MOE-Hair: Toward Soft and Compliant Contact-rich Hair Manipulation and Care

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ABSTRACT

Hair-care robots have the potential to alleviate labor shortages in elderly care and enable those with limited mobility to express their identities through hair styling. In this work, we highlight two advantages that soft robotic manipulators have in hair-care applications: safety through mechanical compliance and sensing through observing deformation. To demonstrate these advantages, we introduce a soft robotic end-effector which we call Multi-finger Omnidirectional End-effector (MOE) for hair-care applications. We validate that in hair-grasping tasks, MOE exerts 74.1 % less force on the head while being able to grasp a similar amount of hair compared to rigid grippers. We further demonstrate that we can reliably estimate the mesh shape of MOE during interaction with a head and that we can infer useful information about the head such as its occluded shape. The results suggest that soft robots are uniquely advantaged in hair-care tasks.

CCS CONCEPTS

• **Computer systems organization** → *Robotic autonomy*.

KEYWORDS

Assistive robotics, Soft robotics, Manipulation

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Figure 1: Proposed Multi-finger Omnidirectional End-effector (MOE) and a force-sensorized mannequin head in contact. Contact between the head and MOE deforms MOE's fingers, resulting in safer interaction forces.

1 INTRODUCTION

Hair plays an important role in people's identities and self-esteem [1, 9]. Notably, the importance of hair to a person's self-esteem tends to increase with age [17]. With aging and loss of independent mobility, hair care becomes an increasingly time-consuming and difficult daily task. Despite this, most elderly care and hospice facilities heavily rely on volunteers for hair-care assistance [3]. Toward addressing the gap in hair-care services, researchers have proposed deploying robotic assistance for combing [4, 7]. A notable challenge in previous works was that human subjects tend to perceive rigid robots as being "rough." [4] Hair-care and manipulation tasks additionally pose a perception challenge for robotic systems because hair can often occlude the underlying scalp. To safely interact with the head in the real world, mechanical rigid robotic manipulators require high-cost force sensors to be safe for human subjects [7].

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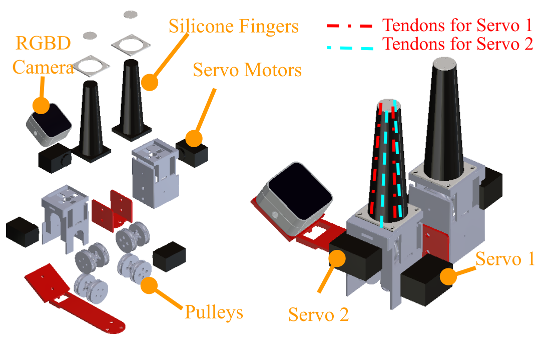

Figure 2: Design of the proposed MOE end-effector. Left: exploded view and assembly of MOE. Right: fully assembled MOE

We propose that soft robotic manipulators have unique advantages in addressing these challenges in close contact with human users. A soft robotic manipulator's compliance makes them safer in unstructured environments [11] and more robust in contact-rich manipulation tasks [2]. These properties make soft robotic manipulators particularly useful in human-robot interaction tasks [12]. Furthermore, in human-robot interaction tasks, human subjects tend to perceive soft robots as being safer than their rigid counterparts [8]. Additionally, soft robotic manipulators deform when they make contact in contrast to rigid robots [20]. Observing such deformations offers a promising direction for using soft robots for interactive perception.

In this work, we propose a soft robotic manipulator that we call Multi-fingered Omnidirectional End-effector (MOE) for hair-care applications as shown in Fig. 1. We demonstrate with a testbed that MOE's compliant fingers make them uniquely appropriate for human contact. We also demonstrate that our proposed methods allow us to reliably reconstruct the complete shapes of the MOE fingers as they deform in contact with the head. We then explore the possibility of inferring occluded head geometry from observed deformations to handle uncertainties in real-world deployment. We make the following contributions: (1) Design of a novel tendon-driven soft robotic manipulator that we call MOE, (2) Evaluation of MOE compared against a rigid robotic gripper on the hair grasping task, and (3) Extension of a previously proposed single-finger soft robotic mesh shape estimation pipeline to MOE.

2 RELATED WORK

Previous works in hair-care robots that we are aware of have focused on visually estimating hair flow and either following the existing hair flow directions [4] or using a specifically sensorized brush and using a feedback controller with a high fidelity force sensor attached to the end-effector [7]. In contrast to this work, both prior works use systems with rigid grippers.

Researchers have previously studied soft robotic manipulators' advantages in various delicate manipulation tasks including food handling [11], crop handling [6], minimally invasive surgeries [13, 18] and wearable assistive robots [16]. Studies of using soft robotic manipulators for human-robot interaction tasks have demonstrated efficacy with both task-performance metrics and qualitative user feedback. To our knowledge, this paper presents the first exploration of the opportunities and advantages presented uniquely by soft robotic manipulators in hair care.

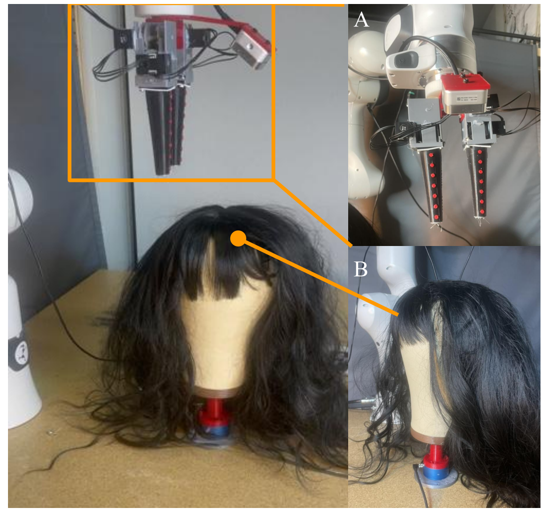

Figure 3: Experimental setup for evaluating the proposed MOE in interaction with a force-sensorized mannequin head. A: Two-fingered MOE soft manipulator with an RGBD camera. B: Mannequin head with a wig and 6-axis force sensor at its base.

3 METHODOLOGY

We outline the design, shape estimation pipeline, and evaluation studies on a force-sensorized mannequin testbed.

3.1 MOE Design

We introduce a soft tendon-driven manipulator that we call Multi-finger Omnidirectional End-effector (MOE). As shown in Fig. 2, MOE has two soft fingers molded from silicone with low hardness (Ecoflex 00-30, Smooth-on). Each finger has four tendons embedded that are actuated by two servo motors (DYNAMIXEL XC330-M288-T, Robotis). Each pair of tendons actuated by a single servo motor controls MOE finger's range of motion in a bending plane. The design is largely modular, where each of the fingers is an independent subsystem that can be detached. MOE design can be extended to variants with more fingers as needed. In the scope of this work and the task of hair grasping that we looked at, we determined that two fingers were sufficient. We placed an RGBD camera (Realsense D405, Intel) on the wrist of MOE to provide egocentric view depth images. Red markers are placed on the surfaces of the MOE fingers for the RGBD camera to track MOE key points as the body deforms.

3.2 MOE Sensing

Shape estimation and representation for soft robots is a challenging problem because of their complex and high degree-of-freedom deformation behaviors [15, 20]. The goal of the MOE estimation pipeline is to infer the overall mesh of the MOE based on the observation of sparse key point movements. We extend a previously

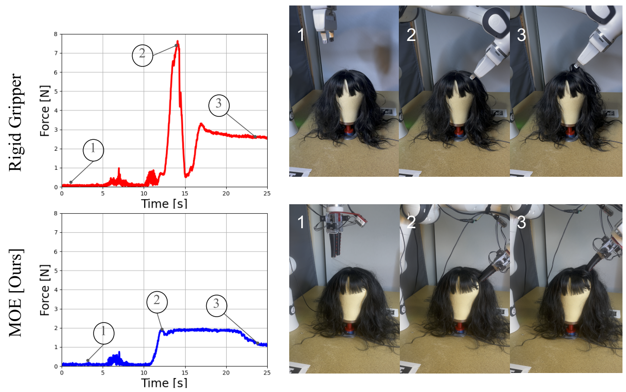

Figure 4: Hair grasping evaluation task experimental procedure and sample result at 6.0 mm depth. Top: experienced net forces and key frame images of the experiment with a baseline rigid gripper. Bottom: experienced net forces and key frame images of the experiment with the proposed MOE.

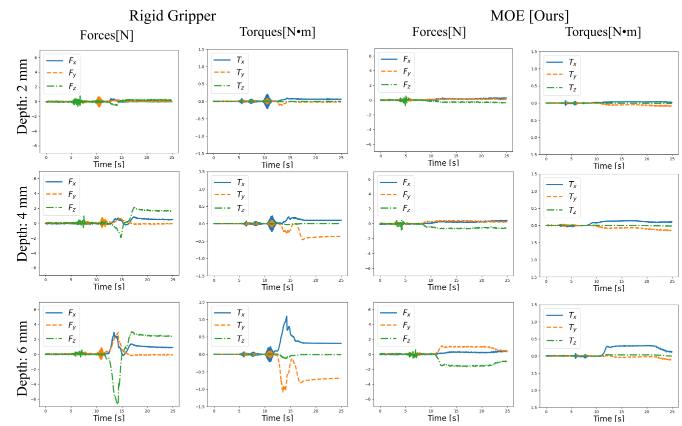

Figure 5: Illustration of forces experienced by the force-sensorized mannequin head during the hair grasping evaluation experiments. We carried out the experiments at three different depths into the hair. The depth measurements were from the point where the end-effector just made contact with the hair to account for different lengths. MOE exerts measurably less force and torque on the head.

proposed POE-M pipeline to multiple fingers [19]. The working principle of POE-M pipeline relies on As-Rigid-As-Possible (ARAP) which is framed as an energy minimization problem over mesh nodes [14].

To guide the shape estimation of MOE, we track the 7 red key point markers placed on each of the surfaces of MOE fingers as shown in Fig. 3A. We segment the markers with color thresholds and apply DBSCAN to cluster the 3D points and find their centers. In the initial frame, we find the nodes on the initial mesh closest to the key points and use them as handle points. From the initialization phase, we account for the movement of each of the key points frame-to-frame. In practice, some of the key points may become occluded due to hair getting in the way. To account for this, we remove the occluded key points from consideration in the ARAP mesh fitting phase.

To deform the mesh based on the key point movements, we define the source surface mesh S and the deformed mesh S'. As previously proposed, we include a penalty on the rotations of the neighboring edges producing mesh manipulation that seems physically admissible [10]. The energy to minimize is

$$E_{\text{smoothed}}(S, S') = \min_{R_1,\ldots,R_m} \sum_{k=1}^{m} \Big(\sum_{i,j \in e_k} c_{ijk} \|e_{ij} - R_k e_{ij}\|^2 + \lambda \hat{A} \sum_{e_l \in N(e_k)} w_{kl} \|R_k - R_l\|^2 \Big).$$

For reconstructing the shape full mesh shape of MOE, we treat vertices corresponding to the key points $p_{1,\ldots,|p_k|}$ as being constrained to the new positions based on the predicted key-point positions, and the rest of the mesh vertex positions are moved to minimize E_{smoothed}.

3.3 Experimental Setup

To extend previous works in the field of hair-care robots, we propose to study direct contact between the human head and robotic end-effectors. Previous works have not made direct notes on the forces experienced by the head. Then, to evaluate the safety of the proposed MOE system around human users, we developed an experimental setup that includes a canvas mannequin head with an attached synthetic hair wig. The base of the mannequin head is attached rigidly to a 6-axis force sensor to measure the applied wrench on the head. The head is placed in the center of the robot arm's workspace as illustrated in Fig. 3.

Table 1: Hair Grasping Evaluation

End-effector	Depth [mm]	Performance Metrics Max Force [N] ↓	Grasped Hair [mm] ↑
Rigid	2.0	1.11	4.0
	4.0	3.38	20.0
	6.0	7.67	25.0
MOE	2.0	**1.09**	**5.0**
	4.0	**1.38**	**18.7**
	6.0	**1.98**	**22.5**

4 PRELIMINARY RESULTS

We evaluate on two tasks: hair grasping and MOE shape estimation.

4.1 Task 1: Hair Grasping Evaluation

Many hair-care tasks require the grasping of hair. For example, rearranging hair often requires grasping hair that is close to the scalp, and in bimanual manipulation tasks such as cutting hair, a hand needs to grasp and bundle the hair. We hypothesized that soft robotic manipulators would be safer and more comfortable for the human subject in hair manipulation and close-contact tasks.

Toward evaluating the hypothesis, we compared the forces experienced by the force-sensorized mannequin head with open-loop experiments, where a rigid parallel jaw gripper (FE Gripper,

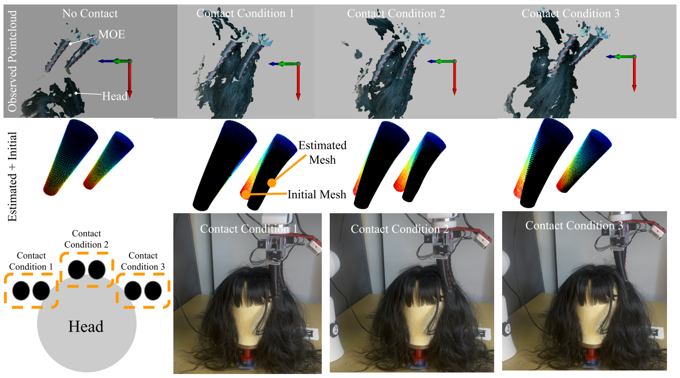

Figure 6: MOE shape estimation experiment images and results. MOE made contact with the head at three different positions along the curve of the head. Based on the relative surface normal of the head, MOE fingers deform differently, indicating that we can infer head geometry information by estimating MOE shapes.

Franka Robotics) and the proposed MOE moved to a specified depth (2.0 mm, 4.0 mm, 6.0 mm) into the hair to grasp. The depths are measured with respect to the position where the robot is barely making contact with the hair to account for different lengths of the end-effectors. As the robot followed specified trajectories, we measured forces at the mannequin head base. After the grippers grasped the hair, the robot hand moved up to lift the grasped bundle of hair. We then measured the minimum packing perimeter of the bundle of hair. Fig. 4 shows a sample result and the experimental procedure. Fig. 5 shows the forces and torques experienced by the force-sensorized mannequin head.

Lower forces and torques experienced by the mannequin head could indicate reduced discomfort if applied to a human subject. Concurrently, a hair-care robot will need to be able to grasp hair that may be close to the scalp, which will likely result in higher forces experienced by the mannequin head. Then, we note that an ideal hair-care robot must be able to grasp hair effectively while also applying minimal force on the head. Table 1 reports the maximum force experienced by the head at varying depths and the amount of hair grasped.

We note that at 6.0 mm depth, the rigid end-effector exerts 7.67 N of force on the mannequin head. At the same depth, MOE applied 1.98 N of force. This constitutes a 74.1 % reduction in the maximum force applied to the head. Meanwhile, on the grasped hair metric, MOE grasped approximately 10 % less hair. A potential explanation of this marginal decrease in the amount of hair grasped is that the compliance of MOE allowed some of the grasped hair to be pried away as the end-effector moved away. This is partially supported by the fact that as the rigid gripper moved away from the head, the mannequin head experienced large changes in the forces applied, indicating possible hair-pulling by the end-effector. This change in forces as the robot hand moves away is not as evident in experiments with MOE.

4.2 Task 2: MOE Shape Estimation

MOE's ability to deform in response to contact with the scalp of the head can help us understand the underlying shape of the head better during hair-care tasks. However, to take advantage of the deformation for perception, we need to be able to estimate the shape of MOE reliably. To validate the efficacy and usefulness of the MOE shape estimation pipeline, we performed an experiment where MOE pushed against the side of the head at three different positions along the head as shown in Fig. 6.

Then, by tracking the key points along MOE's fingers, we apply the MOE shape estimation pipeline. Fig. 6 shows the resulting estimated deformed shapes of the MOE fingers with their corresponding point cloud observations and the initial shape of the fingers. Notably, the shape estimation is precise enough that we can assess what part of the head's curve MOE is touching based on which of the two fingers is deforming more with contact, assuming the known pose of the hand. From the top view as shown in Fig. 6, when MOE is touching the head from the left side, we can observe that the right finger deformed noticeably more than the left finger did, based on the curvature of the head. The opposite is true on the right side of the head. When MOE touches the middle of the head's curve, both fingers deform similarly. These results suggest that the shape estimates of the deformed soft robot fingers can be utilized for inferring useful information about the head in hair-care tasks.

5 CONCLUSION

In this work, we introduce a unique soft robotic manipulator for hair manipulation and care tasks that we call MOE. The results suggest that in comparison to its mechanically rigid counterparts, MOE is safer in close contact with a head and that observing deformations of MOE can provide us with useful information about the scalp morphology that is occluded by hair. The experimental results with the mannequin testbed indicated that soft robots such as MOE could be effectively exploited in hair-care tasks.

A limitation of this study was that the experiments were conducted with a force-sensorized mannequin head and not with human subjects. The head-robot interaction data presented in this work suggested, however, that contact with MOE on the head would be safer and more comfortable than contact with a rigid gripper. We will run user study experiments to evaluate the system with human subjects in the future.

We will also explore how we can estimate MOE contact conditions with proprioceptive sensing and how we can best represent the underlying scalp structure that we can update with each interaction for our future work. Toward this end, we will explore Gaussian process implicit surface [5] as the representation of the scalp shape, which would allow us to not only continuously represent the surface of the scalp but also enable uncertainty-aware planning of hair manipulation trajectories toward safer and more reliable hair-care robotic systems that can be deployed in the real world.

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REFERENCES

[1] D. Batchelor. 2001. Hair and cancer chemotherapy: consequences and nursing care - a literature study: *European Journal of Cancer Care. European Journal of Cancer Care* 10, 3 (Sept. 2001), 147–163. https://doi.org/10.1046/j.1365-2354.2001.00272.x

[2] Aditya Bhatt*, Adrian Sieler*, Steffen Puhlmann, and Oliver Brock. 2021. Surprisingly Robust In-Hand Manipulation: An Empirical Study. In *Robotics: Science and Systems XVII*. Robotics: Science and Systems Foundation. https://doi.org/10.15607/RSS.2021.XVII.089

[3] Rachel Burbeck, Bridget Candy, Joe Low, and Rebecca Rees. 2014. Understanding the role of the volunteer in specialist palliative care: a systematic review and thematic synthesis of qualitative studies. *BMC Palliative Care* 13, 1 (Dec. 2014), 3. https://doi.org/10.1186/1472-684X-13-3

[4] Nathaniel Dennler, Eura Shin, Maja Mataric, and Stefanos Nikolaidis. 2021. Design and Evaluation of a Hair Combing System Using a General-Purpose Robotic Arm. In *2021 IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS)*. IEEE, Prague, Czech Republic, 3739–3746. https://doi.org/10.1109/IROS51168.2021.9636768

[5] Stanimir Dragiev, Marc Toussaint, and Michael Gienger. 2011. Gaussian process implicit surfaces for shape estimation and grasping. In *2011 IEEE International Conference on Robotics and Automation*. IEEE, 2845–2850.

[6] Johannes F. Elfferich, Dimitra Dodou, and Cosimo Della Santina. 2022. Soft Robotic Grippers for Crop Handling or Harvesting: A Review. *IEEE Access* 10 (2022), 75428–75443. https://doi.org/10.1109/ACCESS.2022.3190863

[7] Josie Hughes, Thomas Plumb-Reyes, Nicholas Charles, L. Mahadevan, and Daniela Rus. 2021. Detangling hair using feedback-driven robotic brushing.. In *4th IEEE International Conference on Soft Robotics, RoboSoft 2021, New Haven, CT, USA, April 12-16, 2021*. 487–494. https://doi.org/10.1109/ROBOSOFT51838.2021.9479221

[8] Jonas Jørgensen, Kirsten Borup Bojesen, and Elizabeth Jochum. 2022. Is a soft robot more "natural"? Exploring the perception of soft robotics in human–robot interaction. *International Journal of Social Robotics* (2022), 1–19.

[9] Myrna Lashley. 2020. The importance of hair in the identity of Black people. *Nouvelles pratiques sociales* 31, 2 (2020), 206–227. https://doi.org/10.7202/1076652ar Publisher: Université du Québec à Montréal.

[10] Zohar Levi and Craig Gotsman. 2014. Smooth rotation enhanced as-rigid-as-possible mesh animation. *IEEE transactions on visualization and computer graphics* 21, 2 (2014), 264–277.

[11] Jin Huat Low, Phone May Khin, Qian Qian Han, Haicheng Yao, Yee Seng Teoh, Yadan Zeng, Si Li, Jun Liu, Zhuangjian Liu, Pablo Valdivia Y Alvarado, I-Ming Chen, Benjamin Chee Keong Tee, and Chen Hua Yeow. 2022. Sensorized Reconfigurable Soft Robotic Gripper System for Automated Food Handling. *IEEE/ASME Transactions on Mechatronics* 27, 5 (Oct. 2022), 3232–3243. https://doi.org/10.1109/TMECH.2021.3110277

[12] Panagiotis Polygerinos, Nikolaus Correll, Stephen A. Morin, Bobak Mosadegh, Cagdas D. Onal, Kirstin Petersen, Matteo Cianchetti, Michael T. Tolley, and Robert F. Shepherd. 2017. Soft Robotics: Review of Fluid-Driven Intrinsically Soft Devices; Manufacturing, Sensing, Control, and Applications in Human-Robot Interaction. *Advanced Engineering Materials* 19, 12 (Dec. 2017), 1700016. https://doi.org/10.1002/adem.201700016

[13] Mark Runciman, Ara Darzi, and George P. Mylonas. 2019. Soft Robotics in Minimally Invasive Surgery. *Soft Robotics* 6, 4 (Aug. 2019), 423–443. https://doi.org/10.1089/soro.2018.0136

[14] Olga Sorkine and Marc Alexa. 2007. As-rigid-as-possible surface modeling. In *Symposium on Geometry processing*, Vol. 4. Citeseer, 109–116.

[15] Javier Tapia, Espen Knoop, Mojmir Mutný, Miguel A. Otaduy, and Moritz Bächer. 2020. MakeSense: Automated Sensor Design for Proprioceptive Soft Robots. *Soft Robotics* 7, 3 (June 2020), 332–345. https://doi.org/10.1089/soro.2018.0162

[16] Conor Walsh. 2018. Human-in-the-loop development of soft wearable robots. *Nature Reviews Materials* 3, 6 (May 2018), 78–80. https://doi.org/10.1038/s41578-018-0011-1

[17] Richard Ward and Caroline Holland. 2011. 'If I look old, I will be treated old': hair and later-life image dilemmas. *Ageing and Society* 31, 2 (Feb. 2011), 288–307. https://doi.org/10.1017/S0144686X10000863

[18] Uksang Yoo, Yang Liu, Ashish D. Deshpande, and Farshid Alamabeigi. 2021. Analytical Design of a Pneumatic Elastomer Robot With Deterministically Adjusted Stiffness. *IEEE Robotics and Automation Letters* 6, 4 (Oct. 2021), 7773–7780. https://doi.org/10.1109/LRA.2021.3100608

[19] Uksang Yoo, Ziven Lopez, Jeffrey Ichnowski, and Jean Oh. 2024. POE: Acoustic Soft Robotic Proprioception for Omnidirectional End-effectors. arXiv:2401.09382 [cs.RO]

[20] Uksang Yoo, Hanwen Zhao, Alvaro Altamirano, Wenzhen Yuan, and Chen Feng. 2023. Toward Zero-Shot Sim-to-Real Transfer Learning for Pneumatic Soft Robot 3D Proprioceptive Sensing. http://arxiv.org/abs/2303.04307 arXiv:2303.04307 [cs].