses supervised learning methods and human-annotated data to train the grasping algorithm [18]-[21]. However, the quality of human labeling largely depends on the artificial accuracy. Thus the DRL technology has been more widely used in order to enable robot grasping to learn strategies through the trail-and-error process. These technologies include actor-critic algorithm [22]-[23], deep Q-learning methods [24] and policy-gradient methods [25]. simulation environment is often used to train supervised algorithm and DRL algorithm [26]-[27] to reduce the pressure on data collection. At the same time, in order to grasp various objects with different geometric and physical characteristics, the results of robot grasping system with multiple end effectors are reported in the literature. For example, D Liang et al. [28] proposed a multi-mode grasping fusion system with dual functions of enveloping grasp and finger pinching. It can realize the pinching grasp or enveloping grasp, according to the different positions, shapes and sizes of the target object, which is a self-adaptive process.Similar related work is also reflected in this paper [29] .They propose a soft hand that can operate continuously to complete the grasping task with high efficiency. The autonomous grasping we proposed is also improved on the basis of this algorithm.

To overcome the limitations of previous work, in this paper, we design a dual-modal soft gripper (DSG) with enveloping and pinching . Soft gripper achieves pinching and enveloping through tendon actuation and spring steel plate variations, and it can switch between two different models for objects of various shapes.

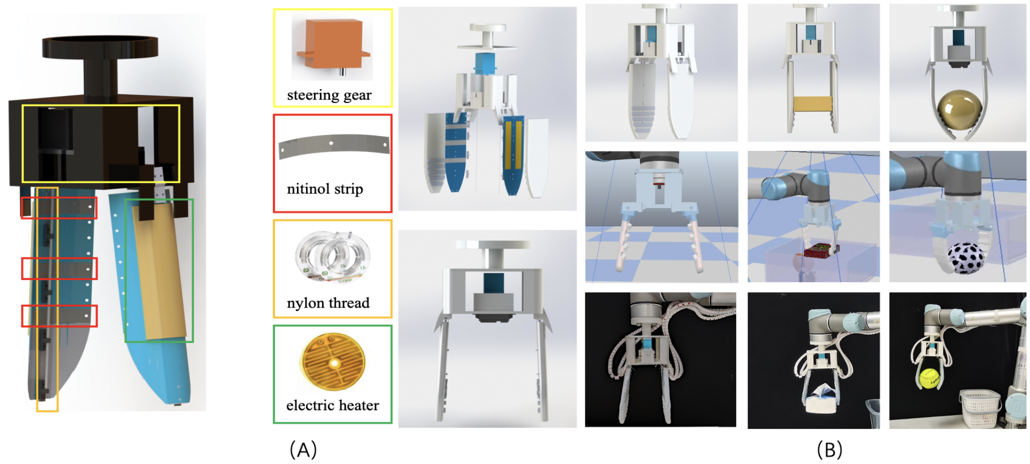

Fig. 2. Design and grasping demonstration of soft gripper. (A) Soft gripper can accurately pinch or envelop different types of objects. (B) Rows 1, 2, and 3 of Figure 2 demonstrate prototyping and two ways of 3D modeling, simulated environments, and real robotic grasping (envelop or pinch), respectively.

III. DESIGN OF SOFT GRIPPER

The gripper uses two grasping modes of pinching and enveloping to deal with the generalized grasping problem in practical applications. The system currently designed is mainly composed of two parts: digital steering gear, memory alloy, traction rope, driving module composed of heating plate and grasping module. The grasping module is composed of two shovel-shaped spring steel metal sheets, each of which is attached with three nickel-titanium memory alloy sheets to drive the module to switch. In the heating state of the heating plate, the memory alloy shrinks to the inside of the gripper due to its properties, which drives the spring steel plate to produce arched deformation. At this time, the bending moment of the spring steel plate in the normal direction is greatly improved, and the maximum grasping force is improved. At this point, the grasping mode is switched to pinch. When the heating sheet is turned off and heated, the memory alloy sheet is flattened, and the bending moment in the normal direction is small, so that the spring steel sheet can be bent on the opposite side to achieve the enveloping effect. as shown in Fig. 2.

IV. METHOD

The process of grasping objects by the dual-modal soft gripper involves firstly, object detection, identification and positioning, and then the selection of grasping methods, control of the gripper and appropriate trajectory planning. Our dual-modal soft gripper features deformability. In simulation experiment, we simplified bendable finger of the grippe into a pad with four degrees of freedom. Our aim is to optimize a strategy model to minimize the number of actions in a single grasping trial (i.e., improving the grasping efficiency), and enhance the success rate. DSG interacts with an uncertain grasping environment, and its behavior may affect future situations. Therefore, we use reinforcement learning to generate multi-modal grasping actions that guarantee optimal grasping efficiency in this work.

A. Problem Formulation

Hybrid grasping tasks can usually be described as a Markov Decision Process (MDP), that is, given a state S_t at time t, the robot chooses and performs an action at policy π, and as a result of its action, the robot moves to a new state S_{t+1}, and get a new reward R_{t+1}. The goal of reinforcement learning is to learn the optimal policy to maximize the expected discounted return:

$$G_t = \sum_{k=0}^{n} \gamma^k R_{t+k+1} \tag{1}$$

where γ is the discount rate, $0 \leq \gamma \leq 1$.

Q-learning is a model-free algorithm employed in reinforced learning. With the rewards of different actions a_t in state s_t recorded, Q-learning features a Q-table, whose value comes from a function $Q(s_t, a_t)$ that maps s_t and a_t to scores r_t. The agent performs actions, and the environment responds to those actions and presents the agent with new situations.

According to the Q-learning algorithm, when for the state sequence s', if the optimal Q value of all possible actions $a^{'}$ is known, then the optimal strategy is to maximize the score expectation $r + \gamma Q^* \left(s^{'}, a^{'}\right)$, where

$$Q^*(s,a) = E_{s' \sim \epsilon}\left[r + \gamma max_{a'} \cdot Q^*\left(s^{'}, a^{'}\right) |s, a\right] \tag{2}$$

We want to make the Q-function gradually approximate the optimal Q-function through iteration, i.e., $t \rightarrow -\infty$, $Q \rightarrow -Q^*$. In Playing Atari with DRL, a method of estimating the Q value using a deep neural network is proposed, that is, using a neural network to fit the Q-function, namely DQN (Deep Q Network). This method trains the Q-network by minimizing the loss function L_i in iterations,

$$L_i\left(\theta_i\right) = E_{s,a \sim \rho(s,a)}\left[\left(y_i - Q\left(s, a, \theta_i\right)\right)^2\right] \tag{3}$$

where $y_i = Es\prime \sim \epsilon \left[r + \gamma max_{a'} \cdot Q\left(s^{'}, a^{'}, \theta_{i-1}\right) |s, a\right]$ is all target of the i-th iteration, ρ is all moves possible distribution. This gives the gradient of the loss function.

$$\nabla_{\theta_i} L_i(\theta_i) = 2E_{y_i s' \sim \epsilon}\left[(y_i - Q(s,a,\theta_i)) \nabla_{\theta_i} Q(s,a,\theta_i)\right] \tag{4}$$

In this work, the robot selects each grasping action in a series of discrete time steps under a given policy. We define state s, action a and reward r according to the specific hybrid grasping tasks.

*1) **Simulation state setting**:* The environment arrangement in simulation includes several different parts. Firstly, we employed a UR5 workspace with the size of 0.45 $\times$ 0.45 square meters. At each trial, objects are randomly placed on the workspace. An RGB-D camera with an image resolution of 640 $\times$ 480 is fixed over the center of the workspace to record the state information at a certain moment.

*2) **Grasping Actions**:* The action set is defined as A_e,A_p , where A_e is the envelope action set, and A_p is the pinch action set. Each action can be described by the combination of the operation center point (x, y), the operation height H and the operation angle θ, i.e. $A_e(x, y, H, \theta)$, $A_p(x, y, H, \theta)$. Each grasping action is perpendicular to the work area, and θ represents the angle between the gripper jaw and the x axis.

*3) **Rewards**:* We define the successful placement of the target object into the storage area as a successful grasping, and set it to 3 points; successfully grasp the object to the specified height, but not successfully put it into the storage area, define it as a semi-grasping success and set it to 1 point; failure to grasp the object to the specified height is defined as a grasp failure, set to 0 points. Compared with pinching, enveloping does less damage to the object itself, especially for fragile objects such as high-value fruits, so we prefer to envelop objects. Therefore, an additional 0.5 points are given for successful and semi-successful operations obtained using envelope, but still 0 points for grasping failures with enveloping.

B. Training and Test

Our Q-function networks share the same parameter values (e.g., step size, discount rate, exploration parameters). The network weights are reset using normal initialization before training. Our models are trained in PyTorch, and the system uses NVIDIA RTX 3080Ti and Intel Core i9K-12900KF processors for computation. We employ a greedy exploration strategy, with ε initialized to 0.6 and then annealed to 0.1 after training. The future discount is set to constant at 0.5. During simulation and real-world testing, we give the network the same learning rate (10^{-4}) to prevent infinite loops where a given action is repeated while the state space remains the same. Also, at the beginning of each new experiment, the network weights are set to their original state (post-training and pre-testing).

C. Algorithm process

*1) **Recognition**:* First, the RGB-D camera acquires two pictures (colored and depth) of the present state. Each image will be continuously rotated by 18 degrees to obtain a group of 10 images. The colored image group is sent to YOLOv5

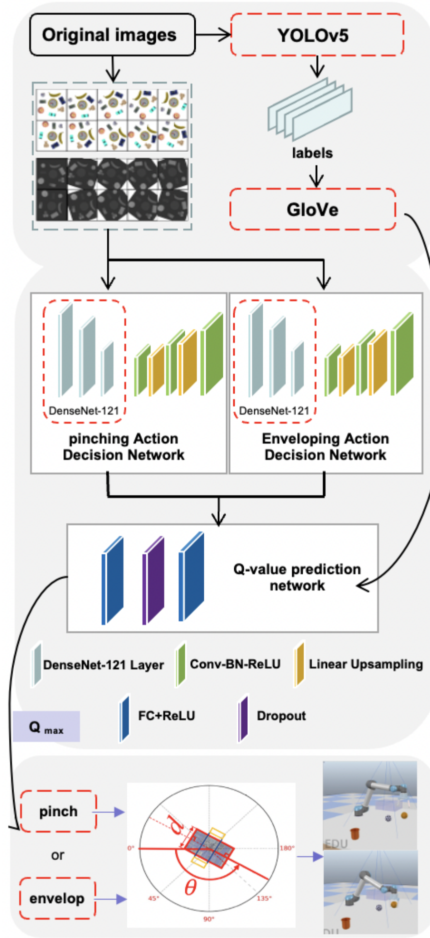

Fig. 3. Algorithm flow diagram. It consists of three parts: identification, decision-making and execution.

to get bounding box and classification label for each target object, while the depth image group is fed into the Q-value prediction network.

*2) **Decision**:* The envelope and pinch Q-value prediction network share the same structure, which is composed of the DenseNet121 model, convolution, and upsampling. The Q-value prediction graphs are obtained by the envelope Q-value prediction network and the pinch Q-value prediction network are taken to the maximum values, respectively. In addition, we use the object labels detected from color image to get embeddings with a pretrained GloVe model. The selected optimal envelope and optimal pinch are sent to the final action decision network together with this additional semantic information. Here the decision network is formed by a multi-layer fully connected neural network and generates the final decision grasping strategy.

*3) **Execution**:* The gripper starts from the top of the storage area to the highest point above the center point of the operating object and perpendicular to the desktop, and the opening angle of the gripper is adjusted to the maximum. Then, the gripper gradually descends to a desired height below the center point of the manipulated object and start the enveloping or pinching operation. After a success grasp, the gripper plans its trajectory first to the highest point above the operation center point, then move to the storage area with a smooth shortest path. The fingers of the gripper then open to its maximum to release the object. Finally, a reset operation is performed after each grasping task.The complete process is shown in Fig. 3.

V. EXPERIMENTS AND RESULTS

In this section, we use multiple experiments to evaluate and verify the performance of our designed dual-modal soft gripper and the effectiveness of the proposed grasping method.

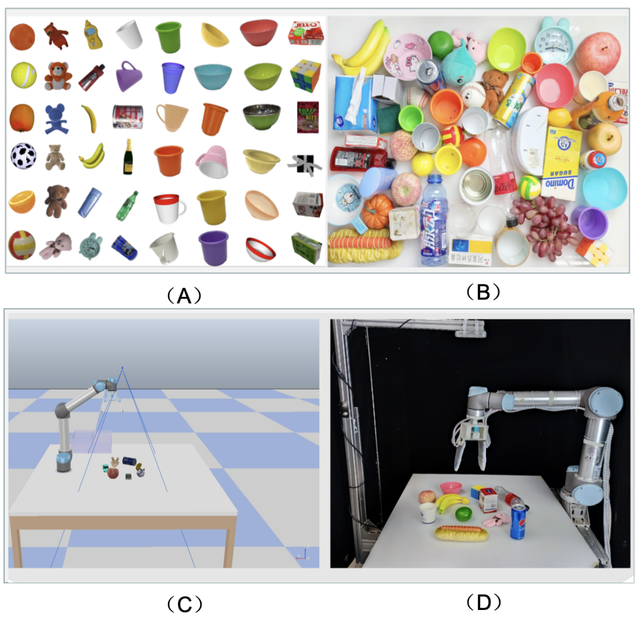

Fig. 4. Data set and experimental environment construction. (A) Training dataset. (B) Real test dataset. (C) Simulation environment. (D) Real test environment.

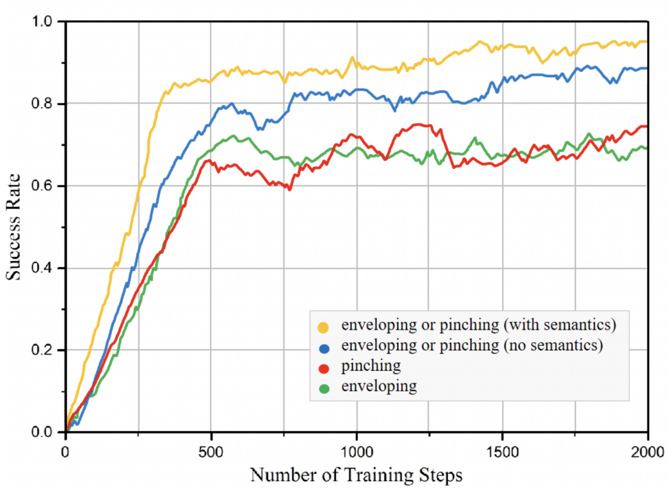

Fig. 5. Training performance. In the training step, mixed grasps are more likely to succeed than single grasps, and the addition of semantic information is even better.

A. Datasets and Experiment Setup

Dataset of simulation and real world: We start from employing an open dataset designed for object detection, which contains annotated fruit images of 4 categories, and further expanded it to create a dataset with a total of around 700 annotated photos of 36 objects from 17 categories. Objects in our dataset are selected to expose and challenge our gripper with items of different shape and hardness. The table below provides an overview of the object categories in our dataset. In actual testing, we select two types of objects: one is an object that is outside the training dataset but belongs to a specific class included. Another is that objects do not belong to any of the classes seen in the training dataset. Meanwhile, the test subjects were taken from the four different shape groups mentioned in Table I. as shown in Fig. 4. (A) and (B).

Experiment setups of simulation and real world: The experiment uses the robot simulation software CoppeliaSim developed by Coppelia Robotics as the main virtual experiment platform, and uses the Vortex Studio engine of CM Lab. We added a table to the virtual environment, mounted a vision and depth sensor above it, and fixed a Universal Robots UR5 robotic arm on the table. A self-designed and modeled gripper model is installed at the end of the gripper. The environment for testing is arranged both in simulation and real world, where we employed the same simulation setting used in the training environment. We used black cover to encompass the experimental space to ensure a stable lighting condition,as shown in Fig. 4. (C) and (D).

B. Training

We conducted a series of simulation experiments using the robot simulation platform CoppeliaSim. We simplify the dual-modal soft gripper to a rigid body with four degrees of freedom for simulation. We imported the simplified gripper into the simulation platform and combined it with the UR5 robot to carry out gripping experiments. To simulate a real-world grasping environment, we used the Vortex physics engine to dynamically simulate a simplified gripper and 3D objects in the simulation. All simulations were repeated 5 times.

Evaluation metrics: We also consider the grasping success rate when evaluating the hybrid bimodal grasping performance. If an object is successfully picked in this action, we define an envelope or pinch action as a successful action. Both actions are marked as failed if either one fails to pick up the object. Please refer to Section 3 Reward for specific setting details.

Training: In each trial during training, 1 to 5 objects were randomly selected from the two grip types and placed in the workspace. Therefore, the total number of objects placed in the workspace varies from 2 to 10. For each training set, the gripper iteratively performs the grasping action until there is no object on the table or the number of attempts reaches a maximum. In a simulation, objects are first randomly selected from the 3D model database and then placed in the workspace with random positions and orientations.

TABLE I

OBJECT CATEGORIES IN OUR DATASETS

Category	Rigid	Flexible
Cuboid	small box, Rubik's cube	
Cylinder	Bucket, can, cup, packaging tape	Pumpkin
Sphere	Ball	Apple, lemon, orange
Irregular shape	Alarm clock, bottle, bowltoy car model	Hotdog, plush toy

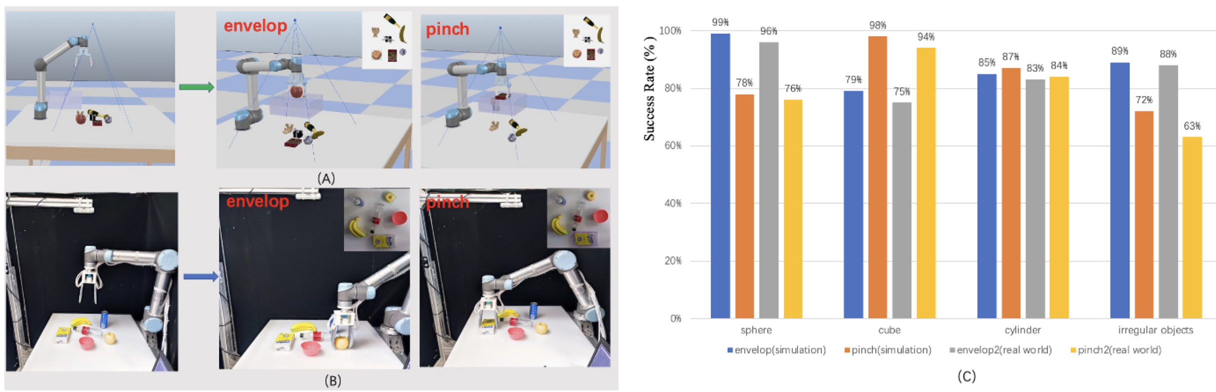

Fig. 6. Grasping experiment and result statistics. (A) Enveloping action and pinching action in the simulation environment. (B) Enveloping action and pinching action in real world environment.(C)Results.

The curve showing the variation of the average success rate is shown in Fig. 5, and a success rate of over 90% can be obtained in 2000 training steps,And mixed grasping are more likely to be successful than single grasping.

C. Test

Here we conducted three experiments. The experiment results are presented with both quantitive metrics and graph illustration, which vindicated the effectiveness of both our gripper hardware and algorithm design.

Efficiency test: To verify the effect of the experiment, we conduct object grasping tests in the virtual environment and the real environment, respectively. We roughly divide objects into four parts. The grasping experiment display and grasping results in virtual environment and real environment are shown in Fig. 6. It can be seen from the experimental results that envelope grasping has better grasping performance for spheres, lying cylinders and irregularly shaped objects, while pinching has better grasping performance for cubes and vertical cylinders. In order to prevent small objects or boxes containing liquid from slipping out or tilting during the grasping process, we purposely added several anti-slip grooves on the inside of the gripper to avoid the above situation to a certain extent.

Effectiveness of semantic information: We conducted this experiment to particularly test the effectiveness of the semantic information added in the decision model. Fig. 5 illustrates that for both the semantically assisted and the original model, there is a positive relationship between the number of training steps and success rate of grasping. Fig. 6.(C) further visualizes a comparison of the semantically assisted and the original model in terms of training time and the grasping efficiency. The results above show that the increase in training time is well worth considering the remarkable enhancement in grasping efficiency and success rate.

VI. CONCLUSIONS

In this work, we put forward a learning-based hybrid grasping framework for robotics, including gripper design, grasp modeling, simulation-based training, and simulation to real world transfer. Our goal is to minimize the number of actions in each grasping trial and improve the grasping success rate. The operation is based on our prediction of ideal grasping method according to physical properties of each target object for both robustness and protection of the object. The DRL framework is evaluated in different scenarios, and manifested privilege in grasping efficiency compared with uni-modal grasping. Our method yields an average success rate of 86% in simulations and 82% in real robotic experiments, indicating that our semantically augmented hybrid grasping model outperforms the traditional single grasping modality method. Furthermore, the strong generalization ability of our DRL strategy enables stable grasping of novel objects and can be robustly transferred to various grasping tasks in the real world for both industrial and daily use. In future work, we will work on to reduce the size of the DSG while exploring new applications of our gripper design to achieve even more accurate and stable manipulation. Another possible task of interest would be grasping specified objects in chaotic environment, where, for example, objects are piled and overlap with each other.

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