Modeling Perceived Force of Electrical Muscle Stimulation to Improve User's Recall

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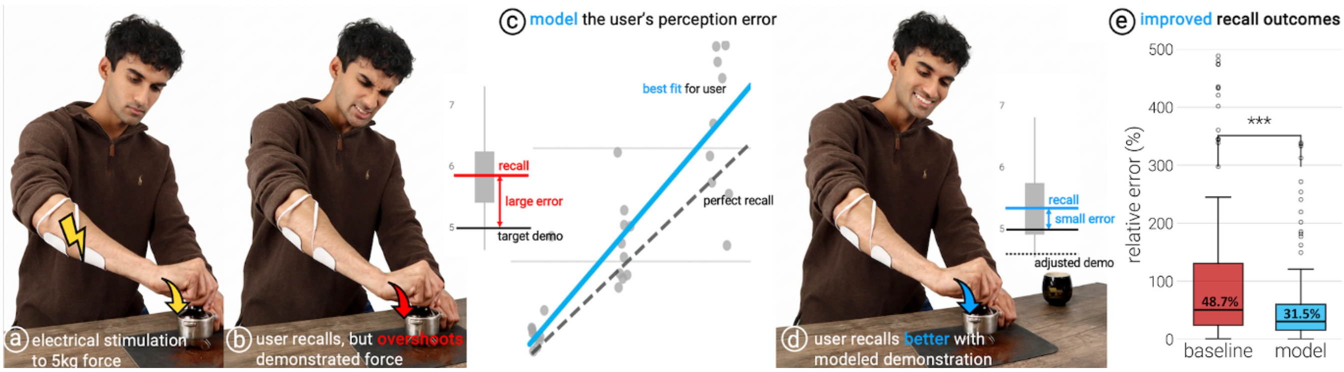

Figure 1: *Force* is critical for motor skill acquisition. For instance, making an espresso requires tamping down the grounds on the portafilter with the right force (not too much, not too little). (a) Recent interfaces based on electrical muscle stimulation (EMS) can assist users with physical skills. (b) However, we found that when users recall a force felt via electrical muscle stimulation, they tend to *overshoot*. To tackle this, we (c) modeled users' force perception to EMS forces. Using a regression model, we (d) render a new target force (adjusted, not the original force) that when recalled matches the original force better (i.e., less error than before). (Boxplots bars represent Q1, median, and Q3. Whiskers represent range excluding outliers. O represents outliers, which fall below Q1 - 1.5 x IQR or above Q3 + 1.5 x IQR).

Abstract

Interactive electrical-muscle-stimulation (EMS) supports motor-skills by actuating the user's muscles. However, existing EMS-interfaces exclusively focus on demonstrating movements/sequences (e.g., which fingers to actuate to play a piano melody) and have not investigated EMS for skills requiring precise force application (e.g., playing musical instruments, practicing culinary techniques, operating force-sensitive tools). Our user study found that when EMS-interfaces demonstrate a force, participants trying to recall this force, overshoot by a median 19%; with especially larger overshoots at lower target-forces (e.g., produce a ~1.2 kg force, after a 1 kg demonstration). This force mismatch renders EMS-interfaces unable to accurately demonstrate forces—drastically limiting the growing potential of EMS for HCI. To significantly improve on this, we modeled users' recall of EMS-demonstrated forces. This model allows to adjust EMS-interfaces to render a target force that, when recalled, matches the intended force best—in our study, this improved median force recall by ~35%.

CCS Concepts

• **Human-centered computing**; • **Hardware** → **Haptic devices**;

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Keywords

Electrical Muscle Stimulation, Haptics, Force, Force-feedback, Motor skills

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1 Introduction

Acquiring physical skills (e.g., culinary techniques, musical instruments, input-devices) requires the repeated practice of movements—including understanding trajectories (i.e., limb's path in space) and **forces** (i.e., tensions enacted by the limb). During skill acquisition, novices rely on real-time feedback to ensure they are performing the movements correctly. When unassisted by technology, this feedback is given by demonstration from a mentor. While effective, these methods tend to focus "on how the movement should *look* rather than how it should *feel*" [10].

Conversely, force-feedback devices (i.e., haptic devices capable of directly moving the user's body), offer promise for interactive skill acquisition by reducing dependence on in-person expert training (often inaccessible or expensive). In recent decades, HCI research has increasingly turned to interactive electrical-muscle-stimulation (EMS), which provides force-feedback in a wearable form-factor

[38]. A significant body of this work has been dedicated to improving the shortcomings of EMS movements. **But what about the accuracy of EMS forces?** While many advances pushed the boundaries of EMS' ability to render more accurate trajectories [25, 28, 32, 64, 73]; or more complex poses [19, 32, 46, 51, 52, 60, 61], there is a significant knowledge-gap with *no studies* on the use of *EMS for demonstrating forces.*

This raises a challenging question: *do users accurately perceive a force if it is involuntarily demonstrated by electrically actuating their muscles?* As we found in our study, **users cannot always accurately perceive the magnitude of an EMS induced force.** When users recall a force felt via electrical-muscle-stimulation they might overshoot, recalling it as a much stronger force.

As it stands, this force mismatch would render EMS interfaces unable to adequately demonstrate forces, drastically limiting its potential in HCI, despite growing interest (~150 EMS explorations in HCI [14]). To mitigate this perceptual mismatch, we propose modeling user recall of EMS-demonstrated forces, shown in Figure 1, enabling EMS interfaces to adjust the target forces to yield better perceived forces—our study showed this improved median force recall by ~35%.

2 Related work

Our work builds on force-feedback systems that demonstrate physical skills by actuating the user's body. We focus on interaction systems based on electrical-muscle-stimulation, given its wearable, unencumbering form-factor when contrasted to mechanical devices [38] and its rising interest in HCI (i.e., ~150 papers) [14]. We also review prior work in force perception, addressing the broader challenge of perceptual calibration in haptics.

2.1 Primer on interactive electrical-muscle-stimulation (EMS)

Electrical-muscle-stimulation (EMS) achieves force-feedback by electrically contracting muscles. The excitement around EMS in HCI stems from its simplicity—the hardware required is only a stimulator and electrodes. Thus, EMS actuates a wide-range of muscles—wrists [40, 56, 61, 63], arms [11, 41, 42, 49], legs [3, 20, 54, 72], neck [64]— without complex infrastructure (e.g., exoskeletons) [38]. Thus, it gained popularity in HCI [71].

Popular uses of interactive EMS include rendering force-feedback in VR/XR [43], speeding up reaction time [27], skill acquisition [10]—just to cite a few (a survey of EMS applications areas can be found in [14], including ~150 papers in HCI)—of special interest to our short paper, is the use of EMS to *demonstrate physical movements.*

2.2 EMS for demonstrating physical movements

EMS can demonstrate movements to users, from sports (e.g., golf [13, 49]), musical instruments (e.g., piano melodies [50]), and even tool use (e.g., showing the movements to use a spray-can [41]). This is an active area of EMS research, with some of these systems already shown to train users (i.e., retention of EMS movement-sequences [10] and EMS movement-trajectories [67])—further highlighting the potential of EMS in demonstrating movements.

2.3 EMS' limitations for movements

However, the aforementioned applications were not possible when EMS first garnered interest in HCI, due to critical limitations of EMS, documented in early HCI works: **(1) Rapid force build-up of EMS induced movements** as denoted by from Kruijff et al.— "This contraction is hard to control"— in their seminal work [33]; similarly, Tamaki et al.'s seminal paper in [63] demonstrated empirical measures where the rapid buildup of an EMS contraction was revealed (see Figure 5's plot in [63]). **(2) Lack of accuracy in EMS induced poses** as denoted by Tamaki et al.—"We confirmed that PossessedHand could control 5 independent and 11 linked joints [i.e., 11 out of 16 joints exhibited unwanted movements]"—in [63]. **(3) Unreliable trajectory control:** early systems actuated the body using an open-loop strategy; however, this proved impossible as Kaul et. al denoted "For complex movements (. . .) feedback loop is necessary to control movements" [28]. (There are other open challenges in EMS, such as optimizing comfort, however, these are not unique to demonstrating movements with EMS, and thus not our focus).

Improving the accuracy of EMS *trajectories* lead to breakthroughs. To tackle the latter limitation of EMS when used to demonstrate movements (i.e., its trajectory inaccuracies), the HCI community responded with a concerted effort around closed-loop control strategies to minimize trajectory error—leveraging PID controllers [25, 28, 32, 64, 73]. By pushing the boundaries of the control used to drive EMS trajectories, new applications were possible, such as drawing shapes in mid-air [28], drawing on paper [44], or moving users' limbs to spatial-targets [25, 64].

Improving the accuracy of EMS *poses* also lead to breakthroughs. Simultaneously, many advances in EMS focused on increasing the *accuracy of EMS poses*, e.g., dual-controllers [52], back-of-hand actuation [60], EMS-brakes [51], cross-sectional stimulation [61], and so forth. To illustrate how useful these advances in dexterity have been, back-of-hand actuation was rapidly adopted in [19, 36, 46] leading to new EMS-systems that demonstrated more complex hand-poses to users, enabling, for instance, the EMS skill acquisition of piano melodies [10, 43].

But what about the accuracy of EMS forces? While many advances pushed the boundaries of EMS' ability to render poses and trajectories, the situation is stagnant with respect to pushing the boundaries and our understand of force perception and rendering with EMS. In fact, of the aforementioned ~150 papers EMS in HCI [14], only 15 of these papers address the force component of electrical-muscle-stimulation, with a non-existent focus on *unassisted* force recalls.

2.4 The deceptive area of forces with EMS (XR forces)

One could argue that the previous argument is paradoxical, if EMS was popularized as force-feedback, then rendering forces is a well-established use case. In fact, one of the most popular areas of EMS forces is immersive interactions (e.g., contact forces in VR [15, 17, 42], impact from virtual punches [39], or pushing AR walls [43], etc.).

The false-case of EMS forces in XR. These EMS-forces for XR are a "red herring"—these systems are not dedicated to demonstrating *exact* forces to users, but simply leverage EMS-forces to increase realism [42]. In fact, prior work using EMS not in *virtual* reality, but in *augmented* reality [43] noticed that participants suspected that the magnitude of EMS-forces was off, with one participant stating "but this [EMS] marble that I see cannot possibly be that heavy, I can see the world around me, so I can imagine the weights [of things]" [43].

Exploration of forces with EMS. While there has been research in understanding how EMS creates forces (e.g., understanding how EMS' intensity [17, 26, 35, 74], pulse-width [17, 35, 74], or style of controller [17, 35, 74] changes its output force), there has been no systematic effort to characterize how users *perceive* such EMS-forces and *recall* it. Yet, there has been a growing enthusiasm about the promise of EMS for force learning, such as by stimulating muscles for fingertip control [48], or by indirectly stimulating facial muscles to create an illusion of force [47]. The closest an investigation of EMS-forces comes to our proposal is [58], which continuously stimulates the user's muscles to move away from a force-sensor when the force exceeds a very light-force target—this is an *opposite* strategy to ours since in their case, EMS-force is *indirectly* used. While this can assist users in not exceeding this light-force, it is unlikely that users would memorize the opposing EMS-force, and then, be able to mentally discount it during their recalls (their focus was on one-legged postural control during forces). Moreover, likely for this reason, [58] did *not investigate unassisted recalls*, which is the central focus of our work.

Our contribution. We argue that, unfortunately, there is a large asymmetry, i.e., interactive systems use EMS to demonstrate forces, yet no studies have been put forward to understand how users *perceive* and *recall* forces demonstrated via EMS. This need is critical and represents the gap our work addresses by asking the question: *Can we improve force perception and control with EMS by measuring and adapting to a user's perceptual offset?*

3 User study overview

We conducted a study comprised of three phases. In **phase 1 (data collection**) we uncovered if users overshot forces demonstrated by EMS, by measuring recall of forces demonstrated by EMS. In **phase 2 (modeling)**, we modeled participants' force-perception, deriving straightforward perceptual models that best fit their data. Finally, **in phase 3 (validation)**, we compared our models to standard EMS-demonstration to understand if these models can adjust target forces to compensates for force-mismatches during recall.

Participants' task. Regardless of the phase, participants performed a standard *force demonstration-recall* task.

Trial design. At the start of each trial, participants relaxed and let the EMS acuate them to *demonstrate* a force. Subsequently, after a 3 second delay, they were asked to relax their grip, and then *recall* this exact force magnitude by themselves (i.e., an unassisted recall). This 3 second delay was selected to give participants time to perceive the demonstrated force and is inspired by prior work in force-matching tasks [68]. Our key metric was relative recall error, or the percent difference between the peak of the EMS-demonstrated force and the peak of the participant's own recall force.

Study apparatus. To minimize variability in participants' pose and to prevent them from compensating with other muscles, we stabilized their hand using a table-mounted handle, which they gripped to input forces. Forces were recorded using a grip-force dynamometer (90 kg load cell, sampled at 400 Hz, 12-bit ADC). Electrical-muscle-stimulation was provided to participants' non-dominant arm (finger flexors) using pre-gelled electrodes. Stimulation was delivered via a medically-compliant electrical stimulator (*HASOMED,* P24), which was controlled using its low-level USB Serial API (latency <1ms).

EMS force-based closed-loop controller. To reach target forces, we utilize a closed-loop PID controller—most popular method to implement robust EMS control, used widely in rehabilitation [5, 16, 19, 32, 34, 54, 55, 73] and in HCI [28, 40, 69]). The PID adjusts the stimulation pulse-width (20-720 µs) to minimize error between the intended-target and current force on the load cell. Once a force is reached via PID, the stimulation stops. We settled on the following PID coefficients P=2.0, I=1, D=1.

Calibration of EMS and force-range. Per-participant, we calibrated the position of the EMS electrodes to ensure: (1) pain-free operation, and (2) actuation resulted in a reliable and isolated *grasp* gesture with no visible wrist movements. This palmar grasp movement was chosen for its use in daily activities [7, 65], while also minimizing the chance of compensatory movements during recall (e.g., wrist based movements can be compensated with shoulder/torso, but palmar grip strength cannot). Then, we measured the maximum comfortable grip-force generated by EMS (M=4258.3g, SD=1480.5g), which we set this as the maximum EMS-force for a given participant. The minimum force was set at 500g, since it is on the lower end of grip forces observed during actual daily tasks [6, 7, 37], and we found it, via pilot testing, to be a lower bound for robust performance in our EMS controller.

Participants. We recruited 12 participants (*M*=25.8 years old, *SD*=7.9, 1 left-handed), consisting of 1 non-binary, 5 female and 6 male participants. Participants received $20 USD as compensation for their time.

Ethics. Our study was approved by our ethics review board (*IRB anonymized for review*).

Data. To enable readers to perform their own analysis and accelerate the research in this area, we provide the raw data in our *Supplementary Material.* Data This includes raw trials, participants' maximum voluntary contraction (MVC), and maximum EMS contraction that was deemed comfortable by each participant.

4 Phase 1: do users overshoot when recalling EMS forces?

4.1 Phase 1 hypothesis & design

In this phase we investigated recalling a force that was demonstrated by EMS. As such, participants experienced 30 demonstration-recall trials (3 randomized target forces (min, max, mid-point) × 10 repetitions). We intentionally sampled only three target forces to minimize time spent on this force calibration (data collection), while still using different force levels to capture some variability of responses to different stimulation intensities.

Hypothesis. (H1) Participants will overshoot when demonstrating forces that they felt by means of EMS.

4.2 Results

We analyzed *relative error* ($\frac{\Delta F}{F} = \frac{(F_{recall} - F_{intended-target})}{F_{intended-target}}$) while participants recalled forces they felt via the EMS-demonstration. The aggregated (all participants) data did not follow a normal distribution via Shapiro-Wilk test, so we conducted a Wilcoxon signed-rank test, which found that recall forces were significantly higher than demonstrated forces (W=47179, p<0.001), validating our above

H1. We measured an overall median relative error of 19.0% (Q1=-13.7%; Q3=117.7%; M=147.4%; SD=367.4%), suggesting that participants tend to overshoot when trying to replicate forces that they felt via EMS. Diving deeper, different force levels exhibited different errors across participants, which we evaluated via Bonferroni-corrected comparison tests: at the **min**imum force of 500g, we measured a median error of 80.2% (Q1=33.5%; Q3=275.6%; M=295.4%; SD =475.1%); at the **mid**-point of a participant's force-range, we measured a median error of 12.8% (Q1=-10.2%; Q3=33.8%; M=88.7%; SD=203.7%); and, at the **max**imum of a participant's force-range, we measured a median error of 4.3% (Q1=-13.0%; Q3=34.4%; M=61.3%; SD=147.5%).

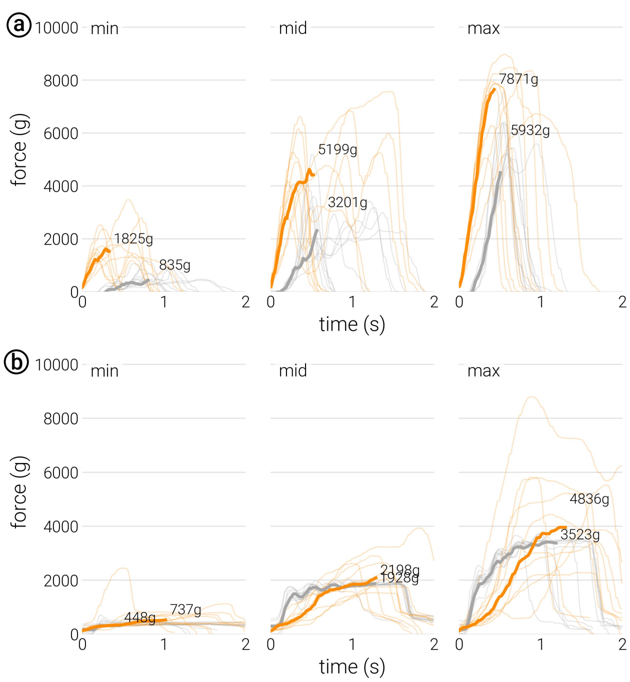

Figure 2: Two distinct participants: (a) the typical participant that overshoots (P7); and (b) the rare participant that stays close to target (P11). Plot depicts in grey the demonstrated forces (bold line is median) and in orange the recalls (bold line is median).

Exemplary participant trials. Figure 2 depicts sample force-time graphs for two distinct participants (a) P7—representative of a typical result, where participants tend to overshoot the recalls (especially in the lower force ranges); and (b) P11, data from a top-participant (similar only to only one other participant) who exhibited near-perfect recalls. As we will discuss later, these individual differences, which contributed to the larger means and deviation—typical of EMS research due to the fact that different individuals can respond differently to EMS [9, 14, 28, 29, 53]—further underscored the need to model perception of EMS forces per-user.

5 Phase 2: modeling the perception of EMS forces

Following data collection, we sent participants to a designated 5-minute break, and we constructed their *perceptual regression models*. We later use these, in the phase 3 (validation), to test if adjusting the target forces can compensating for this perceptual mismatch.

5.1 Phase 2 models

We evaluated three pre-defined regression models to capture participant's force perception:

(1) Linear (monotonic)—linear mappings between stimulation and sensation are often used for designing haptic-controllers [18, 34], and force-perception [2, 68]; $F_{recall} = a + b \cdot F_{demo}$ where $b \geq 0$.

(2) Quadratic (shape-constrained)–second-order polynomials are used in perceptual modeling to capture non-linear effects [2, 18, 57]; $F_{recall} = a + b \cdot F_{demo} + c \cdot F_{demo}{}^2$ where $b + 2c \times F_{demo} \geq 0$ for $F_d \in [F_{\min}, F_{\max}]$.

(3) Power law (monotonic)—low-order polynomials are motivated by perceptual mappings following Steven's law [8]; $F_{recall} = a + k \cdot F_{demo}{}^p$ where $k > 0,\ p > 0$.

Model evaluation and selection. We compared per-participant models by employing grouped cross-validation using the data from phase 1. In each fold, we held out trials of one target force level and trained on the remaining target force trials to test how well the model generalized to unseen target forces. Individual participants' force distributions were normal, so we minimized Huber loss to limit outlier trial influence and evaluated the folds via root mean square error (RMSE). We then selected the model family with the lowest mean RMSE for each participant.

Global regression model. To assess the value of personalization, we also constructed a "global" model post-study by pooling all phase 1 data (360 trials across 12 participants) by performing an identical model selection and cross-validation.

5.2 Results

Figure 3 (a) depicts our key result by detailing the mean RMSE for each of the three models, per participant. We found that, for all participants, the models that minimized error the best were: linear (6 out of 12 participants), constrained-quadratic (4 out of 12), power (2 out of 12). The suggestion that linear-models best represent EMS perceptual-overshoots aligns with prior work in physiology, where participants overshot when asked to replicate the force of weights added on top of their fingerpad's skin [68].

Personalized vs. global model. Given that the aggregate participant data needed to construct a global model was found to be

(a)

participant	personalized-linear	personalized-quadratic	personalized-power
P1	624.6	**603.2**	819.4
P2	4219.2	**3067.3**	5356.5
P3	**3293.5**	3811.2	3989.3
P4	**996.1**	1219.9	1585.9
P5	**729.5**	1521.2	1705.2
P6	1000.4	**962.1**	972.7
P7	1780.9	2316.3	**1294.6**
P8	**794.5**	2564.7	1097.8
P9	1246.4	**1149.2**	1262.7
P10	950.9	904.9	**742.1**
P11	**1284.5**	1318.3	2366.5
P12	**4777.9**	4805	4841.2

(b)

best personalized-model	global-quadratic
603.2	1186
3067.3	10918.8
3293.5	3352.7
996.1	1023.7
729.5	1801.6
962.1	**763.9**
1294.6	2117.5
794.5	964
1149.2	**807.8**
742.1	1079.4
1284.5	1525.9
4777.9	7987.5

Figure 3: (a) RMSE results for each type of model, and for each participant. Selected model in blue. (b) Contrasting RMSE results of participants' best personalized-model with the global-model.

non-normal (see phase 1), we utilized a quantile (median) regression. We found that a quadratic global model outperformed the remainder global models. To explore differences between the performance of global model vs. each participant's best personalized-model, we conducted a Wilcoxon signed-rank test. We found a statistically significant difference (W=3; p<0.01), with the best personalized-model exhibiting less error (10 out of 12) than the global (2 out of 12), as depicted in Figure 3 (b). Thus, for the remainder of our study (phase 3), we utilized each participant's personalized model.

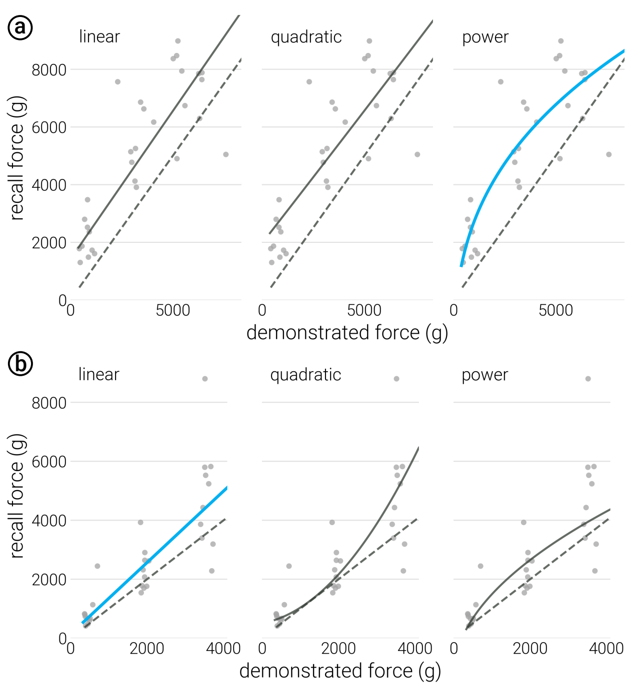

Figure 4: Exemplary personalized-models to contrast the linear (left), quadratic (middle), and power (right) regression models for: (a) P7, and (b) P11. Best performing model is highlighted in blue.

Exceptions. There were two exceptions to the average results (P1, P11) were close to ideal-recalls, thus, modeling their force-recalls provided marginal returns (also emphasizing the value of a personalized-model; otherwise, these participants would be penalized by a global-model.

Exemplary participants. Figure 4 depicts two exemplary cases of two participants for whom different models best fit their data from phase 1: (a) P7 was best approximated using a power-regression, while (b) P11 was best approximated with a linear-regression.

Summary of findings. Our results suggest that: (1) modeling perceived EMS-force may minimize errors—cross-validation already confirmed it, yet, we put it to a more stringent test in phase 3 (validation) by using an array of new unseen target forces (not part of the model's data) and using these models in real-time; and (2) while a global-model is likely to reduce some EMS-force mismatch, a personalized-model will reduce it more effectively.

6 Phase 3: can a user's perceptual model minimize their overshoot?

6.1 Phase 3 hypothesis & design

Hypothesis. **(H2)** Using a participants' personalized model to alter the demonstrated-force based on the intended-force, will improve force recall, when compared to non-adjusted EMS targets (*baseline*).

Trial design. Each participant underwent 30 trials comprised of 15 new forces (not used in phase 1) repeated twice: 15 as *baseline* (non-adjusted EMS targets) and 15 as *model-adjusted* EMS targets. Importantly, to prevent any learning effect, all 15 trials from each condition merged into one set of 30 trials, which were then presented in a randomized order (i.e., no condition blocks were used—mitigating learning effects). We then measured absolute recall error relative to the intended target force for each condition. This paired design allowed us to directly compare whether model-adjustment improved recall accuracy for the same intended forces, while controlling for practice/learning effects from phase 1.

Unseen target forces. To test the model's effectiveness on unseen data, we randomly generated 15 *new* target forces within each participant's defined force-range from phase 1 (i.e., demonstration

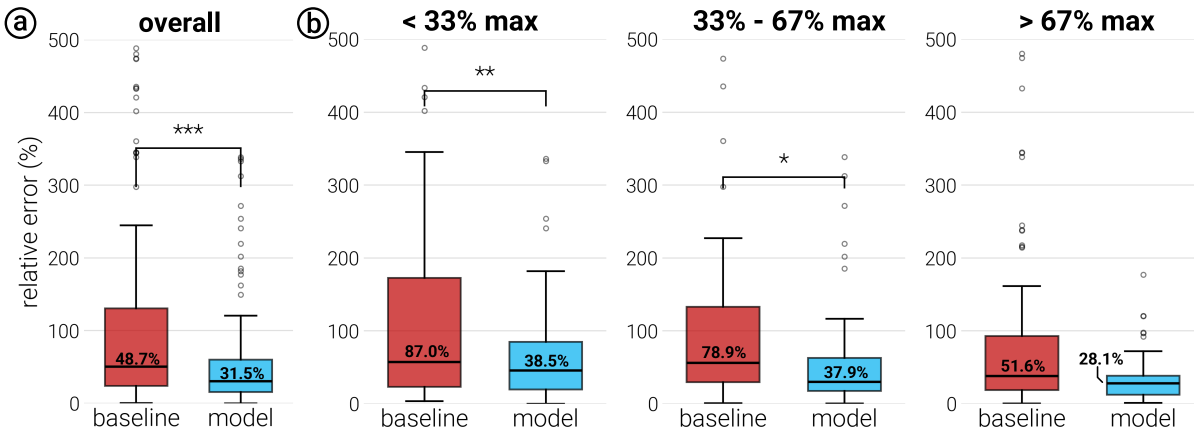

Figure 5: a) Overall recall error for baseline EMS (red) vs. modeled EMS-demonstration (blue). (b) Results for force ranges. (Boxplots bars represent Q1, median, and Q3. Whiskers represent range excluding outliers. O represents outliers, which fall below Q1 - 1.5 x IQR or above Q3 + 1.5 x IQR. Non-annotated comparisons are non-significant).

forces not used in phase 1 with a ±5% force margin). These serve as the "baseline" target forces for our final validation. We then inverted each participant's selected model to compute 15 "model"-adjusted target-forces designed to minimize error from the intended (i.e., non-adjusted) force-target. When model inversion yielded values outside valid demonstration force-range, we clamped these to participants' lower/upper force-range.

6.2 Results

We analyzed *relative error* ($\frac{\Delta F}{F} = \frac{(F_{recall} - F_{intended-target})}{F_{intended-target}}$) while participants recalled adjusted-forces (using our *model-condition*) vs. baseline-forces (non-adjusted, i.e., normal EMS *baseline-condition*).

Overall results. We found that model-adjusted demonstrations significantly reduced recall error from the intended target force when compared to recall error from baseline demonstrations. By Wilcoxon signed-rank test (W=77, p<0.001; non-normal by Shapiro-Wilk), we found statistical evidence that participants exhibited lower relative error in the *model-condition* (median=31.5%; Q1=27.6%; Q3=57.7%; M=59.8%, SD=62.0%) compared to *baseline-condition* (median=48.7%; Q1=38.5%; Q3=97.3%; M=112.5%; SD=138.3%). This was a 35% reduction in relative error, as depicted in Figure 5 (a).

Per-force level results. To explore if personalized-models operate across different force levels, the data is further divided into three intended force bins of equal size: lower force (<33% of maximum EMS-force); mid-force (33%-67%); and higher force (>67%). To achieve this, we assigned each participant's baseline-condition trials into its corresponding bin. Then, assigned each paired-target on the model-condition to its corresponding bin, which resulted in the distribution depicted in Figure 5 (b). We performed Bonferroni-adjusted Wilcoxon signed-rank tests to compare the recalls in *model-condition* and *baseline-condition* at these three force levels. In the lower force range (<33%), we found a statistically significant improvement (W=69, p<0.01; non-normal by Shapiro-Wilk) of the *model-condition* (median=38.5%; Q1=28.0%; Q3=59.0%; M=94.5%; SD=146.7%) when compared to the *baseline-condition* (median=87.0%; Q1=38.5%; Q3=196.1%; M=158.8%; SD=178.8%). In the mid-force range (33%-67%), we found that a statistically significant improvement (W=68, p<0.05; non-normal by Shapiro-Wilk) of *model-condition* (median=37.9%; Q1=24.3%; Q3=62.7%; M=58.7%; SD=61.1%) when compared to *baseline-condition* (median=78.9%; Q1=42.6%; Q3=123.3%; M=121.1%; SD=142.6%). Finally, in the higher force range (>67%:), we did not find a statistically significant difference (W=49, p=0.09; non-normal by Shapiro-Wilk), for *model-condition* (median=29.1%; Q1=25.3%; Q3=36.7%; M=35.0%; SD=22.3%) compared to *baseline-condition* (median=51.6%; Q1=27.6%; Q3=70.3%; M=89.8%; SD=112.9%). These results indicate that at lower and mid force ranges, we observed recall improvements.

7 Discussion of findings and study limitations

7.1 Study limitations

We acknowledge that our study is not without limitations.

Few trials to generate models. To generate our per-participant models, our phase 1 only captured three calibration trials from three different targets. Certainly, adding more calibration trials could increase the precision of the models, enhancing the robustness of its statistical modeling[1].

Multiphase design. Since our design is based on phases (i.e., first acquiring data to model, and later testing unseen targets from model data), there is a chance that participants adapt to EMS as trials progress, which could lead to confounds (e.g., improved task understanding, perceptual learning, improved motor control, adapting to EMS sensations, etc). However, it is critical to note that these possible confounds would, in fact, *ease* force-recalls for *both conditions equally*, since in the final phase participants randomly executed trials with and without our model—in fact, participants were not aware of the condition type for each trial (i.e., condition types were mixed in the same testing block to prevent confounding). Thus, our findings suggest that our model was able to reduce the recall error even if some practice was acquired throughout phase 1.

[1]However, it is worth underscoring that increasing the amount of data used to generate the per-user model increases the calibration time needed before a user can benefit from the model-adjusted forces—unfortunately, calibration time is already one of the main downsides of EMS [12, 30, 31, 53, 62, 66]); as such, in this work, we opted to keep calibration time as short as possible.

Exploring other modeling approaches. As the first work to explore this overshoot with EMS forces, we intentionally focused on straightforward models (regressions) to model perception from a broader analytical perspective (as its typical of psychophysics and HCI), rather than machine-learned models, which may be suitable but require far more data. We believe these are worthy of future work, but they have downsides such as yielding less generalizable insights, and significantly increased EMS calibration due to the vast amount of data required.

Generalization. It is important to acknowledge that different individuals can exhibit different sensitivity to electrical stimulation, a well-known aspect of EMS [9, 14, 28, 29, 31, 53, 66]. In our case, to ensure the comfort of participants in our study, we first adjusted the maximum force generated by EMS that they still perceived as comfortable. As expected, we indeed found different responses to EMS comfort, which yielded different maximum force levels. While this is typical of EMS (it, again, also underscores the need to leverage *per-user* models), we caution against immediate generalizations across larger populations.

7.2 Why do EMS-forces feel different?

The likely reason for this force mismatch runs deep into the neuroscience of muscle activation. When we move, our nervous system chooses what *types of muscle fibers* to use—*Henneman's size principle* (1965): "neurons with large cell bodies tend to innervate fast-twitch, 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" [1, 21, 45].

Selecting the type of muscle fibers (i.e., *fast-twitch, high-force,* vs. *slow-twitch, low-force*) is beneficial for a user, because, as more force is needed, more "motor units are recruited in a precise order according to the magnitude of their force output, with small units being recruited first" [21, 45]. This is the engine that powers human-level dexterity, enabling precise control over movement forces, while minimizing fatigue [21, 45].

We can now turn back our attention to EMS, which actuates by passing electrical currents via the path of least resistance. Thus, whichever neurons happen to be in the path of EMS, will likely be activated—regardless of what type of muscle fibers they control. As such, EMS will stimulate random combinations of fibers—likely *both* of them simultaneously [22]. The result is that the *fast-twitch, high-force* fibers drive the movement, in a rapid manner. Unfortunately, this is not an easily surmountable limitation of EMS, there is no simple way to force the current to only stimulate one type of fiber. The result of this is that participants perceive a force that evokes a sensation similar to if they had performed a stronger force (one that would recruit more *fast-twitch, high-force* fibers). This possible explanation is not only logically consistent with neuroscience but also aligns with our study findings *as lower forces had more overshoot* and we did not find a statistically significant improvement on leveraging our model with forces >66% of participants' (own) maximum force range—this is likely driven by the fact that on lower forces this perceptual confusion is highest (typically these would recruit less *fast-twitch, high-force* fibers).

7.3 How can researchers in HCI use our findings to improve EMS systems?

Showing force with EMS can be challenging. The first outcome of our work unveiling this perceptual-exaggeration of EMS-forces. This overshoot seems to increase for lower (precise) forces.

Design EMS systems with multiple modalities (if available). Given the perceptual mismatch that we found, one pathway is to combine multimodal-feedback with EMS, hopefully, landing at a synergistic combination that might compensate for this force-mismatch. This is likely more natural in domains where EMS has already been explored in combination with other modalities, such as EMS paired with audio/visual [42], with tactile feedback [39], and so forth. However, we understand this is only possible if multimodality is an option and beneficial.

For EMS-only systems with precise recalls, consider modeling. If an EMS-application aims at training users to then perform unassisted force recalls (e.g., the applications we will showcase next), we recommend adapting our process to model the target users force perception (this can be done during EMS' mandatory per-user calibration phases) and constructing a model that best assists this user with their recalls. Moreover, for learning to recall small (i.e., precise) forces via EMS, our study's findings suggest more EMS-advances are urgently needed. Thus, we urge researchers to explore these or alternative feedback methods.

For EMS-only without precise forces, a global model may suffice. When designing EMS systems without a stringent force requirement during recalls, prospective researchers might still benefit from a global model based on study's data. While the global model did not outperform personalized models, this speeds up the process (no data collection needed) and is still likely to yield a positive-net result (i.e., some possible improvement on recalls is expected).

8 Envisioned applications

Finally, we illustrate the use of our perceptual-model for EMS-forces in three envisioned-applications. These were chosen to convey how accounting for EMS-force perception can open-up unexplored areas for interactive EMS systems. While the envisioned interactions were chosen as they leverage movements similar to those in our study (i.e., finger/palmar flexions), it is critical to acknowledge that real-world EMS applications are likely to involve more complex situations (e.g., dynamic postures, shifting grip angles, and movement while gripping) that have not been validated as part of our controlled experiment.

8.1 Application #1: playing a barre chord on guitar with the correct force

Figure 6 depicts a user learning to play a *barre* chord on guitar with the correct force—in this chord, only grip force is being demonstrated, not the trajectory to the target fret. While existing EMS systems already have sufficient precision to actuate a *barre* chord [60] our findings add the ability to show the *force* needed (when playing barre chords, it's important to maintain the correct intended force level—notes played with a weak barre chord will sound muted, while notes played with a barre chord that is too strong can sound off-tone [23, 59]). In Figure 6 (a) the EMS demonstrates the intended force for the barre chord grip using an adjusted-force target, derived from this user's perceptual model. This improves the user's own recall at the intended force without EMS assistance.

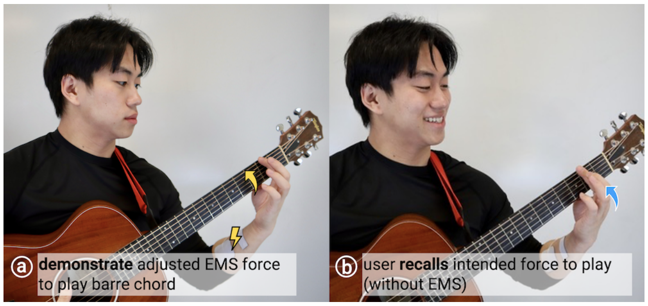

Figure 6: An example of a user (a) feeling the grip, via EMS, need for a barre chord; and (b) recalling it voluntarily.

8.2 Application #2: chiseling wood with the correct pressure force

Figure 7 depicts a user experiencing chiseling wood—with the correct downwards' force—note that no trajectory is being demonstrated with EMS, only grip force. Prior EMS along these lines is limited to adjusting trajectory while teleoperating a robot that sands wood [25]. We depicted a horizontal *paring cut* with a chisel, as it requires a precise downward force [4]. In Figure 7 (a) the EMS-system demonstrates the intended force, again, via an adjusted-target (from the user's model). This improves the user's recall while chiseling without EMS.

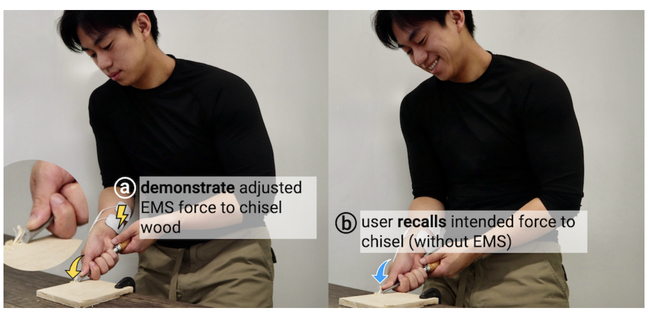

Figure 7: An example of a user (a) feeling the downwards force, via EMS, need for chiseling; and (b) recalling it voluntarily.

8.3 Application #3: maintaining correct grip-force while putting in golf

Figure 8 depicts a user learning to putt in golf—with the correct grip-force—again, no trajectory is being demonstrated with EMS, only grip force. We selected this as putting in golf has been explored in prior EMS work [13, 48]. Expert golfers maintain consistent grip-forces while putting [24, 70]. In Figure 8 (a) the EMS-system demonstrates the intended grip-force, again, via an adjusted-force target. This demonstration continues throughout the putting motion as depicted in Figure 8 (b). Finally, in Figure 8 (c), the user recalls the correct grip-force throughout the putting motion without EMS assistance.

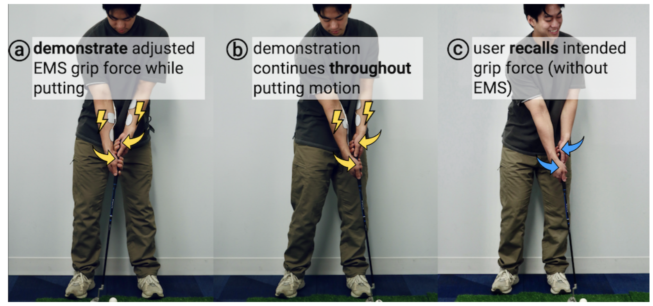

Figure 8: An example of a user (a) feeling the grip-force, via EMS, need during golf putting; (b) a grip-force that EMS demonstrates to them, which is needed throughout the putting motion; (c) the user recalls the correct grip-force voluntarily for a successful swing.

9 Conclusions and future work

We proposed and evaluated a novel modeling approach to improve unassisted recall of force demonstrated by electrical-muscle-stimulation by modeling the perceptual mismatch. We found that participants recalled forces significantly closer to the intended target when the EMS demonstrated model-adjusted forces. Inspired by these findings, we envisioned applications to illustrate the design space this perception modeling approach opens.

Future research building our own groundwork might explore new force-training applications, for instance, testing the optimal *demonstration time* of target forces for accurate recall. This approach could even be extended to measuring and optimizing the *retention* of target forces demonstrated by EMS, ultimately paving way for further work in designing accurate force-focused EMS systems for physical skill acquisition.

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