Increasing Input Accuracy of Embodied Devices via Electrical Muscle Stimulation

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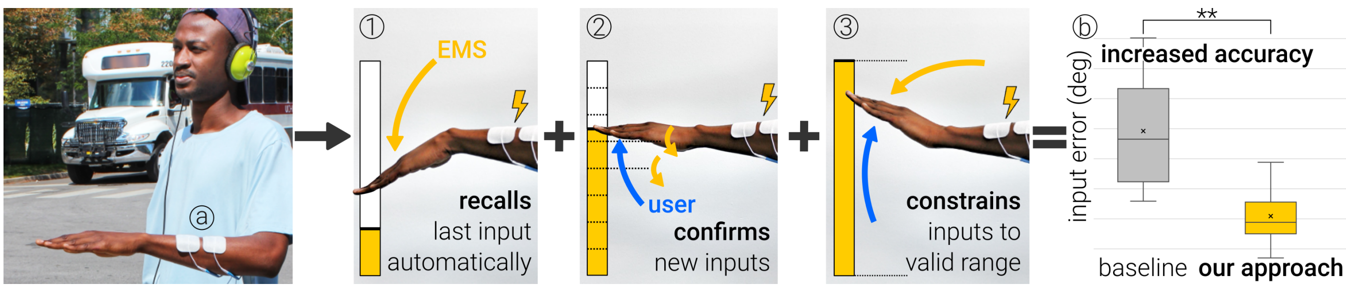

Figure 1: (a) This user walks while listening to music. To control the volume, they use an embodied device—in this case, a volume slider which they control only with the pose of their wrist (via proprioception—no audiovisuals nor vibrations). To advance the design of this emergent class of devices, we evaluate three techniques that use electrical muscle stimulation to improve the user's input accuracy: (1) recall previous interface state; (2) provide cues to confirm state transitions; and (3) constrain input to a valid range. Our user study found that (b) combining these three techniques improved participants' input accuracy.

Abstract

This paper evaluates interaction techniques to increase input accuracy with embodied devices—an emergent type of interactive system where the user's body serves as both the input and output medium (e.g., gestural input via cameras/IMUs; gestural output via motors/muscle stimulation). A shortcoming of existing embodied devices is their failure to enforce alignment between users' proprioceptive inputs and interface state. Thus, we present and evaluate interaction techniques that use muscle stimulation to enable embodied devices to: (1) recall previous interface states; (2) provide confirmation cues on state transitions; and (3) constrain inputs to valid ranges. In our study, participants performed pairs of interactions with an embodied slider, separated by a distraction task. The results showed that, compared to the same embodied slider without EMS, the combination of our techniques increased users': (1) absolute input accuracy; (2) relative input accuracy; and (3) confidence.

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CCS Concepts

• **Human-centered computing** → **Gestural input**; • **Hardware** → **Haptic devices**.

Keywords

Embodied Interaction, Haptics, Electrical Muscle Stimulation, Gestures

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1 Introduction

A growing class of interactive systems seeks to support eyes-free interaction, where users control devices without relying on audiovisual attention. These interactions are beneficial in mobile or situationally demanding contexts (e.g., walking [18], cleaning [19], climbing stairs [44]). To advance systems in these contexts, researchers explore interaction paradigms that shift input and output away from screens/speakers and, instead, *toward the body itself* [7, 28, 40].

We refer to such systems as *embodied devices*: interactive systems in which the user's own body becomes the medium for *both* input and output. This type of interaction achieves input via body movements (e.g., gestures detected by IMUs, cameras, EMG, etc.) and renders output back onto the body through proprioceptive feedback (force feedback that displaces the body via exoskeletons/muscle stimulation) rather than visuals or sounds. Although this approach renders some tactile sensations in the muscle or on the skin [21, 42], the user acts and receives feedback primarily through their proprioceptive sense [28].

Despite their potential, the design of embodied devices remains in its infancy. Unlike traditional UIs based on visual or audio feedback, which have been refined over decades by creating stable design principles [2, 10, 45], researchers have yet to establish techniques to improve interactions with embodied devices.

This paper evaluates techniques based on electrical muscle stimulation (EMS), expanding the set of feedback approaches for embodied devices *during* interactions (Figure 1). Importantly, these techniques are meant to improve input accuracy with embodied devices *without resorting to non-gestural modalities*—thus respecting the proprioceptive nature of embodied devices. We achieve this goal by identifying interaction techniques that were loosely proposed in prior research but never formalized or evaluated. Our key contributions are: (1) systematically defining the working principles of these embodied devices' techniques, enabling future researchers to build on our foundation; and (2) uncovering, through a user study, the benefits offered by these techniques in embodied devices.

2 Related Work

Our work builds on embodied devices. While this type of interface points to a broader shift toward interfaces that integrate with the body [31] (including related areas such as on-body interfaces [16], on-skin interfaces [39], and epidermal computing [34]), our scope is restricted to gestural interfaces where the I/O operates via users' proprioception.

2.1 Evolution of gestures as input

Gestural input via one's body has been one of the most active research areas—from influential work (e.g., *VIDEOPLACE* [26], *Digital Desk* [48], or *Charade* [3]) to mainstream devices (e.g., *Kinect* or hand-tracking VR headsets).

Much attention was given to designing interaction techniques that assist users when their body (e.g., hands) becomes the input device. For instance, *Imaginary Devices* [40] and *Hand Interfaces* [36] allow users to switch input modes by shaping their hands like the desired input device. These types of gesture-input techniques allow users to select which input device their body emulates (e.g., sliders or joysticks). Moreover, considerable effort was also dedicated to designing the bodily feel of input interactions. For instance, in Vatavu's bimanual relative volume slider [46], one hand acts as a reference while the other moves up and down to input. In parallel, many expanded gestural input to other body parts, especially for hands/eyes-free interactions, such as feet [1, 9, 20, 43], tongue [19], head/neck [41], and more.

Early explorations of body input identified additional modalities for supporting users' understanding of the state of the interface. Oakley and Park [35] created a knob-like input device using wrist rotations, which they improved by making transitions feelable via vibrotactile detents. In fact, we draw inspiration from this approach to improving gestural input by also adding output. However, given our scope is confined to embodied devices—which operate primarily through proprioception—we turn our attention to how these interfaces leverage *gestures as output*.

2.2 Gestures as output (enabling embodied devices using electrical muscle stimulation)

While gestural input is a well-established mode of interaction, the use of body actuation as output is a more nascent area of interface research. Embodied outputs engage the proprioceptive system to render interface states directly through the body, enabling interactions independent of audiovisual or tactile cues [28].

Proprioceptive Interaction [28] was one early system to leverage the body as both the input and output interface. Turning the user's wrist into a "slider" enabled control of video playback. Gestural input was achieved using IMUs, and to enable the system to respond and move the user's wrist, they turned to EMS. Given its wearability [27], EMS gathered popularity with ~150 explorations in HCI alone [8]. Similarly, *Electrical Head Actuation* [41] extended proprioceptive output to the neck, turning the user's head nodding into a volume slider.

Important in both [28] and [41] is the proposal that EMS should *recall* the current state of an embodied device once users initiate an interaction; in other words, EMS moves the user's joint to match the current slider value.

Apart from state recall, other systems used EMS to provide confirmatory feedback upon user input registration. For instance, in *MuscleIO* [7], users toggle UI settings via wrist inputs (tracked via EMG) and the system responds with feelable proprioceptive feedback to confirm state transitions (via EMS). Similarly, in [29], EMS provides tactile detents when users cycle between valid UI settings in mixed reality knobs (controlled by rotating their wrist).

Collectively, these works established the foundational principle of embodied devices: both input and output occur via proprioception [28]. However, these implementations of embodied devices rely on EMS to move the user's body. While EMS allows for rendering proprioceptive output back to the user, EMS is known to conflict with users' own movements, diminishing their sense of agency [21, 33], causing distractions from its tingling sensations [21], and even impairing memorization and recall of gestures [33]. **Given these well-established downsides of EMS, we ask an important question: *can these EMS-based techniques improve the input accuracy of an embodied device?*** Prior works provided a foundation for these explorations but never formalized nor evaluated these EMS techniques—this is our contribution.

In fact, recent frameworks, such as *Non-Natural Interaction Design* [47], underscore the critical importance of the *usability* of gestures—an argument central to our investigation which is meant to enhance the usability of gestures by improving gestural input accuracy.

3 Interaction Techniques to Improve Embodied Devices

To increase the input accuracy while using embodied devices, we identified recurring themes loosely explored in prior works and

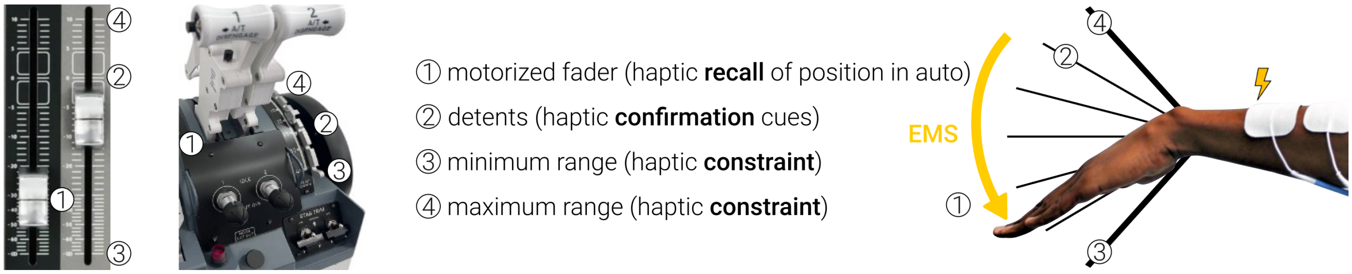

Figure 2: Physical devices intended for eyes-free use (e.g., a motorized fader in a Behringer X32 mixer or a Boeing airplane's throttle quadrant) use techniques that enable users to *feel the system's state without audiovisual cues.* These devices serve as analogous examples to the techniques we evaluate to improve the input accuracy of embodied devices, such as this embodied slider on the wrist.

formalized them into three techniques—**recall**, **confirmation**, and **constraint**—that we evaluated in our study.

Shared principles. The goal is to *align* the user's proprioceptive state (i.e., the pose of the limbs controlling the device) with the device's state (i.e., the current values of the interface). This principle draws heavily from Nielsen's usability heuristic "*visibility of system status*" [32]. More traditional interfaces (e.g., GUIs or physical controls) typically achieve these alignments via visuals (e.g., a GUI slider [2] has a visual representation of its current value, max/min range, and visual detents), sounds (e.g., volume sliders on OSes play "ping" sounds proportional to the current value), or haptics (e.g., detents on a DJ's fader or airplane's throttle quadrant). Unfortunately, achieving this alignment is challenging for embodied devices because the user's I/O is entirely based on proprioception (without audiovisuals or touch) [28]. Thus, these techniques all work through force feedback, informing the user via proprioception about various aspects of the state of the interface they are controlling (e.g., range, transitions, etc.).

Analogy to physical devices. We believe an analogy to physical devices is helpful, since physical devices (e.g., car radio buttons, vehicle pedals, airplane controls, knobs on a DJ mixer) have long been designed with similar principles in mind to enable eyes-free interactions, i.e., without relying on audiovisual cues which are likely to distract from other audiovisual tasks. Given that an embodied slider was used to formalize our interaction techniques, we provide a helpful analogy to its physical counterpart, i.e., physical sliders such as those in Figure 2 (DJ faders or airplane throttle).

3.1 Interaction technique 1: recall (aligning body with system state)

The challenge that embodied *recall* solves. Unlike GUIs, which visually persist on-screen to reflect their state, embodied devices are ephemeral: the body cannot remain posed in perpetuity as it is constantly engaged in other tasks. Thus, task switching via invocation/dismissal gestures is a key feature that gestural interfaces support. Given this requirement, even early explorations of embodied devices featured gestures to start/stop the interface [28, 41]. However, the key challenge is not invocation, but what immediately follows; when a user starts an embodied device, their body posture is unlikely to reflect the current UI state. Without feedback to align the user's body pose with the UI state, inconsistencies will occur. For instance, after invocation, the UI value could jump to a new value based on the user's current pose rather than smoothly tracking from the previous state. The physical sliders in Figure 2 are therefore motorized—if the user adjusts volume from another

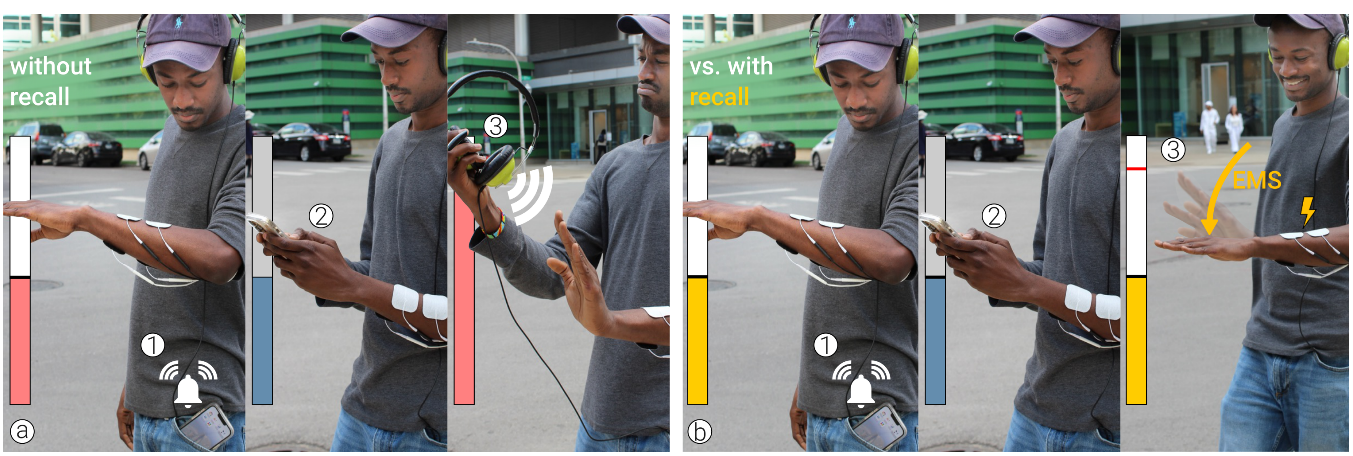

Figure 3: Illustrating the *recall* technique using an embodied slider for eyes-free volume control (via wrist).

GUI, the slider on this X32 mixer [4] aligns itself. Similarly, during autopilot, Boeing's throttle quadrant [11] tracks smoothly to align the system's state with the slider's physical representation.

Definition of embodied recall. Upon invocation, the embodied interface actuates the user's limb to match the interface state, as depicted in Figure 3. Recall reflects continuously changing values (e.g., ongoing playback position [28, 42]) by continuously actuating the limb. During continuous recalls, the interface allows the user to make changes. Conversely, recall stops when the value is unchanged or reached, leaving the limb at the desired position.

Exemplifying recall on an embodied slider. Figure 3 exemplifies how recall solves inconsistencies between a device and its user. In Figure 3 (a), the user controls an embodied volume slider when (1) they receive a smartphone notification, causing them to (2) switch tasks. Upon returning to the embodied device, (3) their wrist position has shifted since their previous interaction, causing a sudden, unexpected change in volume. In (b), the same interaction occurs: (1), they receive a notification and (2), they switch to the phone; however, in (3), the embodied device automatically recalls their previous joint position, avoiding a sudden volume change.

Benefits of embodied recall. The benefits are that users: (1) immediately understand current UI states; (2) do not need to remember previous states—freeing up cognitive resources; and (3) can smoothly adjust from previous states, preventing errors like accidental "jumping". Recall supports Nielsen's usability heuristic "*recognition rather than recall*" [32].

3.2 Interaction technique 2: confirmation (signaling interface state transitions)

The challenge that *confirmation* solves. Interfaces confirm state transitions through persistent visual, audio, or haptic cues (e.g., GUI checkboxes fill in visually, volume sliders provide auditory "pings", and physical faders have feelable detents). Embodied devices are challenged with providing equivalent proprioceptive confirmations for interface state transitions. Without confirmatory feedback, users are likely to make erroneous inputs, undermining their mental model.

Definition of embodied confirmation. Whenever an embodied input changes the interface state (e.g., an embodied slider moves to a new value, an embodied button is pressed, etc.), a proprioceptive *confirmation cue* is issued. These cues signal to users that their input was valid and the system moved into its new state. Confirmations must be provided in ways that are proprioceptively felt (e.g., force resistance, muscular twitches, stopping a movement, etc.).

Exemplifying confirmation on an embodied slider. In Figure 4 (a), a user controls an embodied volume slider when (1) they receive a smartphone notification, but when they (2) reach for their pocket, (3) the movement unintentionally inputs a volume change, since the embodied device was still active. In (b), they (1) respond to the notification but (2) as they reach for their phone, they immediately feel a confirmation cue via EMS, allowing them to realize the system was still receiving input—thus, to prevent mistakes, (3) they dismiss the interface.

Benefits of embodied confirmation. Proprioceptive cues (e.g., detents) make transitions more kinesthetically legible, increasing input certainty. Confirmation supports Nielsen's usability heuristic "*visibility of system status*" [32] (since embodied devices do not rely on visuals, "visibility" is equivalent to "perceptibility").

3.3 Interaction technique 3: constraints (bounding inputs to a range)

The challenge that constraints solve. Most UIs contain boundaries to constrain input. For example, users cannot drag a slider's handles beyond the constraints of its track; similarly, radio buttons constrain users to one input which, upon selection, deselects the previous. Embodied devices face the challenge of enforcing these constraints in the body to ensure users cannot perform gestures that would place the interface in an invalid (e.g., move past the range) or ambiguous state (e.g., activating two mutually-exclusive options in an embodied radio button).

Definition of embodied constraints. During input, the embodied device constrains the user's limb within the interface's possible range by actuating it. If the embodied device uses a segment of a limb's full range of motion (e.g., an embodied slider on the wrist

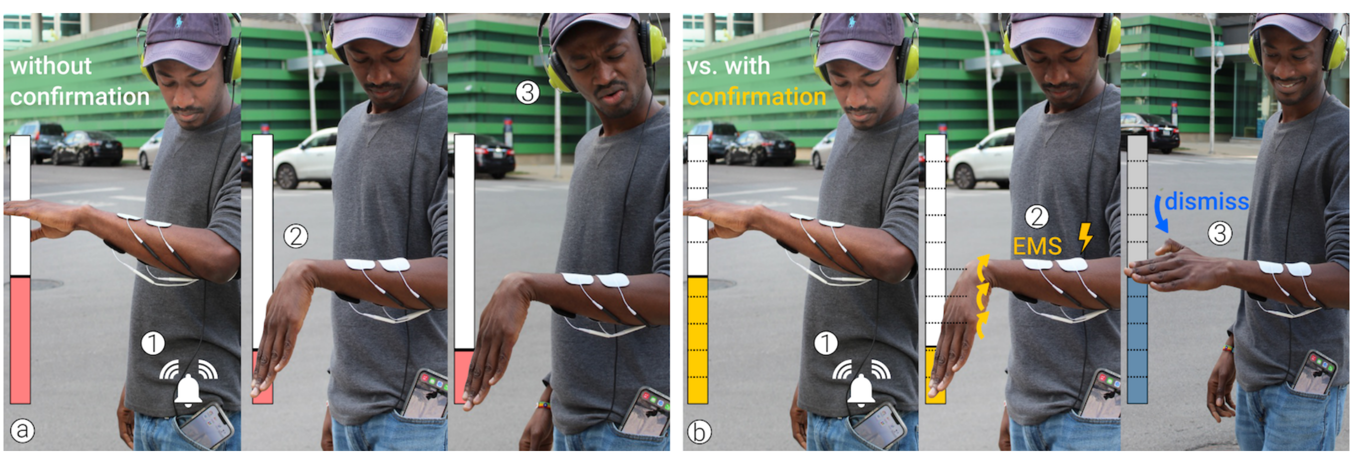

Figure 4: Illustrating the *confirmation* technique using an embodied slider for eyes-free volume control (via wrist).

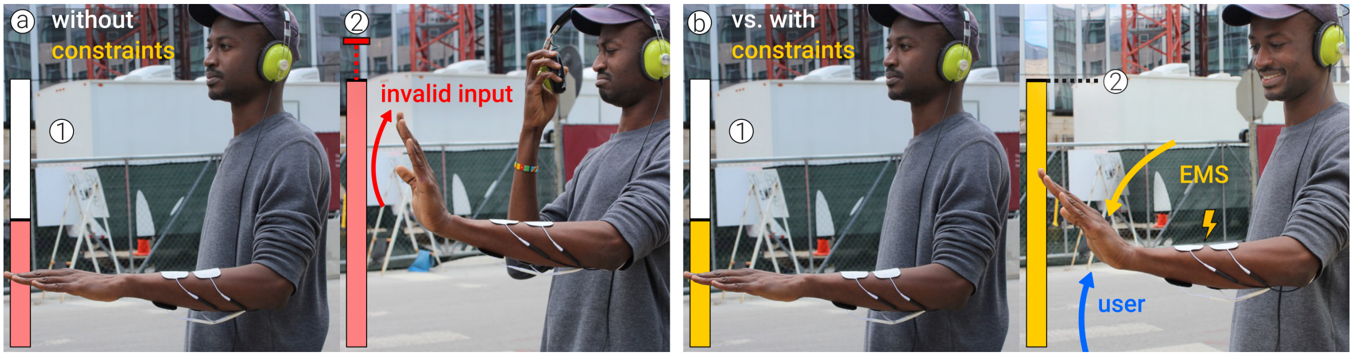

Figure 5: Illustrating the *constraints* technique using an embodied slider for eyes-free volume control (via wrist).

that uses less than the wrist's full flexion-extension range), the interface needs to constrain the user when they move outside of the input range by returning their limb to the valid range. Similarly, if the embodied device features mutually-exclusive inputs (e.g., states that once selected, deselect others), the interface needs to actuate the body to prevent invalid input states.

Exemplifying constraints on an embodied slider. In Figure 5 (a), a user enters a noisy construction area and (1) adjusts an embodied slider to increase their music volume. (2) They extend their wrist beyond the slider's limits, unaware that the device has already reached maximum volume. In (b), (1) the same interaction occurs, but (2) EMS constrains their movement, signifying the device cannot further increase its volume.

Benefits of embodied constraints. Constraints act as both physical bounds and communicative cues, clipping motion to signal that no further input is accepted. Constraints support Nielsen's usability heuristic "*error prevention*" [32].

4 Implementation of an Embodied Device to Evaluate these Interaction Techniques

To measure how these interaction techniques affect input accuracy, we implemented a simple embodied slider controlled via wrist tilting [28, 41]. To assist readers in replicating our apparatus, we provide the necessary technical details.

4.1 I/O implementation

Interaction with our embodied slider is performed by: (1) an invocation gesture (thumb radial adduction, towards the palm); (2) input by changing wrist angle (flexion/extension axis, ignoring radial/ulnar-deviations and pronation/supination); and (3) a dismissal gesture (thumb radial abduction, away from the palm).

Input module is responsible for: (1) starting and stopping interactions by tracking the invocation and dismissal gestures; (2) saving input to the state of the slider; (3) updating applications (e.g., for demonstration purposes, we built a simple volume control); and (4) requesting actuations from the output module. There are ample methods available to track wrist poses, such as EMG [7, 38], IMU [28, 37], flex/bend/encoders [14, 23], optical [5, 24], or even mainstream devices (e.g., *Kinect*, hand-tracking in VR headsets, etc.)—just to cite a few. For the simplicity of the study's apparatus, tracking uses *MediaPipe* [30] and an RGB camera (2.448 mm, 1080P, 60 FPS) viewing the radial side of the hand.

Output module is responsible for actuating the wrist with EMS using a medically compliant *RehaMove 3* stimulator controlled by a low-level Serial USB API (latency <1 ms). A closed-loop PID controller—the most popular way to achieve robust EMS control (used in embodied devices [28, 41] and EMS interfaces [22])—reliably controls the user's wrist. The system achieves recall and constraint by defining a target angle (e.g., slider boundary for constraint). Then, the output module's PID controls its pulse width, minimizing angular error between current and target positions. To prevent near-target oscillations, stimulation deactivates when the error is <4°. The PID's input unit is degrees (for angular error) and its output unit is µs (for PWM control). Via initial pilots, we settled on the PID constants: $Kp = 7.0\,\mu s/°$, $Ki = 0.8\,\mu s/°/s$, $Kd = 1.5\,\mu s \cdot s/°$ and clamped the pulse width between 20–400 µs. The dual-muscle controller operates for both the *extensor digitorum* and the *flexor digitorum superficialis*. Finally, for confirmation cues, the output module delivers a pulse with a weaker stimulation intensity precalibrated to avoid strong movement (see *User Study*).

4.2 Technical evaluation

We performed a simple technical evaluation to ensure our closed-loop system suffices for our *User Study* purposes. We recruited four participants from our local institution (average age = 23.5, SD = 2.87; male). This study was approved by our Institutional Review Board (IRB21-1158). Calibration used the same process from the *User Study*.

Setup. We tested six different target angles: −45°, −27°, −9°, 9°, 27°, 45°. For input module evaluation, participants tilted their wrist at a target angle confirmed by a protractor; this ground truth was compared to the *MediaPipe* measurement. For output module evaluation, the PWM controller stimulated participants' wrists toward each target angle until it stabilized on the target for 2.5 seconds. We recorded the angle of their wrist tilt at the end of this stimulation and compared it to the target angle to obtain the error. We repeated this for 12 trials (six target angles × two repetitions), totaling 48 trials across all participants.

Results. For the input module, we observed a mean overall error of 1.82° (SD = 1.24°), which is lower than the human accuracy for passive wrist position reproduction [12, 28]. For the output module, we observed a mean error of 4.83° (SD = 0.65°), which informed the design of the angular steps of our slider's confirmation detents in the main *User Study*.

5 User Study: Improving the Accuracy of Embodied Devices

To understand whether the combination of these techniques improves accuracy with an embodied device, we conducted a user study. Participants performed a series of *eyes-free* inputs to a slider-type embodied device controlled by the wrist.

5.1 Study design

Task rationale. We chose an embodied slider on the wrist as it is the most explored embodied interface [7, 28, 42]. While our design shares commonality with prior studies (e.g., [12, 28] also asked participants to reproduce a demonstrated wrist position), we went further by exploring a more challenging and realistic task: adding a distraction task between each pair of inputs emulated a situation where users need to switch between controlling their embodied device and performing another primary task (e.g., typing on their phone as in Figure 3, catching a pen as in [28], etc.). Finally, the choice of a continuous (rather than discrete) slider lends itself to finer measurement of angular error and provides insights more readily translatable to both absolute input and/or relative input interfaces [17].

Apparatus. To ensure consistency between trials, participants stabilized their dominant arm on a tabletop armrest while ensuring their wrist could move freely. Tracking the wrist angle and actuating to target angles was achieved via our EMS prototype (see *Implementation*). Participants wore four electrodes (50 × 50 mm pre-gelled *Auvon* EMS electrode): two electrodes were attached atop the *extensor digitorum* muscle to achieve wrist extension, and two electrodes were attached atop the *flexor digitorum superficialis* to achieve wrist flexion. Participants were blindfolded except during the distraction task.

Calibration. As is typical in EMS studies, stimulation was calibrated to operate pain-free and robustly per participant: (1) starting at a pulse width of 300 µs and a current of 1 mA; (2) increasing in steps of 1 mA; until (3) the wrist tilted by >10° (flexion/extension). The highest intensity without strong contraction was used to calibrate the confirmation technique.

Slider Interface. The gesture to invoke and dismiss the slider was radial ad/abduction of the thumb from an extended position (while *MediaPipe* can also detect this gesture, false positives were prevented from contaminating the accuracy by opting for experimenter confirmation with a keyboard press). This slider took *only* the wrist angle as input—rather than the location of the hand or height of the fingertips—allowing invocation from any spatial location or pose. The slider accepted inputs by tilting the wrist between −54° and 54°; inputs outside of this range were considered invalid.

Conditions. All participants experienced each of five conditions: (1) *input-only* as our *baseline* (i.e., control via proprioception alone), (2) *recall-only*, (3) *confirmation-only*, (4) *constraints-only*, and (5) *combined*—condition order was randomized across participants.

Task. Each trial consisted of three phases: *demonstration*, *distraction*, and *input*. In the *demonstration* phase, participants first invoked the slider (thumb adduction). With the system running, the experimenter manually moved the participant's wrist angle to proprioceptively demonstrate the upper and lower ranges of the slider before moving it sequentially to two targets representing the *last* and *new* states of the interface. During the relevant conditions, participants felt confirmation cues and constraints (recall was not activated during demonstration as the experimenter manually acquired targets). After demonstration, participants dismissed the slider (thumb abduction) and entered the *distraction* phase, where they completed a 30 second keyboard typing test. This distraction requires multiple hand muscles in positions that differ from the slider, and participants must read and type sentences, which further disrupts their memory. Finally, participants entered the *input* phase, where they: invoked the slider, repositioned it to the *last state*, adjusted it to the *new state* (e.g., as if adjusting a volume), and dismissed it. The task is thus akin to the *ipsilateral joint position reproduction test* [13, 15], a canonical assessment of proprioception.

Metrics. The key metric was the angle error between the demonstrated targets and the input targets after distraction. Additionally, we also measured participants' input confidence at the end of each condition block.

Targets. We chose six target angles unbeknownst to participants. Given the results of the *technical evaluation* (EMS control-loop error of $E = 4.83°$), we chose a distance between target angles of $I \approx 2E + 8°$ (a padding to minimize error), resulting in an interval of 18° after rounding. Confirmation cues were activated once the current angle was within $\pm I/2$ (half the interval)—in other words, we chose the most conservative confirmation implementation where they acted as haptic detents, but they were never actual targets. Additionally, to keep movements ergonomic [6, 25], we employed a smaller subset of the total wrist angle range at ±54°—these angles are where the constraints were triggered. The resulting slider had the targets: −45°, −27°, −9°, 9°, 27°, 45°. Users were always shown one pair of targets per trial (*last state* and *new state*), resulting in 36 possible combinations. Instead of exhaustively using those combinations, we chose pairs of targets at all possible angular distances, allowing for every participant to experience pairs of equal difficulty, resulting in five pairs separated by 90°, 72°, 54°, 36°, and 18°. Moreover, every target appeared at least once.

Total trials. We ran 600 trials, i.e., 5 conditions × 5 pairs of targets at equalized difficulties × 2 repetitions × 12 participants.

Participants and ethics. We recruited 12 right-handed participants (average age = 23.50 years, SD = 1.89; 9 male and 3 female). Participants gave informed consent and received $10 USD for every 30 minutes of study as compensation. This study was approved by our Institutional Review Board (IRB21-1158).

5.2 Quantitative results

Figure 6 depicts the key results: (a) average absolute error across conditions for all 600 trials; (b) participants' confidence.

Accuracy. We analyze the average error across targets (i.e., the absolute difference between target angles and respective input angles). As the data did not follow a normal distribution (per Shapiro-Wilk test), we conducted a Friedman Test. The analysis revealed significant differences between the conditions ($Q = 22.87$; $p < 0.001$). Post-hoc pairwise comparisons with Bonferroni correction found that the *combined* condition was significantly more accurate than

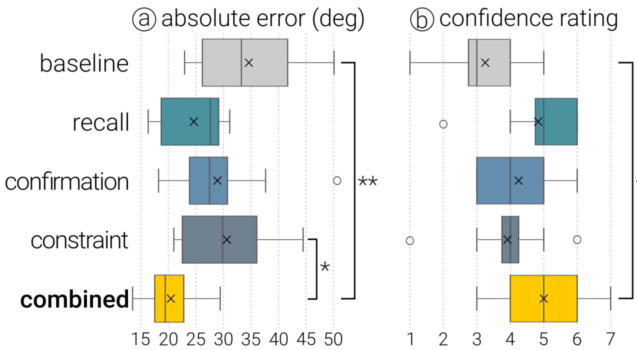

Figure 6: (a) Absolute error of inputs. (b) 1-7 Likert confidence ratings of inputs. Boxplot bars from left to right represent Q1, median, and Q3. Whiskers represent range excluding outliers. X represents mean. O represents outliers, which fall below Q1 − 1.5 × IQR or above Q3 + 1.5 × IQR. All non-annotated comparisons are non-significant.

the *baseline* ($p < 0.01$). On average, participants' inputs were 40.91% more accurate with *combined* (M = 20.45; SD = 4.94) than with *baseline* (M = 34.61; SD = 10.07). Additionally, *combined* was more accurate than *constraints-only* ($p < 0.05$).

Confidence. Since confidence ratings were not normally distributed (per Shapiro-Wilk test), we performed a Friedman test, revealing significant differences between conditions (Q = 24.74; $p < 0.001$). Post-hoc pairwise comparisons with Bonferroni correction found a significant increase in the confidence ratings between *combined* and *baseline* ($p < 0.001$). On average, participants' confidence increased by 53.85% with *combined* (M = 5.00; SD = 1.28) when compared to *baseline* (M = 3.25; SD = 1.22).

Accuracy analysis per target. In Figure 7 (a), we zoom in on the first target from the pair of inputs that participants performed after the distraction task (i.e., the *last state*). This data is normal (per Shapiro-Wilk), and a one-way ANOVA revealed a significant effect of conditions (F = 10.45; $p < 0.0001$). Post-hoc analysis with Bonferroni corrections found that *combined* (M = 9.29; SD = 4.04) was significantly more accurate than *baseline* (M = 19.60; SD = 5.41; $p < 0.001$), *constraints-only* (M = 16.36; SD = 4.57; $p < 0.01$), and *confirmation-only* (M = 15.83; SD = 5.99; $p < 0.05$)—this result agrees with the main finding. Moreover, this analysis found that *recall-only* (M = 9.82; SD = 3.51) was significantly more accurate than *baseline* ($p < 0.001$) and *constraints-only* ($p < 0.01$)—this result is to be expected as the recall technique assists users by moving their hand to automatically acquire the first target. In fact, further zooming in on the top 5% of the most accurate *last state* targets per participant (i.e., the top three trials per participant, accounting for all trials of a particular individual) confirms this interpretation: most of these best-accuracy trials were achieved with the *combined* (12) and *recall-only* (11) conditions compared to *baseline* (4), *confirmation-only* (3) and *constraints-only* (6).

Figure 7 (b) zooms in on the second target from the pair (i.e., the *new state*)—the hardest target since: (1) proprioceptive memory likely fades until one reaches the second target; and (2) it has no assistance from recall (here, one expects recall to play a minor role). Since these errors were not normally distributed (per Shapiro-Wilk test), we performed a Friedman test. None of the differences between conditions were significant for the input error of the second target (Q = 3.40; p = 0.49). Yet, as depicted in Figure 7 (b), the top 5% most-accurate trials per participant revealed a trend where the most were achieved via *combined* (16), compared to *baseline* (5), *recall-only* (4), *confirmation-only* (7), and *constraints-only* (4).

Relative input accuracy. While the previous accuracy analysis accounted for the traditional metric of absolute error to target, we now zoom into the relative input accuracy (Figure 8). This is computed by calculating whether the relative distance between the participant's pair of input targets is correct, regardless of their starting position. This would be equivalent to using an input device in relative mode rather than absolute mode [17]. This data did not follow a normal distribution (per the Shapiro-Wilk test), so we used a Friedman test which revealed a statistically significant difference between conditions (Q = 16.93; $p < 0.01$). Post-hoc analysis with Bonferroni correction found a significant improvement in accuracy ($p < 0.01$) in *combined* (M = 12.54; SD = 3.23) compared to the *baseline* condition (M = 18.50; SD = 4.33). Zooming in on the top

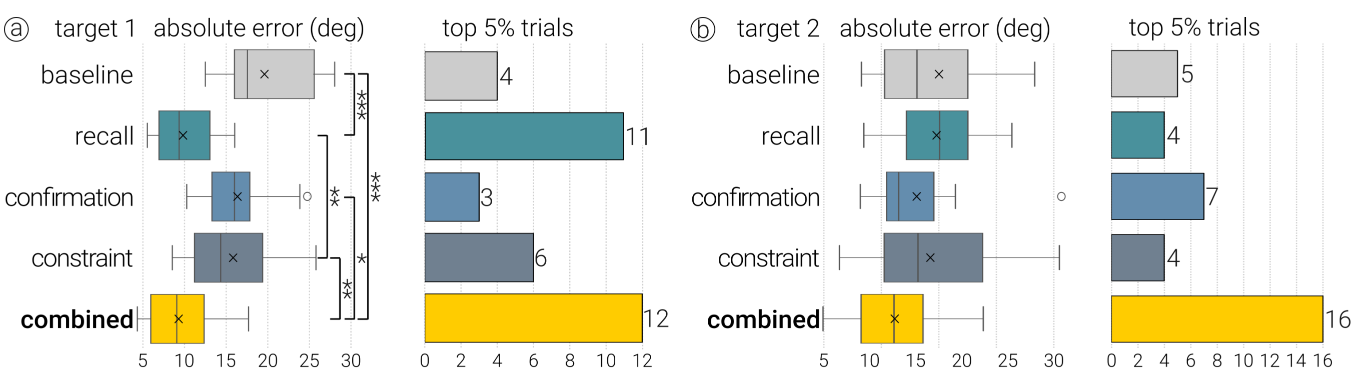

Figure 7: (a) First target (i.e., *last state*) absolute error and histogram of respective top 5% trials per participant. (b) Second target (i.e., *new state*) absolute error and histogram of respective top 5% trials per participant. Boxplot bars from left to right represent Q1, median, and Q3. Whiskers represent range excluding outliers. X represents mean. O represents outliers, which fall below Q1 − 1.5 × IQR or above Q3 + 1.5 × IQR. All non-annotated comparisons are non-significant.

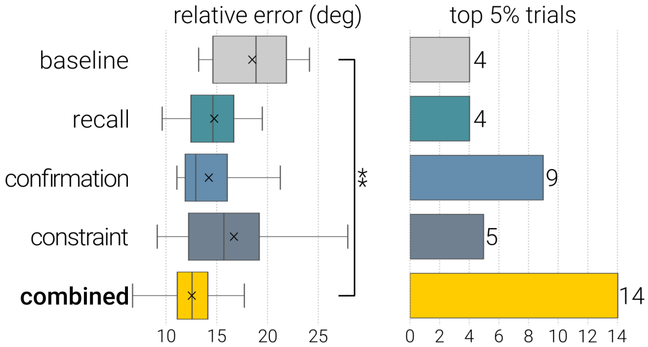

Figure 8: Relative error and histogram of respective top 5% trials per participant. (Boxplot bars from left to right represent Q1, median, and Q3. Whiskers represent range excluding outliers. X represents mean. All non-annotated comparisons are non-significant).

5% most accurate trials by relative error reveals that most were achieved via *combined* (14) and *confirmation* (9) compared to *baseline* (4), *recall* (4), and *constraint* (5). This suggests that a combined technique might also be beneficial for relative control of embodied devices.

5.3 Qualitative results

All 12 participants voiced that feedback from EMS made the task easier, compared to the baseline condition. Nine participants stated that they found the task challenging.

Recall Seven (out of 12) participants denoted recall as the most valuable technique, e.g., "effectively removed one-half of the memory task" (P12). Eight participants stated that it was easier to remember the second target when recall provided a starting point. Five participants stated that recall approximated the interaction to a relative input style, e.g., "only having to know where the target is *relative* to recall" (P1).

Confirmation. Eight (out of 12) participants stated that they counted the detents to remember the targets. Confirmation cues provided them with a mental model, which could be more resilient to the distraction task, e.g., "*Up 4* was easier to remember than *a little up from the middle*" (P11).

Constraints. Six participants (out of 12) stated constraints created a frame of reference, especially for targets close to the constraints, as P10 stated "[constraints] were helpful when the recall and target were close to minimum and maximum"—suggesting that other techniques were necessary for filling in the large space between the constraints.

5.4 Discussion

EMS did *not* disrupt input. Most remarkably, contrary to the well-documented drawbacks of EMS (e.g., conflicting with one's own movements [21, 33], distracting tingling [21, 42], and disrupting gestures [33]), the benefits outweighed the drawbacks. The results showed that these EMS techniques improved input accuracy by ~40% and confidence by ~50%.

Challenging task. We believe these results are important considering our conservative study design: **(1) Previous studies used one target**; instead, we featured two targets to make the task more challenging but also more useful, as many embodied devices will require smooth input from an initial target to a desired target. **(2) Previous studies used immediate input** and asked participants to immediately input the target they felt proprioceptively (e.g., "recreate their hand pose after having been stimulated" [28, 42]). Instead, we not only forced participants to wait between interactions but also included a distraction task which translates into more useful knowledge for the field.

Condition order randomization. Besides not providing participants with any training, the study was challenging in that condition orders were randomized, which added to the task difficulty. For example, some participants (selected at random) experienced the combined condition as their first condition—this condition contained all techniques in it, yet, without extensive training, our analysis confirmed it was the most effective approach.

Techniques in isolation. Despite showing that no technique in isolation greatly increased input accuracy, results still suggest synergistic benefits. Qualitative results revealed that participants understood and used the affordances of each technique. The combination of these techniques created demonstrably superior feedback compared to the baseline.

Study limitations. As with any study, ours is not without limitations which should be taken into consideration before generalizations: (1) this study was limited to a lab/stationary setting, which may not generalize highly-mobile applications; (2) the system was limited by the accuracy of EMS despite using a state-of-the-art PID as is common in EMS systems [22, 28, 41]; finally, (3) as the first in-depth study of these interaction techniques, this study was restricted to slider-type embodied devices given their prominence in prior work [28, 41, 42], leaving other embodied devices (e.g., buttons, knobs, etc.) unexplored.

Alternative designs. Since this study is the first systematic investigation of these techniques, we evaluated them using the same *absolute* input design as in [28, 41, 42]. We acknowledge that other designs might be leveraged to solve these gestural input problems, such as by switching to a *relative* slider (e.g., resets its position at invocation[1]).

6 Conclusions & Design Implications For Future Embodied Devices

This study is the first to demonstrate interaction techniques, based on EMS, that increased input accuracy in one instance of an embodied device, i.e., a wrist-based slider. We argue that this result is important as it might extend to further instances of embodied devices. As such, future work should apply these techniques to more embodied devices. Figure 9 illustrates more possibilities that also render common GUI elements as embodied devices, such as: buttons (which might benefit from *confirmation* to indicate valid inputs), toggles/checkboxes (which might benefit from *recall* to

[1]It is worth noting that relative input interfaces do not allow users to understand the current value based on their sense of proprioception alone, because the invocation resets the current value—in other words, using relative input, a user can adjust but is unable to retrieve, using proprioception, the absolute value of the interface right after invocation.

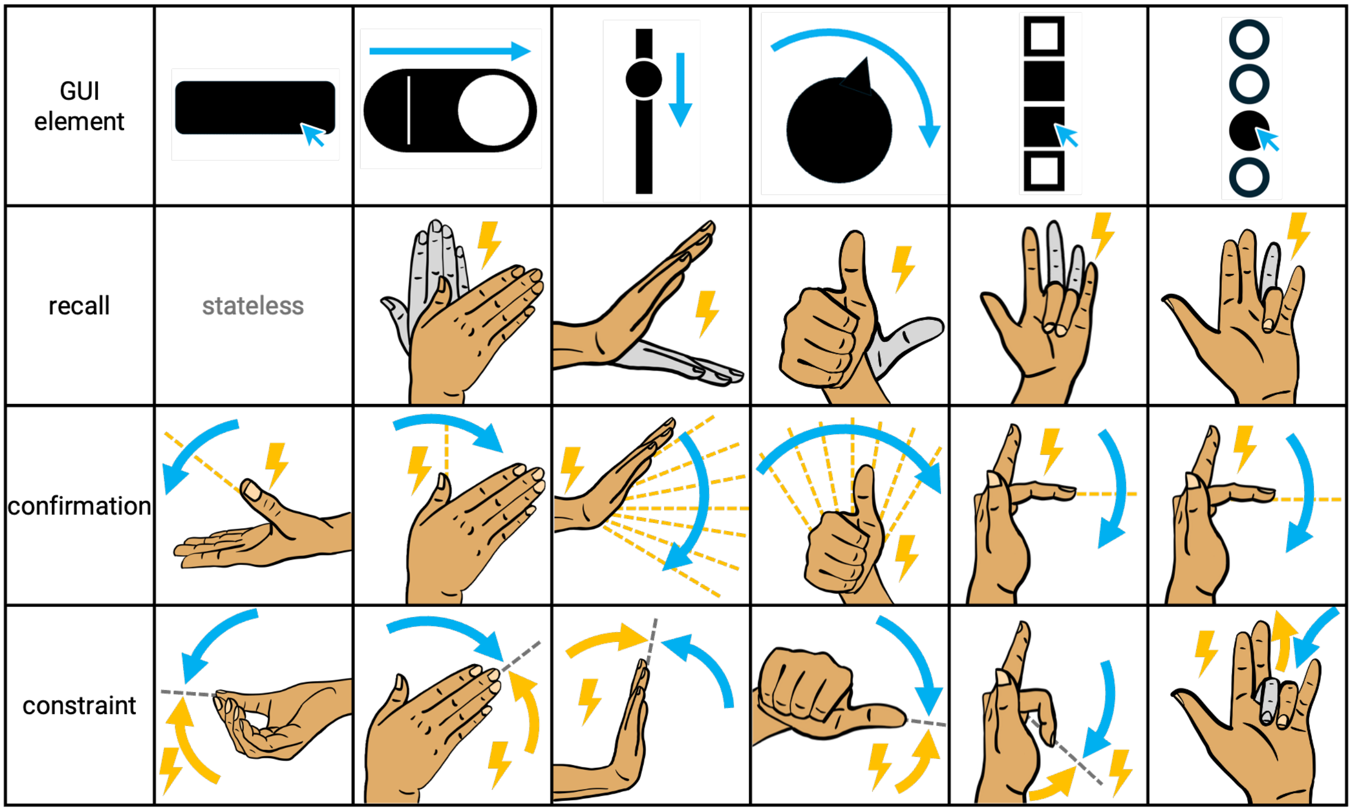

Figure 9: Illustrating exemplary embodied devices (button, toggle, slider, knob, checkboxes, and radio buttons) in which these techniques might be applicable. Note that for clarity we depict all these examples on the user's hand, but embodied devices can be applied more broadly to other limbs.

reflect their on/off state), sliders/knobs (which we have shown, for the case of wrist-based sliders, to benefit from all three techniques), and even radio buttons (which might benefit from *constraints* to prevent users from incorrectly inputting more than one value at a time).

Additionally, embodied devices can be used in other limbs beyond the hands (e.g., the neck-based slider in [41] or ankle-based knob in [1])—in these contexts, we also expect our interaction techniques to prove useful.

Finally, an additional area for future investigation where these techniques might also prove useful is when multiple embodied devices are used (e.g., simultaneously but on different limbs or sequentially on the same limb).

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