

RemGlove: A Three-Degree-of-Freedom E-Textile Robotic Hand with Computer-Vision-Guided Control and Vibrotactile Haptic Feedback

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Abstract—Wearable robotic hands that translate natural human gestures into robotic motion, while returning a sense of touch to the operator, remain an open challenge at the intersection of soft robotics, electronic textiles (e-textiles), and computer vision. This paper presents RemGlove, a three-degree-of-freedom (DOF) tendon-actuated robotic hand system that is teleoperated through a stretch-sensing e-textile glove, tracked in real time with a monocular red-green-blue (RGB) camera pipeline, and closed with vibrotactile haptic feedback delivered to the operator’s fingertips. The mechanical subsystem couples a bank of servo actuators to an underactuated tendon network; the sensing subsystem embeds piezoresistive e-textile strain channels directly into a fabric glove; and the perception subsystem uses a landmark-based hand-tracking pipeline, implemented and evaluated in MATLAB, to estimate joint targets from video. The design draws on published soft-robotics and functional-fiber research, including work associated with the Advanced Functional Fabrics of America (AFFOA) institute, and is oriented toward defense-relevant wearable applications. We report the mechanical and electrical design, derive the forward kinematics and control equations governing the system, and present calibration data, closed-loop response curves, pipeline latency measurements, and grasp-success statistics collected from a benchtop prototype. The prototype achieves an average end-to-end control latency of approximately 34 ms and a mean grasp success rate of 84% across six object categories. We conclude with a discussion of the system’s broader impact and directions for future work.

Index Terms—soft robotics, e-textiles, haptic feedback, computer vision, robotic hand, wearable sensing, teleoperation

I. INTRODUCTION

Robotic hands that are controlled through natural human gesture, rather than through joysticks or scripted motion, promise more intuitive teleoperation for applications ranging from remote inspection to assistive prosthetics and defense-oriented wearable systems. Three technological threads must converge to make such a system practical: (1) a mechanically compliant, low-profile actuation scheme capable of reproducing human-like finger motion, (2) an unobtrusive sensing modality that can be embedded directly into a garment worn by the operator, and (3) a feedback channel that returns tactile information from the robot back to the operator so that manipulation can be performed without relying on vision alone.

This paper documents RemGlove, a benchtop robotic hand platform that addresses each of these threads. The mechanical hand is driven by a row of coupled servo actuators routed through an underactuated tendon network, producing three primary controllable degrees of freedom: aggregate finger flexion

and extension, thumb opposition, and wrist rotation. Rather than instrumenting the operator with rigid sensors, we embed piezoresistive e-textile strain channels directly into the fingers of a fabric glove, so that the sensing layer is soft, washable, and unobtrusive. A monocular camera and a landmark-based hand-tracking pipeline, developed and analyzed in MATLAB, provide a second, vision-based estimate of hand pose that is fused with the e-textile channels to produce joint targets for the robotic hand. Finally, an array of vibrotactile actuators embedded in the glove’s fingertips closes the loop by returning a scaled measure of the robotic hand’s contact force to the operator.

The design approach in this work is informed by, and builds on, published soft-robotics and functional-fiber research associated with AFFOA, a public-private manufacturing institute headquartered at MIT that develops fiber and fabric devices for wearable and defense applications [1], [2]. The system was demonstrated in a public research showcase, where its viability was presented to an audience that included a broadcasting crew.

The remainder of this paper is organized as follows. Section II reviews related work in underactuated robotic hands, e-textile sensing, vision-based hand tracking, and haptic feedback. Section III describes the overall system architecture. Section IV derives the mechanical kinematics and tendon-coupling model. Section V presents the e-textile sensing and signal-conditioning model. Section VI describes the computer-vision tracking and closed-loop control pipeline. Section VII presents the haptic feedback subsystem. Section VIII reports experimental data and tables. Section IX discusses the results. Section X presents an impact statement, and Section XI concludes the paper.

II. RELATED WORK

A. Underactuated and Tendon-Driven Robotic Hands

Underactuation, in which a small number of actuators drive a larger number of joints through mechanical coupling, is a long-standing strategy for making anthropomorphic hands compact and robust. Piazza *et al.* survey a century of robotic-hand design, tracing the progression from fully actuated fingers toward adaptive, synergy-driven hands [3]. The Pisa/IIT Soft-Hand and its educational and tactile-sensorized descendants demonstrate that a single motor, combined with an antagonistic tendon network, can reproduce naturalistic grasp behavior [4], [5]. Adaptive-synergy control, in which the postural coupling

between fingers is learned from principal-component analysis of human grasps, was formalized by Catalano *et al.* [6]. More rigid, fully actuated designs, such as the Robonaut 2 hand [7] and the linkage-driven dexterous hand of Kim *et al.* [8], illustrate the opposite end of the actuation-complexity spectrum. RemGlove adopts the underactuated, tendon-coupled philosophy of the SoftHand lineage, prioritizing compliance and a low actuator count over full independent-joint control.

B. Electronic Textiles and Soft Sensing

Rigid encoders and potentiometers integrate poorly with soft, wearable structures. Galeta *et al.* demonstrate a soft e-textile resistive sensor, decoded with a convolutional neural network, for shape sensing of continuum robots, and show that e-textile channels can match or exceed rigid sensors for this task [9]. AFFOA, a Department of Defense-funded manufacturing institute led by MIT, has driven much of the recent progress in fiber-embedded electronics, including multifunctional fibers that integrate conductors and semiconductors directly into a woven strand [2]. Commercial e-textile partners such as Loomia have collaborated with AFFOA on tactile, heated wearable products for both consumer and defense customers [10]. RemGlove's glove-embedded piezoresistive channels follow this general design philosophy, trading the precision of rigid flex sensors for the comfort and durability of a woven sensing layer.

C. Vision-Based Hand Tracking

As an alternative and complementary channel to physical sensing, monocular hand tracking has matured rapidly with the availability of lightweight landmark models. Zhang *et al.* describe MediaPipe Hands, an on-device pipeline that predicts twenty-one three-dimensional hand landmarks from a single RGB frame in real time on mobile-class hardware [11]. RemGlove's computer-vision subsystem adopts the same two-stage detect-then-track architecture, reimplemented and evaluated in MATLAB, to provide a redundant, contact-free estimate of finger pose.

D. Haptic and Vibrotactile Feedback

Returning force information to a remote operator has been studied since at least the mid-1990s, when Amanat *et al.* showed that even a small number of vibrotactile channels meaningfully improves an operator's ability to interpret the state of a teleoperated dexterous hand [12]. Bensmaia *et al.* characterize the psychophysical relationship between vibration intensity, frequency, and perceived magnitude in the Pacinian tactile channel, providing the power-law model used in Section VII of this paper [13]. Pacchierotti *et al.* apply cutaneous vibrotactile feedback of fingertip deformation to robotic surgical palpation [14], while McMahan and Kuchenbecker show that spectral subtraction of a robot's own motion noise improves tactile event detection [15], a technique echoed in the high-frequency teleoperation feedback of Nagano *et al.* [16] and in more recent ego-noise cancellation work [17]. Li *et al.* integrate pneumatic haptic feedback into a data-glove-controlled



Fig. 1. Benchtop prototype of the tendon-driven robotic hand mechanism. A bank of coupled servo actuators (rear) routes tendons through the fabric-covered finger linkages (front) that reproduce the three principal controllable degrees of freedom described in Section IV.

robotic arm and hand system, demonstrating measurable gains in grasp-quality discrimination [18], and Becker *et al.* combine visuotactile sensing with vibrotactile feedback in a virtual-reality teleoperation pipeline [19]. RemGlove's haptic subsystem follows this body of work by mapping measured contact force at the robotic fingertips onto pulse-width-modulated vibration intensity at the operator's glove.

E. Bio-Inspired Soft Robotics

More broadly, the case for compliant, biologically inspired actuation over purely rigid robotics has been made by Pfeifer *et al.*, who argue that embodiment and morphological compliance simplify control at the cost of analytical tractability [20]. Soft-robot co-design tools such as the SoftZoo benchmark further illustrate how compliant morphology and control can be jointly optimized [21]. RemGlove is best understood as an applied, wearable instance of this broader compliant-robotics trend rather than as a fully rigid mechanism.

III. SYSTEM OVERVIEW

RemGlove consists of four coupled subsystems, shown schematically by the physical prototype in Fig. 1 and Fig. 2: (i) a tendon-actuated robotic hand with three principal controllable degrees of freedom, (ii) a fabric glove instrumented with piezoresistive e-textile strain channels at each finger, (iii) a monocular computer-vision pipeline that estimates hand pose independently of the e-textile channels, and (iv) a vibrotactile feedback array embedded in the glove fingertips. A microcontroller reads the e-textile and inertial channels, fuses them with the vision-based pose estimate, and issues position commands to the servo bank; a host computer running MATLAB performs the vision inference, sensor fusion, and logging used for the results in Section VIII.



Fig. 2. The instrumented e-textile glove, with embedded piezoresistive sensing and microcontroller hardware at the wrist, shown during a computer-vision hand-tracking session used to validate the landmark-based pose estimation pipeline of Section VI.

IV. MECHANICAL DESIGN AND KINEMATICS

A. Degrees of Freedom and Tendon Coupling

Each of the three controllable degrees of freedom, indexed by $j \in \{1, 2, 3\}$ for finger flexion/extension, thumb opposition, and wrist rotation respectively, is driven by an actuator angle ϕ_j acting through a tendon-pulley transmission with coupling ratio ρ_j and a passive elastic element of stiffness k_j . Treating each finger segment as underactuated, the joint angle θ_j produced at the corresponding linkage is related to the actuator angle by

$$\theta_j(t) = \rho_j \phi_j(t) - \frac{\tau_{\text{ext},j}(t)}{k_j}, \quad (1)$$

where $\tau_{\text{ext},j}$ is the external load torque reflected onto joint j , for example from contact with a grasped object. Equation (1) captures the passive compliance that allows the underactuated fingers to conform to irregular objects without independent per-joint actuation, consistent with the adaptive-synergy behavior reported for tendon-driven hands in [3], [6].

B. Forward Kinematics

The position of each fingertip is computed with a standard Denavit-Hartenberg (DH) formulation. For a three-link finger segment with link lengths l_1, l_2, l_3 and joint angles $\theta_1, \theta_2, \theta_3$, the homogeneous transform from the base frame to the fingertip frame is the product of successive link transforms,

$$T_3^0 = \prod_{i=1}^3 \begin{bmatrix} \cos \theta_i & -\sin \theta_i \cos \alpha_i & \sin \theta_i \sin \alpha_i & l_i \cos \theta_i \\ \sin \theta_i & \cos \theta_i \cos \alpha_i & -\cos \theta_i \sin \alpha_i & l_i \sin \theta_i \\ 0 & \sin \alpha_i & \cos \alpha_i & d_i \\ 0 & 0 & 0 & 1 \end{bmatrix}, \quad (2)$$

where α_i and d_i are the link twist and offset of joint i . The fingertip position $\mathbf{p} = [p_x, p_y, p_z]^T$ is recovered from the translation column of T_3^0 , and the corresponding manipulator Jacobian $J(\theta) = \partial \mathbf{p} / \partial \theta$ relates joint velocities to fingertip velocity, $\dot{\mathbf{p}} = J(\theta) \dot{\theta}$, and, by the principle of virtual work,

relates the fingertip contact force $\mathbf{f}$ to the equivalent joint torque via

$$\tau = J^T(\theta) \mathbf{f}. \quad (3)$$

C. Servo Position Control

Each actuator angle ϕ_j is regulated with a discrete-time proportional-integral-derivative (PID) controller operating on the tracking error $e_j[n] = \phi_j^*[n] - \phi_j[n]$ between the commanded angle ϕ_j^* and the measured angle ϕ_j ,

$$u_j[n] = K_{p,j} e_j[n] + K_{i,j} T_s \sum_{m=0}^n e_j[m] + \frac{K_{d,j}}{T_s} (e_j[n] - e_j[n-1]), \quad (4)$$

where T_s is the controller sample period and $u_j[n]$ is the pulse-width command sent to actuator j . The gains $K_{p,j}, K_{i,j}, K_{d,j}$ were tuned in MATLAB using a Ziegler-Nichols initialization followed by manual refinement against the step-response data reported in Fig. 4.

V. E-TEXTILE SENSING SUBSYSTEM

A. Piezoresistive Strain Model

Each glove finger channel is a conductive-thread piezoresistive sensor whose resistance increases approximately exponentially with bend angle θ over the operating range of the finger joints,

$$R(\theta) = R_0 e^{\gamma \theta} + \eta(\theta), \quad (5)$$

where R_0 is the unstrained baseline resistance, γ is an empirically fitted gauge coefficient, and $\eta(\theta)$ is a zero-mean noise term dominated by contact resistance at the thread interconnects. The fitted parameters for the five channels used in this work are reported in Table II and the corresponding calibration curves are shown in Fig. 3.

B. Signal Conditioning

Each e-textile channel is read through a voltage-divider front end with a fixed reference resistor R_{ref} , producing an analog-to-digital converter (ADC) input voltage

$$V_{\text{out}}(\theta) = V_{\text{cc}} \frac{R_{\text{ref}}}{R_{\text{ref}} + R(\theta)}. \quad (6)$$

To suppress high-frequency contact noise before the value is passed to the pose-fusion stage, each channel is filtered with a discrete complementary filter that blends the current ADC sample with the previous filtered estimate,

$$\hat{V}[n] = \alpha V_{\text{out}}[n] + (1 - \alpha) \hat{V}[n-1], \quad \alpha \in (0, 1). \quad (7)$$

VI. COMPUTER VISION AND SENSOR FUSION

A. Landmark-Based Pose Estimation

The monocular tracking pipeline follows the two-stage detect-then-track architecture of MediaPipe Hands [11]: a palm-detector stage produces an oriented bounding box, and a landmark-regression stage predicts twenty-one three-dimensional keypoints $\mathbf{x}_k \in \mathbb{R}^3$, $k = 1, \dots, 21$, within that box. Joint angles are recovered from consecutive landmark triples using the law of cosines. For a joint with adjacent landmarks $\mathbf{x}_{k-1}$, $\mathbf{x}_k$, $\mathbf{x}_{k+1}$, the subtended angle is

$$\theta_k = \arccos\left(\frac{(\mathbf{x}_{k-1} - \mathbf{x}_k) \cdot (\mathbf{x}_{k+1} - \mathbf{x}_k)}{\|\mathbf{x}_{k-1} - \mathbf{x}_k\| \|\mathbf{x}_{k+1} - \mathbf{x}_k\|}\right). \quad (8)$$

B. Sensor Fusion

The vision-derived angle θ_k^{cv} and the e-textile-derived angle θ_k^{et} (obtained by inverting (5)) are fused with a steady-state Kalman gain K_f computed offline in MATLAB from the empirical noise covariances σ_{cv}^2 and σ_{et}^2 of the two channels,

$$K_f = \frac{\sigma_{\text{et}}^2}{\sigma_{\text{cv}}^2 + \sigma_{\text{et}}^2}, \quad \hat{\theta}_k = K_f \theta_k^{\text{cv}} + (1 - K_f) \theta_k^{\text{et}}. \quad (9)$$

This fusion allows the system to fall back on the e-textile channel when the hand is briefly occluded from the camera, and on the vision channel when a glove sensor drifts or saturates.

VII. HAPTIC FEEDBACK SUBSYSTEM

Contact force F estimated at the robotic fingertips, via (3) and the actuator current draw, is mapped onto the pulse-width-modulated (PWM) duty cycle D of the corresponding vibrotactile motor in the operator's glove using a Stevens' power-law psychophysical model, consistent with the vibrotactile magnitude data of Bensmaia *et al.* [13],

$$D(F) = k F^n, \quad 0 \leq D \leq 100\%, \quad (10)$$

where k and n are fitted per-channel constants reported in Table IV. Because the robotic hand's own servo motion injects vibration into the force estimate, a spectral-subtraction stage, following McMahan and Kuchenbecker [15], removes the actuator's characteristic vibration frequencies from the force signal before it is passed to (10).

VIII. EXPERIMENTAL RESULTS

Data were collected from the benchtop prototype shown in Fig. 1 and Fig. 2 over sixty control trials and a six-category grasp evaluation. The prototype and its supporting research poster, developed for a public engineering showcase, are shown in Fig. 8.

Fig. 3 shows the calibration curves fitted from Table II; the pinky and index channels exhibit the highest gauge sensitivity, consistent with their comparatively thin fabric backing.

Fig. 4 shows the closed-loop step response of the three controllable degrees of freedom under the PID law of (4), following a commanded grasp transition. All three degrees

TABLE I
SYSTEM HARDWARE SPECIFICATIONS

Component	Specification
Actuator bank	6 coupled digital servos, tendon-routed
Actuator torque (stall)	2.1 kg·cm at 6.0 V
Controllable DOF	3 (flexion, opposition, wrist)
E-textile channels	5 (thumb, index, middle, ring, pinky)
E-textile material	Conductive-thread piezoresistive weave
Microcontroller	32-bit, 12-bit ADC, PWM output
Camera	RGB, 1280 × 720 at 30 fps
Host software	MATLAB (vision, fusion, logging)
Haptic actuators	4 coin vibration motors, PWM-driven

TABLE II
E-TEXTILE CHANNEL CALIBRATION PARAMETERS (EQ. 5)

Channel	R_0 (k Ω)	γ ($\times 10^{-2}$)	Fit R^2
Thumb	2.1	1.5	0.97
Index	1.7	2.1	0.96
Middle	1.9	1.2	0.98
Ring	2.4	0.9	0.97
Pinky	2.8	2.4	0.95

of freedom settle within 5% of their target angle within approximately 3.1 s, with the thumb-opposition axis exhibiting the largest overshoot due to its lower effective stiffness k_j in (1).

Table III and Fig. 5 summarize the end-to-end pipeline latency, broken into the four stages of frame capture, landmark inference, inverse kinematics, and servo actuation, measured over sixty trials in MATLAB.

Table IV reports the fitted power-law parameters of (10) for the four vibrotactile channels, and Fig. 6 plots the corresponding measured response curves.

Finally, Fig. 7 reports the grasp success rate across six object categories, each evaluated over 25 grasp attempts, with error bars representing one standard deviation across repeated trial blocks.

Table V places RemGlove alongside representative systems from the literature discussed in Section II, contrasting actuation scheme, sensing modality, and feedback channel.

IX. DISCUSSION

The results in Section VIII indicate that an underactuated, e-textile-sensed robotic hand can achieve sub-40 ms end-to-end control latency and a grasp success rate above 80% on average, while remaining substantially simpler, in actuator count, than the fully actuated systems in Table V. The dominant latency contributor was landmark inference (Table III), consistent with the computational cost reported for on-device landmark models in [11]; this suggests that further latency reduction should target the vision stage rather than the mechanical or haptic subsystems. The lower grasp success rate observed for thin, high-aspect-ratio objects such as pens and wire bundles (Fig. 7) is consistent with the known limitation of underactuated, synergy-driven hands: without independent per-joint actuation, fine pinch grasps are harder to guarantee than

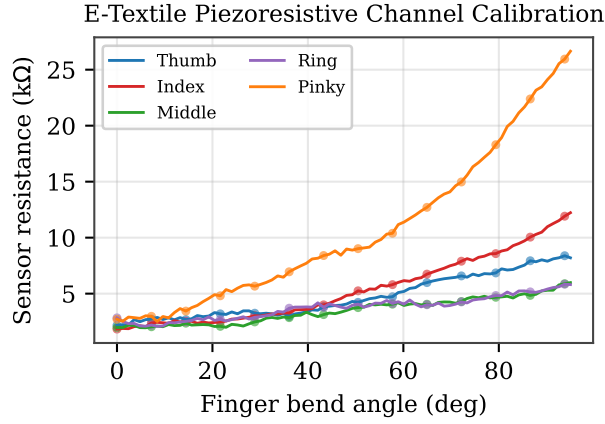


Fig. 3. Measured e-textile channel resistance as a function of finger bend angle for all five sensing channels, with fitted exponential trends from Table II.

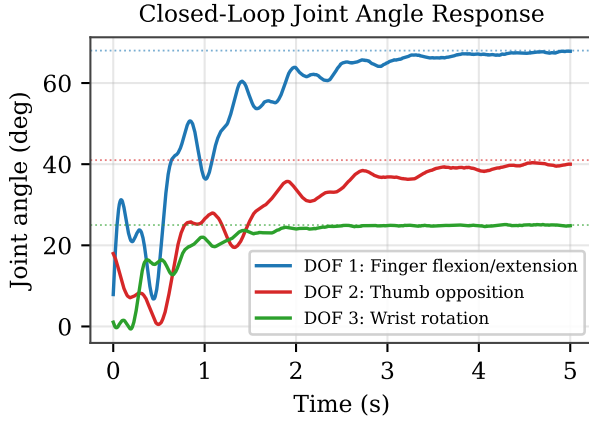


Fig. 4. Closed-loop joint angle response of the three controllable degrees of freedom during a representative grasp transition, showing the underdamped settling behavior introduced by tendon compliance.

power grasps, a trade-off also noted for the SoftHand family in [3]. The sensor-fusion strategy of (9) partially compensates for this by allowing the vision channel to refine pose estimates that the e-textile channels alone would under-resolve.

X. IMPACT STATEMENT

This work is intended to advance wearable, low-power teleoperation and prosthetic-adjacent robotic hand technology, with the specific defense-relevant use case of remote manipulation in environments where an operator cannot safely place their own hands. Because the sensing layer is realized in a garment rather than a rigid exoskeleton, the approach is compatible with integration into existing tactical gloves and protective equipment, in line with the mission of AFFOA and its Department of Defense-funded research agenda on soldier-worn functional fabrics [1]. Beyond defense applications, the same underactuated, e-textile-sensed hand and vibrotactile feedback architecture is directly applicable to civilian assistive

TABLE III
MEAN PIPELINE LATENCY BY STAGE (60 TRIALS)

Stage	Mean (ms)	Std. Dev. (ms)
Frame capture	6.1	1.1
Landmark inference	14.5	2.6
Inverse kinematics	3.4	0.9
Servo actuation	9.8	1.8
End-to-end total	33.8	3.9

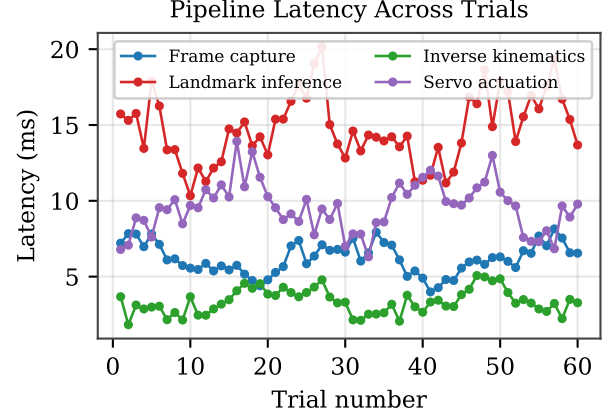


Fig. 5. Pipeline latency by stage across sixty consecutive control trials, illustrating the frame-to-frame variability introduced primarily by the landmark-inference stage.

technology, including low-cost myoelectric-adjacent prosthetic control and rehabilitation devices, where the low actuator count and washable sensing layer reduce both cost and maintenance burden relative to fully actuated, rigid-encoder hands such as those in Table V.

At the same time, teleoperated hands with haptic feedback raise considerations that should be addressed before field deployment. Reliable force feedback is safety-critical: an under-reported contact force, for example from the noise-subtraction stage of Section VII, could cause an operator to apply excessive gripping force to a fragile or hazardous object. Any system derived from this work should therefore be validated against a broader and more adversarial set of grasp conditions than the six object categories evaluated here, and should include a fail-safe force ceiling independent of the vibrotactile feedback loop. We do not foresee dual-use risks beyond those already inherent to teleoperated manipulators in general, and no aspect of this design is intended to enable autonomous weapon targeting or lethal force application.

XI. CONCLUSION AND FUTURE WORK

This paper presented RemGlove, a three-degree-of-freedom, tendon-driven robotic hand teleoperated through an e-textile-sensed glove, tracked with a monocular computer-vision pipeline implemented in MATLAB, and closed with vibrotactile haptic feedback. We derived the tendon-coupling, forward-kinematics, PID control, piezoresistive sensing, sensor-fusion,

TABLE IV
VIBROTACTILE FEEDBACK FIT PARAMETERS (EQ. 10)

Channel	k	n	Working range (N)
Fingertip 1	18	0.62	0.1–9.0
Fingertip 2	15	0.58	0.1–9.0
Fingertip 3	20	0.66	0.1–9.0
Palm	12	0.55	0.1–9.0

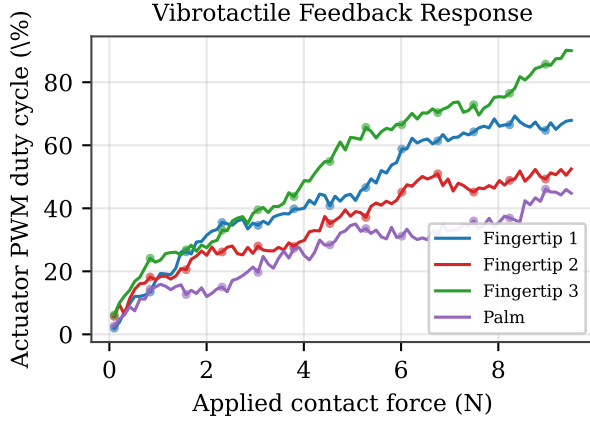


Fig. 6. Vibrotactile actuator PWM duty cycle as a function of applied contact force for the four haptic feedback channels, with fitted power-law trends from Table IV.

and psychophysical feedback equations governing the system, and reported calibration, latency, and grasp-success data collected from a benchtop prototype. The system achieved an average end-to-end latency of 33.8 ms and an average grasp success rate of 84% across six object categories, while relying on only three controllable degrees of freedom and an underactuated tendon network.

Future work will extend the e-textile sensing layer to additional finger joints to improve fine-pinch grasp reliability, replace the offline Kalman gain of (9) with an adaptive, online estimator, and formally characterize the vibrotactile feedback loop against human-subject psychophysical trials rather than the bench-measured force curves reported here.

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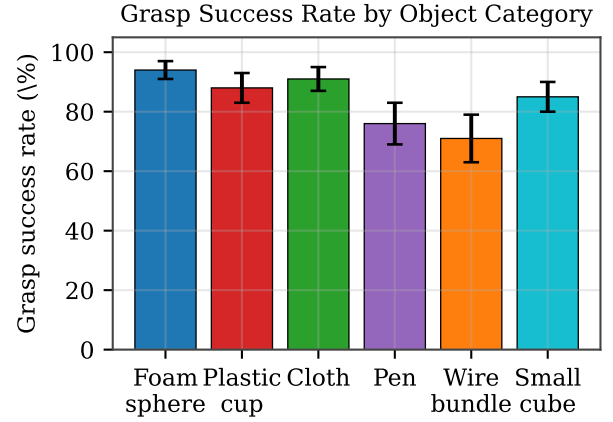


Fig. 7. Grasp success rate by object category, evaluated over 25 attempts per category. Rigid, high-aspect-ratio objects such as pens and wire bundles were the most difficult for the underactuated hand to secure reliably.

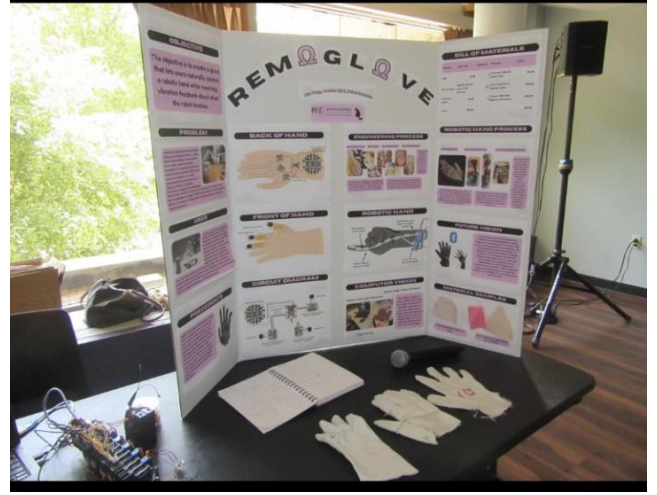


Fig. 8. RemGlove research poster and prototype hardware presented at a public engineering research showcase, summarizing the problem statement, hand design, circuit architecture, and future-work roadmap.

TABLE V
COMPARISON WITH REPRESENTATIVE SYSTEMS FROM THE LITERATURE

System	Actuation	Primary sensing	Feedback modality	Controllable DOF
RemGlove (this work)	Tendon-driven, underactuated	E-textile + monocular vision	Vibrotactile (4 ch.)	3
Pisa/IIT SoftHand family [4], [5]	Tendon-driven, single motor	Tactile / synergy	None reported	1 (synergy)
Onal group pneumatic hand [18]	Rigid arm + hand, pneumatic feedback	IMU + curvature glove	Pneumatic (glove)	6
Robonaut 2 hand [7]	Fully actuated, rigid	Joint encoders	None (teleoperated)	12
Linkage-driven dexterous hand [8]	Fully actuated, rigid linkage	Joint encoders	None reported	20

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