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Programming Passive Fingertip Deformation for Improved Grasping and Manipulation

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***Abstract*— Soft robots exhibit complex behaviors despite simple control, due to their inherently compliant hardware which passively deforms upon contact – a concept commonly referred to as morphological computation. To fully determine the behavior of soft robots, not only their control software but also their passive behavior needs to be programmed. We show that deliberate programming of passive deformation in soft fingertips can significantly influence the grasping and manipulation performance of various robotic grippers. For this, the fingertips display strategically modulated compliance levels across their palmar surface, realized through adjustments to the local thickness of a lattice structure within their soft material, resulting in desired passive deformation. The grippers are operated by human participants, solving diverse tasks involving a variety of objects. We analyze 2025 human trials and show that the distinct passive behaviors programmed into the fingertips significantly affect grasping and manipulation performance. Furthermore, we discovered that specific compliance profiles consistently demonstrate superior performance, indicating that not merely inherent softness by itself, but a purposeful combination of varying compliance levels plays a pivotal role in successful soft interaction.**

Fig. 1. Passive deformation in soft fingertips is specified through patterns of varying compliance levels across their surface. Performance of different such patterns is compared in human studies. Participants solve various tasks, while operating diverse grippers to which we attach the fingertips.

I. Introduction

Soft robotic hands demonstrate robust grasping and manipulation as they compensate uncertainty in perception and actuation when passively adapting to the shape of their environment [1], [2]. This allows these hands, for example, to reliably grasp and manipulate a large variety of objects despite executing an identical open-loop strategy [3], [4].

Soft systems may exhibit diverse and complex behaviors when they passively deform in the presence of contact. Such deformation processes are commonly referred to as *morphological computation* (MC) [5]–[7] and may greatly benefit successful soft interaction. The elasticity and structure in a soft robot can be regarded as an additional source of computation. Based on this premise, specific aspects of the control problem can be outsourced from typical software-based computation to soft hardware-based computation.

However, this hardware-based computation is not always beneficial, but can also be indifferent or even detrimental to the performance, for example, when fingers bend away from the object during hand closure, hindering successful interaction [8]. Therefore, a vital step in harnessing the full potential of soft robotic systems is the purposeful modulation of their passive deformation processes.

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In this work, we present a novel, systematic approach to programming specific morphological computation within soft fingertips, introducing the notion of code, compilation, and function calls in this alternative computational paradigm. We deliberately modulate the passive fingertip behavior by implementing specific *compliance profiles* on the palmar surface, resulting in patterns of varying compliance levels. These profiles are designed based on specific intended behaviors, such as directing objects towards the center of the fingertip or preventing slippage during grasping through steep compliance gradients, thereby greatly enhancing dexterity.

The compliance profiles are realized through lattice structures in the fingertips' soft polyurethane (PU) material, while the local material thickness in these structures modulates the location-specific compliance in a fingertip.

We show that the fingertips' distinct passive deformation behaviors significantly affect grasping and manipulation performance. For this, we analyze human subjects solving diverse grasping and manipulation tasks while operating various types of grippers to which we attached different fingertips (Fig. 1).

By relying on human participants, we circumvent the need for developing fingertip-specific control software that leverages the distinct features in a compliance profile. Instead, we exploit the human brain's ability to quickly learn how to effectively use novel tools. We simplify this learning process by implementing the different robotic grippers as extensions of the participant's human fingers, allowing them to rely on their intuition about operating their own hand.

The results of our experiments highlight that not softness

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by itself, but instead, combining regions of varying levels of compliance in a fingertip profile yields superior performance across grippers, tasks, objects, and participants.

II. Related Work

Relying on the inherent computational capabilities of robots' elasticity and physical structure can significantly reduce control complexity, paving the way for more effective and robust robotic systems. For example, the universal robotic gripper is capable of grasping a large variety of objects based on passive shape adaptation, negating the need for complex control strategies [9]. Passive shape adaptation also enhances the grasping and manipulation capabilities of underactuated robotic hands, facilitating robust grasping of a wide variety of objects [4], [10], [11]. This approach also benefits in-hand manipulation, where passive shape adaptation supports dynamic engagement and disengagement with objects, making object repositioning or reorientation more robust. Here, the soft hardware seamlessly manages low-level contact dynamics, considerably simplifying control complexity [3], [12], [13].

Incorporating soft materials in the context of soft robotic fingertips can enhance the dexterity and versatility of robotic manipulators. For example, air cavities embedded in soft pulps can provide active shape modification, firmly securing delicate objects through form closure, facilitated by dynamic air pressure adjustments within the cavities [14]. Building on this approach, integrating pneumatically controlled deformations with tactile sensing in the fingertips grants augmented control over object translation and rotation, thereby improving dexterity [15]. Other approaches leverage passive deformation for sensorization by employing a camera inside the soft fingertip. This configuration detects marker displacements within the material to accurately estimate contact forces and positions, enhancing performance in grasping and manipulation tasks [16]. Passive deformation in fingertips, combined with varying levels of friction demonstrates dexterous in-hand manipulation of objects. In a simple mechanism, external contact surpassing a predefined intensity suspends a low-friction surface, exposing a high-friction element. This variable friction allows various interaction modes, including sliding, gripping and rolling of objects [17].

Strategically tuning the morphology of soft robotic systems to achieve desired passive behaviors is a focus of ongoing research. For example, the joints and structure of origami and kirigami-inspired robotic systems can be precisely attuned to task specifications via adjustments to their respective folding and cutting patterns, facilitating nuanced control over their passive deformation [18], [19]. Programmed passive behavior is also demonstrated by the parametric design of fin-ray grippers, where adjustments to the thickness in their cross-beams influence local stiffness. This allows precise specification of the fingers' passive bending during grasping, which facilitates firm gripping of diverse objects [20]. Furthermore, the parameterized geometry of soft continuum actuators precisely determines both their flexion and passive deformation [21].

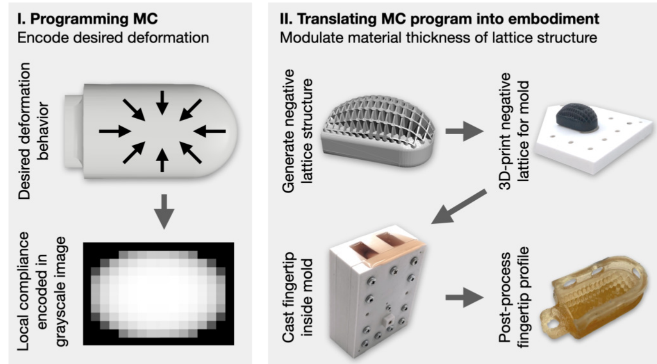


Fig. 2. Programming specific morphological computation in soft fingertips: desired passive deformation behavior is encoded in gray-scale images whose pixel values correspond to local compliance. This image-based code is turned into lattice structures inside soft polyurethane-based fingertips. The material thickness of these structures modulates the local level of compliance, determining the fingertip's deformation during contact.

Similar to these works, we investigate possible contributions of passive behaviors to performance. However, we focus on deliberately combining various levels of compliance and investigate how this can promote successful grasping and manipulation.

III. Programming Passive Fingertip Deformation

We now explain our conceptualization of programming passive fingertip behavior, illustrating the analogy to software programming through the introduction of code, compilation, and function call concepts in this other computational paradigm. In this context, programming passive behaviors is akin to defining physical functions that output desired deformation patterns in response to mechanical input. We showcase this by representing desired behaviors in a code which is systematically translated into alterations of the fingertips' hardware.

For this, we adjust the material thickness within lattice structures present in soft polyurethane (PU) rubber fingertips, with greater thickness corresponding to higher stiffness, and vice versa (Fig. 2). We encode local compliance in gray-scale images whose pixel-intensities denote material thickness at the corresponding locations on the fingertips' palmar surface. Essentially, these pixel values function as the 'source code', specifying the distinct passive behavior.

To transform this code into a tangible entity, we employ the *Rhinoceros* computer-aided design framework to auto-generate 3D mold designs. These designs, which embody the profile-specific negatives of the lattice structures, are then 3D-printed using a stereolithography (SLA) printer (*Formlabs Form 3+*). We fabricate the soft fingertips by casting polyurethane rubber (*VitaFlex 20* from *Smooth-On*), using these molds. We choose PU because of its excellent abrasion resistance, which ensures the robustness and durability of the fingertips for contact-intense interactions with the environment. We argue that this transformative process, from gray-scale images to physical fingertips with respective compliance profiles, mirrors the *compilation* process in software-based programming.

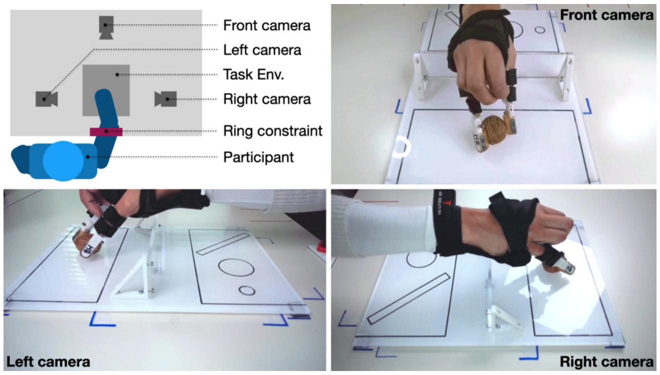


Fig. 3. Experimental Setup for evaluating grasping and manipulation performance. Markings on the table aid in accurately placing the task environments. Top left: schematics of the setup; top right and bottom row: exemplary images taken by the three cameras. Photos show a participant engaging in *Task I*.

Following this premise, a *function call*, i.e., eliciting specified passive behavior, is initiated through mechanical interaction with the environment. We belief that control strategies that purposefully combine morphological computation with software-based computation result in more efficient and robust behaviors compared to strategies that are produced by relying solely on one paradigm.

IV. Experimental Setup for Evaluating Passive Fingertip Deformation

We experimentally evaluate the influence of programming passive fingertip deformation on grasping and manipulation performance (Fig. 3). To achieve this, we compare five different fingertip compliance profiles whose diverse passive behaviors are based on specific hypotheses about beneficial deformation (Sec. IV-A). Furthermore, we examine whether there are specific profiles that exhibit superior performance across different gripper kinematics, tasks, and objects.

A fair comparison between fingertips requires profile-specific control to optimally leverage their distinct features and passive deformation. For automated control, this would imply significant programming efforts. We therefore rely on human participants to operate the robotic grippers. This approach effectively outsources the control challenge to the human brain, capitalizing on its innate ability to quickly and proficiently adapt to new tools and tackle novel tasks.

To thoroughly investigate the influence of the compliance profiles on grasping and manipulation performance, we conducted an experiment in which five participants engaged in three different grasping and manipulation tasks, utilizing three robotic grippers to which we attached five distinct compliance profiles. Each task incorporated three objects, and each specific combination was repeated three times, resulting in $(5 \times 3 \times 3 \times 5 \times 3 \times 3)$ = 2025 trials.

The whole procedure lasted between 120 and 180 minutes per participant, aged between 19 and 26 (mean 21.6) years, including one female and four males. All participants were right-handed and in sound health. The experimental procedure is in partial accordance with the Helsinki agreement (non-conformity concerns the point B-16 of the 59th World Medical Association Declaration of Helsinki, Seoul, October 2008: no physician supervised the experiments).

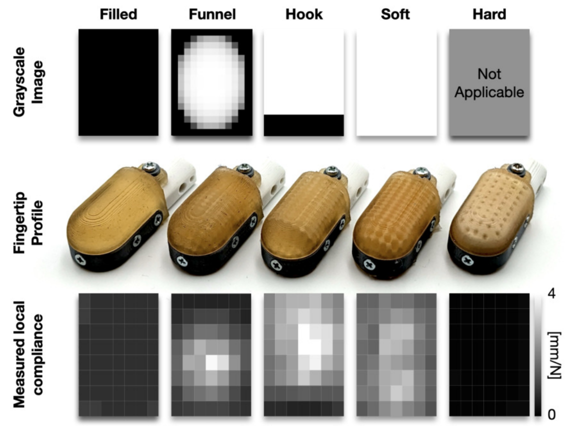


Fig. 4. Fingertip compliance profiles. Top row: pixel intensities of gray-scale images encode local compliance levels; center row: fabricated transparent fingertips allow dim view of their inside lattice structures; bottom row: empirically evaluated local compliance levels, measured by a force sensor (*KM10 25N*) attached to the printing head of a 3D printer (*e3d ToolChanger*).

A. Fingertip Compliance Profiles

We compare the performance of five different fingertip compliance profiles. These profiles share the same shape and are made from identical materials, however, they exhibit unique patterns of local compliance, conceptualized based on hypotheses about how certain deformation behaviors might promote grasping and manipulation capabilities (Fig. 4). Although we do not explicitly verify whether participants utilized the fingertips in line with these hypotheses, we now briefly explain the rationale behind each of them:

The *Filled* profile serves as a baseline, devoid of any lattice structure. Instead, it is characterized by notable uniform stiffness, as it is completely filled with PU material.

The *Funnel* profile exhibits significant compliance at the fingertip's center, progressively stiffening towards its periphery. We hypothesize that this profile facilitates grasping of small objects, funneling them towards the fingertip's center for a more secure grip.

The *Hook* profile is highly compliant across its surface, except at the distal end where a firm barrier is formed by the PU filling. This design aims to enhance manipulation of objects with distinct edges, allowing for compression at the softer regions while preventing further movement through the stiff distal section, thereby ensuring a stable grip.

The *Soft* profile also serves as a baseline, but at the opposite end of the spectrum from the *Filled* profile. It exhibits high uniform compliance, resulting from a lattice structure of minimal thickness across its entire volume, offering potential benefits of increased compliance as a standalone factor.

Lastly, the *Hard* profile serves as a counterargument, advocating for a more rigid approach to manipulation. It incorporates a solid core made of 3D-printed polylactide (PLA) material. To maintain a frictional consistency with the other

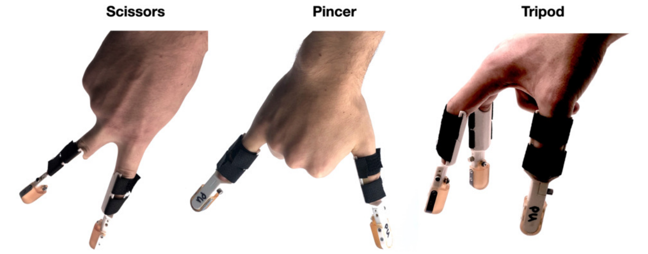


Fig. 5. Participants operate robotic grippers that are implemented as extensions of their own fingers. Left: *Scissors*, including the index finger and the middle finger; center: *Pincer*, including the little finger and the thumb; right: *Tripod*, including the index finger, the middle finger, and the thumb

profiles, it features a $1\,\mathrm{mm}$ layer of PU, securely adhering to the PLA through $1\,\mathrm{mm}$ diameter perforations.

B. Robot Grippers

We investigate whether performance of finger compliance profiles generalizes across varying robotic hand kinematics. For this, participants perform each task with three different grippers of different kinematic structure (Fig. 5). To facilitate rapid learning in efficiently operating these grippers, we implemented them as extensions to a subset of the participants' human fingers, leveraging their intuition and experience with maneuvering their own hands, thereby shortening the time required to develop adept strategies. The grippers were designed to incorporate different fingers of the hand, eliciting diverse, gripper-specific control strategies. Notably, we ensure that the finger choices for each gripper does not subset within another, promoting distinct behaviors.

The *Tripod* includes the index finger, the middle finger, and the thumb, mimicking a common finger selection for a precision grasp. The *Pincer* utilizes the thumb and little finger, facilitating a broad span while retaining a considerable degree of opposability. Lastly, the *Scissors* offers limited maneuverability, involving the index and middle finger.

For the *Scissors* and the *Pincer* configuration, fingertip extensions are oriented so that the profiles face each other, while for the *Tripod*, they are oriented for optimal thumb opposition. The extensions ($80\,\mathrm{mm}$ long, including the profile) are securely fastened to the participant's fingers via Velcro straps. The profiles (30mm long) are affixed through screws, enabling swift replacement and straightforward adjustment

C. Constraining Human Wrist Motion

In our experiments, we encourage participants to perform dexterous in-hand manipulation for reorienting and repositioning objects using fingertip contact dynamics, and we discourage them from altering the object's pose by merely shifting or rotating their whole hand without finger movement. To enforce this, we limit the participants' arm and wrist movements throughout the experiment by incorporating two physical constraints (Fig. 1).

The first constraint is a 3D-printed ring mounted to the table in front of the subjects. Participants are asked to keep their right forearm inside this ring, significantly restricting elbow and shoulder mobility. Consequently, only hand rotations along the forearm's long axis (pronation/supination) and linear movements along the same axis are permitted, with other forms of movement substantially limited.

Furthermore, we introduce a wrist brace as a second constraint, considerably restricting the participants' capacity to rotate their hand in relation to their forearm (both in terms of flexion/extension and abduction/adduction). To further limit wrist motion, we incorporate a rigid, 3D-printed rod made of PLA material within the brace, effectively eliminating any flexion or extension at the wrist.

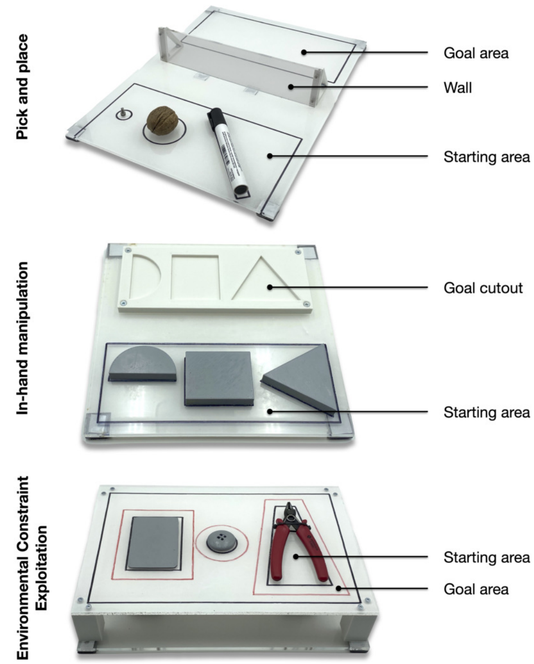


Fig. 6. Grasping and manipulation tasks. Top: pick and place task with the objects screw, walnut, and pen; center: in-hand manipulation task with objects triangle, rectangle, and half moon; bottom: ECE task with objects credit card, button, and pliers (objects are listed from left to right).

D. Grasping and Manipulation Tasks

We investigate whether the performance of the profiles generalizes across tasks. To this end, we asked participants to engage in three distinct experimental scenarios, each designed to elicit unique manipulation strategies (Fig. 6).

1) Task I - Pick and Place: The first task examines the ability of the participants to reliably grasp various every-day objects from a designated starting area, move them across a $60\,\mathrm{mm}$ high acrylic wall, and place them inside a marked goal area on the far side of the task board.

Objects in this task include a screw, a walnut, and a pen. The small screw was chosen to investigate how passive deformation can support grasping objects that fit inside the area of a fingertip. The walnut represents spherical objects while its irregularities prevent it from rolling outside the starting area and allow an identical initial orientation at the beginning of each trial. To enforce stronger contact forces and more significant deformation of the soft fingertips, we increased the weight of the walnut from $15\,\mathrm{g}$ to $150\,\mathrm{g}$ by inserting lead weights. Finally, the pen represents cylindrical objects, while its high length-to-width ratio requires a balanced fingertip placement for a secure and stable grip.

2) Task II - In-Hand Manipulation: The second task aims to analyze whether compliance profiles can facilitate successful in-hand object manipulation. Here, subjects need to pick up objects, rotate them inside the gripper, and place them correctly oriented in corresponding cut-outs inside the target area. Initial object orientation and target orientation are different to enforce object rotation for solving the task.

Objects in this task are simple geometric shapes: a triangle, a rectangle, and a half-moon. Due to their different geometries, the number of possible orientations for correct placement inside the corresponding cut-out varies: the triangle permits six potential orientations, the rectangle four, and the half-moon two. This leads to varied levels of difficulty, as objects with a higher number of possible orientations require less intense object rotation, and vice versa. All objects are made of 3D-printed polylactide (PLA), and the longest edge in each of these objects is $55\,\mathrm{mm}$ long.

3) Task III - Environmental Constraint Exploitation ECE: The third task aims to elicit complex grasping and manipulation strategies that exploit physical constraints in the environment – a strategy documented in previous human trials [22], [23]. For this task, participants are asked to turn three every-day objects upside down. However, the limited height of these objects makes them challenging to lift directly, prompting the adoption of alternative strategies like the edge grasp (where the object is moved to the edge of the supporting surface before grasping) or the flip grasp (where one finger stabilizes one side of the object while another lifts the opposite side).

The selected objects for this task are a credit card, a button, and a pair of pliers. The slender profile of the credit card necessitates an edge grasp for successful grasping. The button, although slightly taller, still presents a grasping challenge due to its restricted height, encouraging nuanced in-hand manipulation at the fingertips to invert it successfully. The pliers were selected for their complex geometry and the potential necessity for regrips during the flipping process.

We colored one side of each object gray to make distinguishing between the initial and the goal orientation easier, both for the participants and the experimenter.

V. Data Acquisition

Prior to the experiment, participants were informed about the experimental procedure, performance metric, data analysis methods, and their rights to withdraw from the experiment at any stage, to which they gave written consent.

We recorded the trials with three cameras (*Razer Kyo*, 1080 pixel resolution at $30\,\mathrm{Hz}$ frame rate), positioned on both sides and in front of the participants, ensuring that at least one camera captures a clear, unobstructed view of the ongoing task at any time. Video recordings from these cameras are used to assess performance based on the task completion time.

To prevent potential statistical artifacts arising from learning effects, the experimental procedure varies across participants. The experiment combines five varying factors: the subjects, the task at hand, the object being manipulated, the type of gripper utilized, and the particular fingertip compliance profile employed. While the sequence of tasks and objects remains constant across participants (starting with Task I and concluding with Task III), the remaining variables underwent pseudo-random permutation: Initially, a random sequence of grippers was selected for each participant-task combination. Following this, a permutation of fingertip profiles was chosen for the first participant, accounting for each task-gripper pair. For subsequent participants, this order was cyclically shifted by one position, ensuring a balanced representation of each profile across participants.

We collected data by following this procedure: At the beginning of each task, each participant familiarized themselves with the rules and object handling by performing the task with their bare hand. This initial familiarization phase was excluded from the subsequent data analysis. For attaching the finger extension, the experimenter assisted the participants to ensure correct fingertip orientation. In particular, fingertips had to oppose neighboring fingers for the gripper *Scissor*, and the thumb for the other grippers.

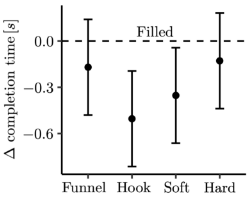
Before a trial started, the experimenter arranged the object in a predetermined starting position and orientation, specific to each task-object combination. Subsequently, an assistant experimenter verified the alignment of the experimental variables before notifying the subject of the imminent start of the trial. The initiation of the recording was marked by an audio signal, signaling the participant to begin the task. Upon task completion, the experimenter conveyed this to the assistant, prompting a second audio signal that denoted the end of the recording session. This process was repeated three times in succession for every combination of task, gripper, fingertip profile, and object.

VI. Data Analysis

We statistically analyze the recorded data to investigate whether deliberate programming of passive fingertip behavior can indeed facilitate successful grasping and manipulation with statistical significance.

For this, we assess participants' performance based on the task completion time which we manually inferred retrospectively from the video recordings (we excluded four of the 2025 trials due to technical issues). A grip was considered successfully completed once the object was placed inside the target area (Task I), the correct cut-out (Tasks II), or the target area and is correctly rotated (Task III). Furthermore, contact between the gripper and the object needs to be broken, and the object needs to have stopped moving.

If the object touched an area outside its starting area, target area, or target cut-out, the trial was labeled as a failure. To penalize these trials, we set their task completion time to $\mu + 2\sigma$, where μ, and σ are the mean and standard deviation of successful task completion times for the specific participant and task, across all grippers, objects and fingertip



Fixed Effect	Estimate
β_0 (Intercept)	4.88
$\beta_{\text{object,card}}$	1.23
$\beta_{\text{object,half-moon}}$	0.04
$\beta_{\text{object,pen}}$	-0.63
$\beta_{\text{object,pliers}}$	0.88
$\beta_{\text{object,rectangle}}$	0.07
$\beta_{\text{object,screw}}$	-0.60
$\beta_{\text{object,triangle}}$	0.49
$\beta_{\text{object,walnut}}$	-0.65

Fixed Effect	Estimate
$\beta_{\text{profile,Soft}}$	-0.35
$\beta_{\text{profile,Funnel}}$	-0.17
$\beta_{\text{profile,Hook}}$	-0.50
$\beta_{\text{profile,Hard}}$	-0.13
$\beta_{\text{gripper,Pincer}}$	-0.45
$\beta_{\text{gripper,Tripod}}$	-0.44
β_{trial}	-0.01

Fig. 7. Results derived from our Linear Mixed Model. Left: effects of the different fingertip profiles on the task completion time, expressed relative to the profile *Filled* (baseline). The diagram shows the estimates and 95% confidence intervals (lower values are better). Right: Estimated model parameter values (in seconds) for our model, as defined by Equation (1).

profiles. This ensures that the penalty time is worse than 95% of the successful trials.

A. *Statistical Analysis – Linear Mixed Model*

We statistically analyze our experimental results to obtain a nuanced understanding of the relationship between the task completion time (the dependent variable) and the experimental factors (the independent variables, listed below). To achieve this, we utilize a *Linear Mixed Model* (LMM) [24], which encompasses both fixed effects (the average effect of the independent variables across the entire population) and random effects (the variations in the effect of independent variables for different groupings within the data). A notable advantage of employing LMMs over conventional methods like repeated measures ANOVA is their inherent ability to model individual differences through random effects, allowing for variations in effects across subjects, and their robustness in handling unbalanced designs, where not all subjects have the same number of trials. Our LMM can be expressed as:

$$y_{ijklm} = \beta_0 + \beta_{\text{object},i} + \beta_{\text{profile},j} + \beta_{\text{gripper},k} + l \cdot \beta_{\text{trial}} + u_{0,m} + \epsilon_{lm}, \quad (1)$$

where y_{ijklm} denotes the task completion time which we model based on the fixed effects of the corresponding categorical experimental factors: *object* $\beta_{\text{object},i}$, *compliance profile* $\beta_{\text{profile},j}$, and *gripper* type $\beta_{\text{gripper},k}$, as well as $l \cdot \beta_{\text{trial}}$, which is the trial-number-dependent fixed effect of learning or fatigue. Indices l and m indicate the *trial number* within a task and the *subject number*, respectively. The term β_0 denotes a constant *intercept*. We opted not to model the effect of the *task*, preventing a rank-deficient fixed effect matrix, as the object implies the task. Moreover, we excluded interaction terms between the fixed effects as they were not significant.

We consider two random effects: a subject-specific random effect $u_{0,m}$, accounting for potential inherent performance differences between the participants, and the residual error ϵ_{lm}. Both random effects are assumed to follow separate normal distributions with zero mean.

We fitted the parameters of our LMM, using the *lme4* library [25] of the programming language *R* [26].

VII. Results

Our analysis reveals that distinct programming of passive deformation in soft fingertips can significantly affect performance. To substantiate this claim, we present insights derived from our model. Specifically, we quantify the relative influence of various experimental factors on the task completion time by examining the fitted model parameters (Fig. 7).

Overall, all fixed effects exhibit a statistically significant influence on the task completion time, which ranges from $1.6\,\text{s}$ to $64.5\,\text{s}$. We speak of statistical significance whenever $p < 0.05$. Unsurprisingly, the object to be grasped has the most influence (the object implies the task). Nonetheless, also the fingertip compliance profiles considerably affect performance, which we now discuss in more detail (Fig. 7).

Our analysis revealed no significant interactions between the fixed effects of the *Compliance Profile*, *Gripper*, and *Object*. This suggests that the performance differences observed between the profiles are consistent across grippers and objects, negating the possibility of a profile excelling or faltering in specific contexts. This level of generalizability is advantageous, as it indicates that the superior passive deformation in certain profiles can generalize to various applications. We now continue with analyses that include all grippers and objects.

With LMMs, statistical results are expressed relative to a baseline case where all fixed effects β have the value zero. An effect is considered statistically significant when its $95\,\%$ confidence interval does not overlap with this intercept (Fig. 7). In cases of slight overlaps, we carefully speak of a *trend*. For our analysis we chose the baseline to be the specific combination of the object *Button*, the profile *Filled*, and the gripper *Scissors*. While we selected *Filled* as baseline due to its lack of a lattice structure, the choices regarding the other fixed effects were not governed by specific criteria.

Through pairwise contrast calculations, we found that the *Soft* profile significantly outperformed the baseline *Filled* by $0.35\,\text{s}$, underscoring the contribution of softness to robust manipulation. Furthermore, our results reveal that the *Hook* configuration surpasses the *Filled* benchmark by a statistically significant margin of $0.50\,\text{s}$, illustrating that strategic combinations of varying compliance levels can enhance performance even further. This clearly substantiates our claim that purposeful programming of passive deformation behavior is central to successful grasping and manipulation.

While not reaching statistical significance, there is a noticeable trend indicating the inferior performance of the *Funnel* profile when compared to the *Soft* profile ($0.18\,\text{s}$). It exhibits this subpar performance, despite displaying the anticipated passive deformation which follows from its unique lattice structure. This highlights that the ability to fine-tune passive behaviors comes with its own challenges, as their efficacy hinges largely on precise, task-appropriate programming.

VIII. Conclusion

We demonstrated effective programming of passive fingertip deformation for improved grasping and manipulation. For this, we encoded desired behaviors as gray-scale images which were translated into distinct compliance profiles in soft robotic fingertips, resulting in desired passive deformation in the presence of external contact. Five such compliance profiles were compared in extensive human manipulation trials. We attached the fingertips to three grippers of varying kinematic structure, implemented as extensions of the participant's human fingers. Trials encompassed three distinct grasping and manipulation tasks involving the handling of three different objects per task. We assessed fingertip profile performance based on the participant's task completion times and statistically analyzed the recorded data with a Linear Mixed Model. Our analysis reveals that the fingertip compliance profiles significantly affect performance across grippers, objects, and participants. The results clearly support the well-established insight that softness promotes successful grasping and manipulation. Furthermore, we found that the *Hook* and the *Funnel* profile performed best across tasks, objects, and participants, indicating that not softness as a standalone property, but instead, carefully designed patterns of varying compliance levels are crucial for improving performance through passive behaviors.

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