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Simulation Data Driven Design Optimization for Reconfigurable Soft Gripper System

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Abstract— **In the soft gripper design work, most of the designs such as gripping width and the design of finger actuator are purely based on experience, and repeated trial-and-error. In most scenarios, the designed actuators cannot achieve the best/optimized grasping performance with a specific design type. This optimized design is important especially for the food grasping application, as a minor improvement of the grasping capability will be helpful to increase the grasping success ratio, especially during high-speed pick and place tasks. That motivates us to develop a design optimization framework, focusing on how to achieve an optimized grasping performance with a multi-objective design optimization. In this work, a simulation aided data-driven optimization framework for guiding the design of a reconfigurable soft gripper system is presented. To achieve an effective optimization, a simulation model is developed based on the Simulation Open Framework Architecture (SOFA) platform. This model can predict the bending and grasping behavior under actuation and external loading. This model is then used in a data-driven design optimization framework for optimizing the actuator design. An artificial neural network (ANN) is built based on the simulation results as training data, and used as a surrogate model in a multi-objective optimization framework, to achieve an optimal grasping capability with design constraints. This simulation and optimization capability can significantly reduce the trial-and-error design work, and has a great potential for effectively developing soft robots in industrial applications, such as food manufacturing and health care.**

I. INTRODUCTION

In the food manufacturing industry, much of food assembly is still carried out manually, presenting opportunities for robotic automation to be applied [1]. For many years, rigid robotic grippers or vacuum systems have been employed in the automation process [2]. However, without proper force control algorithms, the rigidity of these grippers often damages delicate food items, while vacuum systems only work with items that provide clean and flat surfaces [3]. An alternative to the rigid robotic gripper is the soft robotic gripper. Soft robotic grippers can manipulate their shape in line with external reaction forces, instead of resisting them [4]. While maintaining cost and system complexity, these grippers can easily accommodate a wide range of delicate food items for assembly. However, current soft robotic grippers available in the market, such as Suzhou Rochu Robotics *Co., Ltd.* and Soft Robotics *Inc.*, still face issues for improving grasping success ratio [5], [6], since different food items and even similar food items may have very different food geometry.

The key challenge in enhancing the grasping performance is that how to design the soft finger actuator for achieving the best desirable behavior and what is the best grasp pose to handle the items. Up to date, most of the soft actuator design works are purely trial-and-error based, relying significantly on the designer's intuition and experience. In designing soft actuator and gripper for food industry application, a better grasping capability with small pressure actuation is always desirable, which may be efficient in energy consumption and provide greater grasping flexibility.

To optimize the behavior of soft actuator and gripper system efficiently, numerical models are generally required and adopted. Several mathematical models have been proposed to study the behavior of finger actuators [7]. Theoretical models are widely used in predicting the behavior of rigid robotics, because they are very computationally efficient and predictive. However, for soft and hybrid robotics, as the robotics configurations and environment are generally complex, most of these models can only be applied to specific designs and geometry, as well lack generalization ability. The theoretical models are also challenging to deal with contact occurrence, as mostly the environmental factor cannot be predicted in-prior.

Considering the complex situations of soft robotic grasping applications, a simulation tool to help robotic optimization, prototyping and effective control is required. Various simulation tools are available in the commercial market or open-source community, which can be generally categorized into two types. One type focuses on rigid multi-body dynamics such as V-Rep [8], Gazebo [9] or Adams, which adopts physics engines for multi-body collision and interaction, such as PhysX [10] or Bullet [11]. They can be very effective for traditional rigid robotics, whose primary concern is trajectory planning, collection detection, and motion control. However, they generally cannot deal with deformable material, which is essential in the soft robotic research and application community. Another type of simulation methodology is traditional general-purpose commercial Finite Element Method (FEM) software, such as Abaqus or Ansys. While they can accurately solve the deformation of soft bodies, as their modeling functions and solvers are not specifically designed for robotic simulations, they may not be the best candidate for these applications.

In the last few decades, various shapes and designs of soft

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robotics have been developed for fulfilling different tasks. Even though we may have a qualitative description of what function we expect the soft robotic to achieve, it is generally difficult to figure out a precise quantitative measure to help us select the "best" design, which prevents a rigorous optimization task. Up to date, most of the soft robotics design works are purely based on intuition and experience, with repeated trial-and-error tests. This is not cost-effective and cannot guarantee to achieve the optimal design. Few research have been evident to specifically work on the soft pneumatic actuator design optimization. Chen et al. and Zhang et al. [12], [13] adopted topology optimization method for designing a soft cable-driven gripper, while they are not a suitable method for design pneumatic actuator. Chen et al. [14] used BESO based topology optimization to design a soft pneumatic actuator, and Wang et al. [15] used parametric optimization for the designing. Yang et al. [16] conducted a simulation aided optimization work, based on the rotation angle during actuation. However, most of these works simply treat the design objective simply as displacements under actuation, and linear system behavior is assumed. This objective function focus on the stiffness property of the actuator, while it cannot sufficiently represent the requirement to best achieve its function in a grasping task. Because of various functions that soft robotics could undertake, there is no general guideline on how to define the objective function for a specific job. As a result, design optimization becomes a big challenge for soft robotics research and development practice.

In light of these issues, we aim to have a simulation tool that is fast, highly configurable and extensible, while maintaining reasonable accuracy. Commercial software such as Abaqus is a general and powerful FEM software, with a lot of capabilities. Their extensive pre-processing, error-check, and treatment of nonlinear solver is focusing more on general problems, and not optimized for a specific task. Generally, at least hundreds or thousands of simulations are required to build up the surrogate model in an optimization job. When a large amount of simulation run with similar lightweight scenarios is required, this overhead will be a big burden. One available software that comes close is Simulation Open Framework Architecture (SOFA), which is a highly efficient and interactive framework for physics-based simulations [17]. This software has been further developed to investigate various types of soft robotics [18], which demonstrates its highly configurable and extensible capability. Compared with traditional commercial FEM software, SOFA adopted a mapping strategy together with a Lagrangian multiplier to simplify the contact resolution, enabling it to address the contact problem fast without sacrificing much accuracy. The contact solver in SOFA follows a "free motion" to "contact detection", and to "contact response" strategy [19]. Unlike the solvers in Abaqus which try to solve the mechanics motion and contact response simultaneously, the sequential strategy used here can guarantee a result (i.e. improve convergency) without too many iterations and gain faster computational efficiency. Although this improvement is achieved by paying the price that model penetration may occur with a large time step, it is still attractive in simulations with many contacts to be solved. Besides, this SOFA platform can also be integrated with various hardware, making it suitable for robotics research and application. Last but not least, SOFA adopted a scene-based architecture, just like many other robotic simulation tools, for users to rapidly construct and config the simulation model. With open-source software in nature, massive parallel jobs can be performed simultaneously, which is only limited by the number of machines, but not by the number of commercial software licenses. However, little benchmark and numerical validation work have been done on this SOFA platform.

In this paper, we present some benchmarking work to demonstrate the efficiency of SOFA simulation platform for the single soft finger deformation behavior. A simulation model to analyze the soft finger actuator and extend this analysis to grasping performance of the soft robotic gripper using different grasping configurations and scenarios for the gripper optimization is proposed. A soft robotic gripper system that consists of three 3D-printed soft pneumatic actuators and a reconfigurable gripper base for versatile grasping is developed to validate the simulation results. This model is then used for generating data at various design points in a design of experiment (DOE), and used as training data in a data-driven artificial neural network (ANN) to generate a surrogate model. This model is then used in a multi-objective optimization scheme, to work out ideal design parameters for achieving the best grasping capability under certain constraints. The entire simulation-aided data-driven design optimization scheme can be extended to a more general soft robotic design context.

The main contribution of the work is that we proposed a design optimization framework and guideline for this pneumatic type of actuator. We suggested that the design objective has two aspects, one is the center of gravity (COG) position that will make the actuator more stable during working, the other one is the bending reaction force which will be helpful in increasing the grasping capability. Both objectives have not been found and deeply investigated in other literatures using simulation. Consequently, the proposed multi-objective design optimization framework can provide a design that behaves well specifically for the food grasping objective.

This paper is the first in the robotics community to validate the accuracy of SOFA simulation results for a soft pneumatic gripper system, proposed the multi-objective functions specifically for the grasping task, and developed the data-driven based design optimization aided by the simulation model proposed. To the best of our knowledge, limited existing literature has used simulation results data-driven surrogate model to do a mathematical design optimization for soft gripper. Also, no published research work has proposed this bending reaction force and COG offset as objective functions, for an optimization design. We could claim that both objectives are essential in our soft actuator design for food grasping tasks.

This research is organized as follows: In Section II, several methodologies have been introduced, including the actuator prototype design, simulation models, and optimization objective. In Section III, numerical modeling is highlighted and experimental validation is conducted. In Section IV, the entire design optimization framework is introduced, and results are presented and analyzed. The conclusions and discussions are given in Section V.

II. METHODOLOGY

A. Soft Finger Actuator Design

The finger actuator was directly 3D-printed with a type of commercially available thermoplastic elastomers, NinjaFlex filament (NinjaTek, Manheim, PA). NinjaFlex was chosen due

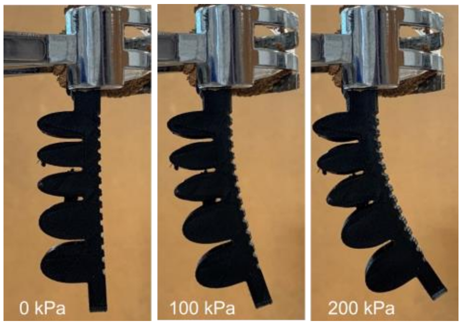
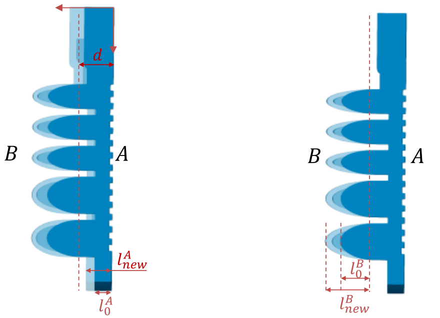


Fig. 1. Photograph of the finger actuator at different air pressures (0 kPa, 100 kPa, 200 kPa).

to its excellent printability and good flexibility. The printing parameters such as layer height, infill settings and temperature settings were presented in our previous work [20]. The finger actuator adopts a bellows-type air channel design, and can be actuated to different rotation angle with different applied actuation pressure, as shown in Fig. 1. Compared to the ribbed-type [21] and tubular-type [22] designs, bellows-type actuator requires lower operating air pressure to achieve same bending profile as the excess material in the bellows unfolds upon pressurization, which results in less strain acting on the material [23]. This will also enhance the durability of the actuator by minimizing the fatigue of the material.

B. *Simulation model of soft actuator*

The single finger actuator model was built with the SOFA framework. Subsequently, a solid model of the actuator was obtained from 3D CAD software and meshed in Gmsh with 35,140 tetrahedron linear elements. The meshed file was used in SOFA for the FEA simulation of the deformation analysis under internal pressure actuation. To simulate the mechanical behavior of the actuator, a reasonable "ForceField" should be selected in SOFA. "ForceField" is the term used in SOFA to describe the force added on the object, which can be either internal or external. Internal force corresponds to the constitutive response of the deformable body, and external force represents the external loading, such as gravity or pressure applied [17]. Based on the simulation requirement, various constitutive force fields are available. Some can achieve fast computational speed, while cannot obtain a reasonable simulation result for large deformation large rotation scenarios. Generally, hyperelastic material model should be used for modeling the mechanical behavior of rubber-like material to get a meaningful result, such as Ninjaflex in this work. We note that for this specific application, the stretch deformation of the actuator is generally below 50%. In this case, different hyperelastic models could yield very similar stress-strain responses [24]. To keep the model simple, we chose Neo-Hookean hyperelastic model in this study, and used the shear modules $\mu = 2.93$ MPa for the printed Ninjafelx component, which can be found in literature [24]. Based on these analyses and considerations, we chose the *TetrahedronHyperelasticityFEMForceField* as the constitutive response in SOFA.



$\xi_1 = (l_{new}^{A} - l_{0}^{A})/l_{0}^{A}$
$\xi_1 \in [-0.2,1]$
For all the points in region A

$\xi_2 = (l_{new}^{B} - l_{0}^{B})/l_{0}^{B}$
$\xi_2 \in [-0.5,1]$
For all the points in region B

Fig. 2. The parametrized soft actuator geometry and design space.

C. *Parametrized geometry for design optimization*

Two main aspects to be considered in an optimization task are 1) Parameterize the design space, and 2) select an appropriate design objective. Both aspects are difficult to determine in a soft pneumatic actuator design job, and have been investigated in limited literatures. In this section, we will address these two aspects, for this specific soft actuator design for grasping tasks. As there is no universal rule or standard on the design of soft pneumatic actuator, its geometries and topologies can change a lot based on the task requirement, yielding a challenging task for parametrizing the CAD model. Endeavors have been conducted for the CAD-based parameterization work [25], [26], while both works focus mainly on establishing a good representation for the mesh relating to the CAD model. In these studies, a good parameterized CAD model is required for the geometry representation, which is generally not available for most soft robotics design practices. In this study, we first analyze the design configuration for the soft actuator illustrated in Fig. 2. Similar to many other pneumatic actuator types [27], this design also contains the "stretchy" region B, which will expand significantly when pressurized, and the "strain limiting" region A, which will restrict the amount of strain that occurs. This difference in strain will yield desired bending motion behaviors. Based on this mechanism, we may intuitively consider that region A controls the flexibility of the actuator, which can enable the good bending behavior of the actuator, while region B controls the rigidity of the actuator, which may provide the strong grasping capability. Increasing the width of region B can increase the bending capacity, while this will cause a large offset of the center of gravity (COG), and hence also increase the instability during working. Increasing the width of region A can increase the contact force during grasping, but it will reduce the flexibility and also yield a large offset of COG. This large offset of COG and bending curvature will cause instability during high-speed movement especially under external stimulus. Therefore, balancing all these effects and achieving an optimal geometry is the key issue to consider during the design. Generally, we desire with the least COG offset value, to achieve the largest grasping capability. This leads to a multi-objective optimization problem.

Since original parameterized CAD model is not available, model parameterization is realized by directly modifying the mesh file through the VTK library [28]. To reflect the influence of region A and region B, we artificially partition the actuator model into two sections, which has been indicated by the dashed line in Fig. 2. Then the widths of these two regions are set as the design parameters separately. Two parameters ξ_1 and ξ_2 are used to indicate the change of the thickness values, which are defined as $\xi_1 = \frac{l_{new}^{A} - l_{0}^{A}}{l_{0}^{A}}$ and $\xi_2 = \frac{l_{new}^{B} - l_{0}^{B}}{l_{0}^{B}}$ where l_0^A is the distance of mesh vertices to the reference base plan $x = 0$

(refer to the coordinate system in Fig. 2) in the original design, and l_{new}^{A} is the mesh vertices in the new design space. The similar definition also applies to l_0^B and l_{new}^{B}, only that the reference base plan is located at the dashed line where $x = d$.

To modify the mesh vertices autonomously, a programme *moveNodePoints* is developed to move the mesh vertices positions of the original design according to the design parameters ξ_1 and ξ_2, and export the new revised mesh as

$$\text{new\_mesh} = \textit{moveNodePoints}(\text{orig\_mesh}, \xi_1, \xi_2)$$

Therefore, as a summary, we may define the optimization problem:

$$\begin{aligned} &max \quad f_1(\xi_1, \xi_2)\ which\ is\ the\ reaction\ force \\ &min \quad f_2(\xi_1, \xi_2)\ which\ is\ the\ COG\ offset \\ &s.t. \qquad \xi_2 \in [-0.5,1], \qquad \xi_2 \in [-0.5,1] \end{aligned}$$

where the constrains $\xi_1 \in [-0.2,1]$ and $\xi_2 \in [-0.5,1]$ are selected to maintain a reasonable design that not distorted too much.

III. EXPERIMENTAL CHARACTERIZATION AND SIMULATION MODEL VALIDATION

In this section, we introduced the experiments design for simulation model validation. Two sets of experiments were conducted to validate the simulation results. The first set of experiments check the behavior of a single finger actuator. Both bending profiles and bending force corresponding to various air pressures were measured to characterize the performance of the finger actuator. The other set of experiments investigates the bending profile of the thumb and one of the finger actuators while grasping various food items.

A. Characterization of Single Finger Actuator

1) Experiments

To obtain the bending profile, the proximal end of the actuator was clamped on a retort stand and images of the inflated actuator corresponding to various air pressures were captured using a camera. The bending angle was obtained by analyzing the images using the Tracker analysis tool. To evaluate the bending force of the actuator, a force sensor is placed in front of the actuator's free end, to capture the bending force value during pressurization. The bending force can be directly obtained from the sensor readout. Three actuators were tested to obtain mean values of bending profile and bending force corresponding to air pressures ranging from 0 kPa to 250 kPa at an incremental step of 25 kPa. The standard deviations are negligible to be plotted in the figure, so only the mean values were used for the simulation characterization and validation.

2) Benchmark simulations

Bending profile and force sensor testing results were examined. For the bending profile testing, SOFA simulation results were compared with Abaqus simulation results, as well as the experimental observation as shown in Fig. 3(a). It shows that simulations can reasonably predict the motion can mechanics behavior of the actuator at different applied pressures. The 1st, 2nd and 3rd columns are the Abaqus simulation results, SOFA simulation results, and experimental observations, respectively. The 4th column is the overlapping view of these three results, which indicates that they have a very good match. Quantitative measurement of bending angles is plotted in Fig. 3(b). The root-mean-square error (RMSE) is used to evaluate the deviation from simulation results to experiment, and we got RMSE= 2.07° from SOFA and RMSE=3.19° from Abaqus. It shows that both Abaqus and SOFA can achieve good agreement compared to experimental measurement, demonstrating the model's validity on both simulation platforms.

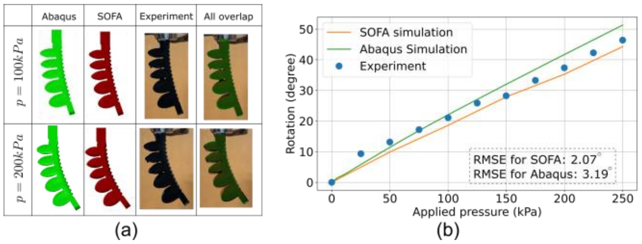


Fig. 3. A qualitative and quantitative comparison between SOFA simulation results, Abaqus simulation results and experimental observation at various applied air pressures. (a) Bending profiles at applied pressure 100kPa and 200kPa, for Abaqus, SOFA, and experiment. An overlapping view of all the three results for each applied pressure value is also presented. (b) Plot of rotation angles at various pressures up to 250 kPa, for SOFA, Abaqus, and experiment.

Fig. 4 presents the results of bending force tests. The green one (a) is the profile of soft actuator with Abaqus simulation, the red one (b) is the result with SOFA, and (c) is the illustration of the experiment test. The plot in Fig. 4(d) quantitatively shows the reaction force at various applied pressure up to 250 kPa, for Abaqus, SOFA and experiments. This plot shows that there is a "turning point" at applied pressure around 175 kPa, where afterward the reaction force has a faster increasing speed compared with the initial stage. This "turning point" is caused by the occurrence of contact between the airbags. It is evident that both Abaqus and SOFA models can accurately capture this point and correctly predict the trend. This result validates that both Abaqus and SOFA simulations can achieve reasonable accuracy, considering contact occurrence in the simulation.

The computational time is also evaluated for both Abaqus and SOFA simulation as in Fig. 4 (d). With the same 35140 linear tetrahedra elements in the model, Abaqus took 91 s to finish the entire simulation, while SOFA only takes 40 s. The time increase mainly comes from the less overhead time to process the model, and the handling of contact problem. This difference is not essential in such small model, but if thousands of simulations are required, the time difference will be significant. The RMSE is used to evaluate the deviation from simulation results to experiment, and we got RMSE=0.041 N for SOFA and RMSE=0.035 N for Abaqus.

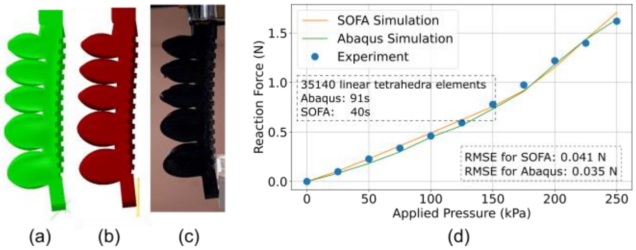


Fig. 4. A qualitative comparison of the actuator profile at applied air pressure 250kPa for (a) Abaqus simulation results (b) SOFA simulation results (c) experimental observation. Quantitative comparison at various applied air pressures up to 250kPa are illustrated in (d).

The benchmark simulation results showed that SOFA could

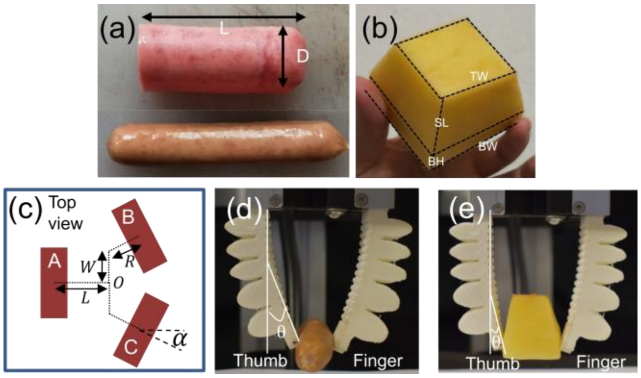


Fig. 5. (a) Sausage samples with short and long length. (b) Potato sample with dimension illustration. (c) Setup of gripper system configuration. (d-e) Measurement of bending profile (rotation angle) for thumb and finger actuators when grasping sausage and potato.

achieve good results within accepted tolerance in a shorter time, compared to Abaqus simulation results and experimental measurement. This conclusion gives us confidence to use SOFA as the simulation platform to continue this work.

B. Characterization of Gripper System Design for Grasping Food Objects

1) Experimental design

A gripper consists of three adjustable finger modules, and each module was connected to a stepper motor. The finger modules can be arranged to different grasping configurations such as scoop (both fingers placed closest to the thumb), pinch (two of the fingers placed at an angle of 180° from the thumb) and claw (all three fingers placed at various degrees apart) to manipulate objects with different sizes and shapes. Finger configurations can be controlled via a user interface, allowing the gripper to adapt to target items with a larger size and shape range. This allows the gripper to handle different types of food items in complex grasping scenarios.

Two food items (sausage and potato) in different sizes were grasped by the gripper at various air pressures, ranging from 200 kPa to 300 kPa at an incremental step of 25 kPa (Fig. 5(a) and (b)). The gripper was formed by three finger actuators system, and mounted on a collaborative industrial robot arm (UR 5e). The configuration for the finger actuator's position is illustrated in Fig. 5(c). During operation, the arm firstly approached the item, which was already placed at the fixed pick-up location. Once the arm reached the item, it stayed in position for 2 seconds to allow the actuators to be actuated to the corresponding air pressures. Next, the gripper picked the object and the arm moved up. An image was then captured using a camera and the bending angle was obtained by analyzing the image using the Tracker analysis tool, as illustrated in Fig. 5(d) and (e) for sausage and potato, respectively.

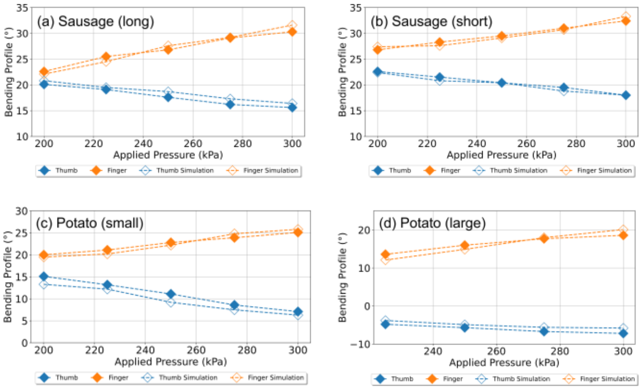


Fig. 6. Comparison of experimental measurement and SOFA simulation results for sausage and potato with different dimensions.

2) Model construction and simulation

To calibrate the friction coefficient value between potato and the actuator material (NinjaFlex), a cubic potato with dimension 33 mm × 33 mm × 32 mm was cut and grasped by the gripper system. Actuation pressure was examined from 100 kPa to 200 kPa, with an interval of 5 kPa, to determine the minimum pressure required to pick up the potato successfully. A simulation model was built in SOFA based on this experimental setup, to evaluate the proper friction coefficient value that can also achieve this minimum actuation pressure. Experimental observation showed that the minimal pick-up pressure was 150 kPa, yielding a prediction value of friction coefficient to be 0.38 based on the SOFA simulation.

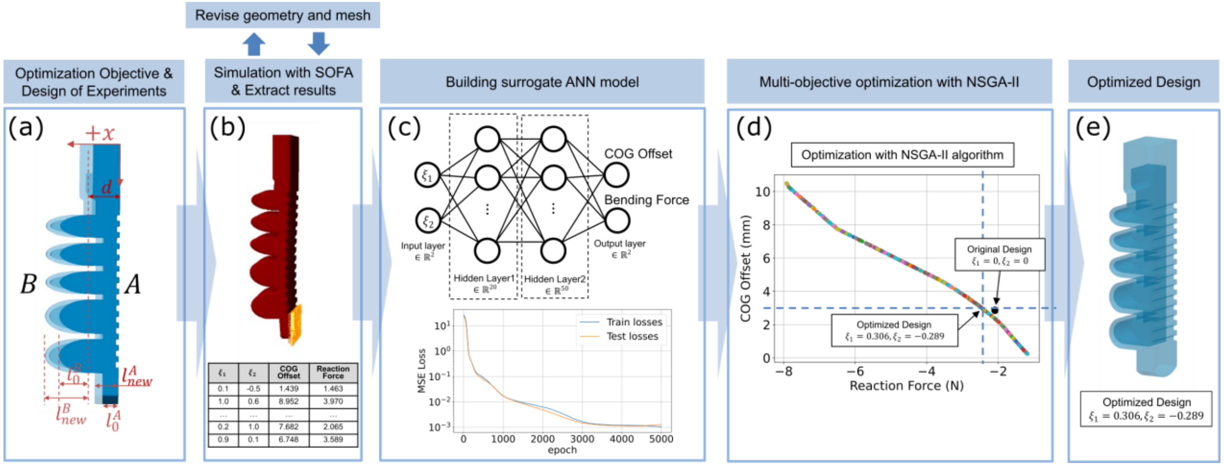
The entire gripper system was modeled in SOFA. Relative positions of the finger actuators followed the experimental setup, based on the configuration illustrated in Fig. 5(c), where A is the thumb module, while B and C are the figure modules. The configuration of the system is parameterized by L, W, R and α. L is the distance from the center of A to the center of gripper system O and W controls the offset of the "rotation center" of fingers B and C. R is the corresponding distance for fingers B and C to their respective rotation center, with α controls the rotations angle. $\alpha = 0$ represents the "claw" gesture, and $\alpha = 90°$ represents the "pinch" gesture. The base of the fingers was fixed at the initial stage, and could be moved through a prescribed trajectory. When the gripper approached the item, actuation pressure was applied on the internal surface of the finger cavity. After stabilization, the gripper was programmed to move upward, and the object was picked up accordingly. When the entire system had stabilized, the finger deformation profile was extracted, and the bending profile was evaluated as what was done in the experiment. Fig. 5(d) and (e) show that the measurement of rotational angle α when grasping sausage and potato.

Four different food samples were used in this testing, i.e. long sausage, short sausage, small potato, and large potato. Measurements of bending angle were conducted on the thumb and finger actuator, at an interval of 25 kPa actuation pressure, to quantitatively compare the bending profile between simulation results and experimental measurement. The results are illustrated in Fig. 6, demonstrating that the simulation model with SOFA framework can well predict the deformation profile and grasping behavior for the gripper system.

IV. SIMULATION DATA-DRIVEN OPTIMIZATION OF GRIPPER DESIGN BASED ON THE SOFA SIMULATION PLATFORM

A. A workflow of simulation data-driven multi-objective optimization design

In the previous sections, the numerical model is validated through a series of benchmark grasping tests. In the section, a simulation data-driven design optimization workflow is proposed by the aiding of this model. The entire workflow is illustrated in Fig. 7. This workflow begins from soft actuator prototyping and parametrization, as shown in Fig. 7(a), which



ξ_1	ξ_2	COG Offset	Reaction Force
0.1	-0.5	1.439	1.463
1.0	0.6	8.952	3.970
...	...	...	...
0.2	1.0	7.682	2.065
0.9	0.1	6.748	3.589

Fig. 7. The workflow of simulation data-driven multi-objective optimization design.

has been demonstrated in Section II (C). After that, the model will be simulated in SOFA simulation platform, by iterative changing geometry and mesh based on the DOE with python scripting. The simulation results will be extracted and stored without any human inference, as shown in Fig. 7(b). The data will be used as training/testing for the ANN model in Fig. 7(c), and a multi-objective optimization with NSGA-II algorithm will be implemented with the aid of the surrogate ANN model in Fig. 7(d). Finally, the optimized design (Fig. 7(e)) can be achieve based on evaluating the trade-off between grasping performance and stability on the Pareto front obtained. As Fig. 7(a) and Fig. 7(b) have already been explained in Section II and III, the Fig. 7(c) and Fig. 7(d) will be explained in detail in this section.

B. *Artificial Neural Network (ANN) model and multi-objective optimization*

To build the surrogate ANN model, we implemented a python script to invoke *moveNodePoints* (as in Section II) and SOFA for automation of simulation and data collection, and no user intervention is required. The design of experiment (DOE) sampling points are selected to be evenly distributed in the design space. A total of 208 sampling points are evaluated. For each sampling point, the COG offset is extracted in the initial undeformed state, and the reaction force is extracted in the force sensor testing simulation at an applied pressure of 300 kPa. The open-source machine learning framework PyTorch [29] is used for building up this model. Fully connected NN is used in this study. The input layer contains the two design parameters ξ_1 and ξ_2 (as in Fig. 7(a)), and the output layer contains the desired output COG offset and reaction force. Two hidden layers are adopted, with 20 and 50 neuron units, respectively. 80 % of the total data are used for training the ANN, while the rest 20 % are used for testing. After 5000 epochs, the mean squared error (MSE) achieves a low value below 0.001 for both training and testing data, as shown in Fig. 7(c).

The trained surrogate ANN model is then used in a multi-objective optimization scheme. Non-dominated sorting genetic algorithm II (NSGA-II) algorithm [30] is used in this work for solving the multi-objective optimization problem. The implementation is also conducted in Python, with the help of pymoo [31], which is an open-source library with many single- and multi-objective optimization algorithms included. By assigning the population size 1000 and evolving generation 200, we may evaluate the Pareto front as shown in Fig. 7(d). This frontline gives us a guideline on the best design choices by trading off the COG offset and reaction force. A design with a greater reaction force generally requires a design with a large COG offset. Based on these optimization results, the designer of actuator may evaluate based on the current machine setup, and decide an appropriate cut-off point for the COG offset value. This COG offset can immediately give the design that yields the largest reaction force value, which can guarantee the best grasping capability.

Numerical optimization sometimes tends to trap in local minimum for complex nonlinear functions with a large number of crests and troughs, which is indeed the situation we may encounter in this problem. Although the derivative-free optimization algorithm is likely to find a global minimum result compared to the derivative-based algorithm, the quality of the optimization results largely depends on the hyperparameters selected, such as population size (PS), maximum generation number (GN), crossover rate (CR), and mutation rate (MR) in the NSGA-II. Some literatures have studied the effects of these parameters on certain problems [32], [33], but for this specific problem we still have concern whether this algorithm can achieve a stable robust result. Here, we performed a convergence study to investigate the hyperparameters used in the NSGA-II, with the design of experiment (DOE) listed as in Tab. 1.

An exhaustive combination of all the parameters were studied. Mean value (MV) and standard deviation (SD) of ξ_1 and ξ_2 were evaluated by 10 standalone tests for each parameter combination with random seed values. A smaller SD value indicates a more stable and robust optimization result with good convergence. Therefore, for each combination of PS/GN, we only consider the results with smallest ξ_1 SD, and named the parameter combination as the "optimized hyperparameter". Fig. 8(a) and (b) plot the trend of SD for ξ_1 and ξ_2, respectively, at different optimized hyperparameter combinations. It shows that PS should be selected larger than 500, to achieve a good convergence when increasing GN. The most optimal result occurs at the largest value of both PS (1000) and GN (200), which is expected. This convergence study proves that for the current case, we can already achieve stable and robust optimization results with the current optimized hyperparameter combination.

Tab. 1. Design of experiment (DOE) for NSGA-II hyperparameters study

Parameters	**Values**
Population Size (PS)	50 / 100 / 500 / 1000
Generation Number (GN)	10 / 50 / 100 / 200
Crossover Rate (CR)	0.9 / 0.8 / 0.6 / 0.4
Mutation Rate (MR)	0.01 / 0.1 / 0.5 / 0.8

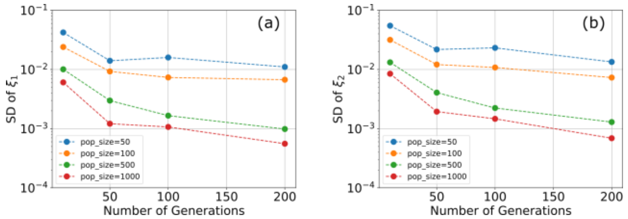


Fig. 8. The convergence study of NSGA-II hyperparameters, with different population size and generation number, at the optimized crossover rate and mutation rate. (a) The plot of standard deviation for ξ_1. (b) The plot of standard deviation for ξ_2

The final optimized design is illustrated in Fig. 7(e), with $\xi_1 = 0.306$ and $\xi_2 = -0.298$, and we name it "Optimal Design with COG offset 3mm" (OD3). This design intuitively gives a larger "strain limiting" region to provide a greater bending force, while reducing the "stretch" region to maintain a reasonable COF offset value, but not reducing too much for keeping the best bending ability.

C. Experimental validation

The modified actuator finger OD3 was printed with the optimized design and same material to validate the optimization results. The same bending force testing was performed with this actuator finger, and reaction forces were measured at various applied pressure up to 250 kPa. Fig. 9(a) and (b) show the profiles of the actuator at 250 kPa in the bending force test for the experimental observation and simulation respectively. The reaction force measured in the experiment is plotted with separate dots in Fig. 9(c) for both original and optimized design, and the corresponding simulated results are plotted with solid line for a quantitative comparison with the experimental measurements. It shows that the simulation can yield reasonable prediction for both original and optimized design. Defining the performance improvement as

$$\phi = \frac{RF_{opt} - RF_{orig}}{RF_{orig}}$$

where RF_{opt} is the reaction force evaluated at 250 kPa for optimized design, while RF_{orig} is the corresponding reaction force for the original design. We may have that $\phi = 12.1\%$ for the simulated prediction, while $\phi = 12.9\%$ for the experimental measurement. These results show that the optimized design is valid, and the entire simulation-aided data-driven design optimization scheme can be helpful in the actuator design.

A further examination of the optimization results was performed by setting the COG offset threshold to 3.5mm and 2.5mm respectively. Based on the Pareto front shown in Fig. 7(d), we can have the optimal design $\xi_1 = 0.374, \xi_2 = -0.229$ for COG offset 3.5mm (OD3.5), and $\xi_1 = 0.236, \xi_2 = -0.363$ for COG offset 2.5mm (OD2.5). Both new designs were printed and tested for the reaction force, and the experimental results are shown in Fig. 9(d). We obtained a performance improvement $\phi = 23.5\%$ for OD3.5, while $\phi = -7.7\%$ for OD2.5. The decreasing in performance for OD2.5 is because of a stricter COG offset constrain compared with the original design. This is meaningful as we need the capability to adjust the optimal design based on the design constrain.

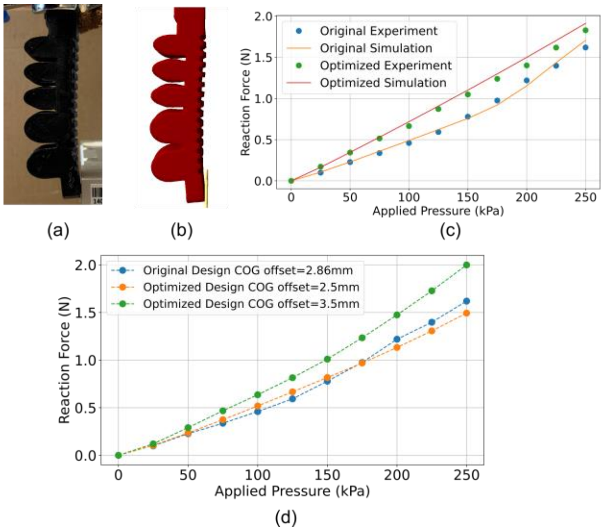


Fig. 9. The profile of optimized actuator in a bending force test of (a) experimental observation and (b) simulation. Quantitative comparison between the original and optimized design for both experiments and simulation are plotted in (c). (d) Shows the experimental tests for optimized design with different COG offset choice.

V. DISCUSSION

In this study, we established a numerical model to simulate mechanical behavior of soft finger actuator with SOFA framework. The model can effectively predict the bending behavior of a single actuator in both bending angle and bending force testings, and achieve reasonable accuracy. Based on this single actuator model, we presented a soft robotic gripper system with three 3D-printed soft pneumatic actuators and a reconfigurable gripper base for versatile grasping. This gripper helps to validate the capability and accuracy of our simulation model built in SOFA. Having finger connection modules and finger actuators that are adjustable and replaceable provides many possibilities for many application areas as well. A numerical model established in SOFA for the entire gripper system can efficiently evaluate the grasping behavior of gripper with different designs and configurations. The results are compared with experimental measurement, and good agreement is evident.

The validated model is then adopted in a data-driven multi-objective optimization framework. After determining the proper objective function, design domain, and constraints, the numerical model is used for generating batch of data on various design points. The obtained data are used for training an ANN to obtain a surrogate model, which can fast predict the desired outcome at arbitrary input design parameters. The developed surrogate model can be used in a multi-objective optimization algorithm to provide the best design options for the designers' pursue. One significant difficulty in this process is to propose reasonable objective functions. In this study, based on evaluating the major tasks of the soft actuator to be designed, we proposed that larger bending force can help the soft actuator achieving better grasping capability in a gripper system.

Increasing COG offset may help achieve a larger bending force, but this offset cannot be arbitrarily large for the stability consideration of the entire system. Hence these two variables are used in this study as the objective functions. Since parameterized CAD model is generally not available in soft robotic design practice, we modify the geometry by adjusting the positions of mesh vertices. After analyzing the structure of the actuator and divide the prototype design into two sections, we may adjust the behavior of each section by tuning the two geometry parameters. These geometry parameters can be eventually adopted as the design parameters in the optimization practice, to determine the final geometry of the design.

Typically, this methodology can be generalized to actuators with more complex designs and geometries. However, two points should be taken care of. Firstly, the preparation of design parameters is more involved. More design parameters are required as more functional structures should be considered. Secondly, with the increasing design parameters, the simulation data points exponentially increase, yielding a higher computational cost. So one needs to compromise between the accuracy of the model and the computational resources during designing. Even though this optimization framework is helpful in the soft actuator design, some limitations also exist. One is that this design optimization should be implemented based on some original prototype, and it is difficult to give a completely new design. Another is that we still need to formulate how to parameterize the geometry structure, which requires some domain knowledge and design experience. However, compared with the traditional trial-and-error design, the improvement of this methodology is still significant.

Overall, this simulation and optimization approach can significantly reduce trial-and-error experimental testing during soft robotic design, saving time and cost. These technologies have great potential for applications in soft robotic development in healthcare and human-related sectors, and can benefit the entire soft robotic research and development communities.

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