Myo Action: Accelerating Voluntary Actions via Electromyography and Muscle Stimulation

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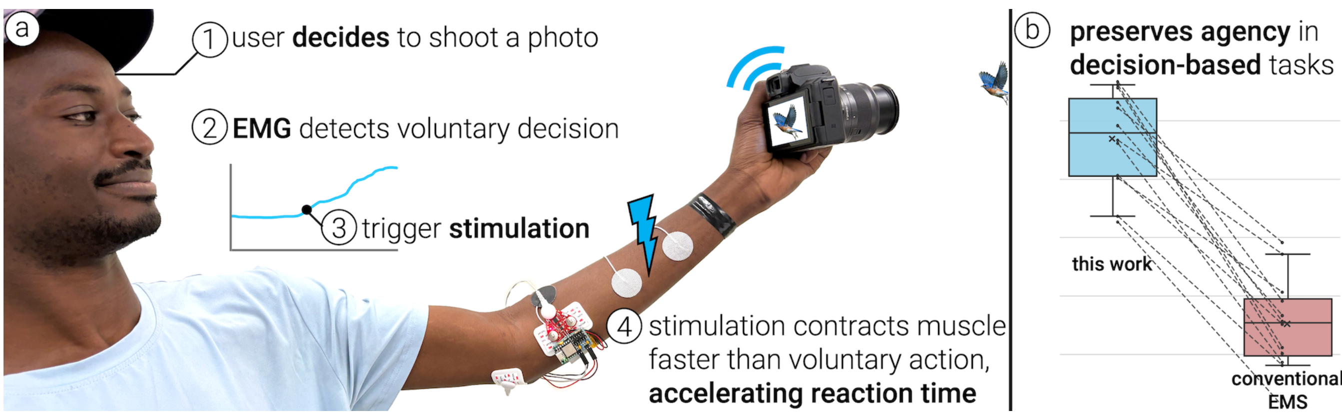

Figure 1: We present Myo-Action, an interaction technique to accelerate users' voluntary action without overriding their intentions. (a1, a2) Our device detects the user's intention to execute a physical action (e.g., shooting a photo of a flying bird) via electromyography (EMG) and (a3) activates electrical muscle stimulation (EMS) at an early onset of EMG. (a4) The key is that EMS takes less time to start contracting muscles compared to typical voluntary actions. In this way, Myo-Action can accelerate users' actions even though the intervention is triggered after the EMG signal detection. (b) As our approach does not override intentions, it preserves agency even in decision-involving actions unlike prior EMS techniques (e.g., Preemptive Action [24, 43]). The box plot represents results from our user study aggregated across trial-types.

Abstract

We propose a technique for accelerating users' action without overriding intention, thereby preserving agency. In our approach, it is the user's muscle signals, detected via electromyography (EMG), that trigger electrical-muscle-stimulation (EMS) without external sensors or stimulation-timing calibration. The key to enable this "agentic speedup" is a synergy between EMG and EMS: EMG can detect an early-onset of the neural-response; EMS can contract a muscle faster than a typical voluntary-contraction. This—coupled with our low-latency system (~290 μs)—results in an accelerated reaction-time, even though the haptic-assistance is initiated after the muscle-signal. In our study, we confirmed that our novel approach: (1) accelerated users' reaction-time by ~23 ms compared to voluntary-action; (2) preserved agency in decision-involving actions (i.e., go/no-go trials), which existing muscle-stimulation techniques cannot achieve; and (3) participants felt it augmented their performance in physical-tasks. This puts forward embodied-assistance that aligns with users' decisions/intentions, which we demonstrate in exemplary applications.

CHI '26, Barcelona, Spain

ACM ISBN 979-8-4007-2278-3/26/04
https://doi.org/10.1145/3772318.3791103

CCS Concepts

• **Human-centered computing → Interaction techniques**.

Keywords

Agency, Electrical Muscle Stimulation, Electromyography, Intention, Haptics

ACM Reference Format:
Yudai Tanaka, Che-Wei Hsu, Bruno Felalaga, and Pedro Lopes. 2026. Myo Action: Accelerating Voluntary Actions via Electromyography and Muscle Stimulation. In *Proceedings of the 2026 CHI Conference on Human Factors in Computing Systems (CHI '26), April 13–17, 2026, Barcelona, Spain.* ACM, New York, NY, USA, 11 pages. https://doi.org/10.1145/3772318.3791103

1 Introduction

Accelerating movements via electrical-muscle-stimulation (EMS) can enhance users' reaction-times in a wide range of physical tasks from high-speed photography [38]; grabbing a falling object before it hits the ground [24, 39]; playing e-sports [52]; and even steering users to safety [41]. These accelerations can even train users [25].

Unfortunately, this approach also deprives users of their sense-of-agency (the feeling of "I did this") by overriding their intention to move—these interfaces do not allow users to opt-out from the EMS-movement.

While recent work has mitigated some loss of agency by fine-tuning the timing of EMS [24, 43], this only makes so-called preemptive accelerations agentic when they are closely-aligned with the user's own timing (demanding a lengthy calibration). However, these techniques fail if the user does not decide to move, in which the system delivers the preemptive stimulation and the user is left with a drastic sensory conflict. Prior work has measured this drop in agency (system does not guess user's intention) and found that it is even more detrimental [43].

While researchers have investigated closed-loop body-actuation systems with various sensing techniques, there has not yet been a successful closed-loop system that accelerates reaction-time. Thus far, the most prevalent sensing modality for closed-loop EMS is motion tracking (e.g., accelerometers, optical marker-based systems). However, such approaches only capture movements that are already underway and are unable to detect the cues preceding an intended movement—required for accelerating a user's physical action. By contrast, it is possible to detect cues that precede a movement by detecting neural-responses (e.g., brain-sensing via EEG or muscle-sensing via EMG).

In this paper, we introduce Myo-Action, a novel approach that accelerates users' movements while preserving their sense-of-agency (Figure 1). Unlike prior techniques, our method leverages the user's neural-signals as the trigger for assistance. Specifically, we use electromyography (EMG) to detect the earliest onset of muscle activation—indicating that the user has already committed to move—and immediately apply EMS to the same muscle. Because EMS induces a contraction faster than voluntary-activation (and our system-latency is only ~290 μs), this results in a measurable reduction in reaction-time. Through our user study, we demonstrate that this approach accelerates reaction-times by approximately 23 ms compared to unassisted actions, preserves agency even in decision-based tasks, and is experienced positively in real-world scenarios, thus establishing Myo-Action as a new direction for haptic-assistance.

2 Related Work

Our work builds on prior literature in HCI and cognitive-science that examines users' agency in interface-assisted action, particularly acceleration of their reaction-time, as well as EMS-systems that incorporate EMG-sensing.

2.1 Physically Accelerating Movements

The most popular way to actuate the body in HCI is EMS—with ~150 publications in HCI [17]. Given this prevalence, it is not surprising that it was used to speedup actions (e.g., tap a button faster) by *preemptively* stimulating muscles [24, 25, 36, 39, 43, 46], giving rise to the term *Preemptive Action* [24].

The early-work in this area [24, 25, 38, 39, 41, 52] used this technique for applications in which movement-accelerations can be beneficial to a user. Examples include the following: timing-sensitive tasks such as high-speed photography [38]; grabbing a falling object [24, 39]; e-/sports training [25, 52]; and even preemptively steering users to safety while walking [41]. Going further, Kasahara et al. showed these accelerations facilitate training with an 8-ms improvement after the device was removed [25].

2.2 Interface-Driven Actions Diminish Agency

The sense-of-agency is essential in interface design [33], in domains such as usability, performance, and ethics of emerging technologies [9]. In HCI, it has been established that automated-assistance in interactions can diminish users' agency [5]; even a slight acceleration added to a mouse-cursor reduces agency [11]. This loss of agency is more detrimental in haptics where interfaces physically override actions. Researchers have confirmed that EMS-accelerated movements lead to a decline in agency [24, 36, 43, 46]. This is most dramatic when EMS actuates before **users formed their movement intention** (i.e., user finds themselves pressing a button "super-humanly" fast) or when their **intended movement differs from the EMS-movement** (e.g., user forced to press a button when they did not intend to).

2.3 Timing-Adjusted Interventions Still Diminish Agency in Decision-Based Actions

The most developed strategy to mitigate loss of agency is adjusting the timing of EMS closer to voluntary timing. Researchers found that this approach improved the sense-of-agency compared to triggering EMS prematurely [24, 46]. However, it presents three challenges: (1) it requires a round of calibration to find "a timing sweet spot that still offers preemption (i.e., faster than ordinary reaction-time) without drastically decreasing agency" as stated by [24]; and (2) preemptive timing is fixed but "is dependent on the user's own reaction-time" as stated by [24]. Thus, once determined for a particular user/task, this timing remains static. In fact, the same group of researchers found that switching to a nearly identical task with slightly-higher cognitive-load (e.g., pressing the red button rather than just pressing any button) further reduced agency—because the task changed, but the EMS preemptive timing remained unchanged. Moreover, there is a deeper problem: (3) Preemptive EMS cannot guess the user's intention. In decision-involving cases, researchers found that this approach dramatically reduced agency, and, worst of all, it forced unintended outcomes.

2.4 Toward Assisting Decision-Based Actions

Recently, two promising directions in supporting decision-involving actions emerged: (1) brain-stimulation and (2) closed-loop EMS.

Brain-stimulation. The first approach [45] resorts to large head-mounted magnetic-coils for brain stimulation and applies the same strategy as *Preemptive Action* (i.e., stimulate before user-movement via a fixed pre-calibrated timing) but does so in a subthreshold manner (i.e., without causing movement). Rather than creating

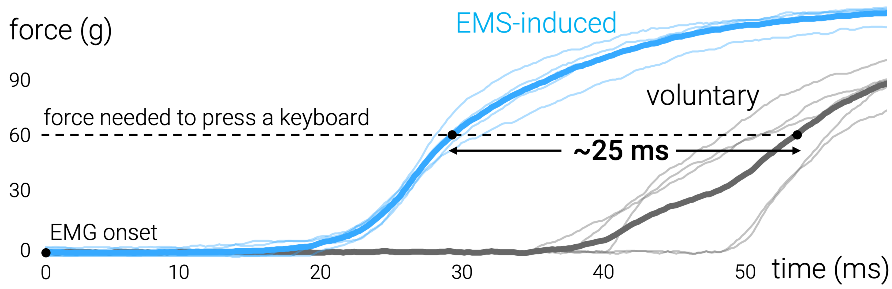

Figure 2: An observation of our key principle: EMS-induced contractions reached the force-level required to register an input ∼25 ms faster than voluntary contraction. Example data from one user is shown (averaged over five trials per condition). Measurements were based on the same force-sensor, EMS stimulator, and oscilloscope employed in our latency evaluation and user study presented later.

an involuntary-movement, it "primes" the neural-pathways to respond slightly faster than normal, giving rise to its name *Primed Action* [45]. Unfortunately, its speedup is only 8 ms; while applicable to fast sports/games, it cannot be widely used. Moreover, this technique has not been validated to support agency in tasks that involve decision-making.

Closed-loop EMS. The latter approach triggers EMS based on EEG-signals [20]. By detecting an EEG-pattern that typically precedes a voluntary movement, EMS is triggered but preserves more of the user's sense-of-agency during reaction-time [20]. However, it remains unclear whether this system would suffice, since no reaction-time measurements were reported [20]. Finally, although monitoring brain-activity can track volition, sensing reliability remains a challenge—the same researchers reported false-positive/false-negative rates of this EMG-based EMS triggering of up to ∼30% [20]. This is why we turned to sensing the peripheral neural-activity.

2.5 EMG for EMS

Sensing muscles with EMG has been a major approach to recognize users' movement-intention, and it has been extensively explored in HCI [3, 14, 23, 32], namely for the development of always-available input devices [42].

Given the popularity of EMG, many have combined it with EMS to enable new applications (yet none used to accelerate users' movement). This includes: *Proprioceptive Interaction* using the body for input & output [13, 30]; synchronizing movements across multiple users, where EMG from one user triggers EMS in another [31, 40]; or leveraging this inter-user synchronization to accelerate one's reaction-time, in the *eTech*-demonstration, *Wired Muscle* [39]. In the context of learning physical skills, Niijima et al. employed EMG to monitor users' muscle fatigue during EMS-assisted instrument play [37]. Notably, Knibbe et al. demonstrated EMG's utility in improving the practicality of EMS-systems through automatic calibration using EMG measurements [26].

The most relevant uses of EMG+EMS for our work are found in rehabilitation where EMS is delivered only when a patient's EMG signals exceeds a threshold, thereby reinforcing the patient's movement [6, 19]. For instance, Francisco et al. reported that the EMG-triggered stimulation better facilitated patients' recovery of their arm/hand function [19]. A review by Meilink et al. discusses that this approach may promote rehabilitation by coupling a patient's voluntary effort with EMS, thereby facilitating motor re-learning through repeated stimulation [32]. Inspired by these EMG+EMS systems, we designed a novel device capable of accelerating reaction-time while preserving users' agency, even if the task involves a decision that the interface cannot predict ahead of time.

3 Myo-Action: Principle of Operation

Our technique, Myo-Action[1], preserves users' agency while accelerating movement by detecting neural activity of a specific muscle via EMG and triggering EMS. Although this may seem paradoxical—i.e., how could a system speed up a contraction that is already ongoing?—we exploit two key principles: (1) EMG detects neural activation in a target muscle prior to any muscular displacement; and (2) EMS can induce faster than voluntary muscle contraction.

EMG detects neural activation in a target muscle before movement. The first principle that enables our approach is that EMG can detect a muscle's neural activity, preceding measurable movement or force. This time window, known as *electromechanical delay* [4, 7], is caused by excitation-contraction coupling and tendon and joint compliance and is typically tens of milliseconds. It is important to note that EMG must target a specific muscle with a pair of electrodes placed over the muscle belly [34]. In principle, this underlying per-muscle selectivity reduces interference from other muscles during detection in multi-muscle movements [8]—though in this work, we limit our device to work in simple movements and have not characterized multi-muscle movements.

EMS causes faster muscle contraction than voluntary control. Figure 2 depicts how an electrically-induced contraction tends to outperform a voluntary contraction (we confirmed this also in our *User Study*). This is in line with findings in neuroscience: "(. . .) delay was greater in the voluntary condition (22.8 +/- 8.2 ms) compared to the involuntary condition (9.7 +/- 3.1 ms; p < .001)" [22] and "delay of the involuntary contractions (. . .) was significantly shorter than that of the voluntary contractions [(. . .) P < 0.05]" [51]. The process that best explains this is from how our nervous system chooses which muscle fibers to use for a movement. This process, known as motor-unit recruitment, follows *Henneman's size principle* (1965): "motor neurons with large cell bodies tend to innervate fast-twitch,

[1]We named it **Myo-Action** since it uses **Myo**graphy (EMG) and its accelerated-movements are felt as "**My O**wn" Action.

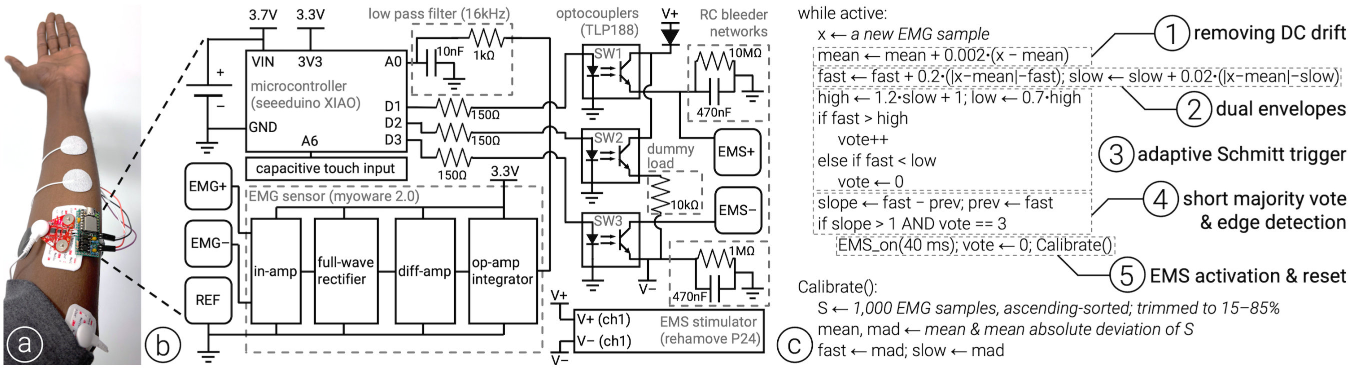

Figure 3: (a) Our hardware system. (b) Circuit design. (c) Firmware-level signal processing to further mitigate false triggering.

high-force, less fatigue-resistant muscle fibers, whereas motor neurons with small cell bodies tend to innervate slow-twitch, low-force, fatigue-resistant muscle fibers" [2, 21]. This allows users to control forces precisely—if motor-units that can only control large-forces would be recruited, human-level dexterity would be challenging. Turning back to the fundamentals of electrical-stimulation, we can deduce the effect of EMS on motor-unit recruiting. Since any type of electrical stimulation is non-selective [28], EMS will recruit both types of fibers concurrently [22]. This results in large motor-units being stimulated, causing "fast-twitch, high-force" movements [22] which accelerate the initial-phase of the contraction [4, 7].

4 Implementation: Engineering Fast EMG Detection to Speed up EMS Response

Hardware overview. As shown in Figure 3 (a), our device is comprised of: EMG-amplifier (Myoware-2.0), microcontroller, optical-switching stage, analog-filtering stage, and a medical-grade EMS-stimulator (Rehamove-P24). Electrodes are placed atop a muscle to cause movement (e.g., the *flexor digitorum* muscle to curl middle/ring fingers was used in our study). The EMG sensor is also attached atop the same muscle via another pair of electrodes plus a reference. We achieve low-latency by having the stimulator continuously output a pulse-train (800-μs pulse-width, 400Hz) and gating the stimulation via optical-switches upon detecting EMG-signals.

Circuit design. Two circuits enable our device (Figure 3b): (1) an optical-switching stage that gates the stimulator output to the user upon EMG detection; and (2) an analog-filtering stage that stabilizes the EMG-sensing by mitigating both background and EMS-induced noise. First, the optical-switching stage uses three optocouplers (TLP188; 350V rating; ∼1-μs turn-on), driven by a SAMD21's digital-outputs. When EMG is not detected, SW1 and SW3 are OFF and SW2 is ON, routing the EMS to a dummy load to suppress residual noise. Upon detection, SW1 and SW3 turn ON while SW2 turns OFF for 40 ms, delivering stimulation to the user. Second, the analog-filtering stage employs RC bleeder networks and a 16kHz low-pass filter. During EMS, the bleeder networks mitigate leakage currents to the sensor-side. The low-pass smooths high-frequency noise at the ADC input, enabling cleaner sampling of the EMG amplified-output.

User input to activate system. Finally, users can toggle the system to enable or disable EMG triggering via a capacitive-touch button (SAMD21 QTouch), allowing them to control when EMG is monitored, potentially reducing unintended stimulation in more mobile or less-controlled activities or during prolonged use (see *Limitations*).

Microcontroller's signal-processing. Our detection-algorithm runs on the microcontroller to improve the reliability of the EMS-triggering (Figure 3c). When the detection system is activated (button press by user), it runs a calibration, which acquires 1000 EMG samples as a baseline of the noise-level; these values seed the filters. During operation, DC-drift removal subtracts a slow baseline from each incoming sample, so only rapid muscle activity remains. A dual-envelope then runs at two timescales: a fast envelope that follows bursts with microsecond-order latency; and a slow envelope that adapts to the ambient noise-floor/EMS-induced-artifacts. From these, we form an adaptive Schmitt trigger with dynamic upper/lower thresholds and hysteresis, preventing chatter near boundaries. Finally, a short majority vote and edge-check require three consecutive hits and a rising slope, rejecting isolated spikes. When satisfied, we gate the stimulator output for 40 ms and then schedule a recalibration to update the noise baseline.

Latency. We evaluated this with a 100MHz-oscilloscope (GWInstek GDS-1102), probing signal input+output. We measured ∼115 μs through the EMG-amplifier and ∼175 μs through our analog-filtering and optical-switching stages. Thus, latency from EMG-detection to EMS-activation is ∼290 μs.

Safety. Our medical-grade stimulator controls electrical currents independent of skin-impedance, and our software limits the maximum output to 20 mA—25 times below the safety limit [27].

5 User Study

Our study evaluated whether Myo-Action (1) shortens reaction-times relative to voluntary action; (2) preserves agency in decision-involving actions; and (3) positively shapes their perceived performance. Participants completed three tasks using our interface: (1) no-decision reaction-time; (2) decision-based reaction-time (i.e., go/no-go), and (3) explored our device in two exploratory applications to elicit feedback (i.e., pen-catching & video-gaming). The study was approved by our Institutional Review Board (IRB21-1158).

Hypotheses. Given the aim of our investigation, our hypotheses were two-fold: (**H1**) Myo-Action's hardware is able to accelerates a participants' reaction-time compared to their own voluntary

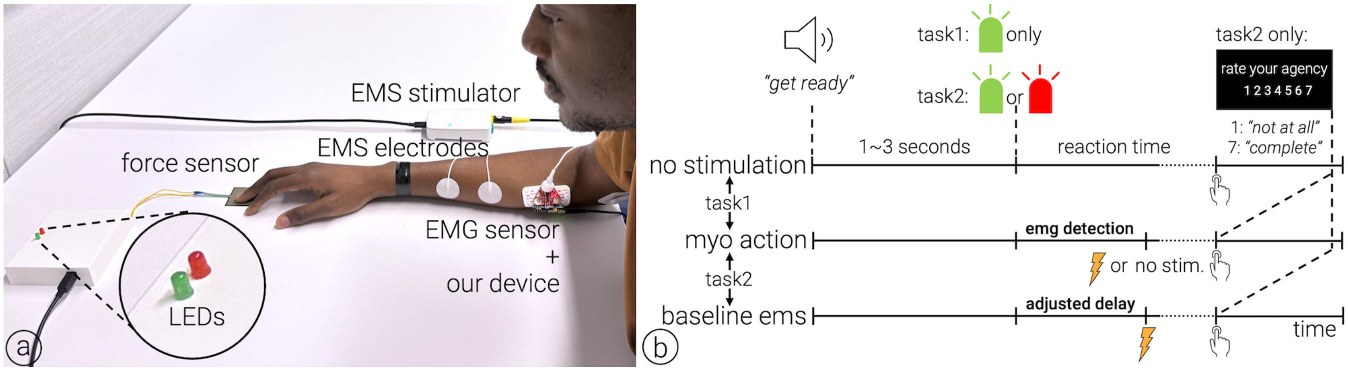

Figure 4: (a) Our study setup. (b) A summary of the task and procedure. Participants performed no-decision reaction-time tests (Task1; green LED) under *Myo-Action* or *No-Stimulation* and decision-based reaction-time tests under *Myo-Action* or *Baseline-EMS* (Task2; green: *go*, red: *no-go*). In decision-based tests, participants rated their sense of agency after each trial.

baseline—this was the aim of our first task, in which participants performed a canonical no-decision reaction-time task; and (**H2**) Myo-Action's accelerations are perceived as more agentic when decisions are involved compared to baseline-EMS (*Preemptive Action* [24])—this was the aim of our second task, in which participants performed a canonical decision-based reaction-time task.

5.1 Conditions

Myo-Action. When our device detects the participant's EMG signals in the *flexor digitorum* muscle during a trial, it outputs 40-ms EMS pulse train (via our custom switching circuit) to accelerate the finger movement. On the contrary, when the device does not detect the EMG signals, it does not output stimulation.

No-Stimulation. The user receives no stimulation/assistance from the device. This condition served as a baseline to characterize the participant's reaction-time based on their voluntary action.

Baseline-EMS. This condition served as a baseline to characterize how existing open-loop EMS approaches (that are already designed to preserve sense-of-agency, i.e., *Preemptive Action* [24]) affect the agency in decision-involving actions. When a participant experienced this condition, the device always delivered the EMS to accelerate participants' reaction-time irrespective of EMG activity or users' context. The stimulation timing was adjusted to match the degree to which Myo-Action accelerated reaction-time relative to voluntary action (see *Procedure*).

5.2 Study Design

Apparatus. As depicted in Figure 4 (a), for the reaction-time tasks, participants sat at a desk, wearing our device (see *Implementation*), facing a green and red LED, and resting their right middle and ring fingers on a force-sensing resistor (FSR-406). An Arduino (32-bit ARM cortex-M4) handled the LED activation and sampled the FSR data at 2000 Hz. This microcontroller was responsible for all time-keeping, which allowed it to be extremely precise and devoid from CPU multithreading/loading issues (same as in prior work [25]). The microcontroller received instructions from a laptop running our Python study application[2] (that selected which trial-type would happen next, saved the reported reaction-times from the microcontroller, etc.). We set the input detection threshold of the force-sensor to be 60gf (the same level of force as a keyboard-press [16]). Finally, during the exploratory applications (e.g., pen-catching and video-game) participants were free to move about the study desk (e.g., standing and holding their hand in mid-air to catch pens, sit down at a laptop to play the game using its built-in keyboard).

No-decision reaction-time. The participants performed simple reaction-time tests—most typical task for evaluating interface-assisted physical reactions [24, 36, 45]—using either *Myo-Action* or *No-Stimulation* (Figure 4b). In each trial, the green-LED lit up at a random interval (1~3 seconds), and participants tapped the force-sensor as quickly as possible.

Decision-based reaction-time. The participants performed go/no-go reaction-time tests using either *Myo-Action* or *Baseline-EMS*. This is an identical reaction-task except that in half of the trials, the red-LED lit up (Figure 4b), in which case participants were instructed not to tap the sensor (*no-go* trials); they were still required to react as quickly as possible when the green-LED lit up (*go* trials). The system registered not-reacting in a *go* trial and reacting in a *no-go* trial as mistakes. After each tap, the system prompted participants to rate their sense-of-agency on a 7-point Likert scale ("How much did you feel that you are in control of your action?"; 1 = "not at all," 7 = "complete"). Additionally, in *Myo-Action*, to probe our device's detection accuracy, they were asked to report whether they perceived the stimulation when they intended not to react (false-activation), or an absence of stimulation when they intended to react (false-inactivation).

Exploratory-applications. With our hypothesis being driven by direct/reported measurements, at the end of the study, we were interested in eliciting participants' feedback. Thus, we invited them to try two exploratory-applications while wearing our device, depicted in Figure 7: (1) pen-catching—catch a falling pen dropped the experimenter without a preemptive warning (inspired by [39]); and (2) video-gaming—play three rounds of Chrome's *Dino game* (a simple, yet fast-paced, rolling-platformer where a key is used to jump over obstacles).

Calibration. Before the trials, we calibrated the EMS amplitude—used in both *Myo-Action* and *Baseline-EMS*—to each participant's

[2] https://lab.plopes.org/#myo-action

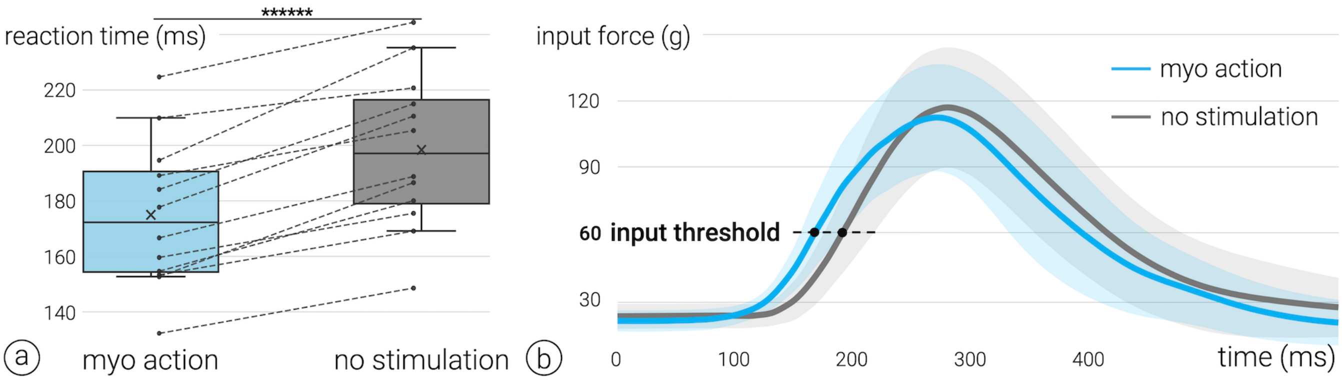

Figure 5: (a) Reaction-times in *Myo-Action* and *No-Stimulation*; **** represents p<0.0001. (b) The mean force trajectories over time recorded by the FSR sensor (shading represents 95% confidence intervals).**

preference. The participants were calibrated to an average intensity of 10.8 mA (SD=2.6).

Procedure. Participants then performed 10 reaction-time trials without stimulation or ratings, used as a practice-round to calculate their voluntary reaction-time. Afterward, participants performed our no-decision reaction-time task, with the order of the two conditions counter-balanced. To invalidate trials where the participant was distracted, each trial timed out after M+1.5×SD of their reaction-times (based on the practice-trials). Participants completed 10 valid trials per condition. Moving to decision-based reaction-time task, participants first completed 20 go/no-go trials without stimulation or ratings—used to adjust the timing of EMS activation in Baseline-EMS (using the same process in *Preemptive Action* [24]); importantly, *Myo-Action* does not require this timing-calibration. On average, the preemptive timing for Baseline-EMS was 179 ms (SD=4.6). Participants then performed 10 go + 10 no-go = 20 trials (condition order counter-balanced, go vs. no-go order randomized). Each trial timed out after M+3×SD their go/no-go reaction-times (based on the practice-round). At the end of each condition block, participants were asked to describe their overall impression of the interface, specifically regarding their agency over their actions. Finally, participants, played the aforementioned exploratory-applications and engaged in an exit interview at the end. The interview included the following questions: (1) "Could you tell us about your experience during the pen-catching and video-gaming?"; (2) "What else could you imagine using this technology for?"; and (3) "Is there any other aspect of your experience you want to share with us?".

Participants. We recruited 12 participants from our institution: 7 identified as male, 4 as female, and 1 as non-binary; average age=23.9 years (SD=3.1); one participant was left-handed. Participants were compensated at $10 per 30 minutes.

5.3 Results from No-Decision Reaction Task: Reaction-Time Acceleration

Figure 5 illustrates our main finding: we confirmed that *Myo-Action* significantly improved reaction-time. Specifically, Figure 5 (a) depicts participants' reaction-times contrasting *Myo-Action* (M=175.3 ms, SD=26.6) and *No-Stimulation* (M=198.6 ms, SD=28.3). Through the Shapiro-Wilk test, we found that distributions did not violate normality. Thus, we investigated for differences using a paired t-test. This revealed a significant difference between *Myo-Action* and *No-Stimulation* (t=8.7, p<0.0001, Cohen's *d*=0.85). This result validates our first hypothesis (**H1**): Myo-Action's hardware is able to accelerate a participants' reaction-time compared to their own voluntary-baseline. Additionally, Figure 5 (b) provides confirmatory evidence by depicting the mean force profiles recorded as participants pressed the FSR sensor to react as fast as possible. Force profiles confirm that *Myo-Action*'s force buildup is faster than that of *No-Stimulation*—this is in line with literature in neuroscience (see *Principle-of-Operation*).

5.4 Results from Decision-Based Reaction Task: Agency with Myo-Action During Decisions

Figure 6 illustrates our main finding regarding agency: *Myo-Action* significantly preserved agency in decision-based tasks. Specifically, Figure 6 (a) depicts participants' agency scores aggregated for *go* and *no-go* trials. We found that mean scores in *go* trials were 5.3 (SD=1.2) for *Myo-Action* and 3.5 (SD=1.4) for *Baseline-EMS*. As for *no-go* trials, we found mean scores to be 6.1 (SD=0.7) for *Myo-Action*, and 1.5 (SD=0.7) for *Baseline-EMS*.

As the Shapiro-Wilk test indicated that *Baseline-EMS* in *no-go* trials violated normality (p=0.004), we conducted the Aligned-Rank-Transform (ART) two-way ANOVA, which supports examining both the trial-type and condition factors in a non-parametric manner [47]. The ART ANOVA indicated significant effects of conditions (F(1,33)=112.8, p<0.0001) and interaction (F(1,33)=28.3, p<0.0001) but did not find a significant effect of trial-types (F(1,33)=3.5, p=0.07). Pairwise contrast tests via a linear model using Tukey's correction [15] indicated significant differences between *Myo-Action* and *Baseline-EMS* for both *go* (t-ratio=4.0, p=0.002, Cohen's *d*=1.34) and *no-go* (t-ratio=11.1, p<0.0001, Cohen's *d*=6.37) trial-types. These results, confirm our second hypothesis (**H2**): Myo-Action's accelerations are perceived as more agentic when decisions are involved.

Reaction-times. We found that mean reaction-times (*go* trials) were: *Myo-Action* (M=242.2 ms, SD=39.9), *Baseline-EMS* (M=231.8 ms; SD=38.5), and practice trials (M=258.0 ms; SD=36.6). Normality was confirmed using the Shapiro-Wilk test; therefore, we conducted a one-way repeated-measures ANOVA which showed a

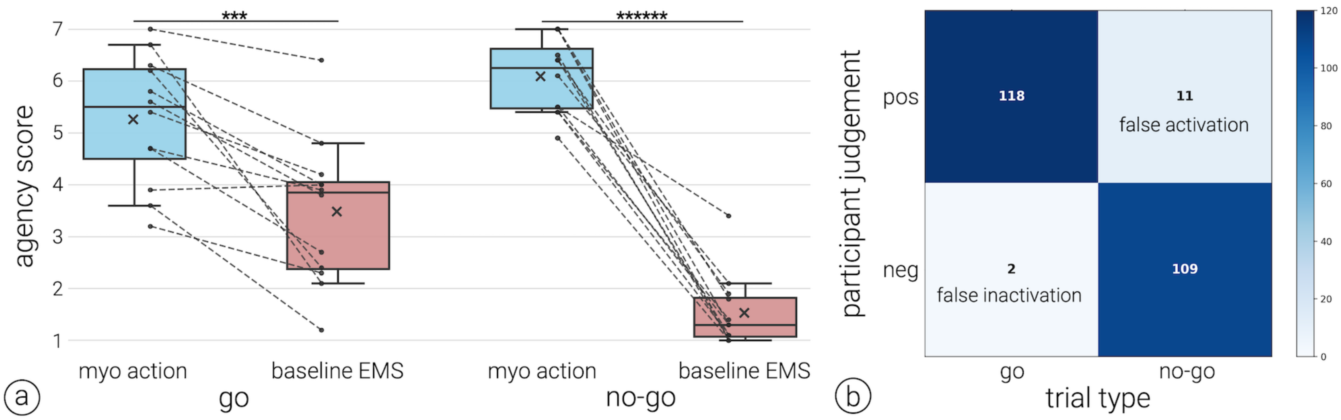

Figure 6: (a) Agency scores in *Myo-Action* and *Baseline-EMS*, aggregated per go and no-go trials; * and ****** represent p<0.005 and p<0.0001, respectively. (b) A confusion matrix of *Myo-Action*'s activation accuracy based on the participants' report.**

significant effect of condition, F(2,22)=31.5, p<0.0001. Bonferroni-corrected post-hoc tests indicated significant differences between *Myo-Action* and *Baseline-EMS* (t(11)=2.9, p=0.04, Cohen's *d*=0.26); between *Myo-Action* and the practice trials (t(11)=6.3, p=0.0002, Cohen's *d*=0.41); and between *Baseline-EMS* and the practice trials (t(11)=7.0, p<0.0001, Cohen's *d*=0.69).

Accuracy in *go/no-go* trials. We found that participants' accuracy in distinguishing *go* and *no-go* trials in *Myo-Action* to be 89.2% (SD=8.7) due to its false-activation reported below. As expected, in *Baseline-EMS*, the accuracy was 50.4% (SD=3.3) as the EMS was always delivered even in *no-go* trials; participants were rarely successful in resisting the stimulation and avoiding tapping the sensor.

Detection Accuracy in *Myo-Action*. Figure 6 (b) shows a confusion matrix regarding false in/activation (F1=0.95).

Participants' comments. Nine participants (out of 12) stated they felt strong sense-of-agency in *Myo-Action*, e.g., "(…) I had control all [the] time and [the actuation] wouldn't go off without me [initiating] the motion" (P2). Particularly, three participants stated it clearly preserved their agency in *no-go* trials: "completely my decision to not move" (P8); and "you can fully control [the movement] (…) there's no stimulation if you don't want it" (P10). Three participants also described the speed-up they felt: "accelerates a bit (…) I only have to (…) twist my finger a little" (P3); and "accelerating me after I decided to move" (P12). During *Baseline-EMS*, six participants stated they got confused regarding whether their movement was self-initiated or EMS-induced: "I had (…) mixed control" (P5); and "sometimes I got confused [if I was] triggering" (P6). On their experience in no-go trials, eight participants stated the system took over their agency: "I wasn't supposed to press (…) it took all sense of agency away" (P2); and "it was completely involuntary (…) I tried not to move" (P4). Three stated they even lost task-engagement through those cases: "I would just go loose because (…) it was gonna trigger" (P5); and "I just stopped paying attention" (P11).

5.5 Results from Exploratory Applications: Participants' Feedback

Perceived augmentation. Eight participants (out of 12) described how they perceived their performance when assisted by our device: "even I just have a very slight intention to grab it, it helps me to finish that quickly" (P3, pen); "I felt my reflexes just got faster" (P9, pen); and "a couple of times it worked pretty well, and it saved me when (…) [I thought] I would have lost the game" (P2, gaming).

Feeling of shared agency. Seven participants mentioned the feeling of "collaborating" with our device: "it triggered at the same time that I wanted to do movement, or I was like trying to do movement" (P2, pen); "like 40% [Myo-Action], and 60% is my brain" (P9, pen); and "amplifying my intention" (P1, gaming).

Figure 7: (a) Agency scores in *Myo-Action* and *Baseline-EMS*, aggregated per go and no-go trials; * and ****** represent p<0.005 and p<0.0001, respectively. (b) A confusion matrix of *Myo-Action*'s activation accuracy based on the participants' report.**

Figure 8: Our envisioned eSports application.

Suggested applications. Participants proposed a range of applications for our device, including sports-training, gaming, emergency-response, and daily-activities: "I was a competitive swimmer (...) and reaction-time is something that we train very frequently, and (...) rigorously" (P9); "rhythm games would be so fun" (P8); "it could help the person steer the wheel away faster [in driving]" (P1); and "stuff in cooking that's time sensitive" (P11).

5.6 Discussion

Myo-Action accelerates reaction-time by >20 ms. *Myo-Action* accelerated users' reaction-time by ∼23 ms. This finding aligns with how an onset of EMG activity precedes an actual body movement (see *Principle-of-Operation*). This >20 ms speedup is critical in various situations. For example, it corresponds to ∼1 m of extra ball travel, enabling more time against a fast serve in competitive tennis [18], reduces the required braking distance by ∼0.3–0.7 m at common driving speeds [12], and allows players to input more than five frames ahead of their opponents in eSports [35].

Myo-Action preserves agency in decision-involving actions. *Myo-Action* improved agency for both *no-go* and *go* trials. The first result was expected, as open-loop EMS baselines could not react and therefore caused involuntary presses in *no-go* trials. A possible explanation for why it also improved agency in *go* trials is that the intervention timing in *Baseline-EMS* (as in [24]) was fixed amid each participant's slightly-variable reaction-time, which may have led them to perceive misalignment. In contrast, *Myo-Action*, by its nature, could adapt to the variable-timing of their reaction.

Reaction-time differs from Baseline-EMS. We observed a difference in reaction-times between *Myo-Action* and *Baseline-EMS*, with the latter faster by ∼10 ms. This may have been due to how the stimulation timing in *Baseline-EMS* was adjusted: it was set relative to each participant's average reaction-time. In practice, this meant that in some trials participants could respond faster than the EMS, while in others the EMS forced their responses to align with the preset timing. Consequently, the overall average reaction-time was shifted toward the faster-end.

6 Envisioned Applications

Inspired by participants' suggestions, we envision applications that illustrate more diverse uses of Myo-Action. (for the sake of visual clarity, we added a Myoware-LED-shield [1] showing real-time EMG activity). Note that our controlled experiment focused only on a simple movement. These envisioned applications do not intend to supplant evaluations or the novel algorithms that might generalize to more complex movements (see *Limitations and Future Work*).

6.1 eSports

The 20-ms speedup in reaction-time might impact video-gaming performance (Figure 8). When gaining a power-up, the player activates Myo-Action to initiate the detection thread (Figure 8a). When they intend to use the power-up, our device detects the EMG onset, enabling its faster activation—and leaving the opponent less time to dodge (Figure 8b-c).

6.2 Performance Augmentation (e.g., PingPong)

Myo-Action might augment users' performance in sports, e.g., ping-pong (Figure 9). For instance, our device could accelerate the movement to hit the ball when the user intends to (i.e., when the ball is

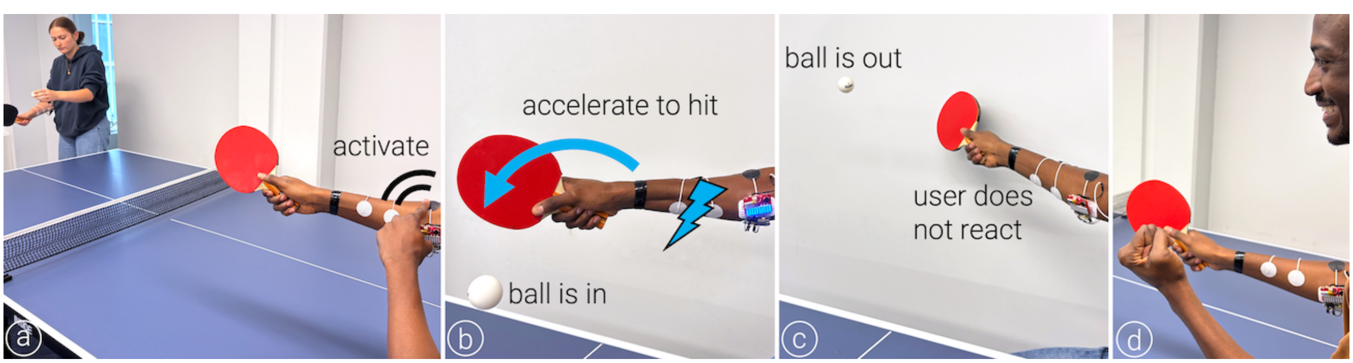

Figure 9: Our envisioned ping-pong application.

Figure 10: Our envisioned bimanual-interaction (driving-simulator) application.

in), whereas when they do not intend to hit it (i.e., when the ball is out), it respects their intention, causing no involuntary movement (Figure 9b-c). Note that follow-up research would be needed to ensure Myo-Action's stability in such unconstrained use cases.

6.3 Accelerating Multiple Muscles (e.g., Bimanual Interactions)

We can extend Myo-Action to multiple muscles, e.g., in bimanual interactions (Figure 10). A user might wear two devices linked to a single activation button, allowing the system to accelerate steering in a driving-simulator, according to their intended way to turn. Again, further research is needed to ensure sensing-stability in such unconstrained use cases.

7 Limitations and Future Work

7.1 Limitations

Myo-Action cannot act beyond user intention; once movement begins, it cannot override or reverse it (e.g., correcting mistakes), which may affect user experience when users attempt to change actions mid-movement. Also, while our approach eliminates the need for stimulation-timing calibration, it inherits the typical limitations of EMS, including per-user intensity calibration, muscle fatigue, and limited force controllability.

Limitations from current implementation. The current implementation supports only one muscle per device. Moreover, to prioritize ultra-low latency (~290 μs), our current signal processing tracks only the amplitude of EMG, not its envelope, which is insufficient for classifying different movements within one muscle.

Study limitations. While a sample size of 12 participants is typical in prior HCI and psychophysics research on this topic [10, 24, 29], it may limit the extent to which our results generalize across the full spectrum of responses. Additionally, our participant pool was relatively homogeneous in age and reaction-time. We also acknowledge the possibility that the agency ratings might have been biased in *Baseline-EMS* as EMS was always applied in *no-go* trials; yet, participants' qualitative feedback suggests that the loss of agency was primarily attributed to intention misalignment. Finally, the lack of sham-EMS or no-EMS conditions in the decision-based task limited our ability to characterize the effects of skin sensations and contextual cues on agency, as shown in prior work [24].

Lack of evaluation in more dynamic environments. Since the task focused on a simple button-press while seated, our system's accuracy may not fully extend to more mobile or less-controlled activities. In such settings, where preliminary movements may occur, reliable operation would require more advanced EMG signal processing to distinguish target actions from incidental activity (see *Future Work*).

7.2 Future Work

More sophisticated EMG processing. Extending from amplitude-based triggering to movement classification is essential for use in more dynamic settings, where the system must separate a wide range of possible actions realized with the same muscle from preliminary movements or from noise. For instance, LSTM- [49] or CNN-based [50] models have been used to capture temporal patterns in EMG envelopes, while multimodal sensing (e.g., EMG+IMU [48]) may further improve robustness. However, it is worth noting that these methods need to be implemented in a low-latency approach (i.e., technically more challenging for complex algorithms) to still result in accelerations.

Expanding to multiple muscles. We demonstrated the feasibility of Myo-Action in a single muscle; a natural extension is to scale this approach by incorporating multi-channel EMG (e.g., [23]) and multi-channel stimulation (e.g., [44]), thereby supporting more dexterous interactions.

Broader understanding of user experience. Future work should examine system performance and user experience in more dynamic scenarios (e.g., situations involving high-intensity or continuous movement rather than static muscle activation). Moreover, future work should explore how different strategies of EMS (e.g., systems that enforce objectively correct decisions based on external sensors rather than user intention) affect agency—for example, by inducing outcome bias in users' sense-of-agency [43].

8 Conclusion

In this paper, we proposed and validated a new concept for accelerating users' action without overriding their intentionality—users have agency to decide if they want to move, not the haptic interface. Our approach combines EMG and EMS to realize this agentic speedup, which we validated in our *User Study*, finding that: (1) accelerates users' reaction-time by ~23 ms compared to their voluntary action; (2) preserves agency in a decision-involving task (i.e., go/no-go trials); and (3) it positively shaped user experience of this type of haptic-assistance.

Acknowledgments

We would like to thank our colleagues, Jasmine Lu and Lonnie Chien, for proofreading the manuscript. We also extend our gratitude to Dr. Lukas Gehrke (Zander Labs) and Prof. Momona Yamagami (Rice University) for their enthusiasm and insightful discussions at the HCI-x-Neuroscience Shonan meeting. We hope to further develop and improve our initial concept with their input. Moreover, we are grateful for the constructive feedback from the reviewers.

Funding. This work was supported by multiple funding sources at different stages of our development cycle, including NSF Grant 2047189 and the University of Chicago Women's Board. Any opinions, findings, conclusions, or recommendations expressed in this material are those of the authors and do not necessarily reflect the views of any of the funding agencies.

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