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TaTa: A Universal Jamming Gripper with High-Quality Tactile Perception and Its Application to Underwater Manipulation

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Abstract— **Large-area and high-precision tactile sensing information can not only improve the stability of robot grasping but also compensate for the lack of visual information in specific environments such as turbid underwater, dimness, and smoke. In this paper, we devise a universal jamming gripper with high-quality tactile sensing capability. The gripper adopts the particle jamming mechanism for grasping, and simultaneously uses a built-in camera to detect the deformation of its surface to obtain tactile information. To make the inside of the gripper transparent, glass beads and liquid with the same refractive index are applied as the internal filling. Besides, special treatments are taken to improve the tactile perception resolution of the gripper. The design perfectly merges visual-based tactile sensing into the traditional universal jamming gripper without changing its original gripping performance, making it possible for simultaneous grasping and sensing. To verify the tactile perception and grasping ability of the gripper in specific environments, we design two underwater experiments for grasping and pipe leak detection based on tactile information. Both have achieved a success rate not less than 95%, which demonstrates the effectiveness of the proposed gripper for manipulation in low visibility environments.**

I. Introduction

Tactile perception and grasping are two important yet challenging tasks for robots to interact with the real world. Unlike the human hands evolving for millions of years, driven by dozens of bones and muscles spread with thousands of neuroreceptors, artificial grippers are deficient in flexibility and sensory feedback. For decades, robotics is committed to integrating precise sensors and complicated actuators into complex control systems, but the high cost and the sensitivity restrict the large-scale application [1]–[3].

In [4], a universal, low-cost jamming gripper is proposed which grips objects by internal particle compression and surface friction. Its flexible surface can grip fragile objects, but also makes the design of its tactile sensors more difficult. In [5], a jamming gripper with a polymer-based strain sensor is designed, which can detect the deformation of the surface but the added sensors also degrades the gripping performance of the gripper.

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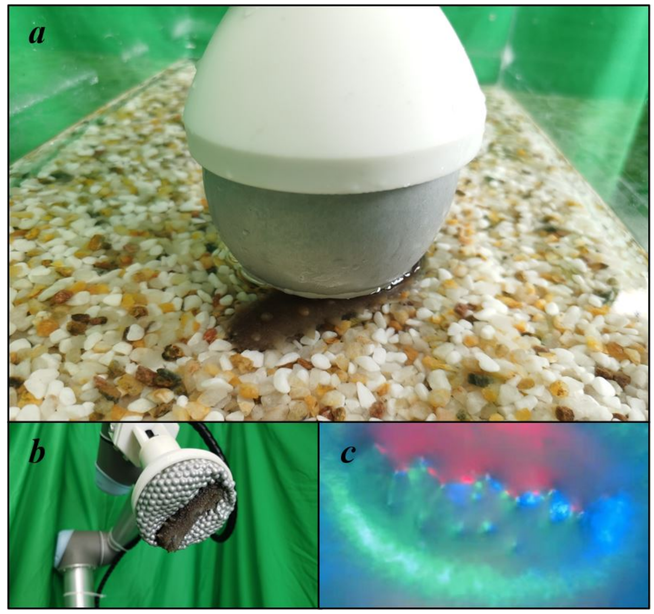

Fig. 1. (a) The picture of TaTa perceiving a trepang; (b) TaTa gripping a trepang; (c) Membrane deformation seen from the inside camera.

With the development of vision-based tactile sensors, a method to obtain tactile information through a built-in camera to observe particles of jamming gripper changes is proposed [6]. However, since the particles are opaque, tactile information can only be obtained by observing the shear strain of the internal particles, which leads to its low accuracy. In [7], transparent particles with liquid are applied as the filling material, which enables optical sensing to detect the deformation of the membrane. Although this is a good idea, the results are still not satisfactory since the quality of the obtained image is low, which makes it hard for tactile sensing.

Inspired by the results above, we present an improved jamming gripper with high-quality tactile sense, named TaTa (touch and take), as shown in Fig. 1. The main contribution of this work can be differentiated as follows:

1) A universal jamming gripper with vision-based tactile sensing is proposed, which solves the problem of low-resolution tactile sensing in previously designed jamming grippers.

2) According to the law of refraction [8] (if the objects have the same refractive index, their boundaries will be invisible after they are mixed), an internal filling scheme of 59% NaI, high borosilicate glass and $Na_2S_2O_3$ is proposed, which does not dissolve gripper nor volatilize and discolor,

and is easy to store.

3) Special treatments are taken to improve the tactile perception resolution of the gripper. A rubber membrane with a silver reflective coating of 0.2 mm thickness is manufactured and the LED lights with fog effect in three colors of red, green, and blue are used. Compared to [7], the resolution of the obtained image is significantly improved, which makes it possible to achieve high-quality tactile sensing for jamming grippers.

TaTa combines the advantages of the jamming gripper and the vision-based tactile sensor, which are listed as follows:

1) TaTa can grasp irregular objects and does not require complex planning algorithms, using the hydraulic drive, which can easily grasp two kilograms of weight, as shown in Fig. 2. In addition, its soft surface can prevent damage to fragile objects in the process of grasping.

2) TaTa uses a vision-based tactile detection method that utilizes the entire soft surface of the gripper as the sensor surface, providing a large detection area and high resolution.

3) The well-designed structure and strong sealing makes it available to be used in some special environments such as deep water.

To test the tactile sensing and operation capability of the gripper in specific environments, two underwater experiments for grasping and pipe leak detection based on tactile information are designed. According to the characteristics of the high-resolution tactile information, the classification method of GoogLeNet (Google Inception Net) [9] and FCN (Fully Convolutional Networks) [10] tactile information extraction method are utilized in the experiments, and the feasibility of gripper for underwater object salvage and valve operation tasks is demonstrated.

The rest of the paper is organized as follows. In Section II, related work on jamming grippers and tactile sensors are introduced. In Section III, the structure of the gripper is introduced. In Section IV, tactile-based underwater grasping and pipe detection experiments are presented. Finally, conclusions are given in Section V.

Fig. 2. TaTa grasping weight of two kilograms.

II. Related Work

A. Jamming-based gripper

In [11], the first particle gripper based on solid powder (which is salt in this design) is introduced as gripping surface of the artificial fingers, but only the flowing peculiarity was considered. A series of grippers actuated by vacuums were developed after that [12], [13]. A seminal work was the mass granular jamming gripper developed in 2010 [4], which can press the target object into the granular mass and then clamp by applying vacuum. Grippers based on jamming materials can change the surface passively to adapt to complicated object shapes, which allows it to have universal gripping capability.

The gripping force derives not only from the friction between the jamming material and the object but also a lot from the clamping force when the particles gather. The connection between the object and the gripper is rigid, which is necessary for manipulation but infrequent in other soft grippers. The particle jamming structure also applies to multiple finger grippers [14]. Jamming fingers endow the gripper with a wrapping ability to grip a larger volume. Solid particles have a high rigidity under jamming, providing a greater modulus than other soft grippers. Jamming particle based joints are introduced into the hyper-redundant grippers, and high strength-to-weight performance is obtained [15]. Jamming grippers provide a promising way to achieve universal grasping at a relatively low cost.

B. Vision-based tactile sensing method

Artificial tactility is another important field in robotics. Tactility provides effective feedback in the gripping control loop which enables stable perception especially in dark or turbid environments. Traditional tactile detection technologies such as piezoresistive [16] and capacitive [17] sensors have a good dynamic response, but their resolution is low and the cost increases significantly with the rise in resolution. In the 2010s, various vision-based tactile sensors were developed, such as GelSight [18], GelSlim [19], FingerVision [20], etc. These sensors sense the texture and material properties of an object by capturing the information of the surface using an internal RGB camera. Although they have a high detection accuracy, most of them have a small area and cannot detect the complete information of an object. A soft-bubble gripper with a large tactile sensor and gripping capability was designed recently [21], but the soft bubble structure limits the ability to grip heavy objects.

III. Design and Fabrication

A. The structure of the gripper

The gripping principle of TaTa is particle jamming. A large number of particles perform as a liquid on the whole under the pressure comparable with the environment and can be cured when negative pressure is applied. Besides, the gripper in this paper possesses the artificial tactile sense by making the particles invisible under the camera. The particles are made by high borosilicate glass and the refractive index is about 1.474. The particles are immersed in 59% NaI solution which also has a refractive index of 1.474, which makes the visual boundary of particles invisible in the camera. Therefore the surface structure information of the object can be obtained by the camera with high resolution.

As shown in Fig. 3, the gripper is mainly composed of a solid-liquid mixture, a pedestal, and a hemispherical soft rubber membrane. The solid-liquid mixture contains transparent balls made of borosilicate glass and 59% NaI solution as the index-matching fluid.

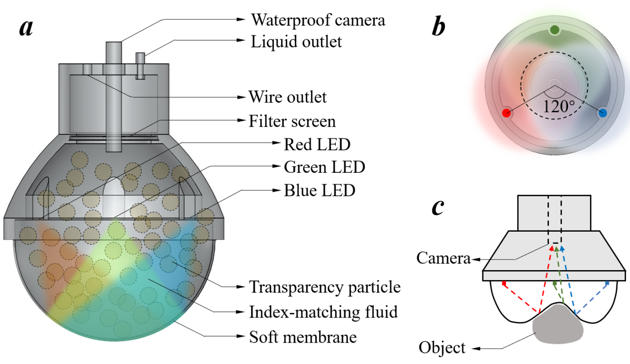

Fig. 3. (a) The schematic diagram of the gripper; (b) The layout of the LEDs plane; (c) The schematic diagram of the light path.

The diameter of the balls is 6 mm. The pedestal and the soft membrane isolate the mixture with a liquid outlet connected to a water pump. The diameter of the soft membrane is 100 mm. There is a filter screen under the liquid outlet separating the balls from the liquid when pumping. A waterproof camera is fixed on the center of the pedestal. The field of view of the camera is 67°, and the resolution is 1280×720.

Three LEDs are fixed along the edge of the pedestal with an interval angle of 120°. The colors of LEDs are red, green, and blue respectively, corresponding to the RGB pixel of the camera.

In addition, to make the light distribute evenly, the flat LED light with fogging effect is used. The LED light area are overlapped on the membrane as shown in Fig. 3(b). To improve the reflectivity of the gripper surface, a rubber soft membrane of 0.2 mm thickness mixed with silver powder is applied. The color of the internal surface of the rubber soft membrane is mixed with three colors and distributes with a gentle gradient if there are no objects. When the gripper touches an object, the soft membrane deforms under force, and then the light way changes as shown in Fig. 3(c), which results in color variation of the light on the soft membrane. Since the top on the deformed membrane can be illuminated by the nearest LED and the low-lying part can be covered by the backlight of the contralateral LED, the color distribution reflects the surface information of the object.

B. The mixture of particles and liquid

In our design, the particles and the liquid are transparent under the camera. Because when the refractive index of the particles and the liquid are equal under the visible light, the interfaces between the particles and the liquid will be invisible. The refractive index of the liquid can be calculated by Lorentz-Lorenz formula [22]:

$$\frac{n^2-1}{n^2+2}=\sum_{i=1}^{N}\varphi_i\frac{n_i^2-1}{n_i^2+2} \tag{1}$$

where n is the refractive index of mixture, n_i is the refractive index of the Nth liquid refractive index and φ_i is the volume fraction. Possible combinations of the mixture are listed in the Table. I along with their defects.

Several combinations with low toxicity and high workability are selected, including 87.25% tetralin-ethanol solution and H-K9 glass particles, p-cymene and organic glass particles, 59% NaI solution and high borosilicate glass particles, water and super-absorbent resin particles. However, some of them are not appropriate for this application. For example, tetralin is a good solvent for most organic products and may damage the diaphragm of the pump and the pipes which are all corrodible in the solution. While in p-cymene and benzene, the soft membrane can swell which destructs the elasticity. Considering all of that, we finally select the combination of 59% NaI solution and high borosilicate.

However, the NaI solution is easy to be oxidized to brown and turbid when exposed to the air and the light, as shown in Fig. 4(a), which may affect the view of the camera. That is because the iodide ions can be oxidated to iodine crystals:

$$4\,\mathrm{NaI}+\mathrm{O_2}+2\,\mathrm{H_2O}\longrightarrow 4\,\mathrm{NaOH}+2\,\mathrm{I_2} \tag{2}$$

To solve this problem, $Na_2S_2O_3$ can be added to reduce the iodine crystal. The mixture can be lucid with less than 0.5% $Na_2S_2O_3$:

$$2\,\mathrm{Na_2S_2O_3}+\mathrm{I_2}\longrightarrow \mathrm{Na_2S_4O_6}+2\,\mathrm{NaI} \tag{3}$$

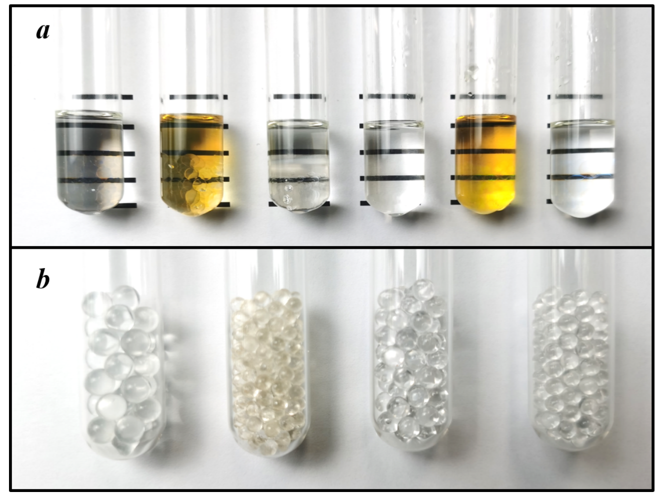

Fig. 4. (a) The mixture picture of particles and liquid, left to right: 87.25% tetralin-ethanol solution and H-K9 glass, 12.4% engine oil-benzene solution and organic glass, p-cymene and organic glass, water and super absorbent resin, 59% NaI solution and high borosilicate glass, 59% NaI solution and high borosilicate glass with $Na_2S_2O_3$ as a decolorizer; (b) The picture of particles, left to right: H-K9 glass, organic glass, high borosilicate glass, super-absorbent resin.

TABLE I
COMBINATIONS OF THE MIXTURE

Composition of the liquid	Composition of the particle	Refractive index	Defect
59% NaI solution [23]	High borosilicate glass	1.473	Oxidized to brown
Water	Super-absorbent resin	1.333	Particle is too soft
59.37% tetrachloromethane-tetrahydrofuran solution	Fluorine crown glass [24]	1.438	Generate virulent phosgene
77.26% trichloromethane-tetrahydrofuran solution			
30.2% gasoline-benzene solution	Barium fluoride	1.474	Dissolve the rubber soft film
12.4% engine oil-benzene solution	Organic glass	1.49	
p-cymene	Organic glass		
43.99% tetralin-ethanol solution	Fluorine crown glass (CDGM mark: H-FK95N)	1.438	Dissolve most organics
54.46 % tetralin-ethanol solution	Fluorine crown glass (CDGM mark: H-FK71)	1.457	
76.64 % tetralin-ethanol solution	Fluorine crown glass (CDGM mark: H-FK61)	1.497	
78% tetralin-ethanol solution	Fluorine crown glass (CDGM mark: H-K1)	1.499	
87.25% tetralin-ethanol solution	Fluorine crown glass (CDGM mark: H-K9)	1.517	

By using high borosilicate glass and 59% NaI solution with $Na_2S_2O_3$ as the filling material, the inner view of the gripper under the camera is shown in Fig. 5.

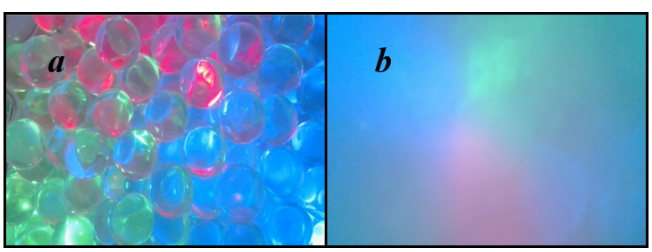

Fig. 5. The picture captured by the camera inside TaTa, (a) without liquid; (b) with liquid.

IV. Experiment

Robots often encounter mud interference and low visibility when working underwater, in which it is difficult for the robot to complete salvage and search tasks through visual information alone. So we intend to use TaTa for underwater tactile perception to compensate for the lack of vision. To test the capability of TaTa in identifying and grasping objects under turbid water, we designed two experiments: (1) Classifying and grasping objects under turbid water. (2) Detecting the location of underwater pipe leaks and closing the pipe valves. For the sake of observation, clean water is used here rather than turbid water, which does not affect the gripping and sensing performance of TaTa.

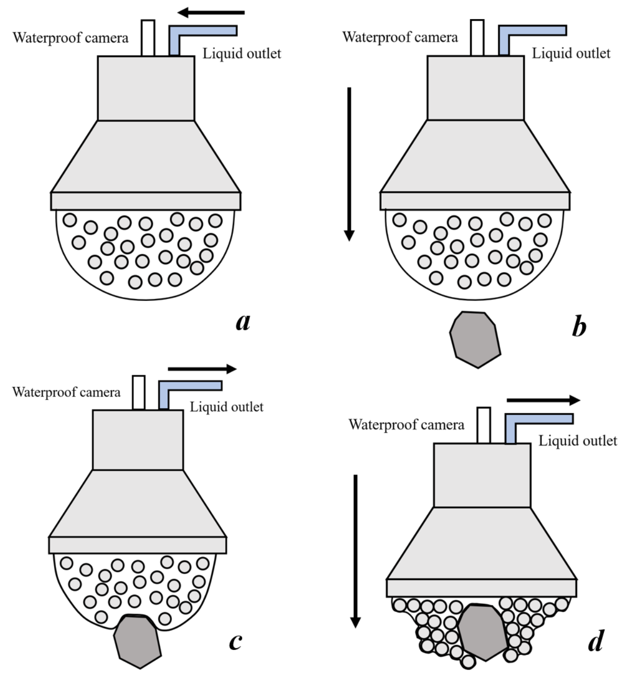

Fig. 6. The process of the grasping

A. Experiments of grasping and classifying objects under water

We simulate the underwater environment with a fish tank and sand grains to verify the performance of the gripper for underwater grasping and recognition.

Five objects are selected as the target objects, including trepang (soft model), conch (specimen), plug, pipe, and bottle cap. These samples cover common marine organisms as well as some infrastructure and garbage that may occur in the ocean, which are distinctly representative.

Since fresh animals are not easy to preserve, we use soft-bodied models of trepang and conch specimens. In addition, we treat the state when the gripper is not in contact with the object as the null state. The gripper only grasps when a sampled object is detected.

To ensure the generalization of the data, the angle and force of the gripper in contact with the objects are continuously changing during data acquisition. For each object, 50 samples of training data and 20 samples of testing data are acquired. The representive data samples are shown in Fig. 7.

To achieve object classification based on tactile, we utilize a lightweight network using GoogLeNet, which has a smaller number of parameters compared to ResNet (Residual Network) [25] and can achieve better training results when the samples are small. The training accuracy can reach 98.9% by the 50th epoch of training.

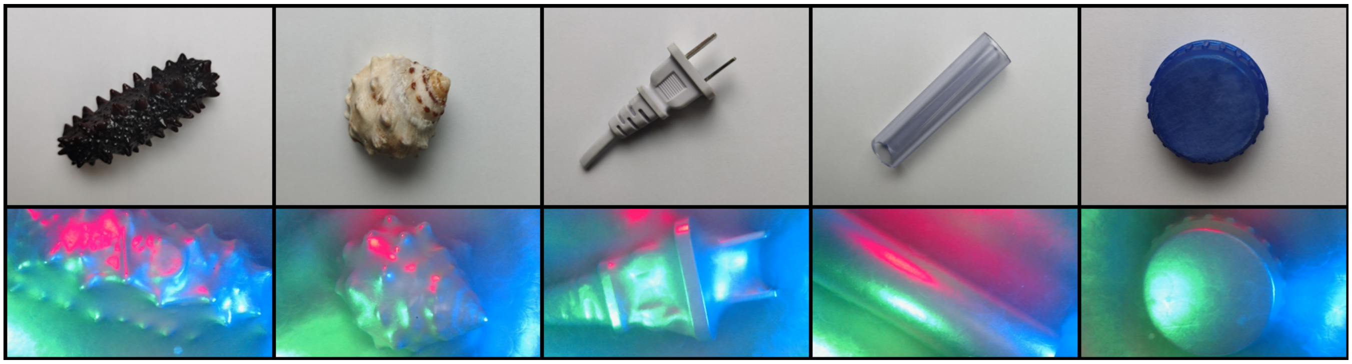

Fig. 7. Tactile readings from TaTa with various objects. From left to right: trepang, conch, plug, pipe, bottle cap.

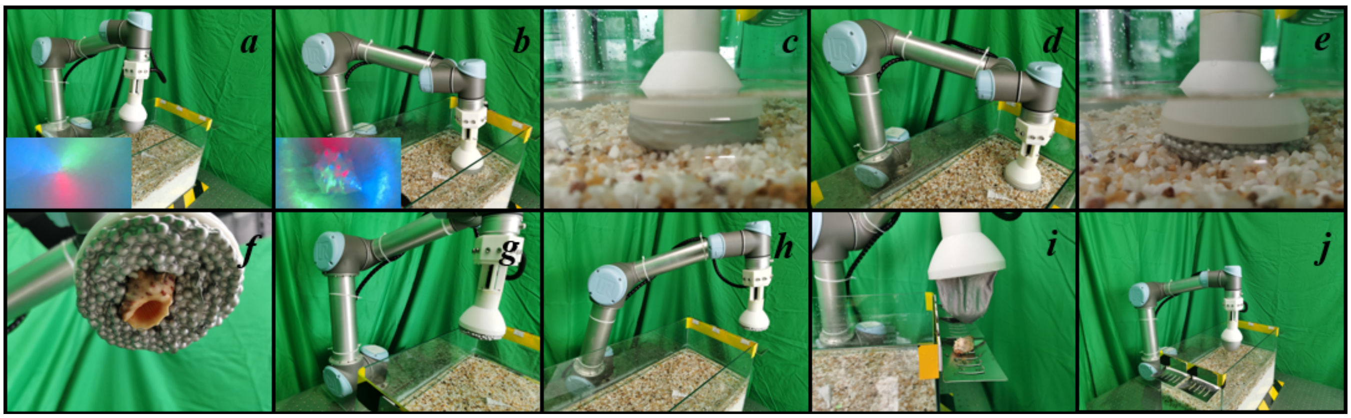

Fig. 8. The experimental process of objects grasping and recognition diagram. (a) The gripper in the initial position; (b) The gripper detects the object, and stops descending when the object is recognized; (c) Water pump pumps out liquid from the gripper; (d) The gripper is lowered again so that the object is wrapped more tightly; (e) (f) The gripper grips the objects tightly; (g) (h) The gripper places the object in the correct position according to the recognition result; (i) The gripper fills with liquid and release the object; (j) The gripper returns to the initial position and performs the next grasping task.

The grasping process of the gripper can be divided into four stages:

1) In the first stage, the gripper is in the initial position and the pump injects liquid into the inner of the gripper, as shown in Fig. 6(a).

2) In the second stage, the gripper reaches the top of the target, as shown in Fig. 6(b). At this time, the interior of the gripper is filled with liquid and the solid-liquid mixture remains highly mobile. The gripper moves down and uses GoogLeNet to recognize the detected image. When the target object is detected the gripper stops going down and enters the third stage. If the object is not detected at a certain position, the gripper moves to the next target position.

3) In the third stage, the pump starts to pump the liquid of the mixture through the liquid outlet and the internal pressure starts to decrease. The particles and the soft membrane begin to wrap the object, as shown in Fig. 6(c).

4) In the fourth stage, during the pumping process, the texture created by the membrane contacting the object becomes increasingly blurred as the tension of the elastic membrane decreases. When the recognition algorithm is unable to identify the object, the gripper moves down a distance again to ensure that the object is grasped tightly, as shown in Fig. 6(d).

To test the performance of TaTa, four objects are randomly selected from the five tested objects and placed at four equally spaced locations in the water tank. The gripper will identify objects in four positions and grasp them to the designated position according to their type. The experimental process is shown in Fig. 8.

The experimental results are shown in Table II, a total of 20 grasping tests are carried out. In each test, four objects are randomly selected as target objects. Therefore, a total of 80 grasping actions are performed. Among them, 77 times can accurately identify and grasp the object, 2 time of failure due to the gripper not grasping tightly, and 1 time of failure due to recognition errors, which finally results in an overall success rate of 96%. This demonstrates the excellent capability of the gripper in grasping and identifying objects.

B. Leak point detection of underwater pipe

In the ocean or rivers, there are often problems with pipe leaks. Pipe leaks often create a turbid environment, and it is difficult to accurately determine the location of the leak in such a low visibility environment with only visual information. To simulate this situation, the experimental equipment in Fig. 10 is designed, includes two pipes and each pipe has a valve. The experimental task is to detect the pipe leak point and close the valve of the pipe where the leak occurred.

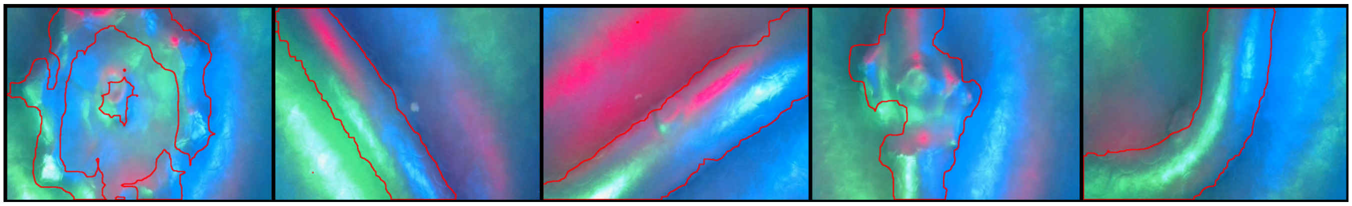

Fig. 9. The data obtained by feature extraction. From left to right: valve, pipe in left direction, pipe in right direction, leak location, bent pipe.

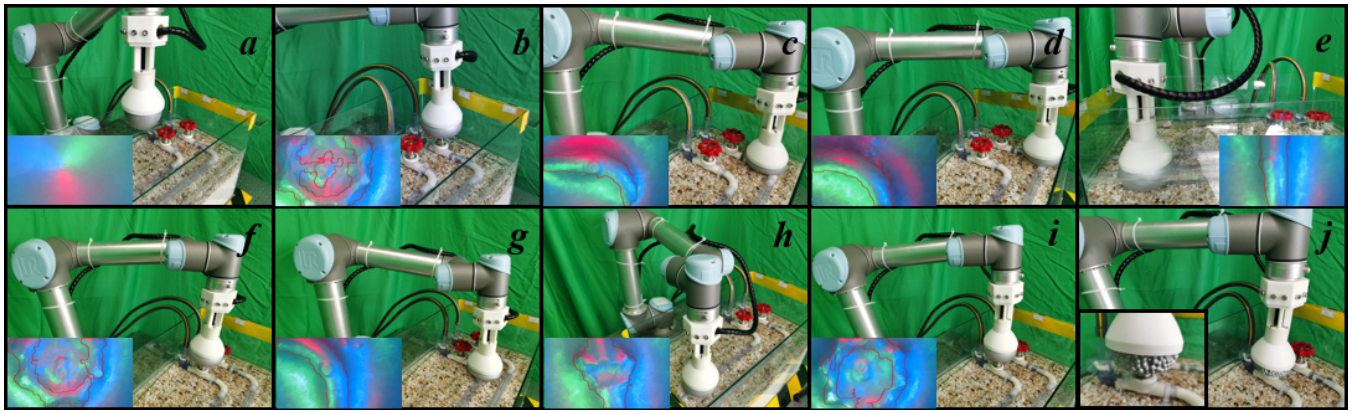

Fig. 10. The experimental process of pipe leak locations detection diagram. (a) The gripper in the initial position; (b) The gripper reaches the first valve position; (c) (d) (e) The gripper detects pipe locations and looks for leaks; (f) The gripper reaches the end of the first pipe and moves to the second valve; (g) The gripper detects the second pipe location and looks for leaks; (h) The pipe leak discovered; (i) The gripper reaches the valve of the second pipe; (j) The gripper grips the valve and rotates it.

TABLE II
EXPERIMENTAL RESULTS OF GRASPING AND IDENTIFICATION

Objects	Number of experiments	Recognition success rate	Gripping success rate	Overall success rate
Trepang	12	100%	100%	100%
Conch	17	94%	100%	94%
Plug	20	100%	95%	95%
Pipe	13	100%	100%	100%
Bottle cap	18	100%	94%	94%

The algorithm used here mainly consists of three parts: pipe information extraction, line inspection, and identification. To extract the pipe information when the gripper contact with the pipe, FCN is used which is more efficient than the traditional CNN (Convolutional Neural Networks) segmentation network. 200 pieces of pipe data with different angles and 200 pieces of leak data are acquired and labeled at the pixel level. After 30 epoch training, the testing accuracy can reaches 98%. The typical segmented data are shown in Fig. 9. Similar to Experiment 1, GoogleNet is used for the data classification. The objects to be tested are divided into three categories: valve, pipe, and leak, and the classification accuracy reaches 99.3%. Using the pipe information extracted from the FCN network for pipe inspection, the strategy is to keep the pipe in the center of the image as much as possible.

A total of 40 tests are carried out, replacing pipes with different leak locations for each test, 38 of which accurately found the leak and closed the valve, while two failed due to a misidentification of the leak, with a success rate of 95%. The experimental process is shown in Fig. 10.

V. Discussion and Future Work

In this paper, we propose a universal jamming gripper with high-quality tactile perception and manipulation capability named TaTa, which has combined the gripping mechanism of jamming gripper and vision-based tactile sensing. TaTa has the advantages of stable gripping performance, large tactile detection range and high resolution. In order to verify the performance of TaTa, we design an underwater gripping experiment and a pipe leak detection experiment based on tactile information, applying GoogLeNet and FCN for object classification and feature extraction, respectively. The underwater objects classification accuracy reaches 98.9%, and the feature extraction accuracy reaches 98%. Finally, the success rate of underwater object recognition and gripping is 96%, and the success rate of finding pipe leaks and closing the valve is 95%. Experimental results show that this gripper can effectively accomplish the searching and gripping tasks in low visibility environments, which is a great advantage compared to other jamming grippers.

There are still some inadequacies remains. For example, the tactile sense is acquired by the processing of planar images rather than three-dimension reconstruction. The next prototype will be an upgrade by the structure design and visual hardware and applied in more practical scenarios.

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