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A Bionic Hand for Semi-Autonomous Fragile Object Manipulation via Proximity and Pressure Sensors

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Abstract— **Multiarticulate bionic hands are now capable of recreating the endogenous movements and grip patterns of the human hand, yet amputees continue to be dissatisfied with existing control strategies. One approach towards more dexterous and intuitive control is to create a semi-autonomous bionic hand that can synergistically aid a human with complex tasks. To that end, we have developed a bionic hand that can automatically detect and grasp nearby objects with minimal force using multi-modal fingertip sensors. We evaluated performance using a fragile-object task in which participants must move an object over a barrier without applying pressure above specified thresholds. Participants completed the task under three conditions: 1) with their native hand, 2) with the bionic hand using surface electromyography control, and 3) using the semi-autonomous bionic hand. We show that the semi-autonomous hand is extremely capable of completing this dexterous task and significantly outperforms a more traditional surface-electromyography controller. Furthermore, we show that the semi-autonomous bionic hand significantly increased users' grip precision and reduced users' perceived task workload. This work constitutes an important step towards more dexterous and intuitive bionic hands and serves as a foundation for future work on shared human-machine control for intelligent bionic systems.**

I. Introduction

It is estimated that in the United States alone there are over 2.2 million individuals with some form of limb loss [1]. Despite myriad efforts in recent decades, upper-limb amputees continue to abandon their prostheses at a rate of up to 50% [2], [3], ascribing their dissatisfaction to unintuitive and poor control, among other reasons [4].

One method to potentially make control more intuitive and reliable is to sensorize and automate the prosthetic hand such that the machine will assist the user. Recent work has demonstrated that embedded or external sensors can be used to automate bionic hands conforming around or grasping objects [5]–[7]. These sensorized, semi-autonomous bionic hands have been shown to improve grasping capabilities and reduce a user's physical effort [7].

Here, we build on these foundational studies by using embedded proximity and pressure sensors to conform the bionic hand to objects while simultaneously minimizing the force output. We demonstrate that this multi-modal sensor approach provides the novel capability of allowing for autonomous manipulation of fragile objects; namely, by reducing total force output and increasing grip precision. We also show that the semi-autonomous bionic hand reduces perceived task workload relative to traditional myoelectric control approaches. These results can be used to inform intelligent prosthesis design and enable upper-limb amputees to more reliably complete dexterous tasks.

II. Methods

A. Human Subjects

Three intact-arm human participants were recruited for this study. All participants were right-handed males (age 23.7 ± 2.9 years) and had no prior experience with prosthesis control. Informed consent and experimental protocols were carried out in accordance with the University of Utah Institutional Review Board.

B. Signal Acquisition

Surface electromyography (sEMG) signals were recorded from a custom fabric sleeve embedded with 32 button-type surface electrodes placed superficially to extrinsic forearm flexors and extensors [8]. sEMG was sampled using the 512-channel Explorer Summit System (Ripple Neuro LLC, Salt Lake City, UT, USA). Subsequent sEMG processing has been described previously in [9], [10]. When using the bionic hand, participants additionally donned a bypass socket described in [11], which allowed them to perform functional tasks using sEMG control.

C. Training Data and Decode Algorithms

To control the bionic hand via sEMG, training data were recorded from the left forearm of the participant while they mimicked pre-programmed movements of the left-handed variant of the TASKA prosthetic hand (TASKA Prosthetics, Christchurch, New Zealand). The pre-programmed movements included five trials of a full flexion pinch between the thumb and index fingers followed by five trials of simultaneous full extension of these same digits. Additional information regarding the training procedure can be found in [12]. Kinematic data were normalized such that full flexion and full extension corresponded to +1 and -1 units, respectively.

A modified Kalman filter (mKF) was trained to estimate motor intent from sEMG using the training data described

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above [13]. This provided the participants full control over the bionic hand. The output of this continuous decoder allows for independent, proportional control of multiple degrees of freedom, although for our experiments, movements were constrained to flexion and extension of the thumb. We placed a 20% threshold [12] and a latching filter [14] on the mKF output to improve decoder performance.

D. Semi-Autonomous Bionic Hand

The thumb, index, middle, and ring fingers (D1 – D4) of the TASKA hand were retrofitted with multi-modal fingertip sensors (Point Designs LLC, Lafayette, CO, USA) [15]. Each fingertip contained both an infrared and a barometric sensor, endowing the hand with the ability to detect objects within 5 cm and detect forces up to 50 N. During the experiments, all sensor data was median filtered at 30 Hz over a time window of 10 samples. The data from each pressure sensor was calibrated using an adaptive baseline derived from the most recent pressure value without proximity detected. Additionally, the pressure sensor data from the thumb was high pass filtered with a gain of 0.85 to account for low frequency drift.

These sensors were used to create an autonomous machine controller that could independently control each sensor-enabled finger by maximizing proximity (i.e., moving closer) to a detected object. Once contact with the object was detected (greater than 10 pressure units), the corresponding digit would cease moving and hold its current position. In this way, each digit could autonomously detect, move towards, and reliably make minimal contact with (i.e., grasp) an object. The minimal amount of contact provided by the machine control was enough to enable the machine control to autonomously complete dexterous tasks, such as holding a fragile object.

In isolation, the machine control is incapable of releasing an object. To address this, the participant could toggle the machine control on and off using the mKF decoder described above. For example, when the participant attempted to make a pinching movement beyond 10% of the full range of the mKF, the machine control would be enabled and take control of subsequent movements of those digits. When the participant wanted to release an object, the machine control could then be disabled if the participant attempted to extend their thumb and index finger beyond 10% of the full range of the mKF. In addition to providing the ability to release a grasped object, this toggling system between the mKF and the machine control had the added benefit of making the participant feel like they were in control of the movements when in fact the machine control was active during object interaction. For brevity, this semi-autonomous combination of sEMG and machine control will now simply be referred to as machine control.

E. Dexterous Fragile-Object Task

A fragile-object task was used to quantity the performance and dexterity of the two control modes: human sEMG control vs. machine control (Fig. 1). Participants were blinded to which control mode was in use. In the fragile-object task, participants must move a mechanical fragile object from one side of a vertical barrier to another in a specified time limit [16]. If too much force is applied to the object, it will "break" and emit a clicking noise. In our experiments, the object weighed 496 g and the vertical barrier was 6.25 cm tall. Participants were instructed to use a pinching movement to

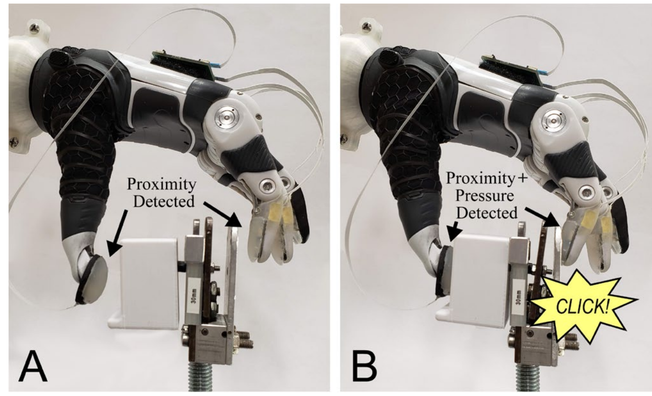

Figure 1. The bionic hand during the fragile-object task. Participants picked up and transferred the fragile object over a barrier. The fingertips of the TASKA hand were replaced with custom fingertips embedded with proximity and pressure sensors. **A)** As the hand approaches the object, proximity is detected by the thumb and index finger. **B)** Upon making contact, pressure is also detected by the fingertips. Applying too much force causes the object to "break" and emit an audible click, resulting in a failed trial. The pressure threshold to break the fragile object was set at ~19 N for an "easy" task and ~17 N for a "hard" task. Under machine control, the hand is capable of semi-autonomously completing the grasp without breaking the object.

move the object from the left side to the right side – a distance of approximately 15 cm. Each trial had a 45-second time limit, with a verbal warning if less than 15 seconds remained. The participants were asked to move the fragile object over the barrier as quickly as possible without breaking the object. Failed trials were those where the object was broken or dropped.

To reduce the number of confounding factors, only the thumb of the TASKA hand was allowed to move during the task. The middle, ring, and little fingers were locked in a fully extended position to prevent contact with the fragile object. The index finger was locked in a slightly extended position, which provided adequate space in which to place the object while still allowing room for the thumb to freely flex and extend. For each trial, the participants were asked to rest the fingertip of the index finger on the backside of the fragile object prior to flexing the thumb forward to make contact with the front of the object. In this way, the distance the thumb traveled during each trial was approximately consistent.

Participants completed the fragile-object task with the break force set at two different levels: an easier setting (approximately 19 N) and a more difficult setting (approximately 17 N). The easier setting was attempted during each participant's first visit, and the more difficult task was attempted in a subsequent experimental session.

For each difficulty setting, the participants first completed the task five times with their native, physiological hand. This was done to compare performance of the bionic hand to the human-hand gold standard. Next, the bypass socket was donned, and the participant would practice the task with the bionic hand for one minute with each of the control modes (human sEMG control vs. machine control). Practice was followed by a randomized, counterbalanced set of 20 trials for both human sEMG control and the machine control. After each set of 20 trials with a given control mode, participants completed a NASA Task Load Index (TLX) subjective workload survey [17].

F. Performance Metrics

We measured the success rate and trial duration of the trials with the native hand and with the bionic hand under each of the two control modes. Additionally, weighted TLX scores and peak applied pressure were computed for the trials using the bionic hand. Statistical tests were performed for success rates, TLX scores, and peak pressure. For each difficulty setting, human sEMG control and machine control success rates and TLX scores were each compared using a paired sample t-test with a significance level of 0.05.

Peak pressure values were dependent on the calibration of the fingertip sensors for a given experimental session. To account for potential inter-session variation, the mean peak pressure applied during human control trials was used to normalize the peak pressure values for both human- and machine-control trials within each session. These normalized trials were then aggregated based on control mode across subjects and task difficulties. We then compared mean peak pressure using a two-sample t-test, and peak pressure variance using a two-sample F-test. Each test used a significance level of 0.05.

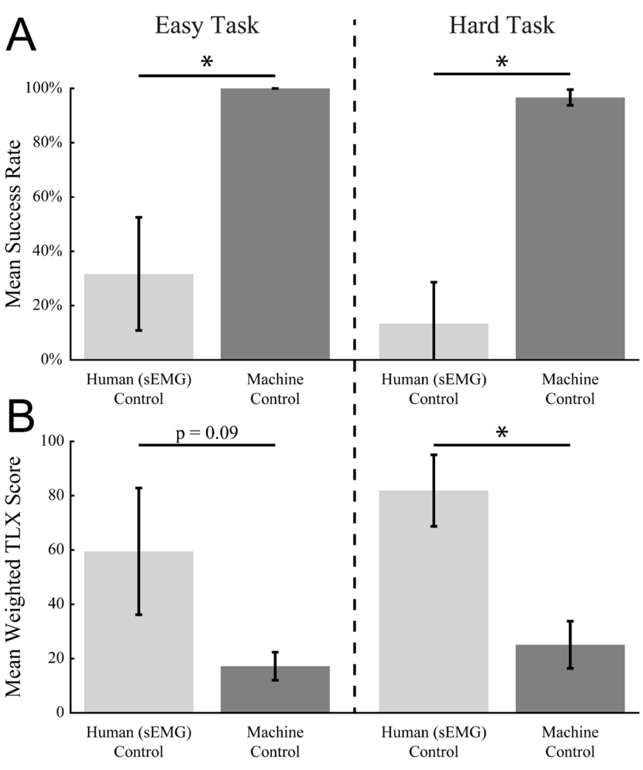

Figure 2. Machine control outperformed human control for both task difficulties across multiple metrics during the fragile-object task. **A)** Nearly all users completed the easy and hard tasks with 100% success using the machine control. Human (sEMG) control was significantly less successful, with a clear reduction in performance with increasing task difficulty. **B)** All participants rated the human control with a higher subjective workload (more difficult) compared to machine control, a trend which was significant for the harder task. $^*p < 0.05$

III. Results

A. Machine control outperformed human control for success rate during both task difficulties

Success rates were recorded for the fragile-object trials. For all three participants, trials completed using machine control consistently outperformed those attempted using human control (Fig. 2A). Aggregate success rates for the easy task revealed that the human success rate was $31.7 \pm 20.8\%$ compared to a perfect 100% completion rate for machine control. Increasing the task difficulty considerably reduced the performance of the human control, yielding a mean success rate of $13.3 \pm 15.3\%$. Increasing task difficulty minimally affected the machine control with a total of two failed trials between all three participants, resulting in a mean success rate of $96.7 \pm 2.9\%$. For both task difficulties, these differences between human and machine control were statistically significant (p's < 0.05, paired sample t-tests). Trials completed with the native hand had a success rate of 100% for all participants and task difficulties.

B. Perceived workload was lower for machine control than human control for both task difficulties

Comparisons of weighted TLX scores for subjective workload further confirmed the performance differences between control modes (Fig. 2B). Higher TLX scores are correlated with a task being perceived as more difficult. When using sEMG control, participants reported a mean subjective workload score of 59.5 ± 23.3 for the easy task. Switching to machine control resulted in a lower mean score of 17.2 ± 5.2, but this difference was not statistically significant ($p = 0.09$, paired sample t-test). The harder task, however, resulted in a significant difference in TLX scores between the two control

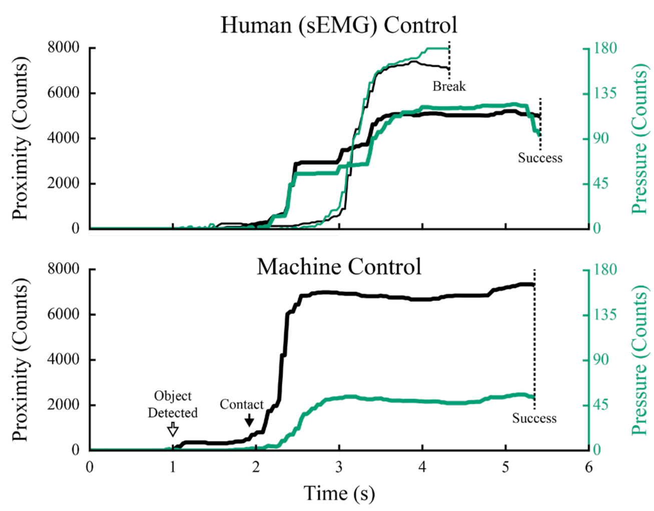

Figure 3. Representative fingertip sensor traces from the thumb during the fragile-object task with the bionic hand under human control (top panel) and machine control (bottom panel). Sufficient pressure to successfully grip the object without exceeding the pressure threshold is accomplished more reliably under machine control, with similar trial duration times for successful attempts between human and machine control. Two trials are shown in the **top panel**: one ending in a break and another ending in success. In the failed trial, applied pressure exceeded ~180 counts, resulting in a broken object. The **bottom panel** elucidates the machine control strategy. The object is detected by the proximity sensor at ~1 s (white arrow) and the thumb moves towards the object until making contact at ~2 s (black arrow).

modes ($p < 0.05$, paired sample t-test). For this more difficult task, the mean scores were 81.9 ± 13.2 and 25.1 ± 8.7 for the human and machine cases, respectively.

C. *Machine control of the bionic hand applied reliable, minimal pressure for task completion with similar task duration times compared to human control*

The fingertip sensors provided a rich dataset to examine proximity and pressure values during individual fragile-object trials (Fig. 3). Trials completed under human (sEMG) control resulted in both breaks and successes, with breaks occurring at pressure values above ~19 N and ~17 N for the easy and hard tasks, respectively. Trials employing machine control showed more stable sensor values, consistent with movements under semi-autonomous control. With machine control, the object was reliably detected by the proximity sensor, and the machine control subsequently moved the thumb and applied the steady pressure required to successfully grasp and transfer the object.

The durations of successful trials with the bionic hand were comparable between the control modes. For the easy task, successful trials using human control lasted 6.8 ± 1.7 s and were 6.5 ± 1.9 s for machine control. For the more difficult task, trials were 7.1 ± 0.6 s and 7.7 ± 5.2 s, respectively. For comparison, participants using their native hand completed the two tasks in 2.7 ± 0.3 s and 2.4 ± 0.2 s for the easy and hard settings, respectively.

The peak pressure applied by the machine control was significantly less than that applied by human control across all trials and task difficulties (Fig. 4). On average, the peak pressure under machine control was 30% less than human control ($p << 0.001$, two-sample t-test). Peak pressure variance was also significantly less in the machine control case compared to human control (25.3 vs. 46.2 counts, respectively; $p << 0.001$, two-sample F test).

IV. Discussion

This work serves as one of the first demonstrations of an intelligent bionic hand capable of semi-autonomously manipulating fragile objects. Consistent with prior work [7], we show that semi-autonomous bionic hands are capable of reducing user effort, and these findings now extend to the previously unexplored area of fragile-object manipulation. Importantly, the novel pairing of proximity and pressure sensors enabled these new semi-autonomous capabilities.

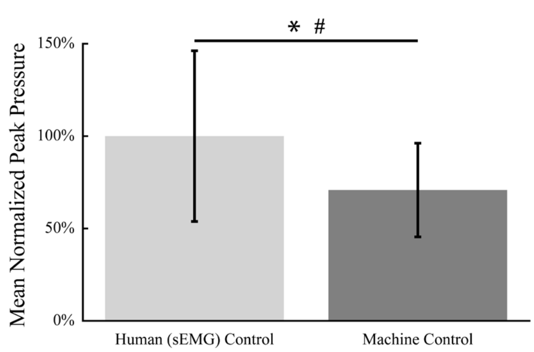

Figure 4. Machine control resulted in less applied pressure and less pressure variability. On average, peak pressure applied during human control was 30% greater than machine control (*$p << 0.001$). Pressure variance was also much less for the machine control case (#$p << 0.001$). Bars were derived from aggregate, normalized data across participants and task difficulties.

We note that participants attempting the fragile-object task under human (sEMG) control were more likely to break the object and exhibited greater variation in applied pressure. One explanation for this variation is that the participants could not feel how much pressure they were applying to the object. In many of these trials, participants would attempt to pick up the object before reliable contact had been made, resulting in frustration, as reflected in the poor TLX subjective workload scores. Even when enough force had been applied to allow for liftoff, participants often broke the object during transfer. Again, this is likely due to a lack of sensory feedback, but also possibly due to changes in sEMG due to hand posture [18]. The machine control, on the other hand, did not suffer from these physiological confounding factors. The proximity sensors ensured a steady approach towards the fragile object, and the pressure sensors provided consistent force throughout the grasp and transfer stages of the task. Given that conventional prostheses lack sensory feedback and are difficult to control [3], [4], semi-autonomous control may improve user satisfaction.

Prior work has shown that light-based sensors [15], [19] or pressure sensors [5], [7] embedded in a bionic hand can be used to automate bionic hand conformations. Light-based sensors provide the ability to confidently grasp objects within proximity, whereas pressure sensors provide the ability to confidently hold an object once grasped. Here we demonstrate, for the first time, that utilizing both proximity and pressure sensors simultaneously can automate both grasping and holding, which uniquely allows semi-autonomous systems to perform more dexterous tasks such as manipulating fragile objects. Embedding additional sensor modalities, such as cameras [6], may further increase autonomous capabilities of bionic hands.

Prior work has also demonstrated that multiple intelligent systems can be used simultaneously under a shared-control paradigm to further enhance dexterity [20], [21]. Although the machine control significantly outperformed the human (sEMG) control, it was specifically tuned to work with fragile objects and is a limitation of the present study. Merging the two control approaches may provide greater performance, task generalizability, and adaptability overall by allowing the user to focus solely on regulating force without the cognitive and physical burdens of having to also grasp and maintain hand posture. Future work should investigate the functional and psychological impact of giving progressively more control to the autonomous portion of the bionic hand.

V. Conclusion

Altogether this work provides a strong foundation for more intelligent bionic hands that can work synergistically with a user to increase dexterity and reduce cognitive demand. Such intelligent systems may ultimately recreate the complete functional and psychological experiences of the endogenous human hand.

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J. L. S. is a founder and shareholder of Point Designs LLC and an inventor on a non-provisional patent application on the prosthetic fingertips used in this work.

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