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Lobster-inspired Finger Surface Design for Grasping with Enhanced Robustness

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***Abstract*— This paper presents a lobster-inspired design of a soft finger's contact surface for grasping with enhanced robustness. The lobsters, while living on the seabed with sediments of various sizes, sources, materials, and life forms, exhibit exceptional capabilities in object manipulation underwater using angled-claws with two fingers. By inspecting the geometric features of the lobster tooth, we proposed a series of finger surface designs molded with silicone. We tested the surface friction using traditional methods to shortlist our design pool, and further verified their performance using robotic arm grasping against a series of challenging objects from the EGAD, the Evolved Grasping Analysis Dataset. Results show that, in certain cases, the lobster-inspired finger surface design yields an enhanced grasping success rate by 56% at most than those without the surface. Furthermore, we propose a minimum setup for robotic grasping using NVidia Jetson Xavier, Intel RealSense D435, and the proposed soft gripper to be compatible with most robotic manipulators as a cost-effective configuration for shareable and reproducible research.**

***Index Terms*— Soft Robot, Robotic Grasping, Bio-inspired Design, Grasping Robustness**

I. Introduction

The contact surface design plays a key role to influence the grasping success in object manipulation. The grasp robustness is closely related to the physical contact between the robotic finger and the target object, which is modulated by the amount of force exerted at the finger. Recent research has been devoted to the adoption of model-based [1], [2], [3] or learning-based algorithm [4], [5], [6], [7] development for finding the optimal grasping point or posture, the sensing and control of fingertip while in contact with the object for refined motor function [8], the development of novel grasping mode through mechanism design at the finger [9], as well as the optimal number of fingers for successful grasp [10]. The design and development of an effective finger surface design, even without extra sensing or motor control, remains a challenging research topic that offers a simplified, practical, and cost-effective value in industrial applications.

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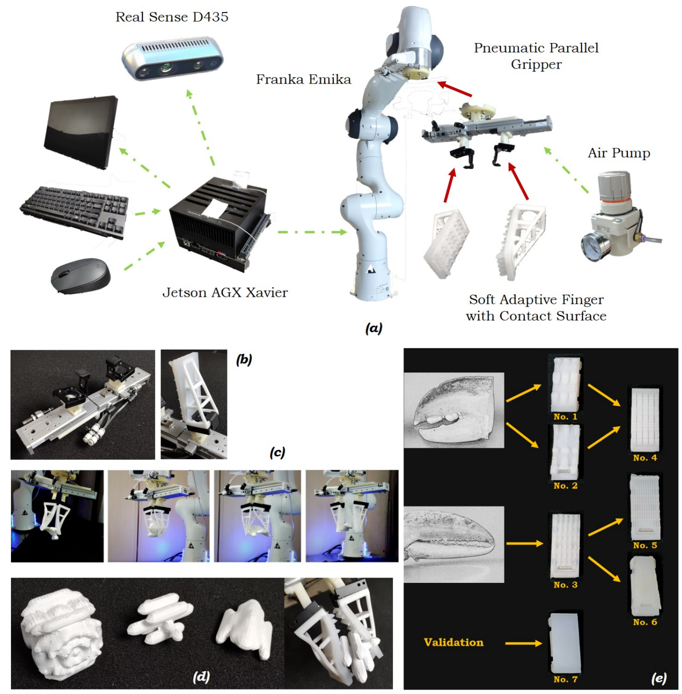

Fig. 1: Lobster-inspired finger surface design with grasping performance verification: (a) system setup that includes a Franka Emika arm, a Nvidia Jetson AGX Xavier, an Intel RealSense D435 and a pneumatic 2-finger gripper with the proposed finger contact surface integrated for grasping; (b) close-up view of the gripper and the finger installation; (c) the four grasping poses used, which are bending outward, bending inward, twisting, and parallel grasping (from left to right); (d) selected objects from EGAD for grasping verification; (e) the six lobster-inspired finger surface designs and one validation.

Soft interfaces designed using deformable material under desired actuation or passive interaction have been a practical solution to the finger surface. Classical solutions often turn to industrial rubber with simple textures to meet the engineering need in mass-production and cost-effectiveness with resistance to wear and tear [11]. Recent growth in soft robotic technologies promotes an integrated approach by combining active deformation and passive adaptation within a single form factor to achieve the goal [12]. The use of soft and compliant interfaces provides a convenient solution at low-cost to increase the contact surface area with redundant constraints to the objects, enhancing the robustness of the grasping outcomes. While the science behind the contact and friction remains a challenging topic without a full understanding, researchers also turn to learning-based methods to exhaust various surface texture design with soft materials [13], hoping to find an optimized solution with learning-based statistical support for an engineering robust design of the finger surface.

In this paper, we propose a novel design of the finger surface by drawing biological inspirations from the lobsters, where a wide range of tooth forms are presented with robust grasping capabilities in challenging environment on the seabed. As shown in Fig. 1, we analyzed a series of soft finger surfaces based on various tooth forms from the lobsters and crabs, integrated them with a soft finger structure with passive adaptation, and empirically tested their performance using a minimum robotic grasping system against selected objects from the Evolved Grasping Analysis Dataset (EGAD) [14] to arrive at a promising design of the finger surface with enhanced grasping robustness.

II. Method

A. Finger Surface Design Inspired by Boston Lobster

Since the material of soft finger focuses on the combination of flexibility and rigidity, the frictional coefficient of it is small. Besides, to ensure flexibility the finger uses a mesh structure, which only provides a limiting contact area in grasping. Due to the two main reasons above, the bare soft finger is not enough to perform well-grasping quality, with sliding and slipping occurs. To solve the questions above and enhance the grasping performance of soft finger, an external layer is considered to be attached to it. To maintain the flexibility of the finger, we choose silicone as the material of the external layer, for silicone possesses a relatively high frictional coefficient but remains flexible at the same time. In the following experiment, whether an external layer can benefit grasping performance will be proved.

For the surface of the layer, our designs are inspired by the claw surface of the lobster. The claw of the lobster also consists of two fingers and achieves an open-and-close pose only by spinning the hinge. Given the two fingers on a claw and the hinge structure, the lobster is able to accomplish a series of tasks, including grasping, cutting, and smashing. We assume the secret that the lobster can be able to accomplish such tasks lies in the shape of its claw and the contacting surface of its fingers. Therefore we further observe and mimic the pattern on the surface of the lobster finger, and transfer it into our contact surface layer design.

Since the size of Boston Lobster's claw is close to the soft finger, it becomes the target for us to mimic. In this paper, we have put out six kinds of contact surface design (Fig.1 (e)) inspired by the claws of Boston Lobster, along with one design from AUTOLAB from UC Berkeley as a validation, which will be illustrated in the experiment part of the paper.

Among all the seven designs, as shown in Fig.2, No.1 is a 1:1 imitation of the upper crusher claw of the Boston Lobster, while No.2 is of the lower crusher claw. Since these two parts hold dissimilarity to each other, they can be regarded as two different patterns. Besides, No.3 is a 1:1 imitation of the cutter claw of the Boston Lobster. The upper and lower part of the cutter claw are similar to each other, thus they are regarded as one pattern. Each pattern is duplicated into multiple rows to fill the whole surface area. Therefore, No.1 and No.2 only possess three rows due to their wider pattern, while No.3 possesses five rows due to its thinner pattern. Besides, the No.1, 2, and 3 are imitated to be as the same as the original one given the limit in size and dimensions, to explore and reveal the performance of design inspired by the Boston Lobster's claws on grasping robustness.

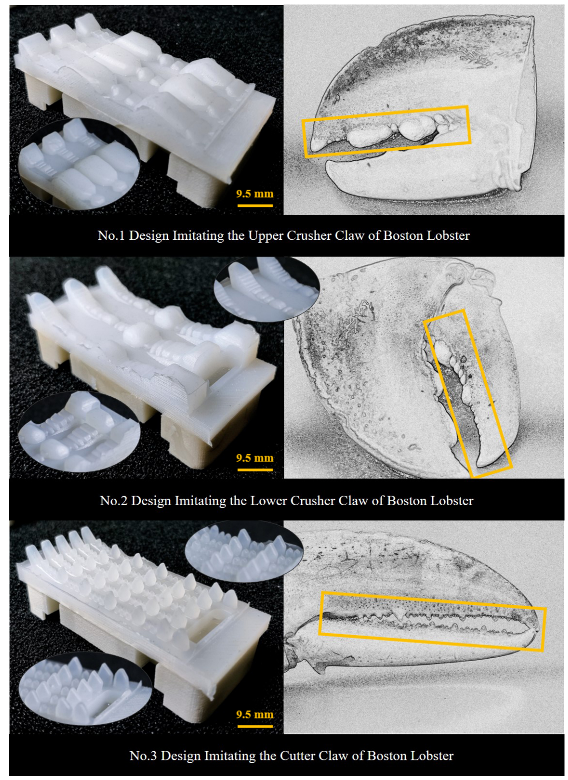

Fig. 2: No.1, 2, and 3 design are imitating the original shape of the claws of Boston Lobster.

For the rest of the design, as shown in Fig.3, No.4 is extracting the feature of No.1 and No.2 while No.5 and No.6 are extracting the feature of No.3. The reason for feature extracting is that the original features are complex and irregular, for they have been evolving for million years to fit nature. Thus the modeling is time-consuming and fabrication requires high accuracy 3D printer, which generates expensive cost. Feature extracting is anticipating simplify the original shape, but can still represent most the performance of the original one while being convenient to model and low cost to fabricate.

To simplify the shape, with further observation we discover that the teeth on the claw can be concluded as the repetition of a single pattern. As for the crusher claw, there includes a big round tooth along with about three small teeth in a pattern. While for cutter claw, there includes a big sharp tooth along with about four to five small sharp teeth in a pattern. Besides, the big round teeth on the crusher claw can be simplified as a trapezoid, while the sharp teeth on the cutter claw can be simplified as a triangle. By repeating that pattern, No.4 and 5 are generated. Besides, No.6 is developed

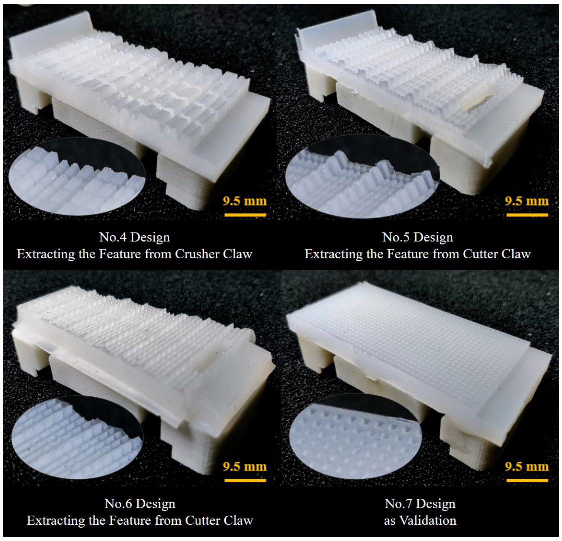

Fig. 3: No.4, 5, 6 design are simplifying the original shape and No.7 is chosen as the validation.

from No.5 but in opposite size. The height of the teeth of No.6 is approximately half of No.5, while the width is two times of No.5's. It is interesting to validate whether the sharper and narrower teeth or the shorter and wider teeth perform better in the following experiments.

To provide the designs a validation, the product, which is No.7 design in Fig.3, from the AUTOLAB at UC Berkeley [13] is chosen. In their research, they have put out 37 finger surface designs and select this one as the best performance. Since No.7 design is based on the size of the human finger, which is about one-fourth the size of our soft adaptive finger, it is unfair to compare this design with our designs directly. The main reason it is chosen as validation is that we hope this design can validate whether our design is effective, valuable, and worth attaching to the finger.

All the silicone materials are Dragon Skin 10 from Smooth-On, with shore 10A, tensile strength 475 psi, and maximum elongation of 1000% at break ensuring the strength of the contact surface while remaining fingers flexible. Besides, all the molds are fabricated by 3D printing using resin as material, with the accuracy of 0.1mm. In addition, the validation No.7 uses Dragon Skin 30 with shore 30A material, which is the best material for this design according to [13].

B. Manipulation Task and Experiment Platform

To accomplish object manipulation task while testing the performance of each contact surface design, a cost-effective and well-performance robotic manipulation hardware system is proposed, with the overview shown in Fig.1(a).

- Franka Emika Panda [15] is a highly recommended robotic arm for researchers who want to setup a robotic manipulation system, as it provides a flexible control interface as well as affordable price, compared with other industrial products.
- For the computation and control unit, the edge computation platform Jetson AGX Xavier from Nvidia, which is a mobile, compact yet powerful platform, can be a good choice [16]. Among Nvidia Jetson series, AGX Xavier can deliver up to 32 TOPS of peak performance, which is close to the GPU workstation-class performance, making complicated state-of-art algorithms deployment and real-time results gaining possible, while remaining relatively small in size (105 mm x 105 mm x 65 mm) and low in power consumption (maximum at 30W).
- For the vision perception module, Intel RealSense D435 is able to provide color frames whose resolution is 1920*1080 at 30 fps with a FOV (Field of View) of $69.4° \times 42.5° \times 77°(\pm 3°)$, while offering depth frame with a maximum range located at around 10 meters at up to 90fps with a FOV of $86° \times 57°(\pm 3°)$. Besides, the resolution of depth frames can reach up to 1280*720. More importantly, it is small in size (90 mm x 25 mm x 25 mm) and therefore is easy to integrate into other solutions. With the technical specification mentioned above, RealSense D435 is considered capable of the perception task required in most normal manipulation scenarios [17].
- For the execution module, to accomplish a variety of challenging grasping tasks, a robust and well-performed gripper is essential. Here a pneumatic-powered parallel gripper is deployed proposing to work both on land and in water. The gripper is powered by an air pump, with the air pressure of 0.1 MPa in closing posture and standard atmospheric pressure in opening posture. Given the previous achievement on the soft adaptive omni-finger design [10], the powerful fingers will be mounted on the gripper and compose an entire execution module.

III. Experiment Results

A. Friction Force Experiment on Finger Surface Design

To evaluate the grasping quality of the finger, one physical parameter that should be taken into consideration is the maximum friction force that a finger can provide in grasping. As an assumption in the experiment by [18], the higher the friction force a finger can provide, the better grasping quality it can implement. In this experiment, the maximum friction force under different loads provided by each contact surface layer is tested, to evaluate the performance of each contact surface layer.

In this experiment, as shown in Fig.4 (a), we will have the surface layer fixed on a linear stepper motor trail slider. Different loads (200g, 400g, 500g, 700g) will be applied to the surface. A force detector will be mounted and be linked to the load through a wire, which helps the load to stay still while detecting the tension on the linking wire. When the experiment starts, the motor will drive the surface layer moving at a constant low speed, which will generate a relative movement between the surface layer and the load, thus generating friction force that aims to disturb the movement.

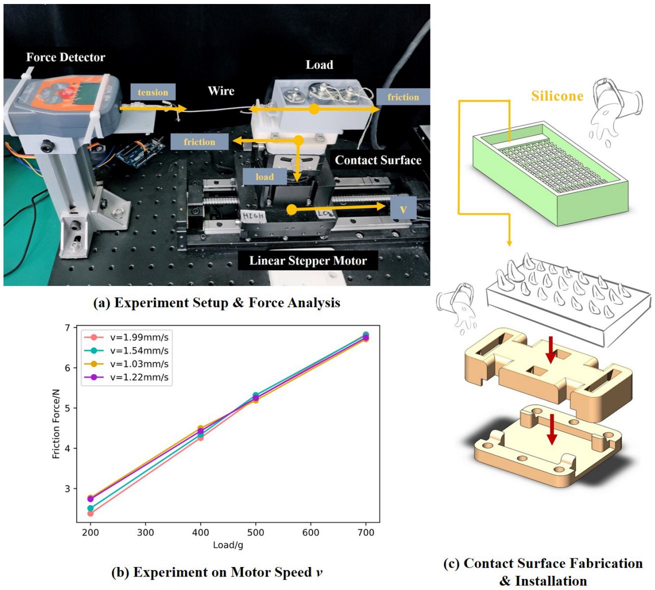

Fig. 4: Experiment on friction force of contact surface layer.

For the speed of the motor, we hold a pre-experiment to test how different speeds influence the experiment. In this pre-experiment the No.4 design is tested under different motor speed, which includes 600 (about 1.99 mm/s), 800 (about 1.54 mm/s), 1000 (about 1.22 mm/s) and 1200 (about 1.03 mm/s). The result is shown in Fig.4 (b), we eventually choose freq = 1000, which is about 1.22 mm/s, as our experiment speed, for it grants the surface layer to provide a relatively stable force under different load, which is almost linear as shown in the figure.

Given a certain speed to run the experiment, all the test results on the six designs along with one validation are coming up shown in Fig.5. As the figure shows, all of our designs perform better than the validation under every load, which indicates that our designs are valuable and worth further exploration. Among them, the best performance designs are No.1, 3, and 5. For No.2, it is close to the first class at the beginning, however it performs badly under 700g load. Therefore, for the next experiment, No.1, 2, 3, 5 will be selected to be mounted on the finger. The reason No.2 is still selected is that the shape of it has a curve, which might help with grasping by locking the object in the curve and this point will be tested in the following experiment.

To give a summary of the test result of the friction force experiment, the simplified design, which are No.4, 5, and 6, both perform worse than the original design. Among the simplified design No.5 still remain in the first class of the results, while No.4 fail to represent the performance of the original ones. In the result No.5 and No.6 have a huge difference, which indicates that the sharper and narrower teeth might be more effective.

B. *Grasp Success Rate of Finger Surface Designs*

Now that No.1, 2, 3, 5 design have been selected through the previous experiment, this experiment aims to mount each

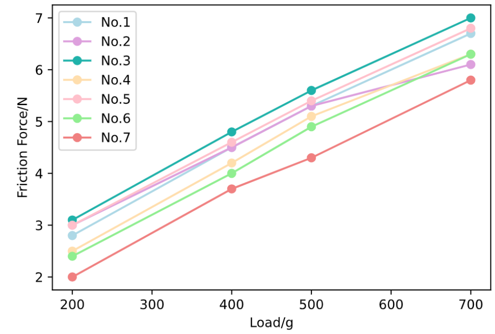

Fig. 5: The result of friction force experiment on seven kinds of contact surface design.

surface design to the fingers of the gripper of the system, to test on their real performance on grasping. The fingers with contact surface layer that will be tested in this experiment and their fabrication process are displayed in Fig.6

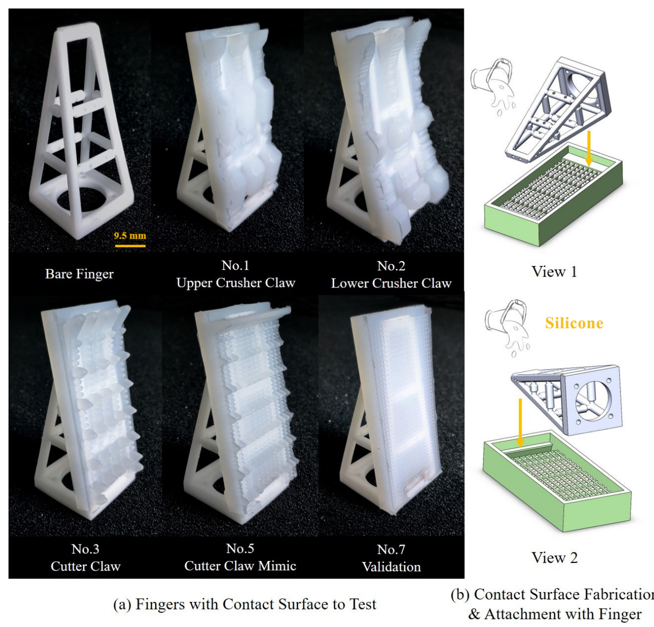

Fig. 6: Overview of the soft adaptive fingers with contact surface layer that will be tested in the following experiment.

In this experiment, three objects are chosen from the dataset of EGAD [14] to test the grasping performance of the finger surface (Fig.1 (d)). EGAD provides a dataset of objects which are challenging to robotic manipulation, with rank in grasping difficulty. The grasping rank level is from "A" to "X" totally 24 grasping levels according to the alphabet, the latter in the alphabet the harder it can be grasped.

The workflow of a single grasp procedure in this experiment is:

- Step 1 Recognizing: the system will recognize the object on the table through its camera and the build-in computer vision algorithm and get the information of the object by RGB and depth images.
- Step 2 Grasping: after calculating the location of the

object by the information obtained from the camera, the system will command its robotic arm to reach that location, and pressuring the air to close the fingers to grasp the object.
- Step 3 Checking: the robotic arm will lift the object and move it outside the grasping area, which is predefined by us by cropping a specific area in the camera vision. As the robotic arm has moved out of the grasping area, the camera will recognize the area again. If there is no object remain in the area, it indicates that the grasping is success that the object has been removed. Otherwise it indicates that the grasping fails that the object has not been grasped or has been dropped by the robotic arm.
- Step 4 Releasing: as the check is finished, the robotic arm will randomly select a location in its grasping area, and is 6.5 cm above the table surface. Having approached that location, the robotic arm will release its gripper, letting the object drop down to the table surface. This is supposed to get the object a random pose and random location for the next grasping to stimulate random situations in the real world.

The four steps above compose one single grasp, and each object will be grasped 200 times for each finger surface. To give this experiment a validation, a pair of bare fingers will be tested to show whether the contact surface contributes to the grasping performance. Besides, similar to the last experiment, No.7 is chosen as an additional validation to make a comparison with our designs. The final result is shown in the Fig.7, Fig.8 and Fig.9.

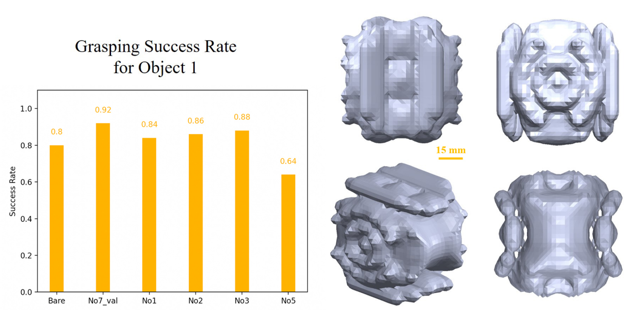

Fig. 7: The shape of object 1 and the grasping success rate for it.

For object 1 in Fig.7, which is a cube-shaped object, has irregular surfaces with multiple small embossments. This object is considered as "W" the second hardest level to grasp in EGAD. The reason why this object is hard to grasp is that the uneven surface provides the rigid fingers limited contact area, while the embossments on the surface further limit the contact area. However, as shown in our test result, object 1 can be easy for the soft adaptive finger to grasp, for the bare finger it can realize 80% success rate. This result shows the advantage of the soft adaptive finger that it can be highly compliant to the surface of the object, no matter the shape and curve of the surface so that it can accomplish successful grasps of the object which can be hard for rigid fingers.

For the rest of the contact surface designs, the success rates are all higher than that of the bare finger, except for No.5 design. Among them, No.7 validation design shows 92% the highest success rate and No.3 shows 88% the second-highest, with only 4% in difference. The reason why No.5 performs 16% worse than bare finger might be its entire row of a tooth at the top. In grasping, the entire row of tooth fails to stuck the object as the individual teeth in No.1, 2, and 3 perform and cause the object to slide.

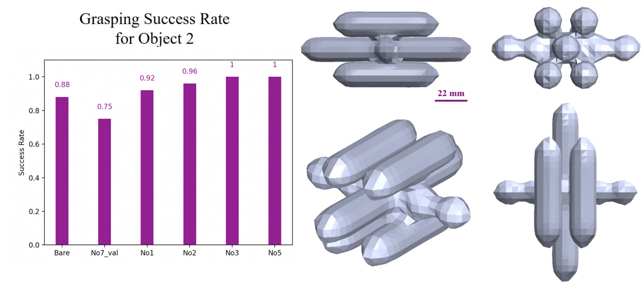

Fig. 8: The shape of object 2 and the grasping success rate for it.

For object 2 in Fig.8, which is ranked as "R" level the seventh hardest level, is a combination of few cylinders. With one cylinder on the X axis while another on the Y axis, the contacting area provided to the finger becomes specific and limited. In general, the ideal grasping position for computer calculation is in the middle of the object. While for object 2 the cylinder in the middle disturb the finger and thus enlarging the grasping difficulty. However, for the mesh structure finger, the cylinder can across the mesh of the finger and lie on the support post, providing more area to contact and thus making the grasping easier. Therefore as for the bare finger, it achieves 88% success rate grasping object 2.

For the validation No.7 design, since it is a plane surface with the contact area limited by the protruding cylinder, it achieves 75% success rate which is lower than the bare finger. For the rest of the designs, both contact surface designs show higher success rates than the bare finger. In particular, it should be mentioned that the No.3 and No.5 design, which are all inspired by the cutter claw of the lobster, shows nearly 100% success rate grasping object 2, which is astonishing. The reason they show such a high and perfect success rate is that their teeth are small but sharp, which can mush into the hollow of the object to enlarge the contact area, while the teeth are narrow to leave enough space between the rows for the embossment of the object to mush in so that the finger and the object can fit into each other tightly.

For object 3 in Fig. 9, which is ranked as "U" level the fourth hardest level, is of a convex curve shape with smooth surfaces. As the result shows the bare finger only achieves 36% success rate grasping this object since the convex curve shape with smooth surface provides an extremely limited contact area for grasping. However, all of the designs both achieve a huge improvement in success rate comparing to bare finger, ranging from 25% to 56%, which further indicate the contribution of the contact surface.

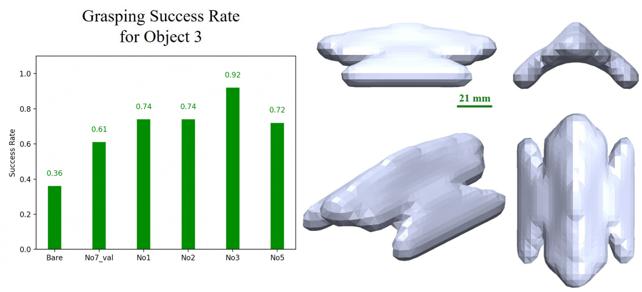

Fig. 9: The shape of object 3 and the grasping success rate for it.

As illustrated above, the validation design No.7 is 36% better than the bare finger, while for all of our designs both perform better than the validation. Among them, No.3 achieves 92% success rate, with 31% improvement compared to the validation and 56% compared to bare fingers, which is remarkable. The reason for No.3 design perform so well on object 3 is similar to object 2 above. The sharp small teeth can mush into the hollow at the bottom of the object and enable the finger to lift it. However, the reason why No.5 shows such a huge gap with No.3 is the difference in the size of the teeth. The teeth of No.3 are higher, narrower, and of pentagon-like shape, while the teeth of No.5 design are shorter, wider, and of triangle shape for easy modeling.

In conclusion, Figs. 7, 8 and 9 illustrate the contribution of the contact surface layer on grasping success rate comparing to bare finger. All of our designs perform better than the best performance design by AUTOLAB except on object 1 with only 4% difference. Among all of our designs, No.3 design perform the best on all the objects. On object 2, it achieves 100% success rate, and on object 3, it is 56% better than that of the bare fingers. Besides, the whole system has been tested in this experiment, with no system break off or collapse, not even stuck during the program running, which indicates that the computational unit of the system is capable and competent for the general grasping task.

IV. Final Remarks

A. Conclusion

In this paper, a cost-effective and small-in-size system setup for general robotic manipulation tasks is proposed. It includes four modules as Intel RealSense D435 for vision perception module, Franka Emika Panda for execution module, Jetson AGX Xavier for central processing and control module, and an air-powered gripper consists of two soft adaptive fingers with contact surface layers for the end-effector module. To enhance the performance of grasping, we come up with six contact surface layer designs inspired by the claws of the Boston Lobster. According to the experiment, the result proves that comparing to bare finger surface, the contact surface layer is of remarkable benefit to the grasping performance of 56% success rate improvement at most in certain cases.

B. Future Work

In the future, a formula description to define the teeth on the claw of lobster and also other crustaceans will be generated, which is missed in the current paper. Thus an integrated design pool should be implemented, with a huge amount of design using different parameters of the formula. In this way, more powerful and more rational contact surface design will be yielded, further enhance and facilitate the robotic grasping performance while revealing the secret of grasping for lobster and also other crustaceans. By choosing air pressure as the powering method, the purpose is to enable the gripper to accomplish the grasping task both on-land and underwater.

References

[1] M. A. Roa and R. Suarez, "Computation of independent contact regions for grasping 3-d objects," *IEEE Transactions on Robotics*, vol. 25, no. 4, pp. 839–850, 2009.

[2] A. Rodriguez, M. T. Mason, and S. Ferry, "From caging to grasping," *The International Journal of Robotics Research*, vol. 31, no. 7, pp. 886–900, 2012. [Online]. Available: https://doi.org/10.1177/0278364912442972

[3] C. Rosales, R. Suárez, M. Gabiccini, and A. Bicchi, "On the synthesis of feasible and prehensile robotic grasps," in *2012 IEEE International Conference on Robotics and Automation*, 2012, pp. 550–556.

[4] L. Pinto and A. Gupta, "Supersizing self-supervision: Learning to grasp from 50k tries and 700 robot hours," 2015.

[5] S. Levine, P. Pastor, A. Krizhevsky, and D. Quillen, "Learning hand-eye coordination for robotic grasping with deep learning and large-scale data collection," 2016.

[6] J. Mahler, J. Liang, S. Niyaz, M. Laskey, R. Doan, X. Liu, J. A. Ojea, and K. Goldberg, "Dex-net 2.0: Deep learning to plan robust grasps with synthetic point clouds and analytic grasp metrics," *arXiv preprint arXiv:1703.09312*, 2017.

[7] J. Mahler, M. Matl, V. Satish, M. Danielczuk, B. DeRose, S. McKinley, and K. Goldberg, "Learning ambidextrous robot grasping policies," *Science Robotics*, vol. 4, no. 26, 2019.

[8] N. Fazeli, M. Oller, J. Wu, Z. Wu, J. B. Tenenbaum, and A. Rodriguez, "See, feel, act: Hierarchical learning for complex manipulation skills with multisensory fusion," *Science Robotics*, vol. 4, no. 26, 2019.

[9] S. Wang, H. Jiang, and M. Cutkosky, "A palm for a rock climbing robot based on dense arrays of micro-spines," 10 2016, pp. 52–59.

[10] F. Wan, H. Wang, J. Wu, Y. Liu, and C. Song, "A reconfigurable design for omni-adaptive grasp learning," *IEEE Robotics and Automation Letters*, p. 1–1, 2020. [Online]. Available: http://dx.doi.org/10.1109/LRA.2020.2982059

[11] J. Zhang, A. Jackson, N. Mentzer, and R. Kramer, "A modular, reconfigurable mold for a soft robotic gripper design activity," *Frontiers in Robotics and AI*, vol. 4, p. 46, 2017. [Online]. Available: https://www.frontiersin.org/article/10.3389/frobt.2017.00046

[12] J. Zhou, S. Chen, and Z. Wang, "A soft-robotic gripper with enhanced object adaptation and grasping reliability," *IEEE Robotics and Automation Letters*, vol. 2, no. 4, pp. 2287–2293, 2017.

[13] M. Guo, D. V. Gealy, J. Liang, J. Mahler, A. Goncalves, S. McKinley, J. A. Ojea, and K. Goldberg, "Design of parallel-jaw gripper tip surfaces for robust grasping," in *2017 IEEE International Conference on Robotics and Automation (ICRA)*, 2017, pp. 2831–2838.

[14] D. Morrison, P. Corke, and J. Leitner, "Egad! an evolved grasping analysis dataset for diversity and reproducibility in robotic manipulation," *IEEE Robotics and Automation Letters*, vol. 5, no. 3, pp. 4368–4375, 2020.

[15] F. Emika, "Panda," 2018. [Online]. Available: https://www.franka.de

[16] N. J. A. Xavier, "The ai platform for autonomous machines."

[17] T. S. et al, "High-speed capture mode of intel realsense™ depth camera d435," 2020. [Online]. Available: https://dev.intelrealsense.com/docs/high-speed-capture-mode-of-intel-realsense-depth-camera-d435

[18] J. Zhou, S. Chen, and Z. Wang, "A soft-robotic gripper with enhanced object adaptation and grasping reliability," *IEEE Robotics and Automation Letters*, vol. 2, no. 4, pp. 2287–2293, 2017.