The Effects of Body Location and Biosignal Feedback Modality on Performance and Workload Using Electromyography in Virtual Reality

Jessica Sehrt
Frankfurt University of Applied Sciences
Frankfurt am Main, Germany
jessica.sehrt@fb2.fra-uas.de

Tim Wißmann
Frankfurt University of Applied Sciences
Frankfurt am Main, Germany
tim.wissmann@stud.fra-uas.de

Jan Breitenbach
Frankfurt University of Applied Sciences
Frankfurt am Main, Germany
jbreiten@stud.fra-uas.de

Valentin Schwind
Frankfurt University of Applied Sciences
Frankfurt am Main, Germany
valentin.schwind@fb2.fra-uas.de

ABSTRACT

Using biosignals through electromyography (EMG) and rendering them as feedback for hands-free interaction finally migrates to engaging virtual reality (VR) experiences for health and fitness-related applications. Previous work proposes various body locations as input sources and different output modalities for creating effective biofeedback loops. However, it is currently unknown which muscles and sensory modalities can provide optimal real-time interaction regarding the performance and perceived workload of the users. In two VR studies (N=18 and N=40) based on a Fitts' law target selection task, we explored sensor placement at different body locations and investigate auditory, tactile, and visual feedback modalities. Objective and subjective results indicate that input performance can be improved by presenting muscle tension as simultaneous tactile and visual feedback. We contribute with recommendations for registration of isometric muscle contraction at different body locations and conclude that reproducing physiological feedback through multimodal channels can assist users interacting with EMG devices.

CCS CONCEPTS

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

KEYWORDS

Electromyography, Physiological Sensing, Virtual Reality, Biofeedback, Accessibility

ACM Reference Format:
Jessica Sehrt, Tim Wißmann, Jan Breitenbach, and Valentin Schwind. 2023. The Effects of Body Location and Biosignal Feedback Modality on Performance and Workload Using Electromyography in Virtual Reality. In *Proceedings of the 2023 CHI Conference on Human Factors in Computing Systems (CHI '23), April 23–28, 2023, Hamburg, Germany*. ACM, New York, NY, USA, 16 pages. https://doi.org/10.1145/3544548.3580738

CHI '23, April 23–28, 2023, Hamburg, Germany

ACM ISBN 978-1-4503-9421-5/23/04…$15.00
https://doi.org/10.1145/3544548.3580738

1 INTRODUCTION

Assessing physiological signals of the human body is important for a widespread range of disciplines. Particularly assessing the muscle activity using electromyography (EMG) is indispensable for a wide range of medical, assistive, and interactive applications [2, 7, 65, 105, 120]. For interactions with computing systems, electrodes of an EMG device can register the physiological activity of muscles at different locations on the human body allowing continuous as well as a discrete input [58]. Thus, EMG can be used to recognize limb movements [92], gestures [123], and trigger events for e.g., hands-free interaction [79]. However, as muscles can have varying functions in the human body their corresponding location while using EMG cannot only affect the signal [69] but also the interaction performance [90] or comfort during interaction [74].

For understanding and improving muscle control as interaction technique it is important to consider the physiological difference between muscle tension caused by *moving a limb* due to a shortening or lengthening of the muscle (isotonic contraction) and *applying muscle force* without changing its length (isometric contraction) [76]. While movement-based muscle contractions are easy and quick for the user to perform (clicking a button, for instance, is basically the result of an isotonic movement), isometric muscle contractions must be consciously activated without any movements. Thus, they allow a new layer of motionless, subtle [14] and unobtrusive (social) interactions [71]. They are relevant in rehabilitation and sports as they can be applied within pain-free joint angles resulting in analgesic effects [78]. Isometric contractions in EMG-based systems are also desired to prevent unintentional motion-based input or when movements are even impossible for mechanical control of electric wheelchairs [72], exoskeletons [64] and remote robotic systems [5, 39, 125].

One possibility to gain increased control and more awareness during interactions with physiological functions of the own body is displaying the biosignal back to the user. Closing the so-called *biofeedback loop* facilitates the phenomenon of *neuroplasticity* [34] and increases the body awareness often causing changes to one's own behavior, thoughts, and even body functions, which are typically not consciously perceived such as brainwaves, skin conductance, heart rate, or gastric activity [51, 57, 113, 121]. In particular, closing the biofeedback loop using EMG sensors is helpful for a number of use cases where (isometric) muscle control can support motor functions and information about the physiological signal of the muscle activity is required to gain control over it [13, 63, 85]. This approach can even support the restoration of neural pathways when only the intention to move a limb is trackable e.g., after a stroke [25, 101].

Previous work discussed how the biofeedback loop can efficiently be closed using different modalities [46]. Generally, vision, audio, and haptics are perceived faster compared to senses like temperature or olfaction [37, 50]. However, researchers tend to prefer the use of multi-modal biofeedback – the simultaneous rendering of the physiological signal using multiple perceptual channels [27, 46, 88]. One of the most versatile approaches to enable multi-modal interaction is using augmented reality (AR) or virtual reality (VR). As the technologies provide high levels of immersion, motivation, and engagement [2, 67, 94], the usage of AR and VR is subject of a number of use cases in many EMG-related disciplines such as in fitness and sports [27], for hands-free interaction [79], health [60], and rehabilitation [75, 80, 110].

This paper contributes to the human-computer interaction (HCI) by reporting on two VR studies based on a Fitt's law task investigating how muscle-based interactions, as well as multi-modal biofeedback with EMG devices, can be improved. We found that the input performance does not significantly differ among isometric-controlled muscle contractions, however, that the performance can be improved through combined visual and tactile biofeedback. Qualitative analyses provide additional insights on the participants' usage, impressions, and opinions on EMG in interactive systems. We discuss implications and recommendations for researchers, bioengineers, and developers seeking to enable biofeedback-assisted interaction with EMG.

2 RELATED WORK

Measuring EMG signals, using those for computational interactions, and rendering EMG as biofeedback is subject in multiple disciplines of the related work. In this section, we built upon relevant research in the context of registering and using muscle activity as well as rendering that activity as biofeedback considering different modalities in VR or AR.

2.1 Electromyography (EMG)

EMG deals with the detection, analysis, and utilization of electrical signals emitted from the skeletal muscles of the human body. A small electrical current is produced by the exchange of ions across those muscle membranes, gets amplified, and recorded using electrodes [45]. EMG is used for medical application and diagnostics of muscle-related disorders or diseases [105, 116], rehabilitation [7], and for the control of prostheses [9]. While using surface electromyography (sEMG) electrical signals are measured with the help of electrodes attached to the skin surface, EMG can also refer to invasive needle electrodes where the electrical current is measured within the muscle. For consistency with related work and in the following, however, we refer to sEMG when EMG term is used. Due to the noninvasive usage of EMG, the sensor technology is also in focus of non-medical research. Engineers and developers of biomedical applications use the EMG signal to control hardware or software [69]. Common standards for assessing signals with the sensor technology have been proposed by the European Recommendations for Surface Electromyography (SENIAM) [35].

Related issues affecting the EMG signal are individual tissue properties, physiological cross-talk in-between two muscles, and potential distance changes between muscle and electrode [20, 69]. Factors of interest are EMG signals based on movements or voluntary tension. When a muscle moves a limb joint along a distance the muscle changes its form because of the applied tension inducing a so-called *isotonic contraction* [38, 76]. Isotonic contractions are suitable for detecting movements, e.g., gestures [1, 47, 95] or locomotion [114], and can be combined with other sensors for improved recognition accuracy [123]. In contrast to isotonic contractions, *isometric contractions* generate and maintain constant tension without changing the length of the muscle and are frequently used in fitness training to maintain posture [87]. So-called maximum voluntary isometric contractionss (MVICs) are recommended when investigators desire no corresponding movements with cross-talking muscles, employ multiple muscle positions [16], and aim to isolate the signal of actual muscle tension from artifacts caused by movements [87, 95, 107]. Isometric muscle contractions are suitable for people with an injury or medical condition that restricts movement [36] and can increase muscle stability, for example, the ability to hold weight over longer periods of time [55] or address muscle stiffness and reduce blood pressure [56, 70]. After a fracture and when the arm is being fixated to prevent any movements for further injuries, isometric contractions based on biosignal-supported feedback with EMG can help to prevent muscle loss without holding weights destabilizing the fracture [104]. However, the assessment and conscious application of isometric contractions can be difficult because no displacement occurs except within the muscle itself and at a microscopic level [115]. Thus, isometric muscle contractions are often used together with biofeedback to visualize the EMG signal for improved awareness and body control [13, 42, 63].

2.2 Biofeedback with EMG

Rendering a biological signal from a physiological activity to its user in real-time is commonly referred to the term *biofeedback*. This allows the user to influence that signal. Biofeedback is used to increase awareness and consciousness on that physiological function [28]. Using biofeedback with EMG signals mainly emerged from the field of medical and clinical rehabilitation [7]. Actively monitoring one's own physical activity of the muscles can be supportive to react, adapt, or understand the own physiological-based parameters such as behavior, movements, and postures [82]. The concept behind multi-modal biofeedback in rehabilitation is facilitating neuroplasticity necessary to regain e.g., lost motoric abilities or disorders [100]. EMG biofeedback can, for example, be used to facilitate or inhibit muscle contraction and is considered a suitable treatment for a wide range of musculoskeletal disorders [122], neuromotor [40] and stroke rehabilitation [106]. Yoo et al. [120], for example, treat a neuromuscular imbalance between the triceps and biceps using EMG and visual biofeedback in VR with children with spastic cerebral palsy. Typically, biofeedback is presented visually, but the signal can also be reflected using other perceptual channels [10, 12, 46, 97]. In particular, rendering biofeedback using multi-modal systems such as in VR or AR has been extensively investigated by previous work [61, 80, 94].

Biofeedback for active control in VR applications further opened the field of motor imagery for e.g., post-stroke rehabilitation [41] or even for direct limb control in AR for amputees [80]. Beside the advantages over traditional treatments in clinical practice [83], biofeedback in VR has shown potential to improve sports, training, and fitness efficiency [15, 21, 112]. As currently mentioned, biofeedback techniques are predominantly based on vision [102], but there are also techniques rendering physiological signals using tactile [12, 46, 97] or auditory [46, 111, 121] feedback, which all can be provided in AR or VR. According to Gazzoni and Cerone [27] current biofeedback techniques are simplistic and not intuitive limiting the clinical effectiveness and suggest to use such a multi-modal approach. In a study by Karolus et al. [46], the authors investigate the effect of visual and auditory biofeedback for physical training exercises. However, based on their findings, the authors conclude that "multi-modal feedback systems should provide a choice for the user to prevent sensory overload" [46]. While it appears that addressing two senses simultaneously can lead to an increased cognitive processing [86, 108, 119], there are also cognitive models predicting that combining too many external influences can increase the likelihood of information overload [6, 44, 117].

2.3 EMG in HCI and AR/VR

Research in HCI explores the feasibility of muscle-computer interfaces as interaction methodology between humans and devices [4]. While early approaches showed an interest in decoding human-muscular activity rather than relying on physical device actuation [95], recent research envisions systems closing the loop between physiological input and output. Such interactive systems can not only read but also directly influence the user's body over physiological sensors [62]. Gesture recognition [95] or translating the intensity of muscle activity to select letters while typing [52] are additional use cases of EMG devices in HCI research. EMG has also been explored providing off-desktop mobile or wearable interaction systems [53] and as interactive communication tool between persons [96]. Also the daily use of EMG devices is an issue in the domain. For example, Constanza et al. [17, 18] use EMG for mobile interfaces to realize unobtrusive and intimate communication based on isometric muscle contractions allowing subtle and minimal interactions with connected devices to stay unnoticed towards non-informed observers and thereby integrate EMG by being discrete enough for an application in public space and motion-less gestures. There is even research in that field facilitating the EMG biosignal for social interactions and interpersonal communication [71].

Research has reported different effects of EMG sensor placement at different body locations for interaction [16, 58]. For example, in terms of adaptive gameplay participants in a study by Nacke et al. [74] report headaches when EMG sensors were placed on forehead to imitate joystick input. The authors also refer to positive effects of isotonic contractions from physiological sensors when EMG is being placed at the leg, evaluating them as convenient and fun to use, leading to high subjective ratings of the game mechanics [74]. Also related to games is when EMG is connected to game mechanics to support rehabilitation and motivation. For example, Ma et al. [65] present an EMG VR system that aids muscle rehabilitation through a balloon shooting game, which uses the actions of rotation and grasping of the hand as input and delivers visual feedback. Consequently, Garcia-Hernandez et al. [26] concluded that gamified EMG and VR therapy can lead to engagement and motivation. Supporting muscle training in multi-modal VR/AR environments can also improve learning, for example, how to use a new prosthetic [73, 75] or even a virtual hand [54, 81]. To interact with EMG in VR related work mostly used threshold-based action triggers (ca. 20 - 50% of the maximal signal strength) to translate the continuous signal into discrete events for target selection or event triggering [8, 59, 90, 90]. For target pointing or aiming researchers use eye gaze [79, 93], upper and lower arm rotation [32, 90] (c.f. Thalmic Labs' discontinued Myo Gesture Control armband), hand rotation [65, 79], and head rotation [65, 79] as input, whereas Hansen et al. [31] showed that pointing with an head-mounted display (HMD), used for many use cases in hands-free interaction [118], works better concerning the information throughput [66] than gaze pointing.

2.4 Summary

EMG at different muscles is used in a wide number of health-related and even interactive applications [11, 41, 48, 60, 94, 110]. Single- and multi-modal biofeedback can be presented to the user to gain control over one's own muscle contractions [7, 15, 21, 28, 46, 112] and within the VR for immersion and engagement [26, 54, 65, 73, 75, 81]. However, it is currently unclear, which muscles provide optimal throughput and workload. Furthermore, it is unknown which biofeedback modalities [46, 97, 111] can be used for optimal interaction with EMG devices. Therefore, we conducted two experimental studies to investigate the effects of body location and modalities on the users' interaction performance.

3 STUDY 1: BODY LOCATIONS AND EMG INTERACTION

Previous work uses EMG for the registration of muscle activity as an input method for VR. However, it is still unclear which body areas are well-suited for interaction with such systems. As humans do not activate and use their muscles in the same way, we hypothesize that there are differences in the users' input performance between different areas of the human body. Therefore, we conducted a VR user study using a within-subject design with the independent variable Body Location. Based on a standardized Fitts' law target selection task using EMG and an HMD as the pointing device (cf. ISO 9241-411 [43, 66]) as well as subjective assessments, we measured performance and workload.

3.1 Body Locations

Research investigating EMG as muscle input uses the *upper front arm (Biceps bracchii)* [2, 102], the *upper back arm (Triceps brachii caput laterale)* [2], the *temple (Temporalis anterior)* [52, 109], the *inner calf (Gastrocnemius)* [74], or *forearm (Flexor carpi radialis)* [2,

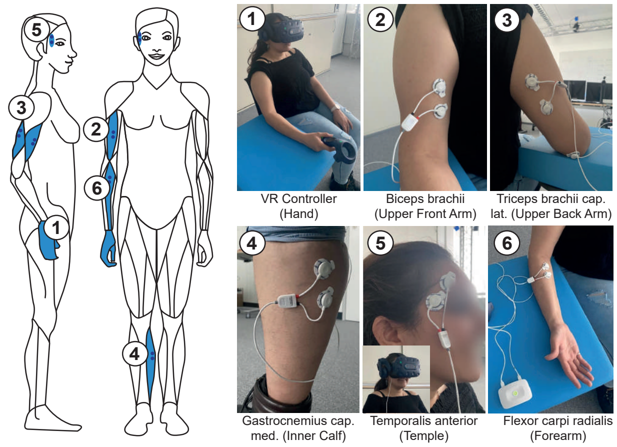


Figure 1: The six conditions with corresponding muscles (blue) and body locations (1-6) for EMG sensor placement used in the first user study.

95]. During system development we found that EMG signals from the shoulder muscles (Infraspinatus) [124] are being compromised by the head rotation with the HMD and did not include the location. As control condition we included the *VR Controller (Hand)* of the headset.

3.2 Apparatus

We created a virtual 3D environment for the Fitts' Law task using Unity Engine (Version 2019.4.1f) running on a PC with AMD Ryzen 5900X, GeForce RTX 3070, and 16 GB RAM. The virtual scene was kept as simple as possible and contained a panel in front of the participant for calibration instructions and targets. An HTC Vive Pro with 90 fps was used as HMD and tracked using four lighthouse boxes for high accuracy. The head orientation of the headset was used to control the camera view ray casting towards the center of the view and indicated by a small red dot. In the muscle controlled conditions, the EMG signal was used for action triggering during target selection. In the VR controller condition, action triggering was performed using the index finger on the trigger button of a regular HTC Vive Controller. A Biosignalplux 4-Channel Hub[1] with EMG sensors and Kendall H124SG electrodes was used to assess muscle activity. Sampling rate of EMG frequency measurement was set to 1000 Hz in 16-Bit resolution according to the datasheet. The integrated low-noise high-speed operational amplifiers performed bandpass filtering and amplification on the base of bitalino technology [30]. Signal strength above 20% was accepted as trigger-threshold. To ensure that muscle tension was released between target hitting edge-detection was implemented. To prevent constant triggering, the signal strength had to drop below 10% to release the EMG trigger again. Controlled variables in the Unity scene were target amplitude (A = 1.4, 1.8, 2.0 & 2.2 meters) and target width (W = 0.1, 0.2, 0.3, 0.6 & 1.1 meters), resulting in the indices of difficulty (IDs) 1.5, 2.0, 2.5, 3.0, 3.5, 4.0, and 4.5. Targets were activated reciprocally clockwise, beginning with the uppermost target (at 12 o'clock) and were hidden until activated.

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

3.3 Measures

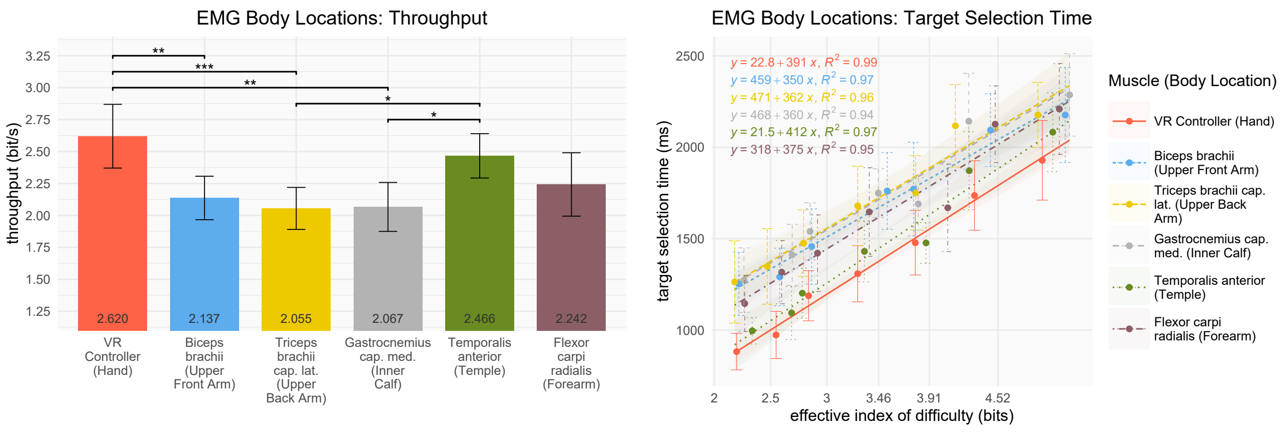
As recommended by Biosignalplux and in line with previous research on EMG for event detection, a Taeger-Kaiser energy operator was applied for EMG signal processing and it was rectified to improve onset detection [103]. The mean of all EMG values within one received package was calculated to provide a reasonable level of signal smoothing. For determining the throughput performance, we recorded target selection time, the corresponding IDs, target position, and actual hit point coordinates. In addition, we recorded the timestamps of the experiment. For perceived workload, participants filled out the Raw NASA Taskload Index (RTLX) as widely used tool in HCI for workload assessments [33] with a digital questionnaire in VR. This avoids putting off the headset and potential inconsistencies of placement of body posture and hardware [98]. Qualitative feedback was obtained by a post-VR interview and noted by the experimenter.

3.4 Procedure

After signing the informed consent, the participants were asked about their demographics and introduced to the goals of the study as well as the functionality of the EMG and VR system. Participants were brought in a comfortable seated position with elbows and knees were brought in an approximate 90° angle. The dominant arm and leg were identified as stated by the participant and all conditions were tested on this body half. To ensure correct sensor placement, the experimenters were provided with a scheme of human anatomical landmarks. The skin at each location was prepared with an alcoholic pad, shaving the hair with a disposable razor, if necessary. Two electrodes were placed at a distance of 1 cm on the muscle stomach for each condition repetitively and a reference electrode consistently to the elbow joint bone. The experimenter put on the HMD for the participant. Lens distance was adjusted according to the participants' individual preference. Participants were orally instructed how to use their muscle tension as trigger and that they should "select the targets as fast as possible". Before calibration, participants were free to ask questions.

During calibration process, a text on a virtual panel was presented: "Please tense your muscle with effort...". The participant's biosignal was rendered for the experimenter to ensure that the desired amplitude has been registered. In cases where participants were not able to activate their muscle correctly, they were guided by the experimenter, who touched the muscle section with the fingertips. Maximum muscle strength was then derived from at least three intensive but still comfortable muscle tension phases as the individual and muscle-specific trigger threshold. Each muscle of the recent condition was separately calibrated. In cases where the experimenter had issues with the correct sensor placement on the muscle stomach, we brought the participants' limb into zero position as recommended by SENIAM [35] except for the temple. Afterward, we brought the participants back into a seated position.

Before starting, the participant was explicitly instructed to not move any limbs to ensure isometric muscle activation and to "select the targets as fast as possible". Then, the participant performed the



(a) EMG throughput between the body locations

(b) Target selection time as function of the IDe

Figure 2: Objective performance measures of the first study. The bar chart in 2(a) shows the average throughput results from the Fitts' law task for each muscle location. The regression slopes in 2(b) show the target selection time of each muscle as a function of the effective index of difficulty (IDe). All error bars show 95% confidence intervals (CI95).

Fitts' law task with pseudo-randomized IDs and filled the RTLX on the virtual panel. After each condition, a new set of disposable electrodes was attached to the subsequent body locations in counter-balanced order according to the randomization by a Latin square. During the procedure, the experimenters noted any interesting comments or suggestions from participants. After finalizing the last condition, participants were debriefed and could express individual observations about their experience.

3.5 Participants

Eighteen students (5 female, 13 male) from computer science courses were invited via social networks, mailing lists, and word of mouth to participate in the study. Their mean age was 25.888 ($SD = 4.600$) ranging from 21 to 41. All participants were informed that they can withdraw from the experiment at any point without penalty. No volunteers were excluded from the study. No participant desired to quit or pause the study. All participants were student volunteers in the field of computer science or mechanical engineering and were rewarded with credit points for their lecture. The study received ethical clearance according to the regulations and hygiene protocols for user studies during the COVID-19 pandemic as required by our institution.

3.6 Data Analysis

The objective data of two participants could not be taken into account due to broken data stream recordings during the experimental trial. As their interaction was not affected, their subjective feedback has been taken into account. The effective throughput (TPe) was calculated using the target selection model for 2D tasks as proposed by MacKenzie and Buxton [66]. Their model is part of ISO 9241-411 [43] for the evaluation of physical input devices and provides an improved link to information theory, better fits, and IDs that cannot be negative. With A as amplitude (distance between two targets) and W_e as the effective target width calculated by the distribution of targets over a sequence of trials. To calculate the effective throughput (TPe) we used the effective IDe and the mean time (MT) as shown in Equation 1:

$$ID_e = log_2\left(\frac{A}{W_e} + 1\right), \quad TP_e = \frac{ID_e}{MT} \tag{1}$$

3.7 Quantitative Results

3.7.1 Throughput. Shapiro-Wilk's test was performed to detect any violations of normality of the objective throughput data of the target selection task, which could not be found (all conditions with $p \geq .529$). Thus, we performed a parametric one-way repeated measures analysis of variance (RM-ANOVA) to compare the effect of Body Location on the throughput. Effect sizes were labelled following recommendations by Fields [23]. The analysis revealed a statistically significant effect, $F(5, 75) = 11.283$, $p < .001$, $\eta_p^2 = 0.429$ (large). Pairwise comparisons using Tukey's HSD test (see Table 1) showed that the mean values between *VR Controller* and *Biceps brachii*, *VR Controller* and *Triceps cap. lat.*, *VR Controller* and *Gastrocnemius cap. med*, *Triceps brachii cap. lat.* and *Temporalis anterior*, as well as between *Gastrocnemius cap. med.* and *Temporalis anterior*, were significantly different. Thus, both *Triceps brachii cap. lat.* and *Gastrocnemius cap. med.* had a significantly lower throughput than the *VR Controller* and *Temporalis anterior*. Moreover, the *VR Controller* was significantly faster than the *Biceps brachii*. Any significant differences between *Flexor carpi radialis* and the other Body Locations or between other condition pairs could not be found (all with $p \geq .065$). No gender-related effects or interactions were found (all $p > .05$). All means and CI95 are shown in Figure 2(a).

3.7.2 Mean Target Selection Time. We further analyzed the log-transformed mean target selection time on participant level and included the ID as co-variate in a repeated measures analysis of covariance (RM-ANCOVA) to understand if the difficulty during

Table 1: P-values of pairwise comparisons between the tested muscle locations for throughput (TP) and workload (RTLX) scores.

	VR Controller (Hand)		Biceps brachii (Upper Front Arm)		Triceps brachii (Upper Back Arm)		Gastrocnemius cap. med. (Inner Calf)		Temporalis anterior (Temple)	
	TP	RTLX	TP	RTLX	TP	RTLX	TP	RTLX	TP	RTLX
Biceps brachii (Upper Front Arm)	**.007***	.053								
Triceps brachii (Upper Back Arm)	**.001***	.183	.990	1.000						
Gastrocnemius cap. med. (Inner Calf)	**.001***	1.000	.995	1.000	1.000	1.000				
Temporalis anterior (Temple)	.862	1.000	.150	.092	**.034***	**.024***	.042	.657		
Flexor carpi radialis (Forearm)	.065	1.000	.969	1.000	.730	1.000	.780	1.000	.558	.229

the target selection task affected the performance of the Body Location. As Mauchly's test showed a violation of the assumption of sphericity ($W = 0.751, p < .001$), we used Huynd-Feldt correction ($\epsilon = 0.892$) to adjust the degrees of freedoms. There were statistically significant effects of Body Location, $F(6.00, 103.00) = 51.548$, $p < .001$, $\eta_p^2 = 0.750$ (large) and ID, $F(4.69, 482.65) = 33.050$, $p < .001$, $\eta_p^2 = 0.243$ (large), however, there was no interaction effect , $F(28.12, 482.65) = 0.596$, $p = 0.952$, $\eta_p^2 = 0.034$ (medium), indicating that the throughput of the EMG device is independent from the difficulty during target selection. The regression fits for the mean target selection time of the individual Body Locations based on the IDe and the resulting slope parameters (constants a and b from the Fitts' task) can be found in Figure 2(b).

3.7.3 Subjective Workload. Subjectively perceived workload was assessed using the RTLX questionnaire. Shapiro-Wilk's tests on the scores could not detect violations of normality (all conditions with $p \geq .245$). A one-way RM-ANOVA with Body Location as factor revealed a statistically significant effect, $F(5, 80) = 4.449$, $p = 0.001$, $\eta_p^2 = 0.218$ (large) on the workload scale. Bonferroni-corrected pairwise comparisons revealed a significant difference between *Triceps brachii cap. lat.* and *Temporalis anterior* ($p = 0.024$), on the performance measure and *VR Controller* and *Biceps brachii* ($p = 0.019$), for perceived effort. An analysis of the subscale scores revealed no effect on mental demand, $F(2.9, 46.32) = 0.65, p = 0.582$, $\eta_p^2 = 0.039$ (medium). However, there were significant effects on physical demand, $F(5, 80) = 4.482$, $p < 0.001$, $\eta_p^2 = 0.219$ (large), temporal demand, $F(3.49, 55.84) = 2.812$, $p = 0.04$, $\eta_p^2 = 0.149$ (medium), performance, $F(5, 80) = 3.052$, $p = .014$, $\eta_p^2 = 0.160$ (large), effort, $F(5, 80) = 3.052$, $p = .014$, $\eta_p^2 = 0.170$ (medium), and frustration, $F(5, 80) = 3.052$, $p = .014$, $\eta_p^2 = 0.161$ (medium). Bonferroni-corrected pairwise comparisons, however, only revealed significant differences between *VR Controller* and *Triceps brachii cap. lat.* ($p = 0.015$), on the performance measure and *VR Controller* and *Biceps brachii* ($p = 0.019$), for perceived effort. All means and CI95 are shown in Figure 3.

3.8 Qualitative Results

After the experiment, we asked participants which body location (without VR controller) they finally prefer based on overall comfort. The post experimental semi-structure interview feedback was transcribed verbatim and analyzed by two of the researchers.

Twelve participants (63.2%) stated they prefer the EMG sensor at the *Temporalis anterior (temple)*, four participants (21.053%) preferred the *Gastrocnemius cap. med. (calf)*, and three (15.8%) the *Flexor carpi radialis (Forearm)*. One of the comments revealed that the participants probably did not activate their muscle using isometric movement despite our instructions: "temple is only good to control because you can press the jaw to activate the temple muscle" (P2). Similarly, P4 just learned that "temple muscle activation needs movement of the eyebrow and forehead if you do not want to involve the pressing of the jaw". The participant also complained that his eyebrow movement was irritated by the headset. Without not allowing to move any limb the instructions definitely prevented non-isometric activation of the arms and legs: "If you would have been allowed to lift the arm for biceps, triceps or press towards the table these would the same way be easy to address" (P2). A number of participants particularly highlighted that triceps, calf, as well as forearm were "extremely hard to address" (P4, P8, P11, P12, P14, P15). P15 mentioned that one muscle (triceps) was hard to activate as he "couldn't find a connection to control it". When placing the sensors, we asked the participants to activate the muscles. An interesting observation was done by two participants, who stated that for finding a connection to a muscle, it was "helpful, when an external person touched the body region".

3.9 Discussion

In our first exploratory user study, we compared the ability of participants to control their muscle tension at different locations at their body and to interact with the EMG system in a target selection task with the headset as directional pointer. Highest input performance was found at the temple with 94.1% compared to hand-based control. However, qualitative feedback from the participants indicated that they used eyebrow movement or jaw pressure during that condition to activate their muscles despite being specifically instructed to not perform any movements and only to tense their muscles by isometric contractions. Consequently, the participants likely performed isotonic muscle contractions at the *Temporalis anterior*. While the participants wore the VR headset it was not possible for the experimenter to externally validate or even intervene when the muscle tension in the condition *Temporalis anterior* at the temple was not induced through isometric contractions during the calibration or the experiment. We cannot rule out whether the participants deliberately ignored the instruction to "select the targets without movement" or whether they were actually forced to move their temple muscles as long as the weight of the headset put pressure on their head. However, the finding was informative insofar as it

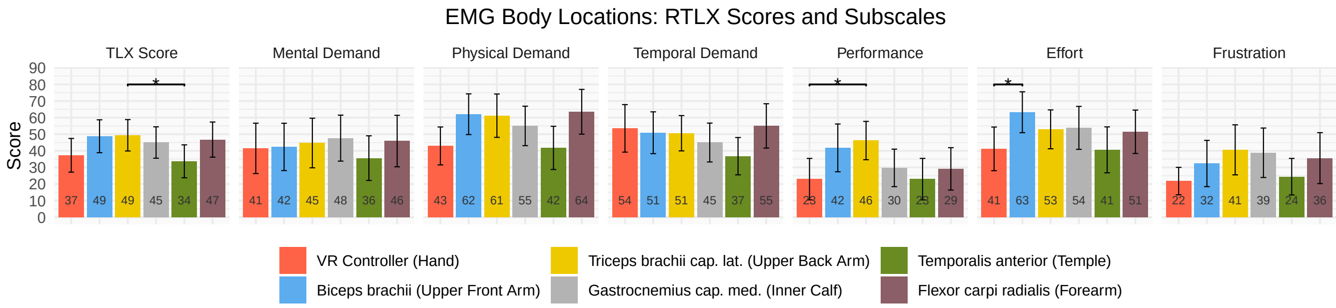


Figure 3: Bar charts of the RTLX task workload score and subscales in the second study. Regarding the main score, the triceps received a significantly higher workload rating than the muscle at the temple. The VR controller received significantly lower ratings for perceived performance than the triceps and also significantly lower ratings for effort than the biceps.

was previously unclear whether the electrodes can actually be used under the HMD and could be of interest to manufacturers of such headsets, who could simply build in the electrodes into a device to allow more interactions using facial parts.

The performance of muscles activated through isometric contractions was correspondingly lower. The lowest throughput was found on the triceps with 78.4% compared to hand-based control. However, no significant differences were found between biceps, triceps, calf, and forearm with the highest throughput at the forearm (85.6%). Thus, the results suggest that stationary, isometric muscle contractions do not significantly differ in terms of their input performance between the muscle groups tested. Importantly, there were no interaction effects with the index of difficulty. This finding indicates that the participants tend to point equally well during conditions with all body locations independent from the level of difficulty.

4 STUDY 2: BIOFEEDBACK MODALITIES AND EMG INTERACTION

Previous work showed that EMG biofeedback,i.e., rendering a user's own physiological signal can help users to focus on their own muscle tension. However, which sensory cues are suitable for rendering EMG signals and closing a biofeedback loop is currently unknown. As humans have a limited set of resources available for mental processes [117], one could assume that task performance based on biofeedback from *multiple* cues can cause difficulties in sensory-level processing, mental operations, and, thus, issues in performing tasks. While sensory cues such as temperature, smell, taste, or perception of organs in the vestibular system are being perceived with some delays, our study focuses on the rendering of biofeedback using the high-paced Visual, Auditory and Tactile cues.

Thus, we investigated the three modalities in a three-way full-factorial within-subject design. As each of the three modalities (and their combinations) were either present or not we had eight conditions (*none*, *visual*, *auditory*, *tactile*, *visual + auditory*, *visual + tactile*, *tactile + auditory*, *visual + auditory + tactile*) ordered in an 8×8 balanced Latin square study design. As in our first study, we conducted a Fitts' law target selection task [43, 66] to measure performance and workload. Due to the low variance of the throughput in the first experiment, its observability during the experiment to

Figure 4: Screenshot of the user's view in VR during the visual feedback modality performing the Fitts' law task. Left: 30%, right: 60% muscle strength amplitude.

ensure isometric contractions, and its relevance in related literature [2, 11, 60, 120, 124], we used the *Biceps brachii* (at the front of the upper arm) for EMG input.

4.1 Biofeedback Modalities

Auditory feedback was rendered via the headphones of the HMD and consisted of a neutral summing sound that changed its pitch depending on how strongly the participants tensed their biceps. As the discrimination power of pitch sequences is higher compared to loudness [19, 68] we used sound pitching as one-parametric modulation of the audio cue keeping the loudness constant and best recognizable for the participants. For tactile feedback we used amplified vibration of a coin-type vibration motor. As the index fingers have a high density of nerve cells, we placed the motor at the index finger of the opposite arm where the EMG signal has been recorded. To ensure that participants were not able to ignore it, we placed the visual feedback as an orange-colored torus-shape indicator of muscle strength in the center of the participants' field of view (see Figure 4). A concept of how the modalities closed the biofeedback loop in our experiment is shown in Figure 5.

4.2 Apparatus

As calibration and task were similar as in our first study, we reused parts of our Unity3D application running it on a PC with the same specifications. As in our first study, edge-detection was implemented with 20% upper and 10% lower trigger threshold. We used the same Biosignalplux 4-Channel Hub with EMG sensors and head-mounted display (HTC Vive Pro). We used Unity 3D Ardity

API (9600 Baud) to communicate with an Arduino UNO R3 microcontroller that outputs a pulse-width modulation (PWM) to power an Iduino TC-9520268 coin-type vibration motor with an operating voltage of 3.0 V/DC - 5.3 V/DC. The duty cycle of PWM was controlled in steps from 80 to 255, 255 being 100% duty cycle at 5 V. The vibration motor was operated at maximum speed capacity possible, modulated by PWM with frequency 490 Hz in linear relation to the amplitude of the muscle strength tension. An audio source in Unity was a looped A-major chord[2] with a pitch value starting at 0 % pitch to 100% pitch. Pitch value was modulated using the calibrated muscle strength value amplitude multiplied by a constant of 0.4 for noticeable and optimal hearing differences. The orange-colored (RGB: 255,133,57) circle was clipped using radial fill (radial 360°) in Unity starting from 0 fill to 1. The animation of the visual feedback and the pitch of the sound were also linearly mapped using the amplitude of the muscle strength tension.

4.3 Measures

We recorded the Fitts' law-related measures as in our first study (target selection time, effective IDs, target position, and actual hit point coordinates) and the subjectively perceived workload using the RTLX. To gain a deeper understanding of how participants perceive the individual modalities and how well they were able to control their muscle tension using that feedback, we conducted a semi-structured interview. The questions in the survey were focusing on the participants' opinion (positively and negatively) on the modalities and their combinations, the system, and the task. The subjects were also asked on any other remarks they might have regrading the experiment.

4.4 Procedure

As in our first study, participants signed the informed consent and were introduced to the system. The general procedure regarding the EMG sensor placement at the dominant arm was identical to the first study, except that the muscles were not changed, but only the biceps was tested. Additionally, the non-dominant arm has been identified and was placed on a pillow beside for comfort. In addition, we put the vibration motor between two rubber finger cots on the index finger at the non-dominant hand, followed by comprehensive instructions. The participant received and adjusted the HMD. To ensure correct operation of the device, headphones and vibration motor were tested with constant intensity and vibration at full level. Participants were asked if they perceived all signals clearly and the intensity was adjusted if desired. Participants were free to ask any questions.

Calibration without any feedback was started while the EMG raw biosignal was visible for the experimenter to ensure that the desired amplitude has been registered correctly. Maximum muscle strength was then derived from at least three intensive but still comfortable muscle tension phases as the individual trigger threshold, following the same procedure as in the first study. There was one calibration for all conditions of an individual participant. Participants were pleased to "select the targets as fast as possible" and were also instructed to "think aloud" in case of any concerns during system usage. The Fitts' law task then started with pseudo-randomized

[2]https://samplefocus.com/samples/atmosphere-loop-choir-5 (Public Domain)

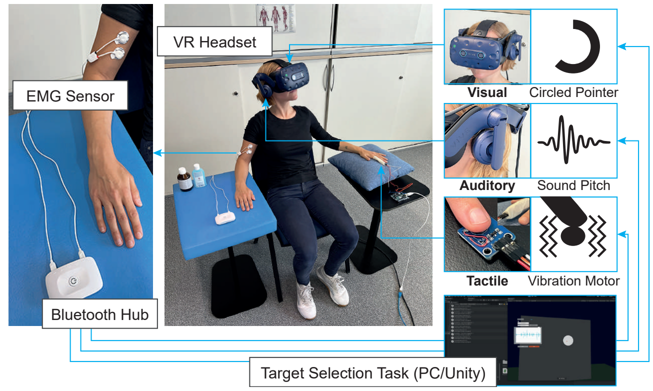


Figure 5: User in the second study in VR experiencing the three feedback modalities. The system renders the EMG signal from the user with visual, auditory, and tactile cues. A circled pointer in the shape of a partial torus renders the visual feedback. A pitched sound is used as auditory cue from the EMG device. A vibration motor fixated under the index finger renders tactile feedback.

IDs The following conditions with the corresponding modalities and their combinations were randomized using the balanced Latin square design. After each condition, the participants filled in the RTLX within the virtual environment. After the VR experience and removal of headset and electrodes, we collected the participants' qualitative feedback in a semi-structured interview.

4.5 Participants

Participants were recruited using social networks and mailing lists of our institution as well as via word of mouth. A total of 47 members of our institution participated in the study. No volunteers were excluded. The mean age of the participants (18 female, 29 male) was 29.106 (SD = 6.312) ranging from 22 to 58 years. All students were from a Master course in the field of computer science and were compensated using credit points for their lecture. They were informed that they can withdraw from the experiment at any point without penalty. Staff members were reimbursed for their working hours. No participant desired to quit or pause the study. The study received ethical clearance according to the regulations and COVID-19 protocols required by our institution. Seven participants could not be taken into account in the further analysis due to multiple reasons (unilateral vision, invalid sensor placement, or broken vibration motors during the interaction trial). Thus, a total of 40 participants (12 female, 28 male) were considered in the final analysis of the results.

4.6 Data Analysis

For data analysis of the recorded data samples from the target selection task, we performed simple outlier filtering (Q1/Q3 ± 1.5 IQR rule) and included 17105 from a total of 18179 samples (94.1%). Duration of the experimental procedure was M = 25.536 minutes (SD = 7.159). As in our first study, the TPe of the Fitts' law target selection task was calculated using the model for 2D tasks as proposed by MacKenzie and Buxton [24, 43, 66].

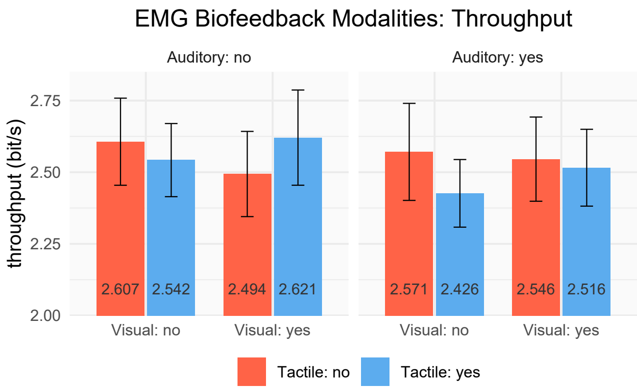


Figure 6: Bar charts of the throughput performance measures for each biofeedback modality used in the second study. Highest throughput was achieved using visual and tactile feedback as well as when no feedback was rendered. A main effect for the auditory feedback indicates that the average throughput was significantly lower when auditory cues were present compared to when not. All error bars show CI95.

4.7 Quantitative Results

4.7.1 Throughput. Shapiro–Wilk's test among all conditions (all with $p > .203$) indicated normal distribution of the throughput measures. We conducted a three-way RM-ANOVA to investigate the effect of Auditory, Tactile, and Visual feedback modalities. The results are shown in Table 2. There were statistically significant effects for Auditory and Tactile × Visual biofeedback modalities. Statistical power and probability of correctly rejecting the null hypothesis for the two-way interaction between Tactile × Visual was 83.9%. No gender-related effects or interactions were found (all $p > .05$). The lacking three-way interaction indicates that the throughput decreased when auditory and tactile cues were present and increased when tactile and visual cues were present. Thus, the main effect for Auditory indicates that the average throughput was significantly lower when auditory cues were present compared to when not. Regarding the two-interaction of Tactile × Visual, the throughput means show that the performance was higher when both cues were present or not compared to visual or tactile cues only. Individual throughput results of all conditions are shown in Figure 6. The target selection time as a function of difficulty and the condition-wise regression equations can be found in Figure 7(a).

4.7.2 Mean Target Selection Time. We performed an RM-ANCOVA of the log-transformed mean time adding the ID as co-variate. The analysis revealed a significant main effect of Auditory, $F(1,269) = 6.140$, $p = .014$, $\eta_p^2 = 0.022$ (medium). We also found two-way interaction with all three possible combinations, Auditory × Tactile, $F(1,269) = 8.950$, $p = .003$, $\eta_p^2 = 0.032$ (medium), Auditory × Visual, $F(1,269) = 3.993$, $p = .047$, $\eta_p^2 = 0.015$ (medium), and Tactile × Visual, $F(1,269) = 8.367$, $p = .004$, $\eta_p^2 = 0.030$ (medium). Interestingly, there was no three-way interaction Auditory × Tactile × Visual, $F(1,269) = 0.010$, $p = .919$, $\eta_p^2 = 0.000$ (undetectable). The analysis further revealed a significant main effect of the co-variate ID, $F(6,269) = 61.579$, $p < .001$, $\eta_p^2 = 0.579$ (large),

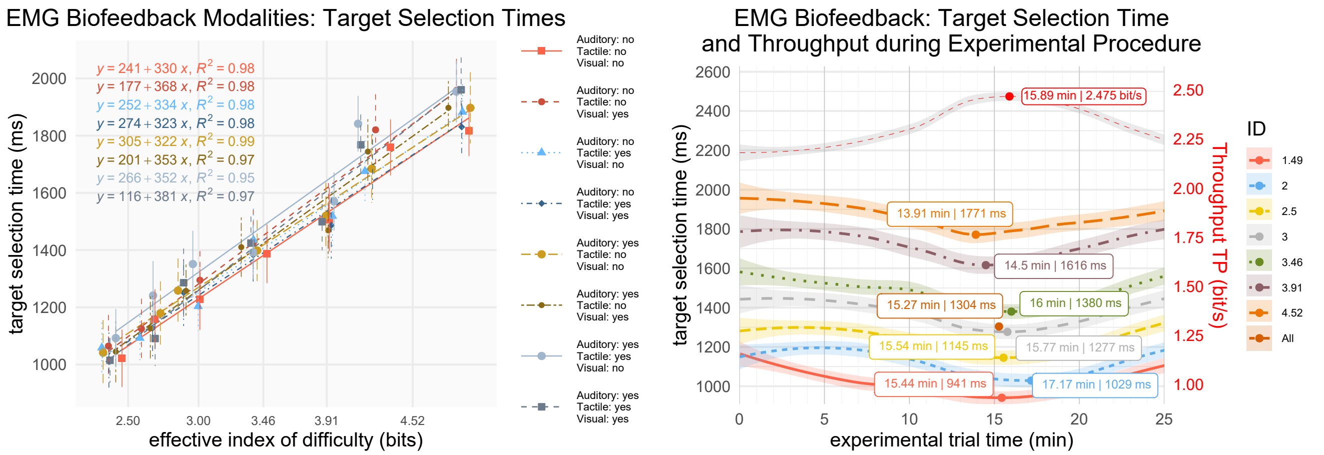
Table 2: Summary of the RM-ANOVA results of throughput and workload measures depending on the three modalities tested.

	Throughput			Workload (RTLX)		
	F(1,39)	p	η_p^2	F(1,39)	p	η_p^2
Auditory	4.857	**.033***	0.111	4.214	**.047***	0.067
Tactile	1.373	.248	0.034	1.254	.270	0.032
Visual	0.084	.774	0.002	2.741	.106	0.067
Auditory×Tactile	2.133	.152	0.052	1.300	.261	0.033
Auditory×Visual	0.679	.415	0.017	1.494	.229	0.038
Tactile×Visual	4.706	**.036***	0.108	2.186	.148	0.054
Auditory×Tactile×Visual	0.637	.429	0.016	2.346	.134	0.058

however, showed no interaction effect with the other factors (all with $p > .136$), indicating that the target selection time does not depend on Auditory, Tactile, or Visual cues. Considering the absence of no overarching three-way interaction, the analysis of the target selection time revealed that the time independent from the difficulty is affected by always two modalities.

4.7.3 Response Time vs Fatigue. All conditions were performed in counter-balanced order using the same muscle (*Biceps brachii*) and over a relatively long period of time ($M = 25.536$ min., $SD = 7.159$). Average trial time (without questionnaires and calibration) per condition was $M = 3.192$ min ($SD = 0.895$). The participants reported strong learning as well as potential fatigue effects (see qualitative results) indicating that there is a non-linear relationship between the duration of the experimental trial and muscle response time. Thus, we evaluated the data to determine a functional relationship between the target selection time and trial duration regarding the different levels of difficulty. We performed a locally estimated scatterplot smoothing (loess) fit to determine the convergence and inflection points when the learning and potential fatigue effects had their best trade-off. Bias-corrected local polynomial regression with automatic smoothing parameter selection and generalized cross-validation (GCV) determined a smoothing matrix with 5.53 parameters based on 17105 observations. The fit ($df = 1$) determined 0.696 as an optimal span control parameter. The final loess fit for movement time among the individual IDs is shown in Figure 7(b). For control, we computed the inflection points and found that the lowest movement times ranged from 13.907 to 17.173 mins ($M = 15.449$, $SD = 0.978$). Spearman correlations coefficients of the IDs with a second-wise sampling of the function fits ranged from 0.650 (strong) to 0.990 (very strong), (all with $p < .001$), indicating that learning and potential fatigue effects converge similarly among the IDs.

4.7.4 Subjective Workload. Shapiro-Wilk test on all conditions did not show any evidence of non-normality on the RTLX score (all with $p > .15$). The results of the analysis are summarized in Table 2. A three-way RM-ANOVA revealed a significant interaction main effect of Auditory feedback. An analysis of the RTLX subscales revealed a main effect of Visual on *performance*, $F(1,39) = 6.029$, $p = .019$, $\eta_p^2 = 0.134$ (medium), a main effect of Auditory on *frustration*, $F(1,39) = 5.245$, $p = .027$, $\eta_p^2 = 0.119$ (medium), and an interaction effect of Tactile × Visual, $F(1,39) = 9.145$, $p = .004$, $\eta_p^2 = 0.190$ (large), no further main or interactions were found



(a) Target selection time for each biofeedback modality

(b) Target selection time during the experimental trial

Figure 7: Target selection time as a function of the IDe 7(a) and target selection time in course of the experiment 7(b) in the second study. All error bars show CI95. The fitted curves in 7(b) indicate a decrease of target selection time due to learning effects and a decrease after potential fatigue. Difficulty-dependent inflection points were found between 13.907 mins (ID=4.52) and 17.173 mins (ID=2). Colored areas in 7(b) indicate the standard error of the loess fit.

between those and other RTLX subscales. Thus, perceived performance was higher when visual cues were on. Frustration was lower when audio was on, and higher when tactile and visual cues were rendered compared to when the modalities were off. All RTLX scores and subscales results are shown in Figure 8.

4.7.5 Modality Preferences. We also asked participants, which feedback they finally prefer and not prefer. A majority of 23.4% ($N = 11$) preferred Visual feedback only. Auditory, Tactile, Auditory & Visual, Tactile & Visual were preferred by 12.8% ($N = 6$) each. All modalities at once were preferred by 8.5% ($N = 4$). Least preferred was Auditory & Tactile with 4.3% ($N = 2$). Only one participant (2.1%) desired no feedback. 10.6% ($N = 5$) participants were too vague or undecided about the best modality. Regarding the worst experience, most participants 25.5% ($N = 12$) rejected Auditory modality. 19.1% ($N = 9$) found that lacking feedback at all worst. 17.0% ($N = 8$) found Tactile worst, 7.50% ($N = 4$) Visual. 6.4% ($N = 3$) each rejected the Auditory & Visual, Auditory & Tactile, or Auditory & Tactile & Visual combinations. Only two participants (4.3%) found Tactile & Visual to be worst, three (6.4%) were not sure or remained vague.

4.8 Qualitative Results

Thematic analysis was used to build a structure and deeper understanding of the qualitative assessments after verbatim transcription. Two researchers went independently through the comments and coded them to identify when and where common categories and patterns occurred. In the next stage, we combined the codes into overarching themes and a coherence meeting was held to merge the results and solve the final discrepancies.

4.8.1 Biofeedback is generally appreciated. The participants found that the feedback methods "were coherent to muscle tension" (P3), "helped me to feel like I have control over my muscle" (P20), the feedback "came pretty quick and accurate to represent the strength imposed" (P44), and that it "made the task easier to complete" (P4, P32). The participants pointed out that all feedback methods were generally "helpful" (P46), "responsive" (P17, P35), "enjoyable" (P25), "interactive" (P31), and that "the apparatus worked quite well" (P42).

4.8.2 Informativeness for usability and flow. Due to the repetitive nature of the task, comments on *usability* were often related to the concept of *flow* and distractions interrupting it. The supportive relationship between *informativeness* and *flow* becomes evident in statements about the feedback as it "increases concentration, reduces stress levels, reduces mental stress and physical exertion" (P39) and that "the pressure indicator helps to focus" (P25). Fifteen participants found the visual feedback as being generally informative, nine of them additionally highlighted that it helps to estimate the muscle tension correctly. It received the most unequivocal positive comments regarding its *informativeness and usability,* considered as "very clear and understandable" (P3), "best compared to tactile and audio" (P38), "noticeable and easy to understand, how it represented the muscle activation" (P13), and "useful to notice the strength I put in the muscle" (P24). Tactile cues were particularly highlighted by P29, "as supportive co-information" alongside with visual feedback. Similarly, P18 mentioned that "the visual feedback was good to have as co-information, but vibration would be preferred by me". Seven participants perceived tactile feedback as the most preferred one. Most of the comments were related to its *usability*. The vibrations were perceived as "very unobtrusive" (P30), "quick and very easy to sense" (P27), "very pleasant" (P10), and "easier to perform the task" (P33).

The least informative and usable cue was the auditory feedback. Only six participants found the auditory feedback as being supportive, one of them acknowledged "the coherence of the required

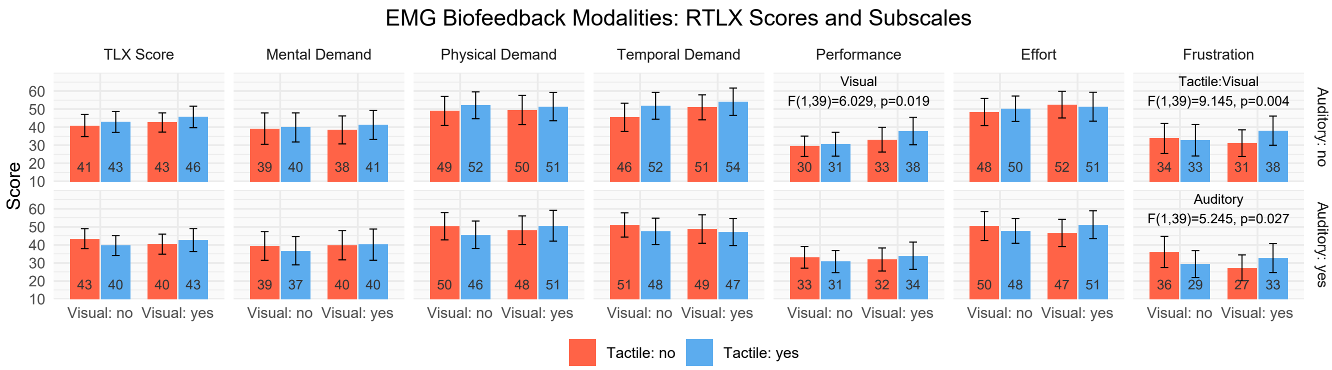


Figure 8: Score and subscale ratings of the NASA Raw-TLX questionnaire of the second study. All error bars show CI95.

muscle tension" (P3) and others found that the feedback "helps to concentrate" (P25) and mentioned that the "sound was a confirmation of the selection" (P26). Participants stated that "some feedback methods on their own were very powerful and could perform better than the other combinations" (P40), and some particularly highlighted that only combined feedback is more informative. For example, P23 pointed out that "the more feedback methods, the better you knew if you hit the points". Still only two participants (P40, P42) preferred a single modality feedback compared to multi-modal feedback, indicating that more cues provide more *informativeness* about the state of the muscle.

4.8.3 Information overload, obtrusiveness, and repetitive patterns distract. P20, for instance, highlighted that the "combination of all feedback methods stressed me", and saw an effect on the own physiological response: "and sometimes even made me tensing my muscle" (P20), concerned regarding an *information overload*. Similarly, P23 stated that "the more feedback, the more stressed I was. Sound was the most stressful". Particularly, the *repetitive patterns* in the auditory modality was considered to be "annoying" (P7, P30, P41, P27) and "stressing" (P14, P23, P41). Participants wondered about the "sound might be better if it was a simple beep" (P30) or considered the circular shape of the visual feedback as sometimes "distracting" (P29, P30). Lacking *obtrusiveness* could also be perceived negatively. P40, for example, mentioned that "without visual feedback, it was a little difficult to follow" or P38 was not able "to focus on vibrations" as it was "not very much influencing during the tasks", both indicating that the participants tried to find support for their *flow*.

4.8.4 Fatigue/exhaustion, inconsistency, and habituation. Many of the suggestions around *fatigue/exhaustion* were related to the ergonomics of the system and the procedure in general, stating the headset felt "heavy after a while" (P6, P37), one had "to bend my neck down a lot for the lower circles as the virtual wall was pretty close" (P14) and "the eyes start straining after using for more than 30 minutes" (P6). The upper arm as a trigger was also criticized because "physical strain on muscle discourages to continue" (P25), "contracting muscle over a long period of time is inconvenient." (P18) and "triggering via the upper arm can be difficult because [...] my head moves slightly when I tense my muscle" (P34). P17 complained that the system was generally "not consistent with actual muscle contraction", some participants had difficulties anticipating between muscle activation and sound, such as P31 stating that "auditory [feedback] took time for me to get it" and one participant found that the vibration baseline was "too intense", pointing to perceived *inconsistency*. Interestingly, one participant particularly highlighted that "tactile feedback increased the inner frustration with wrong targeting" (P28).

A convergence of learning and *fatigue/exhaustion* became evident statements such as from P36, who mentioned that "frustration started peaking at the end because I started to feel that it was on purpose that sometimes I had to tense my muscle longer or harder to make the dot disappear, whereas, in the beginning, I thought it was because I wasn't good at clenching the specific muscle needed". Participants noted that "it was a great experience" (P16), "like playing a video game" (P38), and that they became more proficient after a period of time (P22, P23). Thus, the participants perceived learning as a positive side effect of *habituation*. One participant also desired to improve the system usage through more training sessions (P1) indicating that not all participants suffered from fatigue/exhaustion and even desired to become more familiar with their own muscle activity.

4.8.5 Summary. The participants appreciated *informativeness* and *usability* in their biofeedback modalities as support for their *flow* while using the system. Importantly, the results show that some modalities can produce stress due to their *obtrusiveness*, through *repetitive patterns*, or even by *information overload*, e.g., while using too many modalities. More *unpleasant emotions* were caused by *fatigue/exhaustion* of the muscle or through the system in general, and an *inconsistency* between the signal and the biofeedback modality. Interesting findings here were that some participants noticed an interplay of learning and fatigue effects on their own performance, and reflected on learning the procedure by improving their own performance as well as that *habituation* supported their learning.

4.9 Discussion

The analysis of the results revealed significant main and interaction effects of the feedback modality on objective and subjective measures. The results also show that there is no single modality that systematically improves the target selection time or workload. Even when the qualitative feedback revealed that most participants rather tend to prefer visual feedback, there is no evidence that visual feedback alone increases the objective input performance. However, a main effect of the sound-based conditions revealed that the throughput was generally and negatively influenced by auditory feedback. An interaction effect of auditory with tactile feedback on the mean time indicates that performance can decrease when more feedback is being rendered. Interestingly, while the main effect indicates that audio has a negative impact on throughput and audio was the least favored in the qualitative comments, the subjective frustration was lower when audio was on.

A two-way interaction effect on the throughput while using tactile and visual feedback indicates combined modalities can have a positive impact on the input performance. This is in line with qualitative comments stating that some combinations of feedback modalities can support the participants. However, rendering all modalities at the same time are rather being perceived as distracting and does not necessarily increase objective performance measures.

The participants' qualitative comments provided additional insights into the usage of EMG systems. In particular, the participants noticed a learning effect that converged with potential muscle fatigue after a certain period of time. This was also evident in the objective data and we were able to determine a maximum throughput after 15.9 mins (without calibration phase) at which the participants could optimally activate their biceps. A non-linear relationship between experimental trial time and input performance indicates that participants became familiar with the EMG input after a certain period of time, but also that the muscles then began to tire after a short time span. Thus, the results may depend on the nature of Fitts' tasks, since participants who select potential targets faster also tire more quickly. As participants went subsequently through the conditions and some were faster than others, we can only conditionally assume that everyone experienced sets of muscle fatigue in the same way – which is why we define these as *potential* fatigue effects, as other factors (general fitness, endurance, body awareness, etc.) also could play an individual role after reaching an average optimum.

5 GENERAL DISCUSSION

In two studies, both based on a standardized Fitts' law task in VR, we investigated how isometric muscle contractions, registered with an EMG device, affect the interaction while target selection. Objective and subjective measures from both studies showed that continuous performing voluntary contractions without movements are challenging. In our first study, we found that the input performance between the body locations changed significantly, but, not between the muscles activated isometrically. In the second study, we showed that the input performance with those contractions could be improved using biofeedback – rendering the physiological signal back to the user. We tested three modalities (auditory, tactile, visual) and found that the combination of tactile and visual cues positively and auditory negatively affect the control over the own body function. Lacking interaction effects with the index of difficulty in both studies indicate that the ability to select targets using the HMD and muscle is robust regarding the targets' size and distance, which is important for the design of EMG-based user interfaces [93] or therapeutic applications in VR [2].

The challenging nature of performing voluntary contractions was particularly evident in the qualitative comments. The participants reported learning effects as well as muscle fatigue, which could be found in turning points of the response times in course of the second study. Muscle fatigue caused by isometric contractions is intensively discussed by related work [3, 22, 29]. However, many applications using subtle [71], health-promoting [25, 91, 101], or motionless [14] interactions depend on or even require isometric muscle control [2, 22, 92]. Here, VR has established as a stimulating and motivating kind of application not only to support training but also multi-modal muscle control [42, 84, 89, 101].

The findings are important for designers of (immersive) applications using multi-modal biofeedback based on EMG sensors, however, are not necessarily be limited to applications in VR. We assume that multi-modal feedback using visual and tactile cues can also support users in real-world scenarios, in AR or with other devices registering muscle activities. Bioengineers can facilitate e.g., visual and tactile feedback to train or support people with artificial limbs. The findings can also be transferred to games when multi-modal feedback of physiological signals is desired. However, extensive muscle usage, as in our Fitts' law task, should be avoided when possible. An interesting observation before calibration was that some participants had issues with initially locating the target muscle under the sensor. After touching the corresponding muscle site with the experimenter's fingertips, we observed that the participants were then quicker in forcing their tension in that muscle. This indicates that tactile cues could assist people in directing their isometric contractions and facilitate easier usage while initial application.

5.1 Limitations and Future Work

Our findings on using body location for EMG are limited to the tested muscles and while seated. Consequently, more body locations such as butt, thighs, or shoulders can be tested for EMG input and potentially benefit from (more) biofeedback modalities (c.f. [99]). Isometric muscle contraction at those locations is a sensor-muscle-human dependent process that can also be detected using signal classifiers, e.g., machine learning for improved signal processing. This form of classification becomes potentially significant when conscious and voluntary muscle activity interferes with continuous muscle activity, e.g. while walking or in non-sedentary settings, which can be investigated by future work. Subject of future work could also be an investigation of alternative biofeedback visualizations rendering the visual, audio, and tactile feedback as well as combined electrical muscle stimulation (EMS) and EMG (c.f. [49, 77]) or comparison of different body locations for vibro-tactile feedback.

Our findings can be applied to multi-modal games engaging their users in hands-free interactions or ubiquitous EMG wearables for interaction with virtual or augmented content beyond the lab. EMG applications in physiotherapy, gait and motion analysis, and sports training could be enhanced by interactive multi-modal biofeedback in VR or AR supporting therapists and patients via feedback on quantity and quality of muscle work. We highlight that people with certain disabilities, such as muscular dystrophy, or elderly have varying perceptual thresholds and feedback modalities (e.g., the vibration or sound intensity) as provided in our study might be customized by or adapted to the user. To replicate our studies and for further investigations, we provide the source code with instructions including the Unity Project and Arduino code at Github[3].

5.2 Conclusion

In this paper, we investigated if and how muscle-based input using VR and multi-modal biofeedback with EMG devices can be improved regarding the users' performance and workload. While isometrically activated muscles are more difficult to control than movement-dependent (isotonic) contractions, no difference in input performance was observed among the different body locations with isometric muscle contractions. However, our research shows that interactions with EMG-based systems in VR designed to register voluntary muscle contractions can be improved with combined visual and tactile multi-modal biofeedback. Qualitative feedback pointed to the phenomenon of muscle fatigue and more research is required to understand its role in long-term interaction and the usage of biofeedback. We highlight the necessity of discrimination between isotonic and isometric contractions and to register voluntary contractions in non-sedentary settings.

ACKNOWLEDGMENTS

This research was funded by the Hessian Ministry for Science and Art, Germany (FL1, Mittelbau). We thank Diana Völz, Artus Malech, Valentin Buss, Julia Filzinger, and René Weil for their support of our research.

REFERENCES

[1] Md. Rezwanul Ahsan, Muhammad Ibn Ibrahimy, and Othman O. Khalifa. 2011. Electromygraphy (EMG) signal based hand gesture recognition using artificial neural network (ANN). In *2011 4th International Conference on Mechatronics (ICOM)*. 1–6. https://doi.org/10.1109/ICOM.2011.5937135

[2] Adel Al-Jumaily and Ricardo A. Olivares. 2009. Electromyogram (EMG) Driven System Based Virtual Reality for Prosthetic and Rehabilitation Devices. In *Proceedings of the 11th International Conference on Information Integration and Web-Based Applications and Services* (Kuala Lumpur, Malaysia) *(iiWAS '09)*. Association for Computing Machinery, New York, NY, USA, 582–586. https://doi.org/10.1145/1806338.1806448

[3] M. R. Al-Mulla, F. Sepulveda, M. Colley, and A. Kattan. 2009. Classification of localized muscle fatigue with genetic programming on sEMG during isometric contraction. In *2009 Annual International Conference of the IEEE Engineering in Medicine and Biology Society*. 2633–2638. https://doi.org/10.1109/IEMBS.2009.5335368

[4] Christoph Amma, Thomas Krings, Jonas Böer, and Tanja Schultz. 2015. Advancing Muscle-Computer Interfaces with High-Density Electromyography. In *Proceedings of the 33rd Annual ACM Conference on Human Factors in Computing Systems* (Seoul, Republic of Korea) *(CHI '15)*. Association for Computing Machinery, New York, NY, USA, 929–938. https://doi.org/10.1145/2702123.2702501

[5] Panagiotis K. Artemiadis and Kostas J. Kyriakopoulos. 2011. A Switching Regime Model for the EMG-Based Control of a Robot Arm. *IEEE Transactions on Systems, Man, and Cybernetics, Part B (Cybernetics)* 41, 1 (2011), 53–63. https://doi.org/10.1109/TSMCB.2010.2045120

[6] Woodrow Barfield and Thomas Caudell. 2001. Basic concepts in wearable computers and augmented reality. In *Fundamentals of wearable computers and augmented reality*. CRC Press, 19–42.

[7] John V Basmajian. 1988. Research foundations of EMG biofeedback in rehabilitation. *Biofeedback and Self-regulation* 13, 4 (1988), 275–298.

[8] Karnika Biswas, Oishee Mazumder, and Ananda Sankar Kundu. 2012. Multichannel fused EMG based biofeedback system with virtual reality for gait rehabilitation. In *2012 4th International Conference on Intelligent Human Computer Interaction (IHCI)*. 1–6. https://doi.org/10.1109/IHCI.2012.6481834

[9] Claudio Castellini and Patrick Van Der Smagt. 2009. Surface EMG in advanced hand prosthetics. *Biological cybernetics* 100, 1 (2009), 35–47.

[10] Aniruddha Chatterjee, Vikram Aggarwal, Ander Ramos-Murguialday, Soumyadipta Acharya, and N.v Thakor. 2007. A brain-computer interface with vibrotactile biofeedback for haptic information. *Journal of neuroengineering and rehabilitation* 4 (02 2007), 40. https://doi.org/10.1186/1743-0003-4-40

[11] Po-Jung Chen, I-Wen Penn, Shun-Hwa Wei, Long-Ren Chuang, and Wen-Hsu Sung. 2020. Augmented reality-assisted training with selected Tai-Chi movements improves balance control and increases lower limb muscle strength in older adults: A prospective randomized trial. *Journal of Exercise Science & Fitness* 18, 3 (2020), 142–147. https://doi.org/10.1016/j.jesf.2020.05.003

[12] Kyung Yun Choi and Hiroshi Ishii. 2020. AmbienBeat: Wrist-Worn Mobile Tactile Biofeedback for Heart Rate Rhythmic Regulation. In *Proceedings of the Fourteenth International Conference on Tangible, Embedded, and Embodied Interaction* (Sydney NSW, Australia) *(TEI '20)*. Association for Computing Machinery, New York, NY, USA, 17–30. https://doi.org/10.1145/3374920.3374938

[13] Yun Lak Choi, Bo Kyung Kim, Yong Pil Hwang, Ok Kon Moon, and Wan Suk Choi. 2015. Effects of isometric exercise using biofeedback on maximum voluntary isometric contraction, pain, and muscle thickness in patients with knee osteoarthritis. *Journal of physical therapy science* 27, 1 (2015), 149–153.

[14] Rubana Chowdhury, Mamun Bin Ibne Reaz, Ahmad Ashrif A Bakar, and Sharif Hasan. 2013. Muscle Contraction: The Subtle Way of Human Computer Interaction. *Research Journal of Applied Sciences, Engineering and Technology* 6 (07 2013), 2192–2196.

[15] Jan Pieter Clarys and Jan Cabri. 1993. Electromyography and the study of sports movements: A review. *Journal of Sports Sciences* 11, 5 (1993), 379–448. https://doi.org/10.1080/02640419308730010 arXiv:https://doi.org/10.1080/02640419308730010 PMID: 8301704.

[16] Bret Contreras, Andrew D Vigotsky, Brad J Schoenfeld, Chris Beardsley, and John Cronin. [n. d.]. A comparison of two gluteus maximus EMG maximum voluntary isometric contraction positions - PubMed — pubmed.ncbi.nlm.nih.gov. https://pubmed.ncbi.nlm.nih.gov/26417543/. [Accessed 09-Sep-2022].

[17] Enrico Costanza, Samuel A. Inverso, and Rebecca Allen. 2005. Toward Subtle Intimate Interfaces for Mobile Devices Using an EMG Controller *(CHI '05)*. Association for Computing Machinery, New York, NY, USA, 481–489. https://doi.org/10.1145/1054972.1055039

[18] Enrico Costanza, Samuel A. Inverso, Rebecca Allen, and Pattie Maes. 2007. Intimate Interfaces in Action: Assessing the Usability and Subtlety of Emg-Based Motionless Gestures. In *Proceedings of the SIGCHI Conference on Human Factors in Computing Systems* (San Jose, California, USA) *(CHI '07)*. Association for Computing Machinery, New York, NY, USA, 819–828. https://doi.org/10.1145/1240624.1240747

[19] Marion Cousineau, Laurent Demany, and Daniel Pressnitzer. 2009. What makes a melody: The perceptual singularity of pitch sequences. *The Journal of the Acoustical Society of America* 126, 6 (2009), 3179–3187. https://doi.org/10.1121/1.3257206 arXiv:https://doi.org/10.1121/1.3257206

[20] Jeffrey R Cram, Glenn S Kasman, and Jonathan Holtz. 1998. *Introduction to surface electromyography*. Aspen publishers.

[21] Ronald V Croce. 1986. The effects of EMG biofeedback on strength acquisition. *Biofeedback and Self-regulation* 11, 4 (1986), 299–310.

[22] Darpan Dhawan, Michael Barlow, and Erandi Lakshika. 2019. Prosthetic Rehabilitation Training in Virtual Reality. In *2019 IEEE 7th International Conference on Serious Games and Applications for Health (SeGAH)*. 1–8. https://doi.org/10.1109/SeGAH.2019.8882455

[23] Andy Fields. 2013. Discovering statistics using IBM SPSS statistics. *Thousand Oaks, CA* (2013).

[24] Paul M Fitts. 1954. The information capacity of the human motor system in controlling the amplitude of movement. *Journal of experimental psychology* 47, 6 (1954), 381.

[25] Ana Belén Gámez, Juan José Hernandez Morante, José Luis Martínez Gil, Francisco Esparza, and Carlos Manuel Martínez. 2019. The effect of surface electromyography biofeedback on the activity of extensor and dorsiflexor muscles in elderly adults: a randomized trial. *Scientific reports* 9, 1 (2019), 1–9.

[26] Nadia Garcia-Hernandez, Karen Garza-Martinez, and Vicente Parra-Vega. 2018. Electromyography Biofeedback Exergames to Enhance Grip Strength and Motivation. *Games for Health Journal* 7, 1 (2018), 75–82. https://doi.org/10.1089/g4h.2017.0054 arXiv:https://doi.org/10.1089/g4h.2017.0054 PMID: 29227162.

[27] Marco Gazzoni and Giacinto Luigi Cerone. 2021. *Augmented Reality Biofeedback for Muscle Activation Monitoring: Proof of Concept.* 143–150. https://doi.org/10.1007/978-3-030-64610-3_17

[28] Christopher Gilbert and Donald Moss. 2003. Biofeedback and biological monitoring. *Handbook of mind-body medicine in primary care: Behavioral and physiological tools* (2003), 109–122.

[29] Alberto Greco, Gaetano Valenza, Antonio Bicchi, Matteo Bianchi, and Enzo Pasquale Scilingo. 2019. Assessment of muscle fatigue during isometric contraction using autonomic nervous system correlates. *Biomedical Signal Processing and Control* 51 (2019), 42–49. https://doi.org/10.1016/j.bspc.2019.02.007

[30] José Guerreiro, Raul Martins, Hugo Plácido da Silva, Andre Lourenco, and Ana Fred. 2013. BITalino: A Multimodal Platform for Physiological Computing. *ICINCO 2013 - Proceedings of the 10th International Conference on Informatics in Control, Automation and Robotics* 1.

[3] https://github.com/JessicaSehrt/EMG-VR-biofeedback.git

[31] John Paulin Hansen, Vijay Rajanna, I. Scott MacKenzie, and Per Bækgaard. 2018. A Fitts' Law Study of Click and Dwell Interaction by Gaze, Head and Mouse with a Head-Mounted Display. In *Proceedings of the Workshop on Communication by Gaze Interaction* (Warsaw, Poland) *(COGAIN '18)*. Association for Computing Machinery, New York, NY, USA, Article 7, 5 pages. https://doi.org/10.1145/3206343.3206344

[32] Faizan Haque, Mathieu Nancel, and Daniel Vogel. 2015. Myopoint: Pointing and Clicking Using Forearm Mounted Electromyography and Inertial Motion Sensors. In *Proceedings of the 33rd Annual ACM Conference on Human Factors in Computing Systems* (Seoul, Republic of Korea) *(CHI '15)*. Association for Computing Machinery, New York, NY, USA, 3653–3656. https://doi.org/10.1145/2702123.2702133

[33] Sandra G. Hart. 2006. Nasa-Task Load Index (NASA-TLX); 20 Years Later. *Proceedings of the Human Factors and Ergonomics Society Annual Meeting* 50, 9 (2006), 904–908. https://doi.org/10.1177/154193120605000909 arXiv:https://doi.org/10.1177/154193120605000909

[34] Donald Olding Hebb. 2005. *The organization of behavior: A neuropsychological theory*. Psychology Press.

[35] Hj Hermens, Bart Freriks, Roberto Merletti, Dick F. Stegeman, Joleen H. Blok, Gunter Rau, C. Disselhorst Klug, Gg Hägg, W. J. Blok, and Hermanus J. Hermens. 1999. European recommendations for surface electromyography: Results of the SENIAM Project.

[36] Uganet Hernández Rosa, Jorge Velásquez Tlapanco, Catalina Lara Maya, Enrique Villarreal Ríos, Lidia Martínez González, Emma Rosa Vargas Daza, and Liliana Galicia Rodríguez. 2012. Comparison of the Effectiveness of Isokinetic vs Isometric Therapeutic Exercise in Patients With Osteoarthritis of Knee. *Reumatología Clínica (English Edition)* 8, 1 (2012), 10–14. https://doi.org/10.1016/j.reumae.2011.08.003

[37] A Hirsch. 1862. Chronoscopic experiments on the speed of different senses and nerve transmission. *Bulletin de la Société des Sciences de Neuchâtel* 6 (1862), 100–14.

[38] David Hryvniak, Robert P. Wilder, Jeffrey Jenkins, and Siobhan M. Statuta. 2021. 15 - Therapeutic Exercise. In *Braddom's Physical Medicine and Rehabilitation (Sixth Edition)* (sixth edition ed.), David X. Cifu (Ed.). Elsevier, Philadelphia, 291–315.e4. https://doi.org/10.1016/B978-0-323-62539-5.00015-1

[39] Xiaoling Hu, Kai Y. Tong, Rong Song, Vincent S. Tsang, Penny O. Leung, and Le Li. 2007. Variation of Muscle Coactivation Patterns in Chronic Stroke During Robot-Assisted Elbow Training. *Archives of Physical Medicine and Rehabilitation* 88, 8 (2007), 1022–1029. https://doi.org/10.1016/j.apmr.2007.05.006

[40] He Huang, Steven L Wolf, and Jiping He. 2006. Recent developments in biofeedback for neuromotor rehabilitation. *Journal of neuroengineering and rehabilitation* 3, 1 (2006), 1–12.

[41] Jianli Huang, Meiai Lin, Jianming Fu, Ya Sun, and Qiang Fang. 2021. An Immersive Motor Imagery Training System for Post-Stroke Rehabilitation Combining VR and EMG-based Real-Time Feedback. In *2021 43rd Annual International Conference of the IEEE Engineering in Medicine & Biology Society (EMBC)*. IEEE, 7590–7593.

[42] Tadaaki Ikehara and Kazuyuki Kojima. 2020. Development of Biofeedback Device Using Optimal EMG Frequency Band for Prevention Muscle Fatigue. In *2020 IEEE 9th Global Conference on Consumer Electronics (GCCE)*. 808–809. https://doi.org/10.1109/GCCE50665.2020.9291801

[43] ISO. 2012. 9241–411 Ergonomics of human-system interaction–Part 411: Evaluation methods for the design of physical input devices. *International Organization for Standardization* (2012).

[44] Thomas W. Jackson and Pourya Farzaneh. 2012. Theory-based model of factors affecting information overload. *International Journal of Information Management* 32, 6 (2012), 523–532. https://doi.org/10.1016/j.ijinfomgt.2012.04.006

[45] Muhammad Jamal. 2012. *Signal Acquisition Using Surface EMG and Circuit Design Considerations for Robotic Prosthesis*. https://doi.org/10.5772/52556

[46] Jakob Karolus, Felix Bachmann, Thomas Kosch, Albrecht Schmidt, and Paweł W. Woźniak. 2021. Facilitating Bodily Insights Using Electromyography-Based Biofeedback during Physical Activity. In *Proceedings of the 23rd International Conference on Mobile Human-Computer Interaction* (Toulouse & Virtual, France) *(MobileHCI '21)*. Association for Computing Machinery, New York, NY, USA, Article 14, 15 pages. https://doi.org/10.1145/3447526.3472027

[47] Jonghwa Kim, Stephan Mastnik, and Elisabeth André. 2008. EMG-based hand gesture recognition for realtime biosignal interfacing. In *Proceedings of the 13th international conference on Intelligent user interfaces*. 30–39.

[48] David T. Kluger, Janell S. Joyner, Suzanne M. Wendelken, Tyler S. Davis, Jacob A. George, David M. Page, Douglas T. Hutchinson, Heather L. Benz, and Gregory A. Clark. 2019. Virtual Reality Provides an Effective Platform for Functional Evaluations of Closed-Loop Neuromyoelectric Control. *IEEE Transactions on Neural Systems and Rehabilitation Engineering* 27, 5 (2019), 876–886. https://doi.org/10.1109/TNSRE.2019.2908817

[49] Jarrod Knibbe, Paul Strohmeier, Sebastian Boring, and Kasper Hornbæk. 2017. Automatic Calibration of High Density Electric Muscle Stimulation. *Proc. ACM Interact. Mob. Wearable Ubiquitous Technol.* 1, 3, Article 68 (sep 2017), 17 pages. https://doi.org/10.1145/3130933

[50] Martin Kocur, Lukas Jackermeier, Valentin Schwind, and Niels Henze. 2023. The Effects of Avatar and Environment on Thermal Perception and Skin Temperature in Virtual Reality. In *Proceedings of the 2023 CHI Conference on Human Factors in Computing Systems (CHI '23), April 23-28, 2023, Hamburg, Germany*, Vol. 1. Association for Computing Machinery, 1–23. https://doi.org/10.1145/3544548.3580668

[51] Thomas Kosch, Mariam Hassib, and Albrecht Schmidt. 2016. The Brain Matters: A 3D Real-Time Visualization to Examine Brain Source Activation Leveraging Neurofeedback *(CHI EA '16)*. Association for Computing Machinery, New York, NY, USA, 1570–1576. https://doi.org/10.1145/2851581.2892484

[52] Zuzana Koudelkova, Roman Jasek, and Martina Zabcikova. 2020. Communication Tool for Disabled People Based on Surface Electromyography. In *Proceedings of the 4th International Conference on Medical and Health Informatics* (Kamakura City, Japan) *(ICMHI 2020)*. Association for Computing Machinery, New York, NY, USA, 86–89. https://doi.org/10.1145/3418094.3418110

[53] Hiroki Kurosawa, Daisuke Sakamoto, and Tetsuo Ono. 2018. MyoTilt: A Target Selection Method for Smartwatches Using the Tilting Operation and Electromyography. In *Proceedings of the 20th International Conference on Human-Computer Interaction with Mobile Devices and Services* (Barcelona, Spain) *(MobileHCI '18)*. Association for Computing Machinery, New York, NY, USA, Article 43, 11 pages. https://doi.org/10.1145/3229434.3229457

[54] Junjie Lai, Yun Zhao, Yanjian Liao, Wensheng Hou, Ying Chen, Yao Zhang, Guanglin Li, and Xiaoying Wu. 2017. Design of a multi-degree-of-freedom virtual hand bench for myoelectrical prosthesis. In *2017 2nd International Conference on Advanced Robotics and Mechatronics (ICARM)*. 345–350. https://doi.org/10.1109/ICARM.2017.8273186

[55] Benjamin CY Lee and Stuart M McGill. 2015. Effect of long-term isometric training on core/torso stiffness. *The Journal of Strength & Conditioning Research* 29, 6 (2015), 1515–1526.

[56] Benjamin CY Lee and Stuart M McGill. 2015. Effect of long-term isometric training on core/torso stiffness. *The Journal of Strength & Conditioning Research* 29, 6 (2015), 1515–1526.

[57] Sueyoon Lee, Abdallah El Ali, Maarten Wijntjes, and Pablo Cesar. 2022. Understanding and Designing Avatar Biosignal Visualizations for Social Virtual Reality Entertainment. In *Proceedings of the 2022 CHI Conference on Human Factors in Computing Systems* (New Orleans, LA, USA) *(CHI '22)*. Association for Computing Machinery, New York, NY, USA, Article 425, 15 pages. https://doi.org/10.1145/3491102.3517451

[58] Sojung Lee, Siyeon Kim, Daeyoung Lim, Dong-Eun Kim, and Wonyoung Jeong. 2021. Analysis of EMG Electrode Locations Using 3D Body Scanning for Digital Pattern Construction of a Smart EMG Suit. *Sustainability* 13, 5 (2021). https://doi.org/10.3390/su13052654

[59] Yurong Li, Jun Chen, and Yuan Yang. 2019. A Method for Suppressing Electrical Stimulation Artifacts from Electromyography. *International Journal of Neural Systems* 29, 06 (2019), 1850054. https://doi.org/10.1142/S0129065718500545 arXiv:https://doi.org/10.1142/S0129065718500545 PMID: 30646793.

[60] Yu Liang, Dalei Wu, Dakila Ledesma, Chris Davis, Robert Slaughter, and Zibin Guo. 2018. Virtual Tai-Chi System: A smart-connected modality for rehabilitation. *Smart Health* 9-10 (2018), 232–249. https://doi.org/10.1016/j.smhl.2018.07.021 CHASE 2018 Special Issue.

[61] Lizheng Liu, Jianjun Cui, Jian Niu, Na Duan, Xianjia Yu, Qingqing Li, Shih-Ching Yeh, and Li-Rong Zheng. 2020. Design of Mirror Therapy System Base on Multi-Channel Surface-Electromyography Signal Pattern Recognition and Mobile Augmented Reality. *Electronics* 9, 12 (2020). https://doi.org/10.3390/electronics9122142

[62] Pedro Lopes, Lewis L Chuang, and Pattie Maes. 2021. Physiological I/O. In *Extended Abstracts of the 2021 CHI Conference on Human Factors in Computing Systems* (Yokohama, Japan) *(CHI EA '21)*. Association for Computing Machinery, New York, NY, USA, Article 161, 4 pages. https://doi.org/10.1145/3411763.3450407

[63] Joseph A Lucca and Susan Jean Recchiuti. 1983. Effect of electromyographic biofeedback on an isometric strengthening program. *Physical therapy* 63, 2 (1983), 200–203.

[64] Mingxing Lyu, Wei-Hai Chen, Xilun Ding, Jianhua Wang, Zhongcai Pei, and Baochang Zhang. 2019. Development of an EMG-Controlled Knee Exoskeleton to Assist Home Rehabilitation in a Game Context. *Frontiers in Neurorobotics* 13 (2019). https://doi.org/10.3389/fnbot.2019.00067

[65] Sha Ma, Martin Varley, Lik-Kwan Shark, and Jim Richards. 2010. EMG Biofeedback Based VR System for Hand Rotation and Grasping Rehabilitation. In *2010 14th International Conference Information Visualisation*. 479–484. https://doi.org/10.1109/IV.2010.73

[66] I. Scott MacKenzie and William Buxton. 1992. Extending Fitts' Law to Two-Dimensional Tasks *(CHI '92)*. Association for Computing Machinery, New York, NY, USA, 219–226. https://doi.org/10.1145/142750.142794

[67] Oishee Mazumder and Ananda Sankar Kundu. 2012. EMG Based Multichannel Human Computer Interface for Rehabilitation Training. In *8th National Conference on Medical Informatics*.

[68] Dennis J. McFarland and Anthony T. Cacace. 1992. Aspects of Short-Term Acoustic Recognition Memory: Modality and Serial Position Effects. *Audiology* 31, 6 (1992), 342–352. https://doi.org/10.3109/00206099209072922 arXiv:https://www.tandfonline.com/doi/pdf/10.3109/00206099209072922

[69] Roberto Merletti and Dario Farina. 2016. *Biophysics of the Generation of EMG Signals*. 1–24. https://doi.org/10.1002/9781119082934.ch02

[70] Philip J Millar, Cheri L McGowan, Véronique A Cornelissen, Claudio G Araujo, and Ian L Swaine. 2014. Evidence for the role of isometric exercise training in reducing blood pressure: potential mechanisms and future directions. *Sports Medicine* 44, 3 (2014), 345–356.

[71] Clara Moge, Katherine Wang, and Youngjun Cho. 2022. Shared User Interfaces of Physiological Data: Systematic Review of Social Biofeedback Systems and Contexts in HCI. In *Proceedings of the 2022 CHI Conference on Human Factors in Computing Systems* (New Orleans, LA, USA) *(CHI '22)*. Association for Computing Machinery, New York, NY, USA, Article 301, 16 pages. https://doi.org/10.1145/3491102.3517495

[72] Inhyuk Moon, Myungjoon Lee, Junuk Chu, and Museong Mun. 2005. Wearable EMG-based HCI for Electric-Powered Wheelchair Users with Motor Disabilities. In *Proceedings of the 2005 IEEE International Conference on Robotics and Automation*. 2649–2654. https://doi.org/10.1109/ROBOT.2005.1570513

[73] Fabricio Muri, Celina Carbajal, Ana M Echenique, Hugo Fernández, and Natalia M López. 2013. Virtual reality upper limb model controlled by EMG signals. *Journal of Physics: Conference Series* 477 (dec 2013), 012041. https://doi.org/10.1088/1742-6596/477/1/012041

[74] Lennart Erik Nacke, Michael Kalyn, Calvin Lough, and Regan Lee Mandryk. 2011. Biofeedback Game Design: Using Direct and Indirect Physiological Control to Enhance Game Interaction. In *Proceedings of the SIGCHI Conference on Human Factors in Computing Systems* (Vancouver, BC, Canada) *(CHI '11)*. Association for Computing Machinery, New York, NY, USA, 103–112. https://doi.org/10.1145/1978942.1978958

[75] Go Nakamura, Taro Shibanoki, Futoshi Mizobe, Akito Masuda, Yuichiro Honda, Takaaki Chin, and Toshio Tsuji. 2016. A High-Fidelity Virtual Training System for Myoelectric Prostheses Using an Immersive HMD. In *Proceedings of the International Convention on Rehabilitation Engineering & Assistive Technology (i-CREATe 2016)*. Singapore Therapeutic, Assistive & Rehabilitative Technologies (START) Centre, Midview City, SGP, Article 18, 4 pages.

[76] Nurhazimah Nazmi, Mohd Azizi Abdul Rahman, Shin-Ichiroh Yamamoto, Siti Anom Ahmad, Hairi Zamzuri, and Saiful Amri Mazlan. 2016. A review of classification techniques of EMG signals during isotonic and isometric contractions. *Sensors* 16, 8 (2016), 1304.

[77] Jun Nishida and Kenji Suzuki. 2017. BioSync: A Paired Wearable Device for Blending Kinesthetic Experience. In *Proceedings of the 2017 CHI Conference on Human Factors in Computing Systems* (Denver, Colorado, USA) *(CHI '17)*. Association for Computing Machinery, New York, NY, USA, 3316–3327. https://doi.org/10.1145/3025453.3025829

[78] Dustin J. Oranchuk, Adam G. Storey, André R. Nelson, and John B. Cronin. 2019. Isometric training and long-term adaptations: Effects of muscle length, intensity, and intent: A systematic review. *Scandinavian Journal of Medicine & Science in Sports* 29, 4 (2019), 484–503. https://doi.org/10.1111/sms.13375 arXiv:https://onlinelibrary.wiley.com/doi/pdf/10.1111/sms.13375

[79] Yun Suen Pai, Tilman Dingler, and Kai Kunze. 2019. Assessing hands-free interactions for VR using eye gaze and electromyography. *Virtual Reality* 23, 2 (2019), 119–131.

[80] Francesca Palermo, Matteo Cognolato, Ivan Eggel, Manfredo Atzori, and Henning Müller. 2019. An Augmented Reality Environment to Provide Visual Feedback to Amputees During SEMG Data Acquisitions. In *Towards Autonomous Robotic Systems: 20th Annual Conference, TAROS 2019, London, UK, July 3–5, 2019, Proceedings, Part II* (London, United Kingdom). Springer-Verlag, Berlin, Heidelberg, 3–14. https://doi.org/10.1007/978-3-030-25332-5_1

[81] Francesca Palermo, Matteo Cognolato, Ivan Eggel, Manfredo Atzori, and Henning Müller. 2019. An Augmented Reality Environment to Provide Visual Feedback to Amputees During SEMG Data Acquisitions. In *Towards Autonomous Robotic Systems: 20th Annual Conference, TAROS 2019, London, UK, July 3–5, 2019, Proceedings, Part II* (London, United Kingdom). Springer-Verlag, Berlin, Heidelberg, 3–14. https://doi.org/10.1007/978-3-030-25332-5_1

[82] Arrigo Palumbo, Patrizia Vizza, Barbara Calabrese, and Nicola Ielpo. 2021. Biopotential Signal Monitoring Systems in Rehabilitation: A Review. *Sensors* 21, 21 (2021). https://doi.org/10.3390/s21217172

[83] Erik Peper, Richard Harvey, and Naoki TAKEBAYASHI. 2009. Biofeedback an evidence based approach in clinical practice. *Japanese Journal of Biofeedback Research* 36, 1 (2009), 3–10. https://doi.org/10.20595/jjbf.36.1_3

[84] Ivan Phelan, Madelynne Arden, Maria Matsangidou, Alicia Carrion-Plaza, and Shirley Lindley. 2021. Designing a Virtual Reality Myoelectric Prosthesis Training System for Amputees. In *Extended Abstracts of the 2021 CHI Conference on Human Factors in Computing Systems* (Yokohama, Japan) *(CHI EA '21)*. Association for Computing Machinery, New York, NY, USA, Article 49, 7 pages. https://doi.org/10.1145/3411763.3443454

[85] Nicolas Place, Boris Matkowski, Alain Martin, and Romuald Lepers. 2006. Synergists activation pattern of the quadriceps muscle differs when performing sustained isometric contractions with different EMG biofeedback. *Experimental brain research* 174, 4 (2006), 595–603.

[86] Matthew S. Prewett, Liuquin Yang, Frederick R. B. Stilson, Ashley A. Gray, Michael D. Coovert, Jennifer Burke, Elizabeth Redden, and Linda R. Elliot. 2006. The Benefits of Multimodal Information: A Meta-Analysis Comparing Visual and Visual-Tactile Feedback. In *Proceedings of the 8th International Conference on Multimodal Interfaces* (Banff, Alberta, Canada) *(ICMI '06)*. Association for Computing Machinery, New York, NY, USA, 333–338. https://doi.org/10.1145/1180995.1181057

[87] Jennifer Reed and Jimmy D Bowen. 2008. Chapter 33 - Principles of Sports Rehabilitation. In *The Sports Medicine Resource Manual*, Peter H. Seidenberg and Anthony I. Beutler (Eds.). W.B. Saunders, Philadelphia, 431–436. https://doi.org/10.1016/B978-141603197-0.10033-3

[88] Holger Regenbrecht, Joerg Hauber, Ralph Schoenfelder, and Andreas Maegerlein. 2005. Virtual Reality Aided Assembly with Directional Vibro-Tactile Feedback *(GRAPHITE '05)*. Association for Computing Machinery, New York, NY, USA, 381–387. https://doi.org/10.1145/1101389.1101464

[89] Lorcan Reidy, Dennis Chan, Charles Nduka, and Hatice Gunes. 2020. Facial Electromyography-Based Adaptive Virtual Reality Gaming for Cognitive Training. In *Proceedings of the 2020 International Conference on Multimodal Interaction* (Virtual Event, Netherlands) *(ICMI '20)*. Association for Computing Machinery, New York, NY, USA, 174–183. https://doi.org/10.1145/3382507.3418845

[90] Alejandro Lopez Rincon, Hiroshi Yamasaki, and Shingo Shimoda. 2016. Design of a video game for rehabilitation using motion capture, EMG analysis and virtual reality. In *2016 International Conference on Electronics, Communications and Computers (CONIELECOMP)*. 198–204. https://doi.org/10.1109/CONIELECOMP.2016.7438575

[91] Aidan D Roche, Ben Lakey, Irene Mendez, Ivan Vujaklija, Dario Farina, and Oskar C Aszmann. 2019. Clinical perspectives in upper limb prostheses: An update. *Current Surgery Reports* 7, 3 (2019), 1–10.

[92] Aidan D Roche, Hubertus Rehbaum, Dario Farina, and Oskar C Aszmann. 2014. Prosthetic myoelectric control strategies: a clinical perspective. *Current Surgery Reports* 2, 3 (2014), 1–11.

[93] Javier San Agustin, John Paulin Hansen, Dan Witzner Hansen, and Henrik Skovsgaard. 2009. Low-Cost Gaze Pointing and EMG Clicking. In *CHI '09 Extended Abstracts on Human Factors in Computing Systems* (Boston, MA, USA) *(CHI EA '09)*. Association for Computing Machinery, New York, NY, USA, 3247–3252. https://doi.org/10.1145/1520340.1520466

[94] Mirella Santos Pessoa de Melo, José Gomes da Silva Neto, João Marcelo Xavier Natario Teixeira, Alana Elza Fontes Da Gama, and Veronica Teichrieb. 2019. An EMG-Based Virtual Reality Application for Motor Rehabilitation. In *2019 21st Symposium on Virtual and Augmented Reality (SVR)*. 170–177. https://doi.org/10.1109/SVR.2019.00041

[95] T Scott Saponas, Desney S. Tan, Dan Morris, and Ravin Balakrishnan. 2008. Demonstrating the Feasibility of Using Forearm Electromyography for Muscle-Computer Interfaces *(CHI '08)*. Association for Computing Machinery, New York, NY, USA, 515–524. https://doi.org/10.1145/1357054.1357138

[96] T. Scott Saponas, Desney S. Tan, Dan Morris, Jim Turner, and James A. Landay. 2010. Making Muscle-Computer Interfaces More Practical. In *Proceedings of the SIGCHI Conference on Human Factors in Computing Systems* (Atlanta, Georgia, USA) *(CHI '10)*. Association for Computing Machinery, New York, NY, USA, 851–854. https://doi.org/10.1145/1753326.1753451

[97] Steven L Schandler and William W Grings. 1974. A system for providing tactile EMG biofeedback. *Behavior Research Methods & Instrumentation* 6, 6 (1974), 541–542.

[98] Valentin Schwind, Pascal Knierim, Nico Haas, and Niels Henze. 2019. Using Presence Questionnaires in Virtual Reality. In *Proceedings of the 2019 CHI Conference on Human Factors in Computing Systems* (Glasgow, Scotland Uk) *(CHI '19)*. Association for Computing Machinery, New York, NY, USA, 1–12. https://doi.org/10.1145/3290605.3300590

[99] Jessica Sehrt, Bent Braams, Niels Henze, and Valentin Schwind. 2022. Social Acceptability in Context: Stereotypical Perception of Shape, Body Location, and Usage of Wearable Devices. *Big Data and Cognitive Computing* 6, 4 (2022). https://doi.org/10.3390/bdcc6040100

[100] Aaron R. Seitz. 2013. Cognitive Neuroscience: Targeting Neuroplasticity with Neural Decoding and Biofeedback. *Current Biology* 23, 5 (2013), R210–R212. https://doi.org/10.1016/j.cub.2013.01.015

[101] Da Shuhan, Hirofumi Tanabe, Yoshifumi Morita, and Zhou Peichen. 2019. Effect of Introducing EMG Biofeedback to a Finger Extensor Facilitation Training Device for Hemiplegic Patients after Strokes. In *2019 19th International Conference on Control, Automation and Systems (ICCAS)*. 184–187. https://doi.org/10.23919/ICCAS47443.2019.8971742

[102] A. N. Silva, K. L. Nogueira, M. B. Silva, A. Cardoso, E. A. Lamounier, and A. B. Soares. 2013. A virtual electro myographic biofeedback environment for motor rehabilitation therapies. In *2013 ISSNIP Biosignals and Biorobotics Conference: Biosignals and Robotics for Better and Safer Living (BRC)*. 1–4. https://doi.org/10.

1109/BRC.2013.6487541
[103] Stanislaw Solnik, Paul DeVita, Patrick Rider, Ben Long, and Tibor Hortobagyi. 2008. Teager–Kaiser Operator improves the accuracy of EMG onset detection independent of signal-to-noise ratio. *Acta of bioengineering and biomechanics / Wrocław University of Technology* 10 (02 2008), 65–8.
[104] James P Stannard, Andrew H Schmidt, Andreas Wentzensen, Florian Gebhard, Paul Alfred Grützner, Steffen Ruchholtz, and Ulrich Stöckle. 2021. *Spezielle Unfallchirurgie*. Thieme.
[105] Catriona Steele. 2012. *Applications of EMG in clinical and sports medicine*. BoD–Books on Demand.
[106] Kotaro Takeda, Genichi Tanino, and Hiroyuki Miyasaka. 2017. Review of devices used in neuromuscular electrical stimulation for stroke rehabilitation. *Medical devices (Auckland, NZ)* 10 (2017), 207.
[107] Atau Tanaka and R. Benjamin Knapp. 2002. Multimodal Interaction in Music Using the Electromyogram and Relative Position Sensing *(NIME '02)*. National University of Singapore, SGP, 1–6.
[108] Drew Tiene. 2000. Sensory Mode and "Information Load": Examining the Effects of Timing on Multisensory Processing. *International Journal of Instructional Media* 27 (01 2000), 183–198.
[109] Tomáš Tisančín, Adam J. Sporka, and Ondřej Poláček. 2014. EMG Sensors as Virtual Input Devices. In *Proceedings of the 2014 Mulitmedia, Interaction, Design and Innovation International Conference on Multimedia, Interaction, Design and Innovation* (Warsaw, Poland) *(MIDI '14)*. Association for Computing Machinery, New York, NY, USA, 1–5. https://doi.org/10.1145/2643572.2643591
[110] Cinthya Lourdes Toledo-Peral, Gabriel Vega-Martínez, Jorge Airy Mercado-Gutiérrez, Gerardo Rodríguez-Reyes, Arturo Vera-Hernández, Lorenzo Leija-Salas, and Josefina Gutiérrez-Martínez. 2022. Virtual/Augmented Reality for Rehabilitation Applications Using Electromyography as Control/Biofeedback: Systematic Literature Review. *Electronics* 11, 14 (2022). https://doi.org/10.3390/electronics11142271
[111] Yasunori Tsubouchi and Kenji Suzuki. 2010. BioTones: A wearable device for EMG auditory biofeedback. In *2010 Annual International Conference of the IEEE Engineering in Medicine and Biology*. 6543–6546. https://doi.org/10.1109/IEMBS.2010.5627097
[112] Laia Turmo Vidal, Hui Zhu, and Abraham Riego-Delgado. 2020. BodyLights: Open-Ended Augmented Feedback to Support Training Towards a Correct Exercise Execution. In *Proceedings of the 2020 CHI Conference on Human Factors in Computing Systems* (Honolulu, HI, USA) *(CHI '20)*. Association for Computing Machinery, New York, NY, USA, 1–14. https://doi.org/10.1145/3313831.3376268
[113] Angela Vujic, Christopher Krause, Georgette Tso, Jiaqi Lin, Bicheng Han, and Pattie Maes. 2019. Gut-Brain Computer Interfacing (GBCI) : Wearable Monitoring of Gastric Myoelectric Activity. In *2019 41st Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC)*. 5886–5889. https://doi.org/10.1109/EMBC.2019.8856568
[114] Qian Wang, Xiang Chen, Ruizhi Chen, Yuwei Chen, and Xu Zhang. 2013. Electromyography-Based Locomotion Pattern Recognition and Personal Positioning Toward Improved Context-Awareness Applications. *IEEE Transactions on Systems, Man, and Cybernetics: Systems* 43, 5 (2013), 1216–1227. https://doi.org/10.1109/TSMC.2013.2256857
[115] Joseph P. Weigel and Darryl Millis. 2014. 24 - Biomechanics of Physical Rehabilitation and Kinematics of Exercise. In *Canine Rehabilitation and Physical Therapy (Second Edition)* (second edition ed.), Darryl Millis and David Levine (Eds.). W.B. Saunders, St. Louis, 401–430. https://doi.org/10.1016/B978-1-4377-0309-2.00024-7
[116] Jay M Weiss, Lyn D Weiss, and Julie K Silver. 2021. *Easy EMG-E-Book: A Guide to Performing Nerve Conduction Studies and Electromyography*. Elsevier Health Sciences.
[117] Christopher Wickens. 2008. Multiple Resources and Mental Workload. *Human factors* 50 (07 2008), 449–55. https://doi.org/10.1518/001872008X288394
[118] Yukang Yan, Chun Yu, Xin Yi, and Yuanchun Shi. 2018. HeadGesture: Hands-Free Input Approach Leveraging Head Movements for HMD Devices. *Proc. ACM Interact. Mob. Wearable Ubiquitous Technol.* 2, 4, Article 198 (dec 2018), 23 pages. https://doi.org/10.1145/3287076
[119] Caglar Yildirim. 2022. Point and Select: Effects of Multimodal Feedback on Text Entry Performance in Virtual Reality. *International Journal of Human–Computer Interaction* 0, 0 (2022), 1–15. https://doi.org/10.1080/10447318.2022.2107330 arXiv:https://doi.org/10.1080/10447318.2022.2107330
[120] Ji Yoo, Dong Lee, Yon Sim, Joshua You, and Cheol Kim. 2014. Effects of innovative virtual reality game and EMG biofeedback on neuromotor control in cerebral palsy. *Bio-medical materials and engineering* 24 (09 2014), 3613–8. https://doi.org/10.3233/BME-141188
[121] Bin Yu, Mathias Funk, Jun Hu, and Loe Feijs. 2018. Unwind: a musical biofeedback for relaxation assistance. *Behaviour & Information Technology* 37, 8 (2018), 800–814. https://doi.org/10.1080/0144929X.2018.1484515 arXiv:https://doi.org/10.1080/0144929X.2018.1484515
[122] TNST Zawawi, AR Abdullah, MH Jopri, T Sutikno, NM Saad, and R Sudirman. 2018. A review of electromyography signal analysis techniques for musculoskeletal disorders. *Indonesian Journal of Electrical Engineering and Computer Science* 11, 3 (2018), 1136–1146.
[123] Xu Zhang, Xiang Chen, Yun Li, Vuokko Lantz, Kongqiao Wang, and Jihai Yang. 2011. A Framework for Hand Gesture Recognition Based on Accelerometer and EMG Sensors. *IEEE Transactions on Systems, Man, and Cybernetics - Part A: Systems and Humans* 41, 6 (2011), 1064–1076. https://doi.org/10.1109/TSMCA.2011.2116004
[124] Yang Zhou, Chaoyang Chen, Mark Cheng, Sreten Franovic, Stephanie Muh, and Stephen Lemos. 2020. Real-Time Surface EMG Pattern Recognition for Shoulder Motions Based on Support Vector Machine. In *Proceedings of the 2020 9th International Conference on Computing and Pattern Recognition* (Xiamen, China) *(ICCPR 2020)*. Association for Computing Machinery, New York, NY, USA, 63–66. https://doi.org/10.1145/3436369.3437434
[125] Yu Zhuang, Shaowei Yao, Chenming Ma, and Rong Song. 2019. Admittance Control Based on EMG-Driven Musculoskeletal Model Improves the Human–Robot Synchronization. *IEEE Transactions on Industrial Informatics* 15, 2 (2019), 1211–1218. https://doi.org/10.1109/TII.2018.2875729