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Optimization of an Underactuated Two Finger Robotic Hand Using Genetic Algorithms *

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Abstract

In this work we focus on the design of an underactuated anthropomorphic tendon driven robotic gripper with two fingers. The gripper is required to be able to perform strong stable flat pinching and enveloping grasps for a fixed actuation force by maximizing the total contact force with the object. In order to design this gripper, we use a Genetic Algorithm (GA) based optimization approach, where geometrical parameters, such as position, stiffness and size of the joints, the length of each link and the palm, the distance from the tendons to the joint centers as well as the starting angle of the fingers are used. The approach runs the whole grasping process for each individual of the GA in simulation, detecting first constraint violations, and then measuring the contact forces. The optimization procedure was experimentally validated by 3D printing a prototype of the optimal design and showing its grasping capability.

1 Introduction

Robotic grippers are an important aspect of modern automation, revolutionizing various industries by allowing robots to grasp, hold and manipulate objects with different shapes, sizes, and materials [12, 16]. In order to allow manipulation of this large variety of objects, different types of grippers have been designed over time, varying the number of fingers and configuration, the actuation methods (vacuum, tendon based, adaptive) and the stiffness (soft, rigid) [21]. Tendon based gripper architectures are often preferred due to their intrinsic anthropomorphic characteristics and optimal weight

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to size ratio. However, controlling such a gripper can become very difficult and complex as the number of tendons increase [15]. In order to overcome this limitation, researchers have proposed underactuated robotic grippers, grippers that can achieve the same movements with fewer tendons [10]. Designing such grippers that can perform stable grasp for different configurations, like fingertip or enveloping grasping, to hold different objects requires a process that involves proper modeling and optimization of several design parameters. For this end, optimization approaches based on Genetic Algorithms (GA) or Reinforcement Learning (RL) have been widely use by researchers [5, 3].

In order to achieve stable powerful grasps, several parameters have been used in the optimization process. Zhang et al. [23] have developed a RL based computational framework that change the number of fingers, the number of links and the position of the fingers. Treratanakulwong et al. [18] proposed a design to reduce the friction loss over the tendon path, by modifying routing through 3D allocated pulleys, while Boisclair et al. [2] reduced the the contact losses between phalanges by introducing rolling contact joints instead of the traditional resolute joints. Yoon et al. [20] proposed a design controlled by two tendons where the finger can elongate, to increase the task space.

In addition to stable and powerful grasps, a goal when using underactuated grippers is to be able to perform different grasping configuration, such as pinching and enveloping, using the same gripper design. Hussain et al. [11] have demonstrated that by defining specific stiffness on the joints, pre-formed shapes could be achieved with the fingers while using only one tendon. Yang et al. [19] demonstrated that different grasping configurations could be achieved by optimizing the torsion spring parameters of the joints using a co-optimization approach that takes into account grasping skills and structural parameters. On the other hand, the grasp shape could be modified by changing the number of tendons as it was shown by Zhang et al. [22]. They used two tendons with different winding paths in order to change the resulting moment of the end knuckle rotating joint.

When trying to obtain the best gripper design that respects multiple requirements, several parameters have to be taken into consideration at the same time. Ciocarlie et al. [4], aiming to grasp a wide range of objects, proposed a design where the length of the links, the entry and exit points of the tendons through the phalanges, and the stiffness and radius of the joints were optimized, using a data-driven approach. Dong et al. [8] optimized the geometric parameters of two fingers, each with three phalanges. The parameters were phalange lengths, width, the radii of the joints, the palm width and the positions of the six pulleys used to modify the tendon route.

Reviewing underactuated robotic hand design optimization studies, we notice two different methods that are mostly used by the research community. In the first one, the physical design is analytically described using equations [5], while in the second one simulation is used [1]. Our literature survey revealed that no work has been proposed that use a data-driven approach to optimize the position of the joints relative to the phalanges and the starting angle of the fingers in addition to the other design variables. In this work we study the optimization of both geometric and mechanical design parameters of an underactuated robotic gripper with two fingers, taking into account these missing variables. In the optimization process we optimize the 21 variables of

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the chosen design, which are length, width and distances between the successive phalanges, the location, size and stiffness of each joint rotation point, the distance between the joints and tendons, and finally, the starting angle of the fingers. Due to the high number of variables in the optimization, we use a GA based approach that optimizes the contact forces using data obtained from grasp simulations.

The rest of the paper is organized as follow. In the next section, we present the gripper model used in the design optimization as well as the specifications of the Genetic Algorithm. The experimental results are presented in section 3. Finally, section 4 gives a concludes the paper and lists our future work.

2 Methods

The goal in this work is to design an underactuated robotic gripper with two fingers and with anthropomorphic characteristics consisting of phalanges which are tendon actuated. The fingers should be able to preform stable flat pinching and enveloping grasps with a minimum actuation force but maximizing the total contact force with the object.

An underactuated gripper, which has a lower number of tendons than normal, is less maneuverable. So an interesting question would be if and how both desired grasping poses are achievable considering that each finger has at least two phalanges. The literature survey showed that, by changing the stiffness of the joints both grasp can be achieved [19]. Similarly, by changing the position of the joints relative to the tendons and phalanges, a desired moment arm could be achieved [22]. Below we present the method to address the how question.

2.1 Gripper model

Considering our goal, we have defined the geometric model of the gripper as presented in Fig. 1, in which it can be seen that the design has two symmetrical fingers with three phalanges each, driven by tendons. The geometries around each rotational joint are locally symmetric to simplify the model, reducing the number of design parameters to a total of 21, which are described next. The lengths are given by L_i ($i \in \{0, ..., 6\}$) where L_2, L_4 and L_6 denote the half phalange lengths, L_0 denotes the half length of the palm, and L_1, L_3, L_5 denote the distance between the phalanges and the point of rotations of the joints. R_1, R_2, R_3, H_1, H_2, H_3, S_1, S_2 and S_3 denote the radii, the heights relative to the center of the phalanges, and the stiffnesses of the three joints respectively. θ denotes the starting angle of the first phalange relative to the palm. K_1, K_2 and K_3 denote the distance of the the virtual pulleys guiding the tendons in and out of the phalanges, to the center-line. Finally W represents the width of the phalanges. The tendon route will always be a straight line between the virtual pulleys (i.e. ends of the phalanges) except when the line passes around the circle of the joints, in which case the tendon will wrap around it.

Let $\vec{x} = (L_0, .., L_6, R_1, R_2, R_3, H_1, H_2, H_3, S_1, S_2, S_3, K_1, K_2, K_3, \theta)$ be the variable vector with respect to which the optimization will be done. Let F_s ($s \in \{0, L_1, L_2, L_3\}$) stand for the normal force of the respective surface s. Let $\vec{F} = (F_0, F_{L_1}, F_{L_2}, F_{L_3})$ be

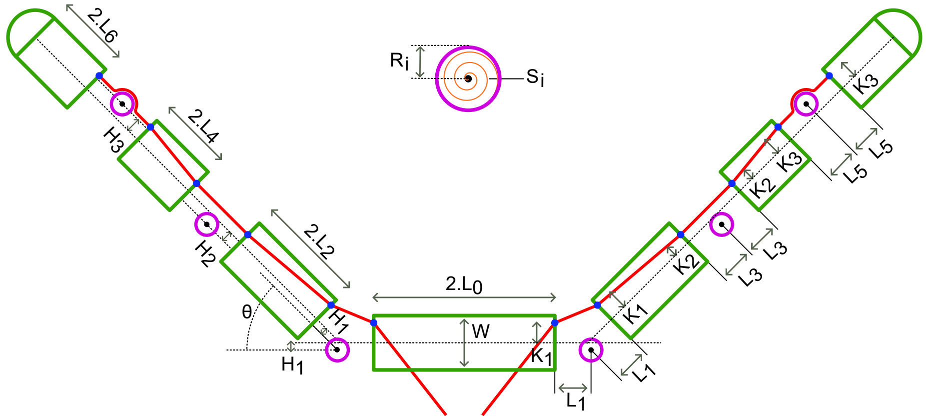

Figure 1: A schematic of the optimized hand with respective design parameters. The red line represents the tendons and the green boxes represent the phalanges. The magenta circles with the black dots represent the joints.

the force vector (variable) containing all the contact forces. Let $\mu(\,.\,)$ and $\sigma(\,.\,)$ denote the mean and the standard deviation functions of their arguments. Similarly, let $\vec{F}(\,.\,)$ be the value of the force vector when grasping its argument. Let L_F be the length of the finger measured from the tip of the finger to the joint connecting it to the palm. Hence

$$L_F = L_1 + 2L_2 + 2L_3 + 2L_4 + 2L_5 + 2L_6 \tag{1}$$

2.2 Problem Formulation

Grasping requires the phalanges apply force on the objects. This force is indirectly applied by pulling the tendons downward. However, the required amount of force depends on the type of object, amount of friction between the surfaces and even the orientation of the hand with respect to gravity. In order to simplify the force calculation, we fix the maximum force applied to the tendons, and maximize the forces applied to the objects to have the best grasp. We also assumed that the amount of friction between the surfaces is high enough that the object does not slip between the fingers, hence we consider only the normal forces in the model. However, we think that it is important to distribute the force uniformly across the different surfaces of the gripper, and hence we set the goal as to maximize the average force over the finger, $\mu(F_0 + F_{L_1} + F_{L_2} + F_{L_3})$, but minimize the standard deviation of the contact forces, $\sigma(F_0 + F_{L_1} + F_{L_2} + F_{L_3})$, for a constant actuation force, F_A (taken as 30 N) for both grasping strategies. This approach also allows to increase the contact to actuation force ratio, eventually providing a more efficient system.

The solution clearly has to obey some sets of constraints. The first set of constraints that is defined for the model are the lower and upper limits, $(\vec{x_L}, \vec{x_U})$, for the geometric parameters, $\vec{x}$, as shown on Table 1, as well as a maximum acceptable length for the fingers ($L_{\text{FINGER MAX}} = 120\,\text{mm}$). The second set of constraints are related to the contact

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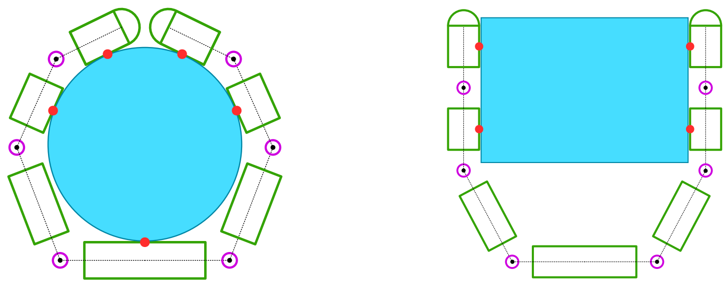
Table 1: Upper and lower limits of the parameter values.

$\vec{x}$	L_0 (mm)	L_i (mm) $i \in \{1,3,5\}$	L_i (mm) $i \in \{2,4,6\}$	R_i (mm) $i \in \{1..3\}$	H_i (mm) $i \in \{1..3\}$	S_i $i \in \{1..3\}$	K_i $i \in \{1..3\}$	θ (^{o})	W (mm)
L.L.	10	5	5	3	-4.5	0	-5.5	0	15
U.L.	40	10	20	5	4.5	2	5.5	45	15



(a) (b)

Figure 2: A schematic of the hand grasping a circular (a) and a rectangular (b) object. The red dots represent the contact points, which also correspond to the locations of the force sensors used in the simulation. The tendons are not shown to reduce image clutter.

between the test objects and the phalanges. For the enveloping grasp it was desired that at least the last two phalanges and the palm to make contact with a minimum force of $F_{\text{MIN CONTACT}} = 0.5\,\text{N}$, and for the pinching grasp, the constrains are the same excluding the palm, which is not required to contact the object.

For optimization a cylinder with a radius of $4\,\text{cm}$ and a prism with $3\,\text{cm}$ of width and $5\,\text{cm}$ of length were chosen, using the first for the enveloping grasp and the second for the flat pinching grasp. These shapes favor the mentioned grasping as can be seen from the representation of the contact points between the fingers and objects in Fig. 2. The cylinder is a good approximation to bottles and cups that the gripper would expected to grasp, and the prism approximates other prismatic objects such as books, boxes, laptops, etc.

The resulting optimization problem for enveloping and flat pinching grasp can be defined as follow

$$\text{maximize } f_1(\vec{x}) = \mu(\vec{F}(\text{Box})) \tag{2}$$
$$f_2(\vec{x}) = \mu(\vec{F}(\text{Cylinder})) \tag{3}$$
$$\text{minimize } f_3(\vec{x}) = \sigma(\vec{F}(\text{Box})) \tag{4}$$
$$f_4(\vec{x}) = \sigma(\vec{F}(\text{Cylinder})) \tag{5}$$
$$\text{subject to } L_F \leq L_{\text{FINGER MAX}} \tag{6}$$
$$F_{L_i} \geq F_{\text{MIN CONTACT}} \quad i \in \{2,3\} \tag{7}$$
$$F_0 \geq F_{\text{MIN CONTACT}} \quad \text{for cylinder} \tag{8}$$

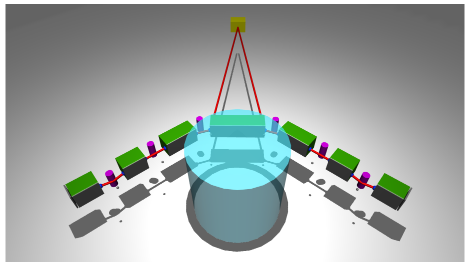


Figure 3: An image from the simulation showing the hand before grasping a circular object.

$$\vec{x_L} \leq \vec{x} \leq \vec{x_U} \tag{9}$$

Note in the above formulation that the constraint on F_0 is checked only for the cylinder object, i.e. the evolving grasp. Above it can be seen that the constraints are defined only on the left finger, because the gripper and the objects have symmetric shapes, and hence the forces on the left and the right fingers are expected to be the same. This symmetry assumption allowed to reduce the number of constraints by half, simplify the optimization algorithm.

2.3 Solution

The above presented optimization problem requires the optimization of 4 functions with respect to several constraints and the 21 variables, which is difficult to track and perform analytically using for example a gradient descent based approach. However, this problem can be solved with numeric methods, such as a GA based approach [14]. For this work we have adopted a fast and elitist multi-objective genetic algorithm, NSGA-II [6], to calculate the optimum parameters of the model of the gripper.

In order to calculate the cost function values for the GA based solver, we resort to simulation of the whole grasping process using the given parameters. For this, the freely available MuJoCo [17] simulator was chosen for this work, both because it allows simulation of tendons and also it was rated as good in a relevant study [9]. In order to use the gripper model with the simulator it was converted to the proper format, representing the bodies, the phalanges, and the components that are doing contact. Then these bodies were connected together and the degrees of freedom of the joints were set. Finally, the connection points of the tendons were specified. Since the used tendons have a constant length, they were connected to a linear displacement actuator, whose actuation force was monitored. To measure the grasping force, force sensors were added to each phalange of the gripper and the palm, giving the forces F_{L_i}, F_{R_i} and F_0 for the left and right phalanges and the palm respectively (Fig. 3).

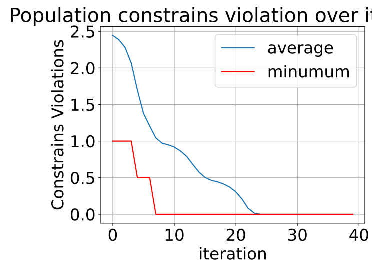


Figure 4: Evolution of the constraint violations over the generations of the genetic algorithm. Non-zero values indicate infeasible solutions. After the 23^{th} generation none of the offsprings of the GA leads to infeasible solutions.

3 Results

3.1 Optimization Results

The parameters of the multi-objective genetic algorithm used to solve the above optimization problem are as follows. The initial population was randomly initialized with a total number of 1000 individuals. The survival of each selected individual depended on the rank and crowding strategy proposed by Kukkonen and Deb [13], and the selection of those individuals was random. The probability of crossover between parents was set to 0.5. Each individual experienced at least one polynomial mutation of the values in each generation of the algorithm as explained in [7]. Finally, the termination criteria of the algorithm was set to 40 generations. In Fig. 4, the evolution of the constraint violation for each generation can be seen, where the first feasible solution was found in the 7^{th} iteration and the whole population started to become feasible from generation 24 onwards. The algorithm was run on a computer with 128GB of memory and 64 cores, and the whole optimization process took 18.71 minutes. Due to the difficulty of visualizing the 4D objective corresponding to the optimization problem, pair-wise 2D plots are shown in Fig. 5, presenting the distribution of the average and standard deviation of the contact forces for both the enveloping grasp and the flat pinching grasp. Although it is possible to reduce the standard deviations of the force for both the cylinder and the box at the same time by choosing a point on the lowest left corner (Fig. 7f), this cannot be said for the means and the standard deviations of the force for the box (Fig. 7c). The force and the standard deviation are inversely proportional. The population shows a similar trend for the forces and the corresponding standard deviations for the cylinder, with the exception of some outliers (Fig. 7e). Hence a point should be selected, ideally based on some metric. A statistical summary of the corresponding gripper design parameters are shown on Table 2 for the joints and on Table 3 for the lengths and starting angle. To produce the final the gripper, configuration of an individual that had σ less then 0.5 and μ more than 1 for the enveloping grasp, and σ less then 0.5 and μ more than 0.5 for the flat pinching grasp was selected from from Fig. 5 (marked with a red dot). The corresponding parameters are given in the last row of Tables 2 and 3. In Fig. 6 the forces on the last two phalanges and some feasible designs proposed by

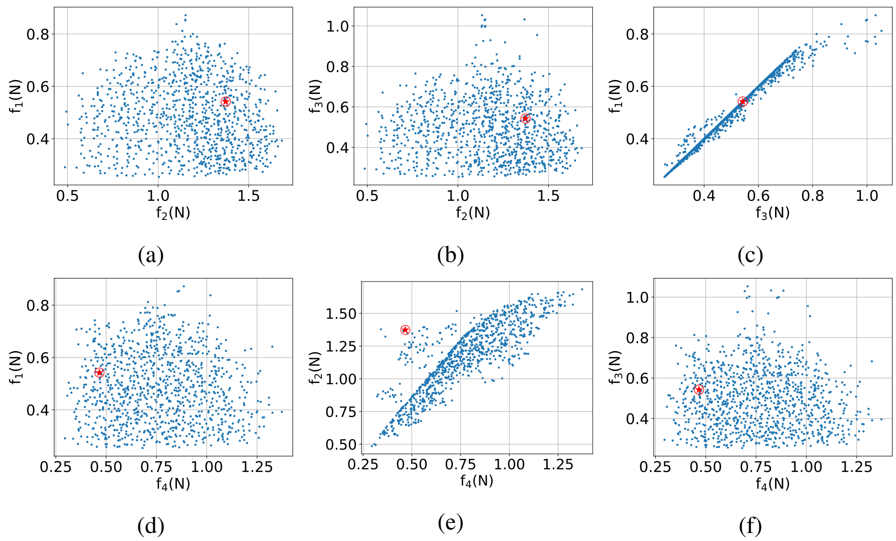


Figure 5: The cost function values (blue dots) of the members of the population of the GA after the last generation.

Table 2: Optimization results for the joint related variables.

	R_1 (mm)	H_1 (mm)	S_1	K_1 (mm)	R_2 (mm)	H_2 (mm)	S_2	K_2 (mm)	R_3 (mm)	H_3 (mm)	S_3	K_3 (mm)
Average	4.39	3.63	0.013	-4.99	3.66	0.78	0.009	-4.09	4.37	-1.42	0.285	-1.70
StdDev	0.29	1.32	0.008	0.70	0.76	1.01	0.005	1.23	0.32	1.76	0.307	2.35
Best	4.44	4.10	0.022	-5.47	3.09	1.01	0.011	-4.51	4.49	-3.22	0.074	-2.84

the GA can be seen. The forces are upper bounded by average line. Depending on where the force is maximized, the designs can be seen to vary clearly in the length of the phalanges and the distance between them. Fig. 7 shows the resulting simulation for both grasping strategies while using the best overall optimized value, with the fingers completely open, half closed and completely closed.

3.2 Experimental results

Taking into account the optimal geometric parameters and the simulation results presented above, a prototype of the optimized design was 3D printed and the parts of the gripper were connected using screws. For the actuation part several pieces of fishing wire were used as tendon, and the tendons were connected to a servo motor, namely a DYNAMIXEL AX-12A. To increase contact friction of the fingers and to add stiffness to the joints, as it was mentioned in the problem formulation, a silicone glove was built for the fingers. The thickness of the glove close to the joints was changed proportionally to the optimal value found by the algorithm (Table 2), achieving accurate relative

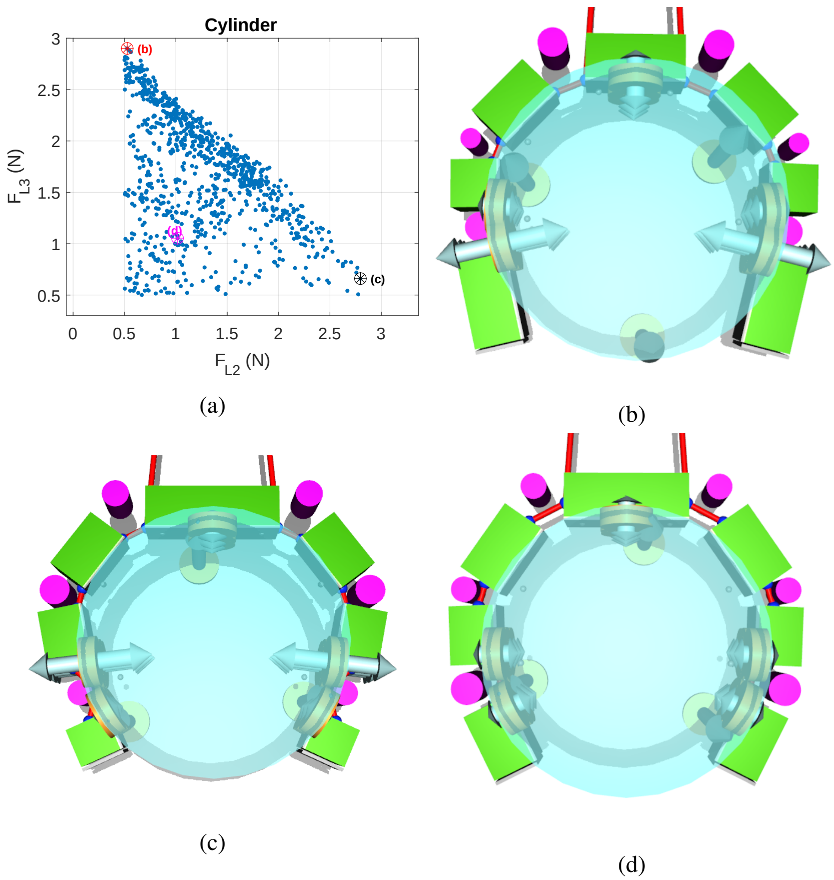
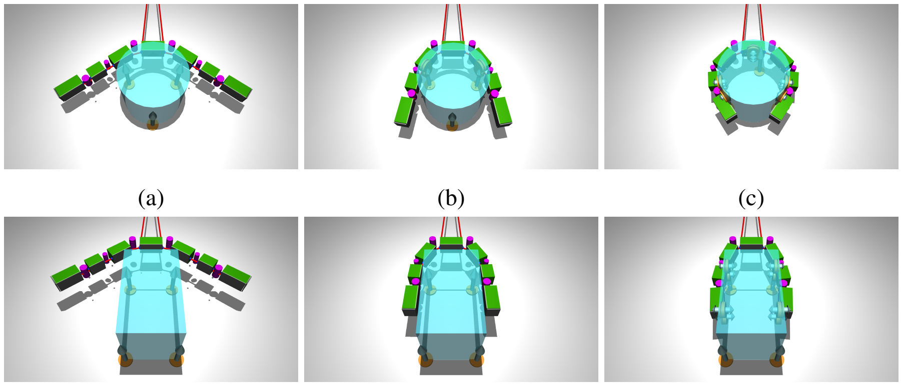


Figure 6: (a) Scatter plot of the forces on last two phalanges when grasping a cylinder. Each point corresponds to a different member of the final GA population. (b,c,d) Three different feasible designs proposed by the GA, corresponding to the three forces marked in (a). Note that (b) and (c) are maximizing the force at the third and second phalange respectively and (d) is minimizing the standard deviation of the forces.

stiffness values. The resulting gripper is shown in Figs. 8 enveloping a cylinder and flat pinching a box.

4 Conclusion

In this work we have focused on design optimization of a two finger three phalange robotic gripper taking into account the shapes of the objects to be grasped. Due to the high number of design variables and the multi-objective nature of the proposed cost function, which maximizes the grasping forces for different objects and minimizes the variance of the force at the different phalanges, a Genetic Algorithm was used to solve



(a) (b) (c)

(d) (e) (f)

Figure 7: The robotic hand grasping a circular object and a box in the simulator.

Table 3: Lengths and starting angle optimised results

	L_0 (mm)	L_1 (mm)	L_2 (mm)	L_3 (mm)	L_4 (mm)	L_5 (mm)	L_6 (mm)	W (mm)	θ (^{o})
Average	16.628	9.839	11.115	6.890	9.013	6.915	13.119	15	37.617
StdDev	3.137	0.262	1.427	1.377	1.855	1.480	3.247	0	2.608
Best	14.949	9.953	13.680	6.179	9.746	5.945	14.736	15	36.694

the problem. The GA populations revealed that the maximization of the forces and the minimization of the variance turned out to be opposing requirements. For future work, we will relax the fixed stiffness requirement and allow variable joint stiffness, which will eventually allow achieving other types of configurations. Then, we will use the extended method to optimize the parameters of a three finger gripper.

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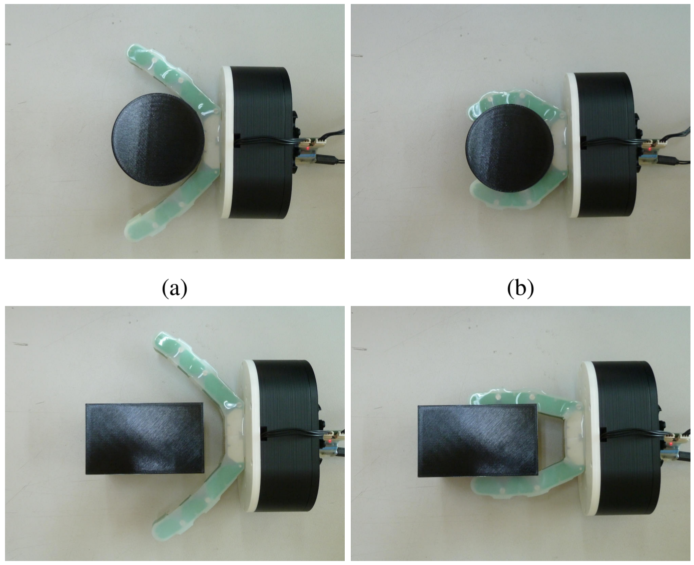

(a) (b) (c) (d)

Figure 8: The designed robotic hand grasping a circular object and flat pinching a rectangular object.

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