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Gesture Selection Strategy of Reconfigurable Soft Gripper System Using a Data-Driven Scheme

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Soft grippers, designed to mimic human fingers, have shown great potential in the automated food handling industry. Due to their highly compliant and flexible characteristics, they could handle rigid or delicate soft food samples of different shapes and sizes, superior to their rigid-bodied counterparts with a lower manufacturing cost and higher flexibility. Individually reconfigurable soft gripper systems, consisting of three or more fingered grippers, has been developed, which could further boost the efficiency and productivity as its dynamic gripping range has been greatly improved. However, the soft nature of gripper and food object also significantly increases the operation complexity. In real application, we generally cannot pre-program all the situations due to the complex scenario in the food pick-and-place task. Therefore, how to automatically adjust the fingers to pick and place an item with the best chance of success becomes a main concern in the food industry application. To address this challenge, this work proposed a data-driven decision strategy to determine the optimized gesture of the reconfigurable gripper system to handle a food object. Firstly, we have established an efficient simulation model to predict the mechanical behavior during grasping, and extract useful information such as reaction forces, with reasonable accuracy. The target items to grasp have been simplified as quadrilaterals, and then parametrized within a fair range. The grasping gestures have also been parameterized within the dynamic operation range of the soft grippers. Then we used the simulation model to generate a large database for different combinations of gripping gesture and objects of various shapes and sizes. Subsequently, we built a surrogate artificial neural network model that can make fast prediction of the mechanical performance of the soft gripper system on a given item of arbitrary design parameters. Finally, this surrogate model was used in an optimization algorithm to obtain the optimized grasping gesture, aiming to enhance the success ratio for picking up the target object. With the help of an object detector, the established model and strategy is expected to provide real-time advice on the optimized gripping gesture to achieve the best grasping success ratio.

NOMENCLATURE

L = the distance between the thumb and the center in mm
α = the rotation angle of finger B/C in degree
β = the rotation angle of the gripper system in degree
x_i = the x coordinates of top and bottom vertices. Unit: mm
y_i = the y coordinates of top and bottom vertices. Unit: mm
RF_1 = the reaction force of the thumb
γ_1 = the regularization items
γ_2 = the regularization items
$y_{i,new}$ = the new y coordinates of the vertices of the rotated object

1. Introduction

Inspired by how human fingers handle objects, soft grippers have been engineered exhibiting highly compliant and flexible characteristics. When grasping objects of different shapes and sizes, they can easily morph to the contacting surfaces and handle the objects securely [1]. Recently, soft grippers have shown great potentials in food industry, such as handling eggs, fruits, and vegetables [2–5]. Superior to their rigid-bodied counterparts, these flexible soft grippers can handle delicate food objects without doing damages and at a lower manufacturing cost. Reconfigurable soft gripper systems usually consisting of more than one soft actuator and provides more compatibility and higher efficiency than their rigid counterparts. However, the soft nature of gripper and food object also significantly increases the operation complexity. In real applications, we generally cannot pre-program all the situations due to the complex scenario in the food pick-and-place task. Therefore, how to automatically adjust the fingers to pick and place an item with the best chance of success becomes a main concern in the food industry application [2,6]. To address this challenge, this work proposed a data-driven decision strategy to determine the optimized gesture of the reconfigurable gripper system to handle a food object.

2. Methodology

2.1 Parameterization of a Food Object and Grasping Gesture

We consider a three-fingered reconfigurable finger system [5] for automated handling chunked food objects, such as potato blocks and broccoli. The soft gripper system consists of three individually reconfigurable finger modules actuated by pneumatic pressure. The position of the fingers is programmable via their mobile base. The thumb, indicated as A in Fig. 1(a), can move forwards and backwards with a linear displacement of up to 20mm. The other two fingers rotate synchronously about the center of the gripper system. Besides, the fingers can rotate together while their relative positions are maintained. Therefore, the grasping gesture of the reconfigurable gripper system is easily characterized by three parameters: L representing the distance between the thumb and the center, α representing the rotation angle of finger B/C, and β representing the rotation angle of the gripper system. The operation ranges for these parameters are listed in Table 1.

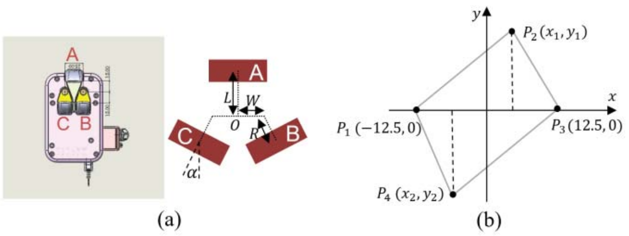

Fig. 1 Parameterization of the grasping gesture of the reconfiguration gripper system (a) and a quadrilateral food object (b)

Table 1 Parameters to define a grasping gesture of the gripper system

Notation	Range	Description
L	$[15,35]$	The distance between the thumb and the center. Unit: mm
α	$[0°, 90°]$	The rotation angle of finger B/C in degree
β	$[0°, 360°]$	The rotation angle of the gripper system in degree

The food object may have a variety of shapes and sizes. We assume it can be simplified as a quadrilateral with two vertices fixed while its shape can be tuned by varying the locations of the remaining two vertices, as shown in Fig. 1(b). Additional constraints have been set to avoid shapes that are unreasonably singular or beyond the working scope of the gripper system, which have been summarized in Table 2. Note that the distance between the vertex P_1 and P_2 is representative, and we further assume that the similar quadrilaterals of different size should share a similar grasping gesture. The heights of the object are fixed as 30mm for simplification.

Table 2 Parameters to define a quadrilateral food object

Notation	Range	Description
x_i	$[-12.5, 12.5]$	The *x* coordinates of top and bottom vertices. Unit: mm
y_i	$[5, 30]$	The *y* coordinates of top and bottom vertices. Unit: mm

2.2 Simulation Automation

We use python scripts to randomly generate quadrilateral blocks geometry parameters and different grasping gestures for each block using Latin Hypercube Sampling method. The CAD models are firstly generated by scripting with FreeCAD, and the cases are modelled and simulated in SOFA-Framework, which is a finite element analysis platform for soft robotic simulations and has been validated with ABAQUS and experiments in our previous work [7]. The reaction force between the thumb finger and the food object is extracted to characterize the grasping performance of the soft gripper system on the target object.

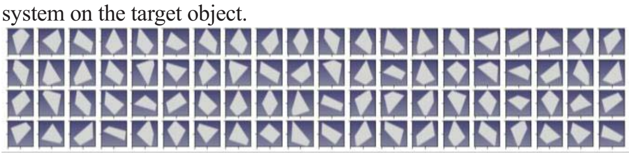

Fig. 2 Selected randomly generated quadrilateral blocks for grasping simulation in SOFA

2.3 Machine Learning and Optimization Model

XGBoost, which stands for eXtreme Gradient Boosting package, is a widely used, highly efficient and scalable gradient-boosted decision tree machine learning method [8]. In this work, we use XGBoost to establish a surrogate model for predicting reaction forces. To guarantee the rotation angle β is smooth and periodic, we encode it as $(\sin\beta, \cos\beta)$ and decode it using $\arctan2(\sin\beta, \cos\beta)$. The gripper system is kept still (except rotating finger B/C) in the simulation, as it is convenient to rotate/move the food object to achieve equivalent gestures. The input parameters for the XGBoost model are $X_1 = \{x_1, x_2, y_1, y_2, \alpha, L, \sin\beta, \cos\beta\}$. Here we assume that success rate of picking up an object is directly related to the reaction force of thumb, and the larger the reaction force, the higher the success rate. The output of the model is the reaction force of thumb $f(X_1) = \{RF_1\}$.

After the XGBoost model is trained and validated, it will be used to predict the reaction forces for given arbitrary objects. Then we adopt the particle swarm optimization (PSO) solver [9] to optimize the grasping gesture, i.e., to identify the best gesture that corresponds to the largest reaction force. Equivalently, the optimization model can be defined as minimizing a loss function $f(X)$

$$\min \quad f(X) = -RF_1 + \gamma_1\alpha + \gamma_2 \sum_{i=1}^{4} y_{i,new}^2$$

Where the $X = \{\alpha, L, \sin\beta, \cos\beta\}$ are the parameters to be determined by the PSO solver, $-RF_1$ is the reaction force of thumb. γ_1 and γ_2 are the regularization item to define preferrable grasping gestures, which are imposed to smooth the loss function and achieve a more consistent minimal result. This is based on the experience that smaller rotation angles of finger B/C usually perform better in the experiments, so α is included in the objective function with a carefully chosen weight factor γ_1. $y_{i,new}$ are the new y coordinates of the vertices of the rotated geometry. This term is based on the the consideration that a flat potato orientation is generally preferable compared to a tall orientation.

3. Results

A total of 400 quadrilateral blocks and 200 grasping gestures for each block are generated. Therefore, a total number of 80 000 data points are collected. 95% of the total database is used for training the

XGBoost model while the rest 5% is used for testing. Fig. 3 compares the predicted (orange dots) and actual (blue dots) reaction forces of the thumb for all the training sets and test sets. Most of the orange dots overlap blue dots, showing that the XGBoost model can make reasonable replication and prediction over all datasets. To statistically characterize the performance of the trained XGBoost model, the coefficient of determination R^2 is calculated with a value exceeding 0.92, which indicates a good fitting effect. Fig. 4 plots the predicted reaction force against the actual data, which shows that the prediction of the model is desirable and acceptable.

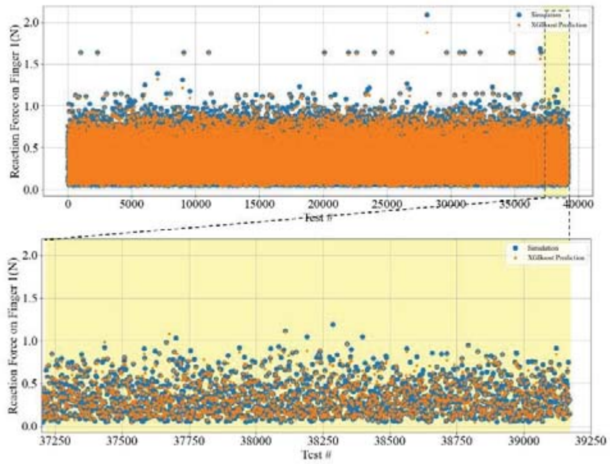

Fig. 3 Comparison between XGBoost predictions and the true values from simulation.

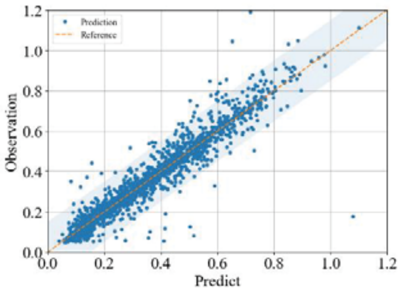

Fig. 4 Predicted versus actual reaction forces of the XGBoost model

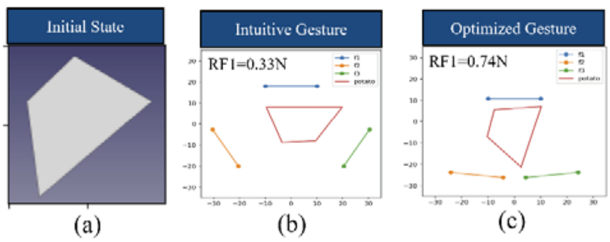

Fig. 5 Initial state of the target object (a) and intuitive gesture (b) and optimized gesture (c). The positions of finger A/B/C are indicated as blue, orange, and green lines respectively. Instead of rotating the gripper system, the object is rotated accordingly for easier implementation in the simulation.

As a simple validation, Fig. 5 shows the initial state of a randomly generated object within the parameters' range, and an intuitive gesture and the optimized gesture from PSO. From an intuitive guess, the gripper system may possibly pick up the object with the longest edge aligned with the finger A. The reaction force from the simulation is about 0.33N. However, the PSO result suggested a different gesture with a simulated reaction force of 0.74N, which is more than twice of the value with the intuitive guess and guarantees a higher success rate of grasping. The example clearly shows the effectiveness of the established surrogate model and the optimization model. This result has also been verified in the experiments.

4. Conclusion

In conclusion, the current work presents a simulation-based data-driven scheme to assist the gesture selection for reconfigurable gripper system. Firstly, we generated a large database from an efficient and accurate simulation model to store the information on the mechanical behavior of the gripper system when grasping an object. Then, we utilize a surrogate model and optimization algorithm to enhance the success rate of picking up an object. We demonstrated in an example that the grasping gesture can be significantly improved by the established model. With the help of an object detector, the established model and strategy is expected to provide real-time advice on the optimized gripping gesture to achieve the best grasping success ratio.

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REFERENCES

1. Trimmer B. "Soft robots." Current Biology. Vol. 23, No. 15, pp. R639–41. 2013.
2. Terryn S., Brancart J., Lefeber D., Van Assche G., and Vanderborght B. "Self-healing soft pneumatic robots." Sci. Robot. Vol. 2, No. 9,. 2017.
3. Jain S., Stalin T., Subramaniam V., Agarwal J., and y Alvarado P. V. "A Soft Gripper with Retractable Nails for Advanced Grasping and Manipulation." In: 2020 IEEE International Conference on Robotics and Automation (ICRA)., pp. 6928–34. 2020.
4. Subramaniam V., Jain S., Agarwal J., and Valdivia y Alvarado P. "Design and characterization of a hybrid soft gripper with active palm pose control." Int. J. Robot. Res. Vol. 39, No. 14, pp. 1668–85. 2020.
5. Low J. H., Khin P. M., Han Q. Q., Yao H., Teoh Y. S., Zeng Y., et al. "Sensorized Reconfigurable Soft Robotic Gripper System for Automated Food Handling." IEEE/ASME Trans. Mechatron., pp. 1–12. 2021.
6. Sinatra N. R., Teeple C. B., Vogt D. M., Parker K. K., Gruber D. F., and Wood R. J. "Ultragentle manipulation of delicate structures using a soft robotic gripper." Sci. Robot. Vol. 4, No. 33,. 2019.
7. Liu J., Low J. H., Han Q. Q., Lim M., Lu D., Yeow C. H., et al. "Simulation Data Driven Design Optimization for Reconfigurable Soft Gripper System." IEEE Robot. Autom. Lett.

Vol. 7, No. 2, pp. 5803–10. 2022.

8. Chen T., and Guestrin C. “Xgboost: A scalable tree boosting system.” In: Proceedings of the 22nd acm sigkdd international conference on knowledge discovery and data mining., pp. 785–94. 2016.

9. Kennedy J., and Eberhart R. “Particle swarm optimization.” In: Proceedings of ICNN’95 - International Conference on Neural Networks., pp. 1942–8 vol.4. 1995.