Improving Electromyographic Muscle Response Times through Visual and Tactile Prior Stimulation in Virtual Reality

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ABSTRACT

Electromyography (EMG) enables hands-free interactions by detecting muscle activity at different human body locations. Previous studies have demonstrated that input performance based on isometric contractions is muscle-dependent and can benefit from synchronous biofeedback. However, it remains unknown whether stimulation before interaction can help to localize and tense a muscle faster. In a response-based VR experiment (N=21), we investigated whether prior stimulation using visual or tactile cues at four different target muscles (biceps, triceps, upper leg, calf) can help reduce the time to perform isometric muscle contractions. The results show that prior stimulation decreases EMG reaction times with visual, vibrotactile, and electrotactile cues. Our experiment also revealed important findings regarding learning and fatigue at the different body locations. We provide qualitative insights into the participants' perceptions and discuss potential reasons for the improved interaction. We contribute with implications and use cases for prior stimulated muscle activation.

CCS CONCEPTS

• **Human-centered computing → Interaction devices**; *Haptic devices*; Empirical studies in accessibility; **Virtual reality**.

KEYWORDS

Physiological Sensing, Electromyography, Electrical Muscle Stimulation, Virtual Reality, Assistive Systems

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1 INTRODUCTION

Surface electromyography (sEMG), hereafter referred to as electromyography, measures the electrical potential generated by skeletal muscles. This technique is extensively used in medical diagnostics, rehabilitation, and human-computer interaction (HCI). By translating muscle activity to input, electromyography (EMG)-based systems enable natural, hands-free interactions, crucial in muscle-computer interfaces, assistive technologies, and for accessibility.

Understanding EMG-based interaction requires distinguishing between *isotonic* contractions where muscles change length during movement [50, 102], and *isometric* contractions, where muscles exert tension without length alteration [102], requiring conscious activation. Isometric contractions with EMG improve control in assistive systems for users with limited movement, aiding therapists, researchers, and developers [100, 125], and provide accessible solutions for users with physical disabilities to interact with computing devices [7]. Isometric EMG interfaces also enable a novel layer of motionless, subtle, and unobtrusive (social) interactions [23, 96, 121]. Its use in rehabilitation and sports is also known for analgesic effects [104].

In all human-machine interfaces, including EMG-based systems, there is a delay between user input and system response. This latency is crucial in disrupting the user experience, especially in real-time applications such as in virtual reality (VR). Reducing this delay is a key challenge in the field of EMG interface design. *Biofeedback*, providing visual and tactile modalities simultaneously with isometric EMG interaction, has been shown to modestly yet beneficially improve user performance, and finger tapping on the muscle site before interaction aided in its localization and activation [121]. The process of *muscle priming*, a phenomenon from neurophysiology, suggests that prior stimulation of muscles can enhance performance and cognitive processing [30, 31, 40, 123]. Similarly, muscle activation during warm-up exercises can lead to improvements in various metrics [12, 42, 134]. Priming could speed up the recognition and interpretation of muscle activity, a principle we explore in our experimental study using prior stimulation of different muscles to improve the input speed of an EMG device. This is important for interaction designers who aim to implement input techniques for real-time and responsive systems (typing, pointing, selecting) for users with and without (motor) disabilities. Stimulation *prior* to the muscle actuation has the potential to maintain the user's sense of agency, as it lets users cognitively associate the initiation of movement to their intent. This is in contrast to stimulation, e.g., via electrical muscle stimulation (EMS), *during* the muscle actuation [68] and may render it particularly advantageous for applications within the realm of learning.

The approach of using prior stimulation can support on-body notifications in VR, which are preferred over visual ones [115, 143], offering new possibilities of assistive systems with EMG response-based commands, e.g., to enhance gamers' VR experiences [99], or supportive systems using tactile alerts, e.g., while driving [3]. Users of prosthetic systems can benefit from shortened training of functional mapping by prior stimulated on-body feedback [1, 71, 113]. Learning scenarios with goal-oriented tasks and repetitions can be improved by muscle priming to (re)gain motor control of dedicated muscle sites for researchers, therapists and their patients in the field of neurophysiology and telemedicine [77, 137], or for (industrial) workers during remote instructions [11].

This paper investigates the impact of visual and tactile prior stimulation modalities on reaction times in EMG-based input using a Vienna Test System approach. We consider visual, vibrotactile, and electrotactile modalities as prior stimulation due to their quick response times over sensations such as temperature, smell, taste, or perceptions from organs in the vestibular system [49, 76]. We did not use auditive stimulation due to its perception as disturbing feedback modality in related studies [35, 121]. Shielded from external influences, we conducted the study in VR. We tested the prior stimulation modalities on four key muscles, finding that such stimulation consistently shortened isometric contraction times. Notably, the Gastrocnemius cap. med. muscle in the inner calf responded significantly faster than the other muscles. Our analysis provides insights into improved interaction performance and implications for EMG-based applications that utilize prior stimulated muscle activation across various locations of the human body.

2 RELATED WORK

In the following, we report on relevant research on muscle activity as an interaction technique and the sensory stimulation technologies we use in our system. We highlight their roles in both medical and interactive fields, emphasizing how they enhance human body perception, and user experiences in HCI, augmented reality (AR) and VR.

2.1 Electromyography (EMG)

Human muscle contractions generate electrical potentials recorded by EMG using surface electrodes on the skin above the muscle [55]. Standardized protocols for EMG signal assessment and electrode placement have been proposed by the European Recommendations for Surface Electromyography (SENIAM) project [48]. EMG is a critical tool in assessing muscular diseases [127, 139] and facilitating functional muscle recovery [8, 48, 135]. It is essential to distinguish between isotonic and isometric contractions [26, 37, 102], allowing for automatic classification of the isometric contraction type [103].

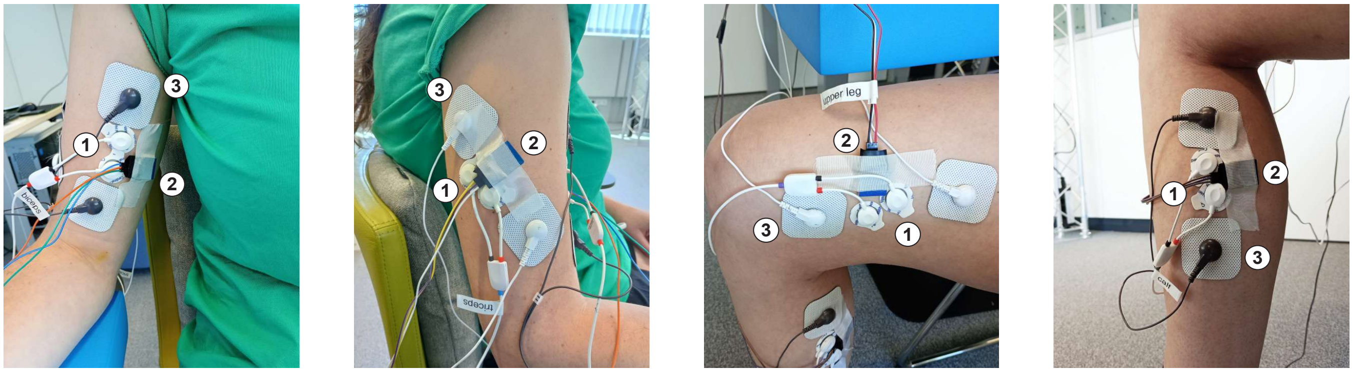
In the fields of biomedical and interactive applications, EMG was leveraged for active hardware and software control [94, 100], thereby gaining popularity in non-medical research, particularly for enhancing body awareness, motion, interactive device control [19, 54, 88], and assisted control of interaction-based selections [7]. Thus, apart from its general relevance in rehabilitation and sports [8, 64, 104, 127], EMG-based input mechanisms find applications in exoskeletons [89, 133], prosthetic control [16, 114], teleoperated robotic systems [5, 51, 144], and VR. Isometric EMG is preferred for avoiding unintended motion-based input, or when movement is infeasible, e.g., in electric wheelchairs for those with disabilities [97, 125].

2.2 Stimulating Sensory Perception

Vibrotactile stimulation, which uses mechanical vibrations to engage skin receptors, has been applied to improve body awareness [92], with research in HCI exploring optimal placement [33], intensity [53], and user perception [141]. Vibrotactile patterns can stimulate tactile sensations in virtual reality [130], affect muscle activity [56, 57, 62, 95], and assist amputees or those with neuropathology [58, 110]. Such stimulations aid in balance rehabilitation [137], enhance EMG-controlled computing systems [83, 136], and *prior* vibrotactile stimulation (at the index finger) can increase force production, likely due to a brain response for limb stabilization and pattern memory [56].

While vibrotactile feedback stimulates skin receptors, electrotactile stimulation applies electrical currents to skin nerve endings to induce tactile sensations [62, 140]. Electrical currents with shorter pulse widths (50-125 μs) and lower intensities are known as transcutaneous electrical nerve stimulation (TENS) [87], providing electrotactile feedback without muscle contraction, in contrary to electrical currents with longer pulse widths (150-350 μs) and higher intensities, causing muscle contraction by depolarization of deeper muscle fibers, known as EMS [108, 131]. TENS can inhibit the transmission of pain signals to the brain by instead targeting dedicated sensory nerve fibers (A-beta fibers) [59, 60], responsible for transmitting tactile sensations from the location of the current [6, 14, 69, 111]. While TENS is used in the rehabilitative field for pain management [60, 74], it can be supportive for dementia [15], for tactile feedback with prosthetics [32], in VR [132], or to simulate muscle proprioception [63].

We employed TENS for electrotactile feedback hypothesizing that repeated muscle priming [45] with electrotactile feedback aids in developing an internal body map. The human body primarily perceives tactile stimuli through mechanoreceptors in the skin [22, 112], which play a crucial role in how an individual perceives their own body [27]. However, visual modalities, alongside tactile ones, can also significantly contribute to body localization and awareness as shown by experiments like the virtual/rubber hand illusion [13, 107, 120]. *Body awareness*, the systematic cognitive processing of sensory cues, involves both visual and tactile stimulation in HCI [29, 93] with recent research focusing on using these for biofeedback in EMG interaction with the own body [36, 64–67, 70, 121]. Similar research in HCI addressed the mechanism using isotonic contractions [78] e.g., while playing music instruments [61],



(a) Biceps brachii (b) Triceps brachii cap. lat. (c) Vastus med. (d) Gastrocnemius cap. med.

Figure 1: The placement of EMG electrodes [1], vibration motors [2], and TENS electrodes [3] at the four tested muscle locations: Biceps brachii (upper front arm), Triceps brachii caput laterale (upper back arm), Vastus medialis (upper leg), and Gastrocnemius caput medialis (calf).

however, it is less understood for isometric contractions with prior vibro- and electrotactile stimulation.

2.3 EMG in HCI and AR/VR

EMG signal research in HCI includes developing muscle-computer interfaces for gesture detecting and human-device interaction [4], remote rehabilitative exercise monitoring [77], and creating haptic full-body immersive experiences using EMG in VR [25]. EMG is widely used in AR/VR for various health-related and interactive applications [18, 52, 72, 85, 118, 135], with feedback stimuli enhancing immersion and engagement [38, 82, 90, 98, 101, 105]. Wearable EMG systems enable off-desktop mobile applications [81] and interactive communication tools [119]. In AR/VR, EMG feedback for active control has expanded into motor imagery applications, such as direct limb control for amputees [2, 28, 106] and post-stroke rehabilitation [52].

2.4 Summary

Previous work uses EMG to measure isometric contractions for various applications including hands-free interaction in real-time systems [33, 53, 59, 60, 62, 92, 95, 130, 141]. Research indicates that vibrations as prior stimulation can affect muscle activity [56, 57]. However, it is currently unknown if this principle applies to isometric contractions and electrotactile stimulation. Additionally, the impact of these factors on muscle reaction time, vital for hands-free, real-time interactions remains unclear.

3 METHOD

To answer the research questions if tactile prior stimulation of muscles could lead to faster reaction times using an EMG device, we conducted a response-based experiment in VR and, thus, shielded users from external influences. As humans use their arms and legs in different ways, we also hypothesized that there are differences in the corresponding muscles' input.

3.1 Study Design

We conducted a user study in VR using a full-factorial within-subject design to investigate the effects of two independent variables: Prior Stimulation and Muscle Location on the reaction time as dependent variable. We used EMG for performance assessment and conducted subjective pre- and post-assessments. Four levels of Prior Stimulation, and four levels of Muscle Location resulted in sixteen conditions presented to the participants twice in randomized order.

3.2 Independent Variables

3.2.1 Prior Stimulation. The four levels of Prior Stimulation were *no*, *visual*, *vibrotactile*, and *electrotactile* stimulation. Prior Stimulation was presented before the signal for the reaction test. The *visual* conditions consisted of a schematic anatomical line drawing with the corresponding muscle highlighted in red (see Figure 3). The *vibrotactile* conditions consisted of a vibration applied at the center of the corresponding muscle, and the *electrotactile* conditions consisted of a TENS impulse at the corresponding muscle. Each Prior Stimulation was presented for the same duration of 3 seconds during the trial procedure (see Figure 3).

3.2.2 Muscle Location. With the paradigm of hands-free interaction in mind, we tested four levels of Muscle Location frequently used by related work: the *upper front arm (Biceps brachii)* [2, 124], the *upper back arm (Triceps brachii caput laterale)* [2, 121], the *upper leg (Vastus medialis)* [77], and the *calf (Gastrocnemius caput medialis)* [77, 99] (see Figure 1). To ensure reproducibility and comparability, we tested the four limb muscles exclusively on the right side of the body. The EMG and TENS electrodes were positioned uniformly with enough space for the vibration motors. Thus, the EMG signal was not influenced by any movements (e.g., head movements at the shoulder), breathing, or talking (e.g., by natural movements of the chest).

3.3 Dependent Variables

3.3.1 Objective Measures. The key quantitative measure in our study is the time the participants needed to tense their muscles. Reaction time was determined using EMG signals recorded at 1000 Hz and analyzed with the raw data (see Data Analysis).

3.3.2 Subjective Measures. We conducted a subjective muscle assessment both before and after the experiment by asking participants to rate the ability to tense each Muscle Location using a visual analog scale (VAS) ranging from 0 to 10. Post-Experiment, participants completed the Raw NASA Taskload Index (RTLX), a standard tool in HCI for workload assessments [46] with two additional questions on perceived pain and fatigue. They also responded to a questionnaire using a 7-point Likert scale evaluating the extent to which various Prior Stimulations aided in identifying the tested Muscle Locations (subjective survey on muscle localization and reaction time), and whether they perceived any changes in their reaction time during the experiment. Finally, we conducted semi-structured interviews to gain further insights into the participant's exhaustion, positive and negative experiences, preferences, and overall impression of the experiment.

3.4 Task

Participants' reaction times were measured using a modified Vienna Test System (VTS) adapted for VR according to Prieler et al. [47]. In its setup, participants responded to alternating red and green lights, with the green light and a beeping tone serving as the stimuli. They reacted by tensing specific muscles, indicated by text and highlighted on a schematic anatomical drawing. Each trial began with 2 seconds of rest, followed by a 3-second prior stimulation phase, then stimuli appeared randomly between 3 and 13 seconds, lasting 2 seconds. Trials were 20 seconds each, with varying combinations of Prior Stimulation, Muscle Location, and stimuli timing, presented twice in random order (see Figure 3). The whole experimental procedure resulted in 192 conditions and a total duration of 64 minutes. The fixed duration of the experiment, with variable timeframes for employing prior stimulation and considering the muscle location, enables the reliable determination of both reaction times and muscle fatigue effects.

3.5 Apparatus

A virtual 3D environment for the simple reaction test was created using Unity Engine (Version 2021.3.5f1) running on a PC with AMD Ryzen 5900X, GeForce RTX 3070, and 16 GB RAM. The minimalistic scene contained a 3D panel for displaying test instructions and stimuli. An HTC Vive Pro with 90 fps was used as head-mounted display (HMD) and tracked using four lighthouse boxes for high accuracy. Muscle activity was monitored using a Biosignalplux 4-Channel Hub[1] with EMG sensors at 1000 Hz sampling rate with 16-bit resolution and Kendall H124SG electrodes. The integrated low-noise high-speed operational amplifiers performed bandpass filtering and amplification on the base of bitalino technology [41]. Two Sanitas SEM 47 EMS/TENS devices were used with self-adhesive electrodes according to the manual (see Figure 2).

[1]https://www.pluxbiosignals.com/collections/research-kits/products/copy-of-explorer

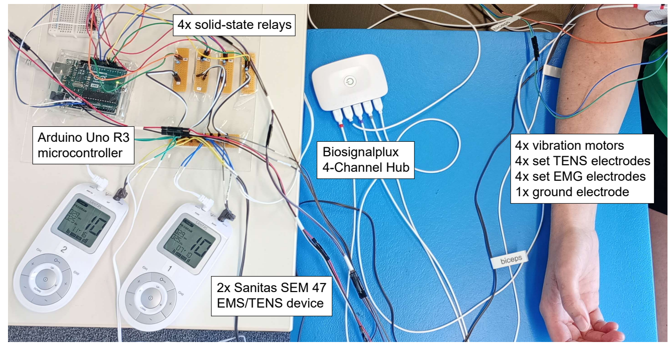


Figure 2: Apparatus with the hardware components, consisting of two EMS/TENS devices, an Arduino R3 microcontroller, and four solid state relays, connected to the participant by four pairs of TENS electrodes on the one hand and a Biosignalplux 4-Channel Hub, connected to the participant by four pairs of EMG electrodes (and a ground electrode).

The Unity3D Ardity API (9600 Baud) with an Arduino UNO R3 controlled four solid-state relays (Vishay LH1546ADF optocoupler) acting like switches of four TENS channels, as well as four coin-type vibration motors (Iduino TC-9520268) operating at maximum duty cycle of 3.3 V. Stimuli audio source was a neutral beeping tone[2]. An orange-colored (RGB: 255,133,57) circle that indicated the muscle strength was clipped using radial fill (radial 360°) from 0.2 fill to 1, presented in the heads-up display (HUD) and linearly mapped using the muscle strength tension from the EMG raw signal. Stimuli lights were made with opaque rendering mode and green-colored (RGB: 0,255,43) and red-colored (RGB: 255,76,52) spot-type light sources. The system featured real-time monitoring of EMG signals and participant VR view.

3.6 Study Procedure

In the following, we divide the study procedure into three phases: (1) introduction and dry run, (2) body/electrode preparation, and (3) the EMG experiment in VR.

3.6.1 Phase 1: Introduction and Dry-run. Participants consented to use their images and video, then provided demographics, working and sports habits. They were introduced to the goals of the study and rated their muscle tensing ability using a VAS scale. We clarified relevant terms and conducted a dry run to ensure understanding of the reaction time test. Participants adjusted their HMD settings, including audio. During the dry run, they responded verbally to stimuli without muscle location descriptions. We confirmed their understanding and repeated the dry run in VR. We explained and demonstrated isometric muscle tension at all four muscle locations on the left side of the participant's body.

3.6.2 Phase 2: Body/Electrode Preparation. We calibrated the TENS device for electrotactile stimulation, initially attaching electrodes to the left side of the body to avoid priming effects. The two digital Sanitas EMS/TENS SEM 43 devices were set to TENS "program 10", 25 Hz impulse frequency, and impulse width to 50 μs. The

[2]https://freesound.org/people/barb/sounds/12637/ (Public Domain)

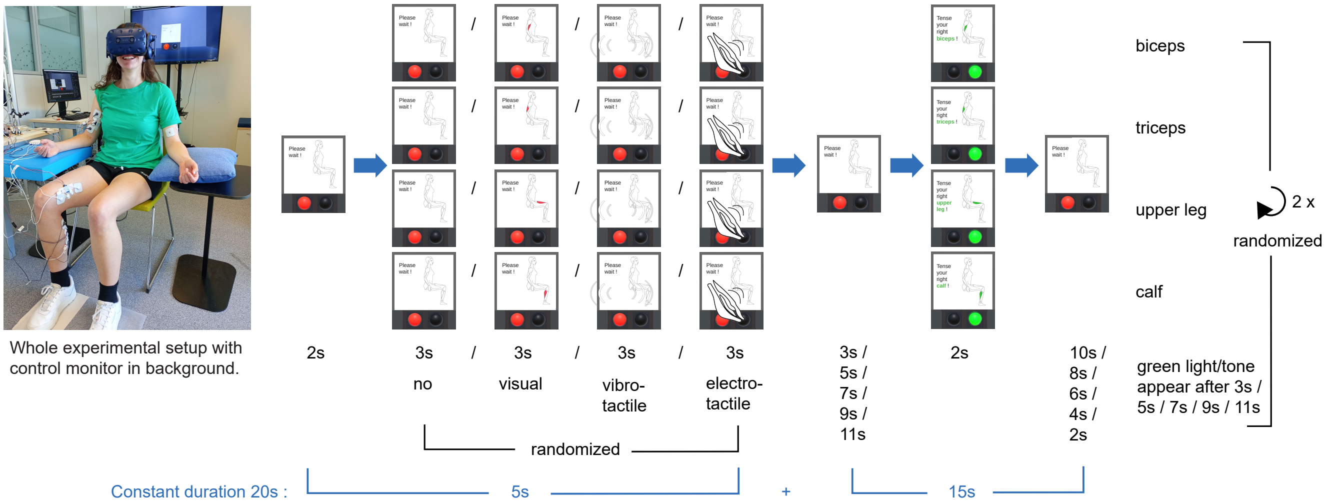


Figure 3: Participant sitting in the apparatus with the hardware components attached (left). The illustration shows the trial procedure scheme of all conditions tested. The trial procedure started with 2 seconds resting, 3 seconds from the pool of randomized levels of prior stimulations (no, visual, vibrotactile, or electrotactile), 15 seconds in which the green light and sound randomly appeared for 2 seconds after 3, 5, 7, 9 or 11 seconds. Thus, all participants experienced the same experimental trial length (64 min). Each prior stimulation, muscle location, and duration until the green light/tone were presented twice and in a fully randomized order.

participants preferred TENS intensities ranging from 8-52 mA for biceps, 20-56 mA for triceps, 20-80 mA for upper leg, and 28-100 mA for calf. Placement followed the manufacturer's manual, with skin preparation involving alcoholic pads and shaving, if necessary. We set the TENS strength for all muscle locations by asking if a stinging or burning sensation or any discomfort was felt. If necessary, electrodes were re-positioned and the intensity was adjusted until a light muscle tension was observable, keeping it just under this threshold. We mirrored the electrode placements to the right side of the participant's body using rulers and visual estimates for accuracy. Participants sat with elbows and knees at a 90°, hand palm up, and feet positioned using a stencil drawing. EMG electrodes were attached to the right side of the body, with adjustments for strong EMG signal, following SENIAM guidelines [48]. One participant desired to reduce the TENS signal strength after mirroring.

We monitored EMG biosignal for correct amplitude registration placing electrodes according to anatomical landmarks. Two electrodes were placed at a distance of 0.5 cm on each muscle bulge and a reference electrode consistently to the elbow joint bone. We stuck vibration motors with adhesive tape next to the electrode arrangements at the center or a maximum of 1 cm apart from the center of the muscle on each muscle location. The setup is detailed in Figure 1.

3.6.3 Phase 3: EMG Experiment in VR. Participants were introduced to the functionality of the EMG and VR system, including an orange circle for muscle strength biofeedback. They were instructed to avoid limb movement and respond quickly to stimuli. Participants were again free to ask any questions before starting the reaction time task in VR. We adjusted the value for calf two steps lower for one participant. The experimenters noted the comments of the participants during the experiment. We kept track of the upcoming conditions in the console monitor of Unity3D on one monitor for a general overview. We checked if TENS stimulation and vibration were working properly during the whole experiment procedure and also if the correct muscles were appropriately targeted, ensuring participants concentration. Post-experiment, participants were debriefed, shared individual observations, rated muscle tensing ability on a VAS, filled out the RTLX, the subjective survey, and we collected their qualitative feedback in a semi-structured interview.

3.7 Participants

The study received ethical clearance according to our institution's regulations and hygiene protocols for user studies. Participants were recruited via institutional email lists, social media, and referrals, excluding those with cardiac issues, metallic implants (e.g., screws), cardiovascular complications, recent infections or surgeries, by explicit advisory. Six interested participants were pre-excluded from the study due to heart problems ($N = 4$) or metallic implants ($N = 2$). All participants had the option to withdraw without penalty.

Twenty-four participants were initially recruited. Student volunteers ($N = 14$) from computer science or mechanical engineering were rewarded with credit points for their study participation. Institutional employees ($N = 7$) were reimbursed with their working hours. External participants ($N = 3$) were remunerated with [3]. One participant withdrew, and data of two were unusable due to technical issues. Thus, the final analysis included twenty-one participants (7 self-identified as female, 14 self-identified as male), mean age was 26.76 ($SD = 4.5643$), ranging from 18 to 37.

[3]https://github.com/JessicaSehrt/ReactionTest_EMG-V_vT_eT_priorStim

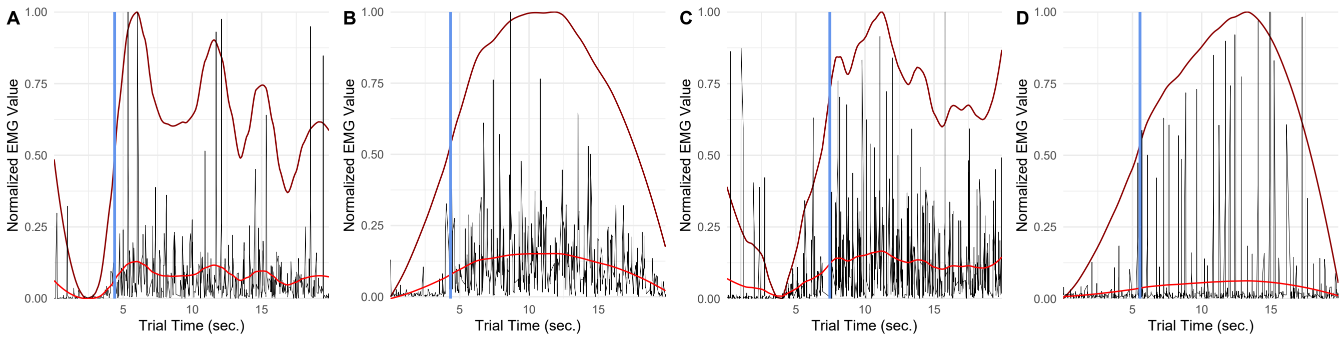


Figure 4: Four randomly selected trial data sets of the 20 sec. onset periods (A-D) illustrating the data processing. The absolute value of the raw signal (black line) was processed and smoothed using the Teager-Kaiser energy tracking operator (red line). The individual reaction time of each trial was then determined using a Bisection Extremum Distance Estimator (BEDE) operator based on the normalized signal (dark red line). BEDE determines the inflection point at the curve incline (vertical blue line) and the final reaction time (RT) measurement.

3.8 Data Analysis

We recorded the EMG signal as raw data and in a frame-based format, including the conditions, timestamps, and metadata. In line with previous research on EMG event detection, a Taeger-Kaiser energy operator (TKEO) [24, 84, 126] using the seawave package for R[4] was applied for EMG signal processing and smoothing with parameters according to Biosignalplux. As recommended by the Vienna test system (VTS), [47], the mean reaction times (RTs) of all trials and repetitions were aggregated for each subject. The actual RT was calculated using the Bisection Extremum Distance Estimator (BEDE) method [20, 21] on the TKEO processed EMG signal during the 20 sec onset period (green light phase) provided by the inflection package[5] for R.

BEDE is an algorithmic method used for efficiently estimating the extremum of a function by iteratively bisecting the interval and evaluating distances to identify the point of extremum. The BEDE method [20, 21] does not require a functional hypothesis for the data, therefore its utility lies in its ability to provide a fast and reliable determination of the inflection point, representing the moment of highest signal increase. This approach eliminates the subjectivity and potential inaccuracies associated with threshold-based criteria, with no need for an initial calibration phase that potentially biases the participants' muscle performance. Based on the BEDE method we calculated the mean and the fastest (and minimal) average reaction time in each condition. Examples of data processed are shown in Figure 4.

Additionally, we analyzed the maximum value of the smoothed EMG signal to pinpoint when the highest amplitude occurred. For this, we employed polynomial regressions with locally estimated scatterplot smoothing fit (loess) using an automatic parameter selection (auto span) identified by generalized cross-validation (GCV). The same method was used to evaluate how the reaction times varied throughout the experiment. The whole data set included 3,838,041 samples and is available at GitHub[6].

[4]https://rdrr.io/cran/seewave/man/TKEO.html
[5]https://rdrr.io/cran/inflection/
[6]https://github.com/JessicaSehrt/ReactionTest_EMG-V_vT_eT_priorStim

4 RESULTS

For statistical analysis, all RTs were log-transformed to remove any skewness from the data and ensure normal distribution. If Mauchly's assumption of sphericity was not confirmed, we applied Greenhouse-Geisser correction for the degrees of freedom on the factor using the rstatix package[7] in R.

4.1 Reaction Time (RT)

Normality was confirmed using Shapiro Wilk's tests for all conditions ($p > .118$) except one (*biceps-vibration* with $p = .042$). However, visual inspection of the QQ plot and histogram showed that the data clearly followed a normal distribution. A repeated measures analysis of variance (RM-ANOVA) revealed a significant effect of Prior Stimulation, $F(3, 60) = 7.868$, $p < .001$, $\eta_p^2 = 0.282$, and Muscle Location, $F(2.00, 39.91) = 8.324$, $p = .001$, $\eta_p^2 = 0.305$, however, there was no interaction effect of Prior Stimulation × Muscle Location, $F(9, 180) = 1.616$, $p = .146$, $\eta_p^2 = 0.075$. We performed a pairwise t-test post hoc comparison using Bonferroni corrected p-values based on the two main effects. Among the modalities, we found a significant difference between *electrotactile* and *no* ($p = .014$, $d = -0.341$), *vibrotactile* and *no* ($p = .002$, $d = 0.405$), and *visual* and *no stimulation* ($p < .001$, $d = 0.442$). Regarding the muscles, the analysis also revealed a significant difference between *biceps* and *calf* ($p < .001$, $d = 0.622$), *biceps* and *triceps* ($p = .047$, $d = 0.297$), *triceps* and *calf* ($p = .002$, $d = -0.401$), as well as between *upper leg* and *calf* ($p < .001$, $d = -0.557$). Other combinations were not significant. All means are shown in Figure 5. The results indicate that the RT depends on Muscle Location and Prior Stimulation. The participants showed the fastest muscle responses when a prior location stimulation was used. As we had no interaction effect, this finding is independent of the muscles tested. The fastest power was the calf.

[7]https://rdrr.io/cran/rstatix/

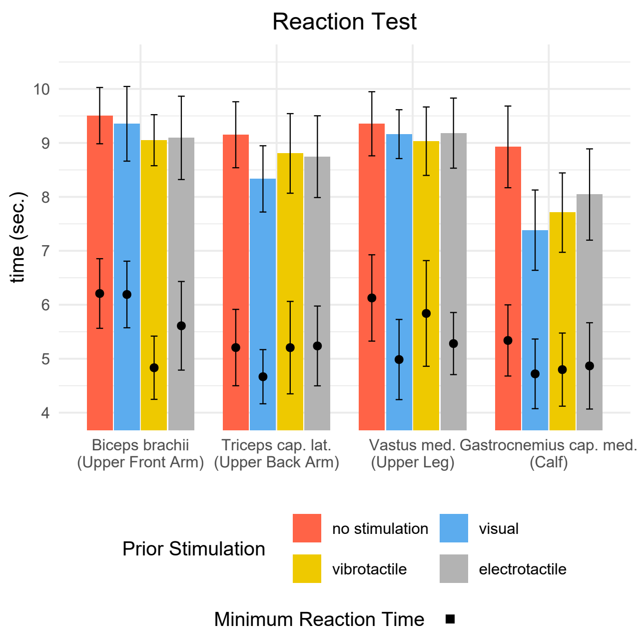


Figure 5: Mean reaction times of the tested prior stimulation and muscles. The faster muscle responses were found for all prior stimulations. The fastest muscle was the *Gastrocnemius cap. med. (Calf)*. The point indicates the mean RTs with the fastest of each participant. All error bars show 95% confidence intervals.

4.2 Minimum RT

We were also interested in the fastest possible response of each participant to learn how the participants could ideally perform during the experiment. Shaprio-Wilk test was significant in one condition (upper leg and electrotactile, $p = .026$, all other conditions $p > .060$), visual inspection of the QQ plot and histogram, however, showed that the data follows a normal distribution. A RM-ANOVA revealed a significant effect of Prior Stimulation, $F(3, 60) = 3.433$, $p = .022$, $\eta_p^2 = 0.147$, Muscle Location, $F(3, 60) = 3.306$, $p = .026$, $\eta_p^2 = 0.142$, and there was an interaction effect of Prior Stimulation × Muscle Location, $F(9, 180) = 1.985$, $p = .043$, $\eta_p^2 = 0.090$. Due to the interaction effect, we performed four univariate ANOVAs on each modality for each muscle. As the tests for *biceps* ($p = .003$) and *upper leg* ($p = .049$) were significant, we performed a post hoc pairwise t-test comparison using Bonferroni corrected p-values and found regarding the *biceps* a significant difference between *vibrotactile* and *visual stimulation* ($p = .004$) and between *vibrotactile* and *no stimulation* ($p = .043$). No further significant differences were found. Thus, the results showed that at the *biceps*, the minimum reaction times were lower using *vibrotactile* than with *visual stimulation* or *no stimulation.* All means of the minimum RTs are shown as points in Figure 5.

4.3 Time of Highest Amplitude

We also determined the inflection points on the saddle of the first EMG signal bulge to understand when the strongest voluntary muscle contraction occurred. The log-transformed times' normality violation test was insignificant, except in one condition (biceps and electrotactile, $p = .002$, all other conditions $p > .107$). However, visual inspection of the QQ plot and histogram showed that the data follows a normal distribution; we performed parametric tests. A RM-ANOVA revealed a significant effect of Prior Stimulation, $F(3, 60) = 3.069$, $p = .035$, $\eta_p^2 = 0.133$, Muscle Location, $F(2.31, 46.3) = 13.628$, $p < .001$, $\eta_p^2 = 0.405$, however, there was no interaction effect of Prior Stimulation × Muscle Location, $F(9, 180) = 1.661$, $p = .101$, $\eta_p^2 = 0.077$. Pairwise post hoc t-test comparisons using Bonferroni correction showed significant differences among the modalities between *vibrotactile* and *no* ($p = .015$, $d = 0.286$), and *visual* and *no stimulation* ($p = .006$, $d = 0.319$). Regarding the muscles, the analysis also revealed significant differences between all comparisons (all with $p < .001$), except between *biceps* and *triceps* as well as *upper leg* and *calf* (both $p = 1$). The results generally support the findings of the effects of Muscle Location and Prior Stimulation. The aggregated signals with the times of the maximal amplitude are shown in Figure 6.

4.4 Reaction Time vs Signal Strength

As the experiment lasted the same duration of all participants and all conditions were performed in fully randomized order, we analyzed how the reaction times and the amplitude of the EMG signal evolved. We were interested in the increase/decrease of the muscles' activity and analyzed the *reaction times* and *max. EMG amplitude* as a function of time using a generalized mixed-effect regression model with Experimental Time and Muscles as predictors. The regressions for reaction times ($R^2 = 0.083$, $AIC = 12283.82$) and max. EMG amplitude ($R^2 = 0.082$, $AIC = -3936.437$) were significant (both $p < .001$). The scatterplots (not illustrated) of standardized residuals indicated that the data met the assumptions of homogeneity of variance, linearity, and homoscedasticity for both regression analyses. All regression equations can be found in Figure 7 and fits of reaction time and EMG amplitude are shown in Figure 7. For reaction times, the slopes for the *calf* significantly ($p = .002$) tend towards a negative value, indicating the reaction times for that muscle decreased over time. No effects were found for the normalized values of the amplitudes. However, the correlations between both variables were significant (all with $p \leq .001$) and negatively and weakly correlated for the biceps ($\rho = -0.20$), triceps ($\rho = -0.19$), upper leg ($\rho = -0.14$), and moderately for calf ($\rho = -0.38$). This indicates that the calf was getting faster during the experiment, however, moderately at the cost of signal strength.

4.5 EMG Classification

To understand how well a standard machine-learning algorithm could classify muscle activation, location, and modality, we performed EMG signal classification in a sliding window approach (0.5 sec./500 samples). This examination allows us to understand our data set, determine if the findings can be incorporated into future applications, and learn the nuances of data differentiation. As all EMG recordings in our data set were labeled by our software, we

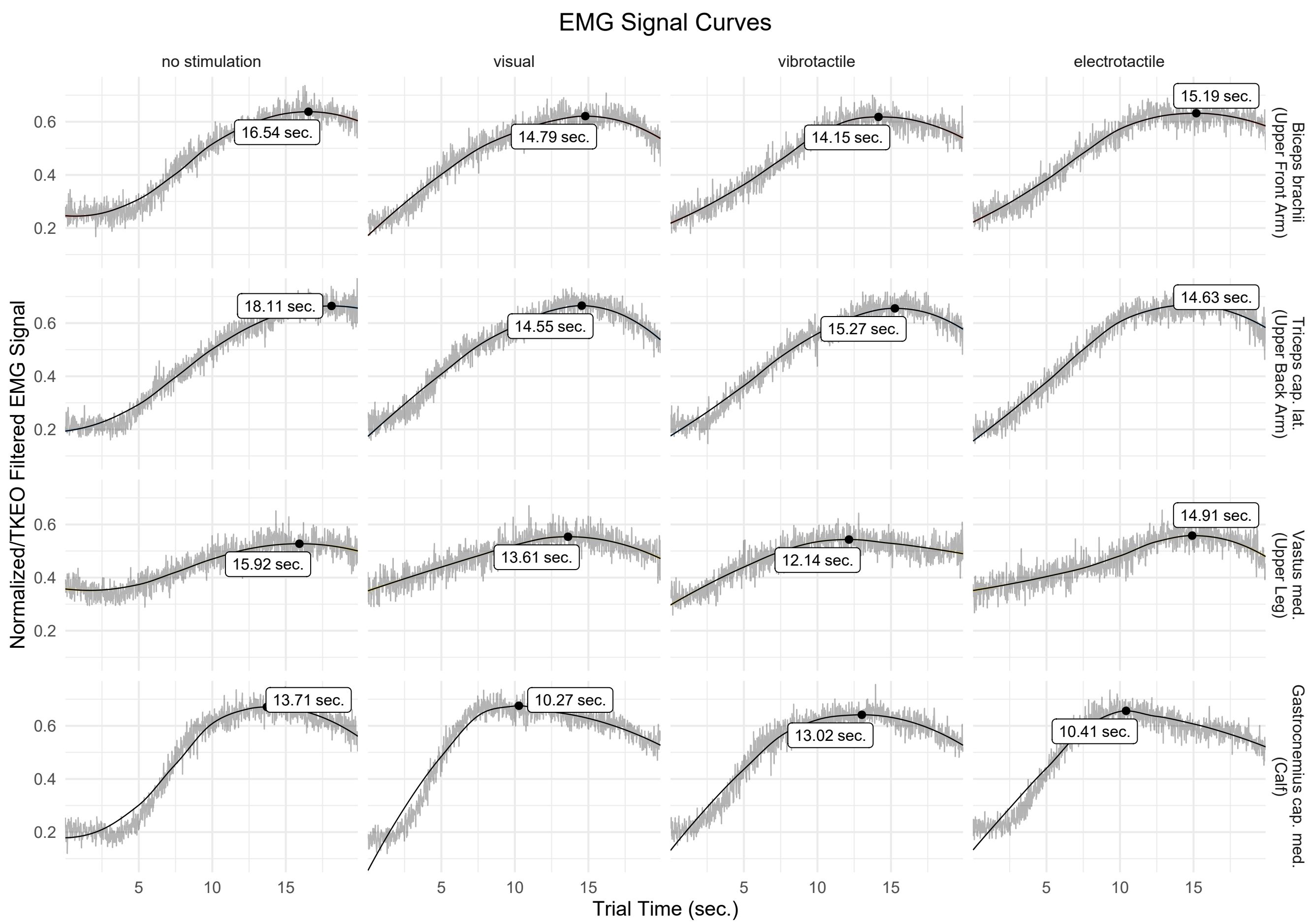


Figure 6: Grid plot of all participants' aggregated EMG signal curves separated by muscles and modalities. The plots illustrate the individual characteristics of the raw data and the loess fit and show the time of the highest amplitude of the EMG signal.

were able to train our models based on ground truth. We used a standard feature extraction of the 24 most commonly used feature metrics stated by the literature [9, 142]: mean, median, standard deviation, minimum, maximum, root mean square (RMS), number of slope sign changes (SSC), waveform length (WL), skewness, kurtosis, Willison Amplitude (WAMP), Absolute Temporal Moment (TM), average amplitude change (AAC), variance, LOG Detector (LOD), integral absolute value (IAV), mean frequency (MNF), median density frequency (MDF), my pulse percentage rate (MPR), signal-to-noise ratio (SNR), and four auto-regressive coefficients using ARIMA (ARC1-4). The data was split into 70% training and 30% test sets. To ensure the validity of muscle classification, we did not use the four input streams from the EMGs in parallel but only took the signal of the corresponding trial. For classification, we used a random forest[8] classifier, which is more robust against overfitting, can handle large feature spaces more effectively, provide importance measures, which can be helpful for feature selection, and generally faster and more scalable in training compared to other approaches such as SVMs [43, 80, 116].

Muscle Location Prediction. The most exciting aspect of the performance analysis of the classifiers was the accuracy of the muscles' location prediction. Determining the location of the EMG signal can help to automatically classify the forces and their movements in a wide range of future applications and wearable devices. We found an overall accuracy of 80.70%, a sensitivity from 78.83% to 82.59%, and a high specificity from 91.84% to 95.76%. The detection rate among all muscles ranged from 19.89 to 20.75% ($\kappa = 0.742$, Mcnemar's Test $p < .001$). The confusion matrix of the result can be found in Figure 8.

Muscle Activation Prediction. While the overall prediction accuracy (94.56%), sensitivity (98.79%), and detection rate (88.82%) of the classifier of tensing the muscles were high, the specificity and ability of the model ($\kappa = 0.650$, Mcnemar's Test $p < .001$) to correctly identify negative cases were relatively low (56.90%). The visual exploration of the data (cf. Figure 4) indicates that this was caused by the late response times of the participants and the time

[8] https://rdrr.io/cran/randomForest/

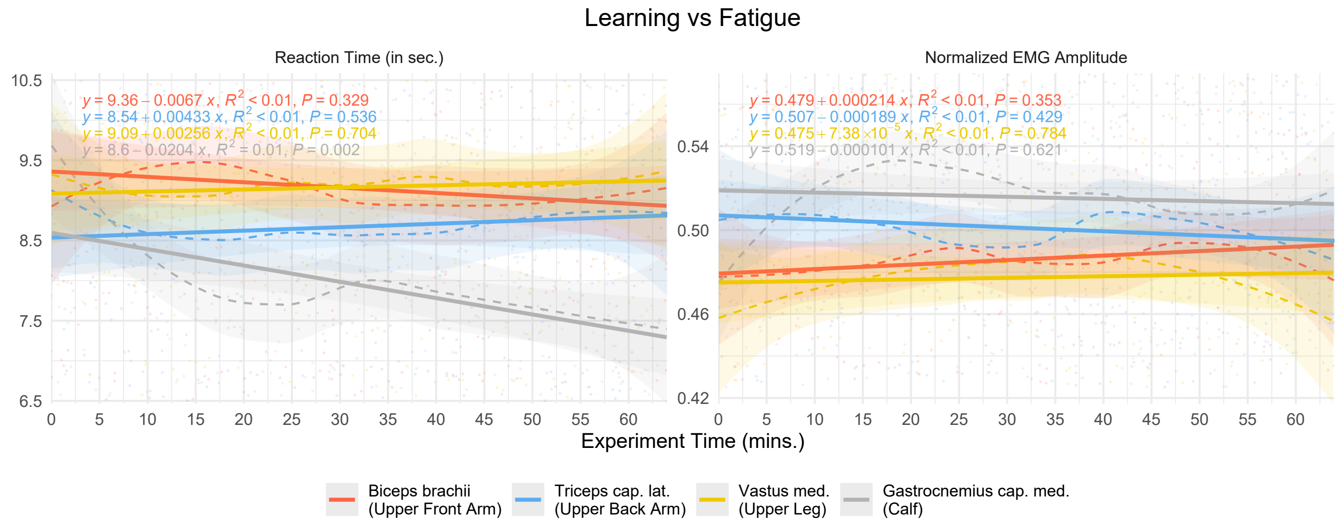


Figure 7: Regression fits of the reaction time and the EMG amplitude in the course of the experiment. The slope parameter for the calf was significantly decreased during the experiment. No signal strength trends were observed, but correlation analysis revealed a potential negative relationship between reaction time and amplitude. Straight solid lines show the linear trends; the dashed curve is the smoothed loess fit.

they needed to tense their muscles. This suggests threshold-based or biofeedback-based approaches will likely perform better than ML-based classifiers trained by data in blind trials.

Stimulation Modality Prediction. The overall accuracy in predicting the modality (27.06%), the sensitivity of the model (from 26.15% to 27.82%), and the detection rate (from 6.56% to 7.09%) was very low ($\kappa = 0.650$, Mcnemar's Test $p < .001$). The results indicate that the EMG signal is no reliable predictor of the muscle activation modality. As the classifier could not differentiate between the modalities, we also assume that the prior stimulation did not significantly interfere with the signals.

4.6 Subjective Assessments

4.6.1 Support of Stimulation. After the experiment, we asked participants to rate to which extent they agreed that a stimulation helped them locate a muscle. An aligned rank transform (ART) RM-ANOVA revealed a significant effect of Prior Stimulation, $F(3, 300) = 160.704$, $p < .001$, $\eta_p^2 = 0.616$, and Muscle Location, $F(3, 300) = 2.792$, $p = .041$, $\eta_p^2 = 0.027$, without an interaction effect between Prior Stimulation × Muscle Location, $F(9, 300) = 0.537$, $p = .847$, $\eta_p^2 = 0.016$. Post hoc pairwise comparisons using Wilcoxon signed rank using Bonferroni correction showed significant differences between all modalities ($p < .038$). Among the muscles, we found a significant difference between *upper leg* and *triceps* ($p = .011$); however, not between the other pairs ($p > .052$). The results (see Figure 9) indicate that the participants tend to agree that best location accuracy could be achieved using *electrotactile* stimulation and that all prior stimulation modalities were preferred over none. Interestingly, the participants noticed that mainly the upper leg and not the calf, such as in the objective measure, benefited from stimulation.

4.6.2 Fatigue. We also asked the participants which muscle location they felt the most and less exhausted after the experiment. As most exhausted *biceps* was mentioned by nine participants (42.86%), *triceps* (28.57%) and *upper leg* (28.57%) were each mentioned by six participants, and *calf* by two (9.52%) while also two (9.52%) stated no muscle was most exhausted. As a less fatigued muscle, eight participants (38.10%) said that their *biceps*, six (28.57%) that their *calf*, three (14.29%) that their *upper leg*, and two (9.52%) that their *triceps* was the least exhausted at the end of the study, while two (9.52%) felt no muscle was less exhausted.

4.6.3 Task Difficulty. VAS ratings of task difficulty were significantly affected by the experiment with an effect of Pre-Post, $F(1, 140) = 7.863$, $p = .006$, $\eta_p^2 = 0.053$, and Muscle Location, $F(3, 140) = 5.137$, $p = .002$, $\eta_p^2 = 0.099$, but without an interaction effect of Pre-Post × Muscle Location, $F(3, 140) = 0.661$, $p = .577$, $\eta_p^2 = 0.014$. Post hoc pairwise comparisons using Wilcoxon signed rank using Bonferroni correction showed significant differences between biceps and calf ($p = .007$), biceps and triceps ($p = .011$), as well as between biceps and upper leg ($p = .009$) indicating that the workload on the biceps ($M = 2.286$, $SD = 2.361$) was significantly lower compared to calf ($M = 3.643$, $SD = 2.694$), triceps ($M = 3.452$, $SD = 2.530$), or upper leg ($M = 3.357$, $SD = 2.685$). Perceived difficulty of tensing was significantly greater after the experiment ($M = 3.452$, $SD = 2.604$) than at its beginning ($M = 2.917$, $SD = 2.589$).

4.6.4 NASA-TLX and Subjective Performance. The mean score of the NASA-TLX Score was 53.056 ($SD = 17.170$), which can be considered a high workload for the assessment [44] of the task. The majority of the participants (9/21) tend to agree with the statement that the modalities increased their reaction times (7/21 neutral, 5/21

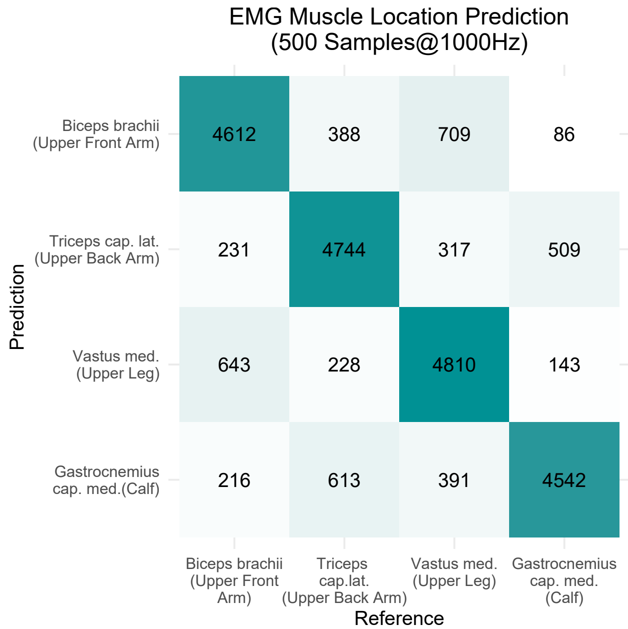


Figure 8: Confusion matrix of the EMG muscle location classification prediction based on 24 features and a 0.5-sec sliding time window (500 samples per entry). The matrix was determined by random forest machine learning classification.

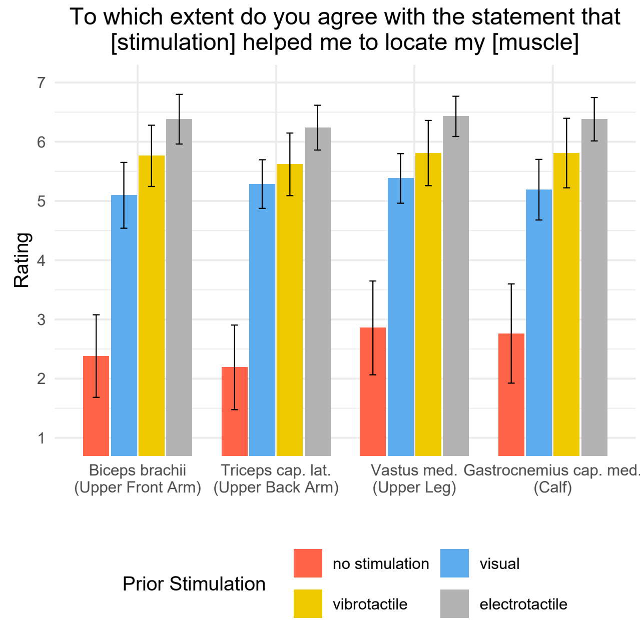


Figure 9: Ratings of the subjective perception of the helpfulness of each prior stimulation and localization to tense a muscle. Electrotactile stimulation was perceived as the most helpful among the prior stimulation modalities. The highest ratings among the muscles were found for the upper leg and calf. All error bars show 95% confidence intervals.

disagree). This contrasts the finding that the majority (8/21) tend to agree that it also decreases their reaction times (6/21 neutral, 7/21 disagree). The majority (14/21) tend to disagree with the statement that the modalities did not affect their reaction times (3/21 neutral, 4/21 disagree). Thus, the subjective metrics indicate that most of the participants assumed that their performance changed in the course of the experiment. This is supported by the non-linear measures (see Figure 6) of, e.g., calf and triceps and the qualitative statements.

4.7 Qualitative Results

Thematic analysis helped structure and understand participant feedback from post experiment interviews and experimenter notes. Two researchers independently coded the statements to identify common categories and patterns, then merged these into overarching themes, resolving any discrepancies through discussion.

4.7.1 Prior Stimulation helps in Localization of the Muscle. The prior stimulation modalities were predominantly assessed as supportive for identifying which muscles had to be activated during the reaction time task in comparison to when no modality was present; participants found that they "... help to locate my muscles" (P1, P6, P8, P9, P17) and were "better than no signal" (P10). Participants noticed they became faster as the prior stimulation modalities "...aid in quicker reaction time" (P3), "...prepare to flex the muscle within a shorter reaction time, compared to no indicator of which muscle to flex next." (P16), and that the muscle localization was facilitated by "...a kind of guide as to where I am supposed to tense the muscles." (P8). Prior stimulation modalities assisted in task preparation, as evident in statements like "...a clear indicator of which muscle to contract next." (P7), "...to *mentally* prepare to flex the muscle." (P16), and "I could better prepare myself to tense the muscles." (P21).

In direct comparison, tactile modalities (vibrotactile and electrotactile) were rated as more helpful for *muscle localization* than visual, especially in the actual task of muscle distinction on one's own body and the control of their responses. Participants noted that tactile modalities "...help to feel the body part to tense." (P8, P19), "...make you feel the muscle." (P11), were "recognizable" (P4, P10, P19), and "a clear signal" (P14). The visual modalities were still evaluated as "...let you recognize the muscle in question more quickly than if it is only named as a word." (P18), while feedback focused on its general effectiveness as "...very eye-catching and therefore sometimes increased attention when I was unfocused." (P1), "...muscle groups were shown clearly in the image." (P2), "...pictures were clear and easy to understand." (P7, P8, P20), and "...everything was clearly visualised what to do." (P14). The participants noticed a specific distinction between the two tactile modalities, and participants commented vibrotactile "...also what helped me to locate my muscles, but less than electrotactile." (P1), and "...is relatively detectable." (P15), opposed to electrotactile as "...easy detectable." (P15, P19), as well as [with electrotactile] "...in contrary to vibration you feel the muscle." (P7, P18), which is "...better to locate the muscle" (P18). The electrotactile modalities were mentioned to enable *muscle localization* (P17, P20) and favored for "activation and location of the muscle" (P17).

4.7.2 *Tactile Prior Stimulation supports Cognitive Processing.*

Tactile prior stimulation was found to be more helpful for cognitively processing *muscle localization*, offering direct bodily guidance, unlike the more abstract assistance from visual modalities. The task was described as "monotonous (P3, P5, P16), which "...affected the concentration." (P13, P16), "...even with electrotactile and vibration" (P3), yet "...feeling your muscle groups contract made it easy to concentrate on them specifically." (P19). The visual modality was criticized as "...more difficult to figure out which muscle is next, than the immediate identification with vibration or electrical stimulation." (P4), "...difficult to imagine the right muscle exactly on your own body..." (P10, P18), "...did not assist in activating the specific muscle more strongly or more accurately, does not necessarily ensure the correct response." (P3), highlighting that the visual cues offered only a schematic representation of the targeted muscles, requiring initial interpretation. That this could even cause a false early reaction, became evident when participants stated "...[with visual] I had the feeling I would sometimes tense the marked body part before getting the signal..." (P21). One participant stated that "...picture represented a clear, understandable and easy to interpret message. (P7), indicating that the additional process of an interpretation of the seen was necessary, and "...[visual] added no value for me, could have also been text." (P6) indicates that participants first had to invest the cognitive effort to *read* the visualization.

The vibrotactile "...signal was small or low when compared with electrotactile." (P7), "...not regarding the whole muscle." (P9), yet helpful to "feel the muscle" (P1, P8, P9, P11). Furthermore, electrotactile modalities were noted as particularly useful for muscle distinction (P8, P15, P17) and "...made feeling the muscle extremely easy." (P20). Electrotactile modalities were favored for assistance as "...makes me alert and focused." (P3, P13), "...prevents you from sleeping." (P3), while visual "...first increased focus, then almost not noticed at all towards the end of the study." (P1), and vibrotactile "...sometimes didn't catch my attention too much." (P13), all pointing to cognitive stimulation (focus, attention) by the modalities.

4.7.3 *Tactile Stimulation promotes Body Awareness.*

Participants consistently highlighted their bodily processes and changing feelings about using muscle tension or sensations from tactile modalities, summarized as *body awareness*. One participant expressed enjoyment in "...feel the own body inside" and suggested using the system "...to get more connected to your own body" (P17). Participants became aware of their inner sensory body map development in statements like "It takes time to understand the experiment. But now I get the connection of the muscles and the interface." (P17), "...felt my body tensing the wrong muscles for the targeting quite often at the beginning, but came to grips with it with time." (P18), and "...tried to tense the muscles by themselves and feeling they did not react as they should." (P21). Interestingly, participants familiar with their body processes suggested challenging user with "...catches, e.g., visual or electrotactile input but a different prompt, e.g., electrotactile on the lower leg and prompt saying please tense biceps." (P20), and "unusual variations" (P5), both indicating a gamification approach for learning new sensomotoric mappings. Especially electrotactile provoked the muscle perception as part of the body in statements like "...clear feeling between [muscle] tension and relaxation." (P9), "Awakens the muscle feeling." (P11), and "It is kind of crazy what happens to the muscles during electrotactile; it first scared me, then I found it interesting." (P18). Electrotactile supported a familiarity with the bodily processes in statements like "I liked the way my muscle moves without me controlling it." (P6), and "The contraction is not identical with the contraction required." (P7). The tactile modalities were occasionally perceived similarly as "...sometimes, I felt like vibration was the same as electrotactile but with the difference that my muscles weren't under much pressure." (P13).

4.7.4 *Higher Comfort and System Tolerance with Visual and Vibrotactile Prior Stimulation.*

The experiment was described as "long" (P15, P18), and "demanding on endurance" (P2, P3, P5, P10, P16), with potential "negative impact on reaction times" (P16). Thereby, modalities enhancing overall *comfort* were appreciated, and participants noted that the visual modalities' "...[eye-catching color] made the interpretation in such stressful situations easy." (P7), they were "less uncomfortable, more tolerable than tactile modalities" (P4, P16, P18), and "...less "annoying than feeling the vibration or electrotactile." (P10), indicating *fairly high comfort and system tolerance* for the visual modalities. Vibrotactile and Electrotactile modalities received a similar count of feedback on comfort, with all comments on vibrotactile being notably positive as "pleasant" (P3, P10), "comfortable"" (P4, P17), "very mild, but still noticeable enough" (P19), "soft" (P5), "subtle" (P6), "very delicate, not unpleasant" (P18), "liked lesser intensity" (P21), and even "...felt fairly relaxing" (P20), pointing towards a *high system tolerance* using vibrotactile modalities. Surprisingly, concerning *comfort and system tolerance*, the electrotactile modality exclusively received negative comments like "uncomfortable" (P4, P10, P19, P16, P17), "unpleasant" (P18), and "sometimes too strong" (P3, P5, P13).

4.7.5 *Summary.*

The participants appreciated the prior stimulation modalities as support for *muscle localization*. Interesting findings were that tactile prior stimulation supported *cognitive task processing* and *body awareness*. Notably, some modalities produced potential *discomfort*. Comments on the visual prior stimulation mainly highlighted its inability to link cues to muscles. Vibrotactile prior stimulation was seen as the most comfortable but only helpful for some. In contrast, the electrotactile prior stimulation received notably lower ratings for *comfort and system tolerance*, yet was the most favored for *muscle localization* assistance.

5 DISCUSSION

5.1 General Findings

In a VR user study, we compared visual, vibrotactile, and electrotactile prior stimulation modalities to no prior stimulation at the biceps, triceps, upper leg, and calf muscles measuring reaction times with EMG. Our results indicate that the reaction times depend on both the prior stimulation modality and muscle location. All proposed prior stimulation modalities (visual, vibrotactile, electrotactile) significantly improved muscle response compared to no prior stimulation modality, with no notable differences among them. Notably, vibrotactile stimulation significantly enhanced reaction times in the biceps, a slower muscle. This means that vibrotactile feedback could significantly support the participants in cases where the interaction was particularly "challenging." Surprisingly, the calf muscle showed the fastest response, aligning with existing research on its high information throughput [121]. However, our experimental investigation is the first one, to our knowledge, to uncover significant differences in calf muscle performance.

We hypothesize that improvements in reaction times observed across both visual and tactile modalities are due to a mental representation of the body schema (c.f. [10]) in the primary somatosensory cortex [107, 122], rather than just activation of local nerve cells. The calf's faster response might be due to lower nerve sensitivity (or density) [91], suggesting multisensory integration prioritizes less variable stimuli [34]. The low nerve sensitivity in the calf leads to a more reliable, "noise-free" signal, aiding the somatosensory cortex in effectively localizing that muscle. This could mean muscles in more sensitive areas are harder to discriminate, warranting further research.

The main effects and lack of interaction effects in our experiment indicate that the findings could apply to more body muscles. The calf's quick response and its negative correlation with EMG signal strength might relate to its role in postural control and locomotion, which often requires a fine-tuned balance between quick responses and adequate force. An effect of the EMG amplitude would be in line with related work on increased EMG amplitude with prior vibrotactile stimulation [56]. However, the lack of significant parameter slopes remains unknown, and it is unclear if this is the case among other muscles. The results from subjective quantitative assessments revealed a significant preference for prior stimulation modalities, especially electrotactile over no stimulation. While the calf showed the fastest reaction time objectively, participants subjectively rated that the upper leg benefited most from prior stimulation. Both quantitative and qualitative data indicated that participants found tactile prior stimulation, particularly electrotactile, useful for muscle localization and favored the electrotactile cues. Participants reflected on the relation of our apparatus to their body awareness in their qualitative comments. This diverse feedback suggests our apparatus could have a highly versatile utility in assisting both able-bodied and disabled individuals, in physical and cognitive aspects.

These insights are valuable for EMG developers and interaction designers, suggesting that prior stimulation using visual and tactile modalities can enhance interaction accuracy and speed across various muscle locations. This has implications for EMG-based user interfaces [117] and therapeutic VR applications requiring isometric muscle control [2, 28, 114]. Systems in VR working with EMG currently only provide visual and tactile cues in closed-loop feedback settings *simultaneously* to the EMG interaction and not *before*. Our system introduces an additional feedback layer for enhancing communication patterns in VR systems using EMG.

Our analysis reveals distinct EMG signal shapes in muscles, enabling precise muscle classification and accurate placement, crucial for future assistive devices with integrated electrodes [73] and automated setup [75]. This is especially vital for *self-applied wearables* in remote scenarios [11, 77], where misapplication is a risk. Our approach empowers these devices to autonomously identify the correct muscle, a significant step towards smarter, self-learning wearables. These wearables could offer real-time, user-friendly feedback on proper placement and sensor positioning. Utilizing inflection points from EMG graphs in Fig. 6 for optimal signal measurement, our system can enhance threshold calibration, customizing EMG-based devices for prior stimulation modalities. We provide the whole dataset for classification of the EMG-based muscle prediction on Github[9].

5.2 Implications

Our study's findings indicate that visual and tactile prior stimulation can enhance muscle reaction times, with tactile prior stimulation modalities being subjectively favored. These outcomes hold particular promise for hands-free interaction scenarios that require quick responses and are designed with a predetermined pattern, allowing the system to anticipate which muscle needs to be activated next. Prior stimulation patterns in EMG-based interaction offer a more accessible approach to learning deterministic input commands. On-body cues could prompt which muscles to activate next, offering EMG-interfaces as affordable, easy way to interact with computing devices beyond traditional hand-based controllers such as for games [99].

Electrotactile prior stimulation could possibly enhance supportive driving scenarios [138] and visual prior stimulation could correct industrial machine use [11] by assisting faster adjustments and facilitating learning of motor control. Tactile prior stimulation could enable physical therapists to remotely stimulate patient muscles, substituting for direct touch. This could facilitate clearer guidance on which muscle to activate next during (tele-)medicine sessions, enhancing neurorehabilitation [77] by promoting quicker adaptation to therapy movements. Visual, vibrotactile or electrotactile prior stimulation could aid patients in regaining balance in mixed reality (MR)-based assisted-training systems that capture the body motion and provide tilt feedback [18, 137].

Tactile prior stimulation in simulated training environments may enhance muscle localization and mental body schema integration, potentially speeding up the adaptation to prosthetic limbs [140] and facilitating quicker movement response in impaired limbs during mirror therapy for stroke rehabilitation [86, 109, 135]. Systems of EMG dexterous prostheses with precise control systems are capable of sending and receiving signals to mimic natural sensations [1, 32]. These devices could benefit from additional tactile prior stimulation, which simulates the sensation of contact against the prosthetic finger to provide feedback comparable to a natural touch. This would then prompt the muscle responsible for controlling the prosthesis' finger movement to adjust its tension, thereby preventing excessive pressure on grasped objects [17, 113].

5.3 Limitations and Future Work

Motor learning research demonstrated rapid neuroplastic changes through activities like juggling or playing musical instruments [31, 39]. We observed that participants often activated incorrect muscles despite knowing the correct muscle-to-computer mappings, hinting at the possibility of intentional "mistaken" activations. Related work has suggested the integration of visual and tactile cues in VR to augment sensory perception, including compensatory mechanisms for deficits in visual perception, proprioception, and spinal cord function [128, 129]. Our system, inspired by these studies, aims to speed up the training of new neuro-muscular pathways, especially from the sensorimotor cortex to the motor cortex using novel visual

[9]https://github.com/JessicaSehrt/ReactionTest_EMG-V_vT_eT_priorStim

and tactile interactions in an EMG-integrated VR framework. We suggest further research on non-linear pre-stimulation modalities to improve EMG response times in target muscles and their relation to cognitive workload [79].

Our current findings are limited to specific muscles, isometric activation, and seated position. Future research could explore additional muscle locations such as the butt, back, or stomach in VR, and extend to isotonic contractions and movements. Given the effectiveness of tactile prior stimulation, we propose comparing mechanical tactile approaches with vibrotactile and electrotactile modalities as additional *mechanotactile* modality, including intensity variations. Our research demonstrates that prior stimulation modalities enhance muscle response in EMG-based reaction tests in VR, subsequently future studies could explore threshold-based EMG interactions in VR, examining metrics beyond reaction time to gain further insights into muscle activation variations across different locations. The key benefit of using prior and multiple muscle stimulations lies in these applications and in providing tactile feedback before threshold-based control. To replicate our findings and for further investigations, we provide the source code with instructions including the Unity Project and Arduino code on Github[10].

5.4 Conclusion

Our research examined the effect of prior stimulation modalities – visual, vibrotactile, electrotactile, and none – on isometric muscle reaction times in VR utilizing EMG. We observed that all prior stimulation types significantly improved EMG reaction times across four muscle locations compared to no prior stimulation, with no significant difference in effectiveness among the modalities. Notably, the calf muscle showed the quickest response, likely due to low nerve sensitivity and enhanced multisensory integration. Subjective assessments corroborated our objective measurements, with electrotactile stimulation rated the most assistive. Interestingly, participants subjectively felt that the upper leg benefited the most from prior stimulation, although objectively, the calf was the fastest responder. Our results suggest that prior stimulation influences not just local neural circuits but also invokes mental representations of the body schema. Our research paves the way for more responsive and accurate EMG-based user interfaces [117] for various applications, including assistive, therapeutic, and hands-free applications [2, 7, 28, 99, 114].

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