Imprecise but Fun: Playful Interaction Using Electromyography

JAKOB KAROLUS, LMU Munich, Germany
SIMON THANHEISER, LMU Munich, Germany
DAVID PETERSON, Chalmers University of Technology, Sweden
NICOLAS VIOT, LII ENAC, France
THOMAS KOSCH, Utrecht University, the Netherlands
ALBRECHT SCHMIDT, LMU Munich, Germany
PAWEŁ W. WOŹNIAK, Chalmers University of Technology, Sweden

Novel input methods for game design often excite users, especially if they extend the way one interacts with the system. Electromyography (EMG) has the inherent potential to provide an intuitive—yet challenging—input channel for interactive systems. While this difficulty in control often limits the scope of applications for EMG in most systems, we argue that these qualities are especially relevant for games and playful interaction. The inherently challenging qualities of EMG input make the modality a prime candidate for designing body-centric playful experiences. Yet, we still need to understand its limitations to create engaging rather than frustrating experiences for users. In this work, we investigate EMG's potential to support playful interaction through exploratory studies, deriving feasible game interactions based on EMG's technical constraints, and study their application in game design. Based on our findings, we highlight design implications and pitfalls to avoid when creating EMG-based entertainment systems.

CCS Concepts: • **Human-centered computing → Interaction paradigms**; *Ubiquitous and mobile computing systems and tools.*

Additional Key Words and Phrases: physiological interaction; electromyography; playful interaction

ACM Reference Format:
Jakob Karolus, Simon Thanheiser, David Peterson, Nicolas Viot, Thomas Kosch, Albrecht Schmidt, and Paweł W. Woźniak. 2022. Imprecise but Fun: Playful Interaction Using Electromyography. *Proc. ACM Hum.-Comput. Interact.* 6, MHCI, Article 190 (September 2022), 21 pages. https://doi.org/10.1145/3546725

1 INTRODUCTION

Physiological sensing broadens our possibilities to augment interaction in games and playful interaction. Biosignals from users can provide insights into the current state of mind [6] while enabling novel ways of interacting with the virtual world [33]. Yet, robustness and deployment are still major challenges for using physiological sensing in interactive systems.

190

Authors' addresses: Jakob Karolus, jakob.karolus@ifi.lmu.de, LMU Munich, Germany; Simon Thanheiser, thansimo@gmail.com, LMU Munich, Germany; David Peterson, davpete@student.chalmers.se, Chalmers University of Technology, Sweden; Nicolas Viot, nicolas.viot@enac.fr, LII ENAC, France; Thomas Kosch, t.a.kosch@uu.nl, Utrecht University, the Netherlands; Albrecht Schmidt, albrecht.schmidt@ifi.lmu.de, LMU Munich, Germany; Paweł W. Woźniak, pawel.wozniak@chalmers.se, Chalmers University of Technology, Sweden.

2573-0142/2022/9-ART190 $15.00
https://doi.org/10.1145/3546725

Electromyography (EMG) [29] has the potential to turn these limitations into opportunities for game design. The inherent potential to allow for challenging—yet intuitive—design of interaction control makes EMG-based input a prime candidate to explore in games [7]. While research has already contributed designs and implementations for utilizing EMG signals, e.g., the seminal work by Saponas et al. [44] introducing the notion of muscle-computer interfaces, the design qualities of EMG as a direct input modality remain an open research question. Further, the intently body-centric character off EMG suggests that the modality could offer new design opportunities for experiences which focus on motion [26] and exertion [30] (see Figure 1). These opportunities are yet to be fully understood.

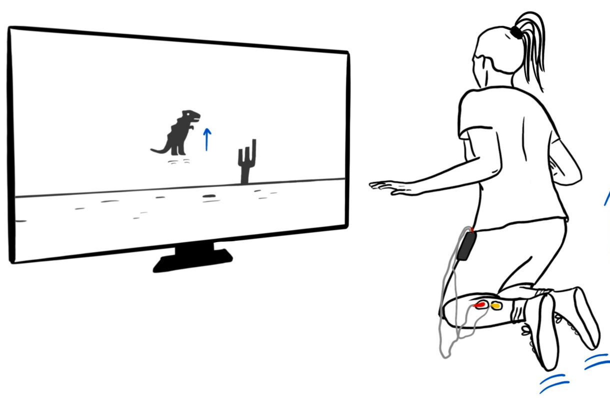

Fig. 1. Possible playful interaction with EMG-based input controls (measuring leg muscle activity) in an exertion game.

Consequently, there is a need to better understand the constraints of our muscular control to allow building interactive experiences which creatively use EMG input. It is yet to be studied how muscle input can be used to provide a challenge, while avoiding frustration. To address this research gap, we present an investigation of EMG's design qualities with regard to creating playful interaction that proves challenging for users. We investigate designs which use the inherent capabilities and limitations of our muscle to offer an engaging experience. This way the difficulty of the task is primarily induced by the limits of the body and not the design of the task. In such scenarios, EMG becomes an input modality which offers challenge instead of efficiency.

We explored the design constraints in EMG-based interfaces for playful interaction in a pilot and two exploratory studies. First, we confirmed that explicit control via EMG input is possible for a basic steering task in our pilot study. Subsequently, we evaluated the constraints of EMG in terms of precision and range of movements in a task where participants controlled an adjustable third hand (soldering help), allowing us to estimate the range of applications which are feasible with EMG-based control. Lastly, we apply the previous findings in a VR game with EMG-based control, drawing implications for the use of EMG as challenging input in games.

Our work contributes design implications for the use of EMG in game design and for playful interaction. Having identified the potential of EMG, we investigated their limits in a motor control task and highlighted how these findings inform elements in game design.

2 RELATED WORK

The primary field of application of electromyography (EMG) lies within the medical domain, used, for example, for detecting muscle diseases [3] or for prosthetic control [13, 36]. Extensive research (cf. [39, 40, 46]) on EMG signal classification has been conducted in this domain with benchmark datasets (cf. Ninapro[1]) being available. Due to the availability of affordable recording equipment, HCI has recently taken an interest in the diverse range of EMG-based applications for interactive systems.

2.1 EMG as a Modality in HCI

The applicability of EMG as a sensing tool for involuntary muscle activity, but also for discretionary use of muscles, has allowed a diverse set of applications scenarios to appear in HCI research.

Facial EMG, for example, plays an important role in detecting emotional states [25, 49], being able to reveal covert behavior [37]. This discreet property of EMG was leveraged by Constanza et al. as well in their work on EMG-based intimate interfaces [4, 5].

Most research on EMG-based interactive systems has been focused on enabling explicit gesture interaction by recognizing their distinct muscle activation signature. Following seminal work by Saponas et al. [44] introducing the idea of muCIs (muscle-computer interfaces), researchers investigated different recording setups [2], modified algorithms for calibration [15, 20], use case scenarios, such as music [19], and the feasibility of low-cost, mobile sensing devices [34, 45]. While these research works have contributed technical requirements for opportune use case scenarios, we provide a first investigation into how EMG can be leveraged as a challenging input control for game design.

A rising trend for EMG-based products can be observed on the consumer market as well. Especially for fitness-related products, EMG sensors are a valid alternative to IMU[2]-based systems. Integrated systems, such as Athos[3], Myontec[4], and Mpower[5] allow users to monitor their muscle activity, making EMG readily available for users. This trend towards greater availability of EMG sensing devices addresses deployment challenges and makes EMG-based games available to a wider audience.

2.2 Physiological Sensing and Game Design

Having access to a user's biosignals is not only beneficial for fitness applications. A variety of signals have been employed successfully for game design [16]. Researchers have explored physiological sensing for both direct game control, such as using a BCI for character movements [33], as well as for indirect control, e.g., adapting the game's difficulty based on the user's cognitive state [6]. Nacke et al. [31] elaborated on the strengths and weaknesses of both approaches and provided guidelines on their usage.

Due to its heritage from the medical domain, games involving EMG-based input are often used for rehabilitation, providing motivation for patients (cf. [10, 24, 41**?**]). Interestingly, work by van Dijk et al. [48] showed that learning EMG control in a game does not necessarily translate to more adequate prosthetic control. Yet, their work also showed that participant improved in their own muscle control. In contrast, non-medical games which involve physical activity, often called exergames [8] make limited use of EMG. While past research did demonstrate prototypes of EMG

[1] http://ninaweb.hevs.ch/
[2] Inertial measurement unit
[3] https://www.liveathos.com/
[4] https://www.myontec.com/
[5] http://www.mpower-bestrong.com/index.html

exergames [9, 43], it sill remains a challenge to systematically understand the properties of EMG as an input modality and its potential benefits to exergaming.

3 METHODOLOGY

While mimicking movements and controlling our extremities is an inherent part of controlling our bodies, exhibiting direct control over specific muscles can be challenging. While learning new movements, we do not rely on direct sensory access to our muscles. Rather, we implicitly solve a complex numerical problem involving numerous muscles through a multitude of iterations. This process of consolidating motor memory is still not completely understood even today [22].

Thus, while using our muscles is intuitive on the one side, it can be very challenging to actuate specific muscles. This highlights the potential for direct muscle input as a challenging input modality for game design. Users could potentially connect movements in both virtual and real world, creating a more engaging experience. To investigate this opportunity, we first confirmed the feasibility of explicit control via EMG for a basic steering task in a pilot study using a low-cost recording setup. In two further studies, we employed the same apparatus to investigate the properties of EMG as a tool for interaction design— constraints in terms of precision and range of movements. By doing so, we explore the possible range of application scenarios, suitability of different sensing locations, and the usage of EMG-based input as an element for designing playful interactions, particularly in games. An overview of how the individual studies contribute to our design implications is depicted in Figure 2.

RQ1: *What are the constraints of EMG-based input for motor control?* After establishing the feasibility of EMG-based input for direct control in our pilot study, we investigated possible constraints of EMG's precision for motor control. It is important to know the limits on what system action is controllable but also which movements are still recognizable. To do so, we tasked our participants in Study I with controlling a steerable third hand inspired by a real-world soldering task. We used this task as an example of finely controlled actuation (hand gestures) as compared to our task in the pilot study, where coarse actuation (whole arm) was necessary. Consequently, Study I (cf. Section 5) provided insights on the level of muscle actuation that is required for suitable EMG input. We measured precision, task completion time and user experience aspects, such as ease of use, fatigue and perceived control. Our findings on technical and movement constraints directly contribute to our design implication and inform the design of Study II, as to what game interactions are possible with EMG-based control.

RQ2: *How can we integrate EMG-based control as a game design element?* We address this research question in our final study after identifying feasible game interactions in Study I. We confirmed that EMG is accurate enough for coarse movements while still pertaining its challenging nature: it is both fatiguing as well as requires effort to control, making it an excellent fit for an exergame-inspired game scenario. Thus, we employed EMG-based control as a design element in a VR flying game. In the game, participants made use of rocket boots, activated through their leg muscles, to follow a given flight trajectory. In this Study II (cf. Section 6), we inquired from participants about their impressions of the EMG-based input control, i.d., whether this form of control created an engaging experience for them. We further analyzed their flight path to get an objective metric of EMG's difficulty. Results of this study complemented our findings on how to design for playful interaction using EMG.

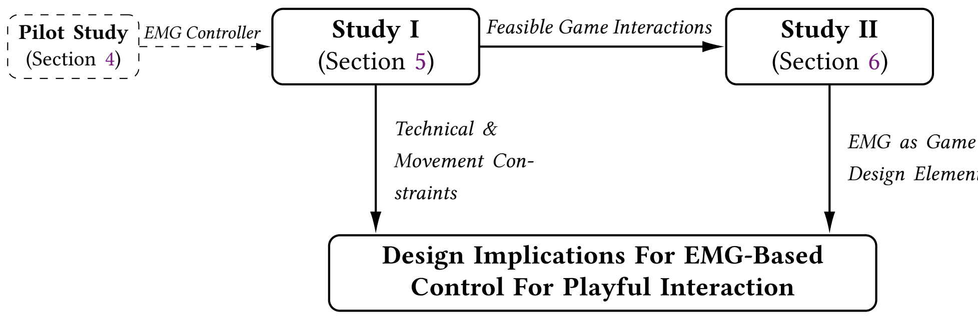

Fig. 2. Structure of our investigation showing the connection between our two studies (pilot study to the left). After confirming the feasibility of our EMG controller in our pilot study, we evaluated the limits of EMG's precision in Study I to identify technical and movement constraints for EMG-based control. These findings also inform the design of Study II, as they provide insights on feasible game interactions using EMG input. This last study informs the design for playful interaction using EMG.

4 PILOT STUDY: EMG-BASED INPUT FOR EXPLICIT CONTROL USING A LOW-COST CONTROLLER

Despite being more difficult to control, EMG-based input should still feel predictable, i.e., actuating one's muscle should elicit an expectable response from the system. Additionally, an EMG-based controller for game interaction should not have high demands in terms of signal-to-noise ratio, thus being readily available for users. In this pilot study, we first confirmed that explicit control using a low-cost EMG-based controller is possible for a basic steering task, where participants were asked to keep a ball on a given trajectory using their forearm muscles. A joystick controller served as an additional baseline condition. We introduced the speed of the animation (6 levels) as a difficulty index, resulting in two independent variables—input modality and speed.

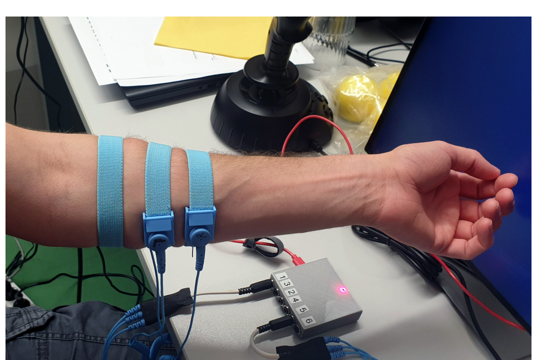

Fig. 3. Electrode placement on the forearm. Each arm was responsible for one direction, i.e., activating the muscles on the left forearm steered the ball to the left and vice versa. Two EMG channels were used in total.

4.1 Apparatus: A Low-Cost EMG-Controller

The system is closely adapted from EMBody[6] [18], a toolkit for EMG-based interface prototyping. In fact, the hardware is identical, only the software components were adapted as outlined in

[6] https://github.com/HCUM/embody

the individual studies. We recorded the EMG signal using this custom device based on an ESP32 supporting up to six channels through soldered amplifiers[7], powered via its USB connection. We used the device with an output rate of about 200 Hz and sent the signals via UDP to the PC that processed the EMG signal. Shielded cables were used to connect the amplifiers to strap electrodes using the bipolar measurement technique [29]. We further processed the signal in accordance with related work (cf. [44]) by filtering and employing a sliding window approach, calculating the epoched root mean square (RMS) of each channel as an indicator of muscle activation. Given our parameters, this corresponded to a latency of 80 ms, suitable for interaction [32]. These preprocessing step were applied for the subsequent studies as well. Please refer to EMBody's [18] github[6] for a complete overview and all resources.

4.2 Procedure & Participants

After providing informed consent, participants were seated in front of the stimulus screen, and we attached the strap electrodes (see Figure 3) on both arms. Values for their muscle activation (cf. Section 4.1) were translated into steering commands, either directly altering the ball's position (position control) or its rate of speed (rate control). To familiarize themselves with the controls, participants were then given time to explore the EMG-based controls as well as the joystick controller under varying speeds. Their goal was to keep the traversing ball (from bottom to top) as close to the shown line as possible by steering it left or right, respectively. When ready, the participants performed a series of trials (for each speed) for a given control, repeating each speed once (later averaged). Order of control and speed were counterbalanced. After each control condition, we inquired about the participants' fatigue, the control's ease of use, and perceived feeling of control (see Table 1 in Study I). A total of 10 participants ($8m/2f$, Age: $\bar{x} = 26.9\,y$, $s = 2.6\,y$) took part in our experiment. The study took approximately 30 min, and participants were remunerated with the equivalent of $5 for their participation.

4.3 Results and Implications

Our pilot study confirmed that explicit control via an EMG-based controller is possible using a low-cost recording setup. Consequently, we employed the same apparatus in our subsequent studies. While EMG-based controls had slightly higher ease of use, ratings on fatigue and feeling of control were in favor of the joystick control. We will have a closer look at these aspects in Study I.

Our analysis on the participants' performance confirmed these results and showed superior control with the joystick as illustrated in Figure 4. Using a linear mixed model with the fixed effects control modality and speed as well as participant ID as random effect, we found a significant effect for both fixed effects: control modality ($F(2, 170) = 5.0, p < .01$) and speed ($F(1, 170) = 13.1, p < .01$). No interaction effects were found. Post-hoc tests revealed that both EMG-based controls were significantly worse than the joystick control.

These findings highlight that the baseline control via a joystick was preferred as it offered more precise control and increased performance, yet we have confirmed that sufficient **explicit control via EMG input is indeed possible for a basic steering task**. For our two following studies, we opted to use position control (directly altering an object's position, rather than its velocity), performing slightly better and having a broader support in literature [17]. While having identified that control via EMG is possible, we also confirmed that it is difficult to control. In Study I, we take a closer look at EMG's constraints in terms of precision and range of movements to identify suitable applications scenarios in game interaction (Study II).

[7] https://github.com/BigCorvus/2-Channel-Biopotential-Amp

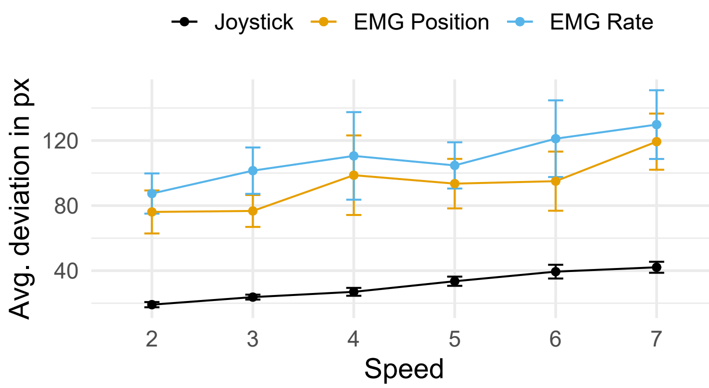

Fig. 4. Average deviation (L2 norm) over speed given the control modalities as line plot (individual data points additionally depict the standard error). The joystick control has significantly lower deviation than both EMG-based controls.

5 STUDY I: LIMITATIONS OF EMG-BASED CONTROL FOR MOTOR CONTROL

To further investigate the design qualities of EMG-based input control in a realistic scenario, we conducted a second study, where participants controlled a steerable third hand[8] in a soldering task. Compared to our pilot study, we rely on finer motor control (hand gestures) to control the third hand. Participants were able to alter the rotation and tilt of the platform, each controlled by two distinct hand gestures[9] performed by the respective arm[10]. We additionally investigated two other modalities to control the third hand—*Pedal* and *Manual*. The *Pedal* condition made use of the participant's feet to steer the third hand. The *Manual* condition represented the baseline control for the third hand, i.e., manipulating it by hand.

5.1 Experiment Design

In a mixed-method evaluation, we analyzed the performance, usability, and user experience of an EMG-based control (*EMG*) and the two additional baselines *Pedal* and *Manual*. We split our investigation into two tasks: *Directive Control* and *Free Control*. In *Directive Control*, we investigated the performance of each modality, measuring throughput and accuracy. *Free Control* focused on a realistic scenario, allowing the user to freely reorient the device as they saw fit to accomplish the task, focusing on task completion time. To gather insights about usability aspects, we administered several questionnaires: NASA TLX [12], creepiness [50], and comfort [21] where applicable. We additionally administered a custom questionnaire on ease of use, fatigue, and feeling of control (cf. Table 1).

Directive Control. Participants were tasked with orienting the third hand into a target position, as measured by an IMU sensor (cf. Section 5.2.1). For the *Manual* condition, participants were free to twist and turn the clamps and arms of the third hand. For the *Pedal* and *EMG* condition, they were required to rotate and tilt the third hand via the robot arm. Both the target and the current position were visualized to participants on a screen. A picture of the target position was displayed

[8]A third hand is a soldering aid which holds electronic components in place so that additional elements can be soldered onto the components.
[9]Rotating clockwise and counterclockwise; tilting up and down, respectively.
[10]Gestures with the right arm controlled the rotation, the left arm controlled the tilt of the platform.

Table 1. Questions after each control modality, polling ease of use (Q1a-b), fatigue (Q2a-b) and feeling of "being in control" (Q3a-d). All visual analog scale from 0 to 100.

Perception of the scoring system	
Q1a	How easy was it to use the prototype?
Q1b	How easy was it to learn the respective type of input?
Q2a	How tiresome was the task?
Q2b	How challenging did the task feel?
Q3a	Did you feel you were in control?
Q3b	How responsive was the system?
Q3c	I felt I had precise control over the ball.
Q3d	I felt I had sufficient control over the ball.

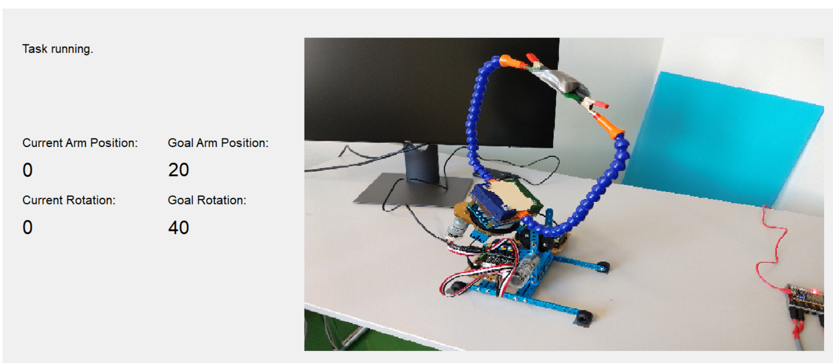

Fig. 5. Stimulus display for participants during a trial for the task *Directive Control*. Target and current position are displayed on the left. An additional image of the target position is displayed on the right.

as well. Figure 5 shows the stimulus for *Directive Control*. We later analyzed the task completion time and accuracy for each modality.

Free Control. Contrary to *Directive Control*, in *Free Control*, the participants were not given a target position but were free to reorient the third hand as they saw fit. This task closely mimics a real soldering task, where components on an electronics workpiece need to be connected. For this purpose, we mounted an example workpiece that was fitted with colored targets. These targets needed to be connected by the participants in a given order by a set of cables to light up corresponding LEDs. This task was inspired by the principle behind an electric contact quiz[11]. Figure 6 shows the example workpiece (left side) and the corresponding stimulus (right side), highlighting the current color target as well as the previous and next target. For this task, we mainly focused on the participants' task completion times.

5.2 Apparatus

Our experimental apparatus consisted primarily of a third hand used for the soldering task. A 27-inch monitor was used to display task information to the user. The experimenter and participant shared the same room separated by a distance of 2.5 *m*, including a physical separation through a

[11] https://boardgamegeek.com/boardgame/31591/electric-contact-quiz

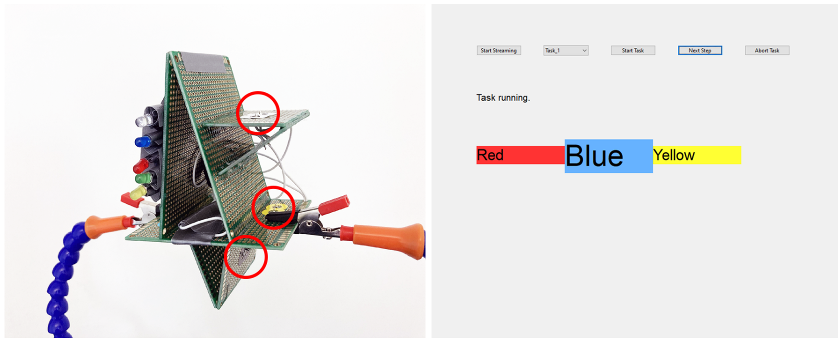

Fig. 6. Example workpiece with colored targets (red circles) which needed to be connected in a given order (left) and corresponding stimulus (right) shown to participants in *Free Control*.

perspex wall[12]. The robot arm allowed controlling the third hand in two directions: rotate around its own y-axis, and tilt the arm up and down (tilt within the xy-plane). An attached IMU measured the 3D orientation of the third hand. The complete apparatus consisted of an EMG recording device (identical to the one used in the pilot study), a pedal-based system, and the steerable robot arm to actuate the third hand for the soldering task. All communication was time-synchronized and recorded via lab streaming layer[13] (LSL).

5.2.1 Robot Arm Actuation and Angle Measurement. We used the Makeblock mBlock Ultimate[14] 2.0 set for building the customized robot, adding a Wi-Fi module and a wooden mount holding the third hand. The robot arm moved at $24\frac{deg}{s}$ for both directions, giving the user a sufficient amount of control while remaining reactive. Commands for the robot arm were sent via Wi-Fi.

An attached IMU (XSens Dot[15]) provided the 3D orientation of the robot arm at a sampling rate of 60 Hz. The sensor was affixed to the workpiece using adhesive tape. The IMU data (quaternions) was first streamed to a mobile device via Bluetooth and, in turn, sent to the processing PC via Wi-Fi using LSL. From the quaternions, we calculated the robot's arm angle as well as its rotation angle, which are displayed to the user.

5.2.2 EMG Recording Device. We used the same device as in the pilot study (cf. Section 4.1). After calculating the RMS values as an indicator for muscle activation, we additionally generated ratio-based features [44] for each EMG channel. Given two channels for each forearm (cf. Section 5.4), this yielded four RMS values and six additional RMS-ratio values that we subsequently supplied for our classification process. Ground truth was collected during the calibration phase of the experiment, where participants were guided by the program and instructed to perform and hold the respective activation gestures. We collected 5 s of EMG data for each gesture[16]. Note that samples were collected when the wrist was flexed/extended, resulting in continuous muscle activation in the forearm. We trained a support vector machine (SVM) with the collected calibration data and used the model during runtime to provide live gesture predictions for the robot arm via an LSL stream every 80 ms. We additionally introduced an input delay to the robot movement to prevent

[12]Note: the study was conducted during the COVID-19 pandemic. A full hygiene protocol was compiled in compliance with the rules of the university.
[13]https://github.com/sccn/labstreaminglayer
[14]https://www.makeblock.com/steam-kits/mbot-ultimate
[15]https://www.xsens.com/xsens-dot
[16]Total of four distinct gestures: wrist flexion and extension for each arm.

accidental activation. This sensitivity level was introduced through a slack variable, a majority voting of the last n gesture predictions. During the experiment, participants were free to choose a comfortable sensitivity level.

5.2.3 Pedal Input System. We used two Lead Foot LFV-1 pedals typically used for adding sound effects during guitar playing. The pedal can be pressed in two directions (forward and back) and does not reset automatically. This property made it suitable for our use case. With two pedals, we covered both steering directions of the robot arm (arm up/down, rotate left/right) simultaneously. By reading the impedance of the internal potentiometer via an electrical circuit connected to an Arduino Uno, we could detect the current pedal state. To allow for robust input via the pedals, we only triggered an input command when the pedal exceeded 75% of its maximum range or fell below 25%, respectively. The signal was transmitted to a connected PC via USB at 13 Hz.

5.3 Participants

We recruited twelve participants ($9m/3f$, Age: $\bar{x} = 27.5\,y, s = 2.8\,y$) for our study through mailing lists, none of whom participated in our pilot study. All participants were right-handed. We additionally inquired about their familiarity with EMG and related technologies (all 5 item likert scale). Six participants already had prior experience with EMG ($\bar{x} = 2.4, s = 1.1$). Similarly, experience in placing electrodes ($\bar{x} = 2.8, s = 1.3$), muscle training ($\bar{x} = 3, s = 1.2$) and wearable technology ($\bar{x} = 3.2, s = 1.5$) was split as well. The total duration of the study did not exceed 120 min, and participants were remunerated with the equivalent of $10 per hour.

5.4 Procedure

Participants were first informed about the study and the installed protection measures due to the COVID-19 pandemic. After declaring their consent, we asked participants to provide their demographic data. For the *EMG* condition, we connected the EMG device and mounted the electrodes, resulting in a total of four EMG channels (two for each forearm) as illustrated in Figure 7. The positioning of the electrodes does not aim for a particular muscle[17], though was derived from applications of exoskeleton control [11]. A detailed mounting guide is available as supplementary material. Afterwards, we confirmed the signal quality of the EMG and the program guided participants through the calibration process (cf. Section 5.2.2). We additionally introduced participants to the other conditions, demonstrating the functionality of the two pedals (*Pedal*) and highlighting flexible elements of the third hand for the *Manual* condition. Participants had the opportunity to familiarize themselves with all control modalities, fine-tuning sensitivity levels (*EMG* only) to their liking before starting the actual experiment. This part did not exceed 5 min and all participants opted for a slightly less sensitive control when activating the robot arm, contrary to when they wanted it to stop moving[18]. Order of conditions (*Manual*, *Pedal*, *EMG*) was assigned using a Latin square design and kept consistent across the two tasks (*Directive Control*, *Free Control*). Participants executed a total of 10 trials for each condition for *Directive Control*, answering the NASA TLX and our custom questionnaire on ease of use, muscle fatigue, and feeling of control after each condition block. Before starting the task for *Free Control*, we allowed participants to examine the workpiece and try out its functionality. Participants executed a total of 20 trials for each condition for *Free Control*, again following up with a set of questionnaires as detailed in Section 5.1. After completing the final task, we polled participants about the wearing comfort of the EMG device.

[17] A multitude of muscle in the forearm control wrist motion. Pinpointing exact muscles was not possible nor was it required given our machine learning setup.
[18] Slack of $\bar{x} = 3.2$ ($s = 0.58$) for starting a robot movement and $\bar{x} = 1.0$ ($s = 0.0$) for stopping the robot, respectively.

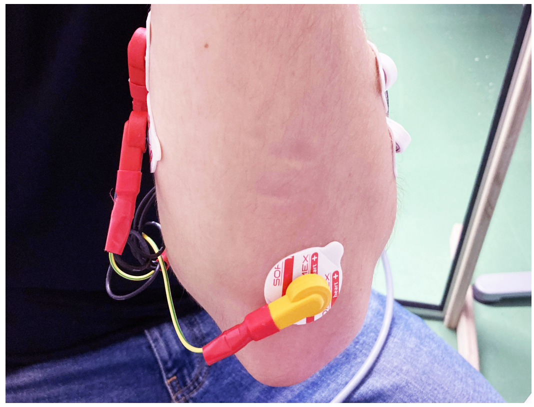

Fig. 7. Placement of EMG electrodes on the forearm, showing one reference electrode near the elbow (yellow) and two measurement electrodes (red and white) for each channel in a bipolar measurement configuration. A total of four EMG channels was used for Study I.

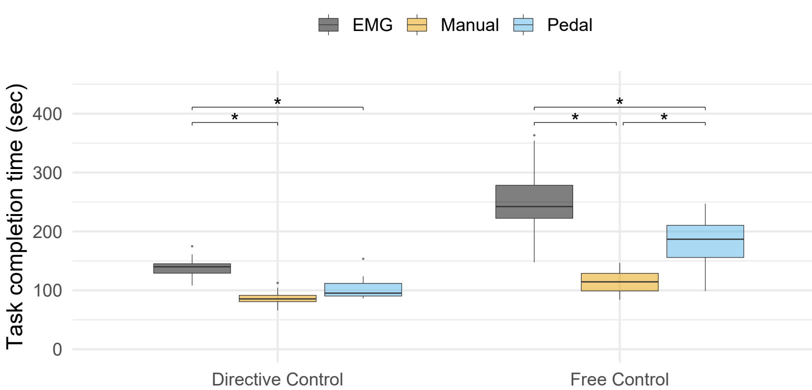

Fig. 8. Task completion times for *Directive Control* (left side) and *Free Control* (right side). Significant differences are highlighted with *.

5.5 Results

We report on collected objective (TCT, accuracy) and subjective metrics (questionnaires) during our experiment. If not stated otherwise, we conducted one-way ANOVAs to analyze the data, followed by post-hoc testing using Tukey contrasts, adjusted for multiple comparisons.

5.5.1 Task Completion Times. For both *Directive Control* and *Free Control*, we measured the total task completion times, i.e., until participants completed all trials. The grand mean was $\bar{x} = 109.8\,s$ ($s = 27.5\,s$). Our statistical tests found a significant difference for the control modality: $F(2,33) = 27.1, p < .05$. Post-hoc tests revealed significant differences for *EMG-Pedal* and *EMG-Manual*. Results for *Directive Control* are visualized in Figure 8 (left).

The grand mean for *Free Control* was $\bar{x} = 190.8\,s$ ($s = 92.0\,s$). We found a significant difference for the control modality: $F(2,33) = 18.7, p < .05$. Post-hoc testing revealed significant difference between all three modalities. The results are visualized in Figure 8 (right).

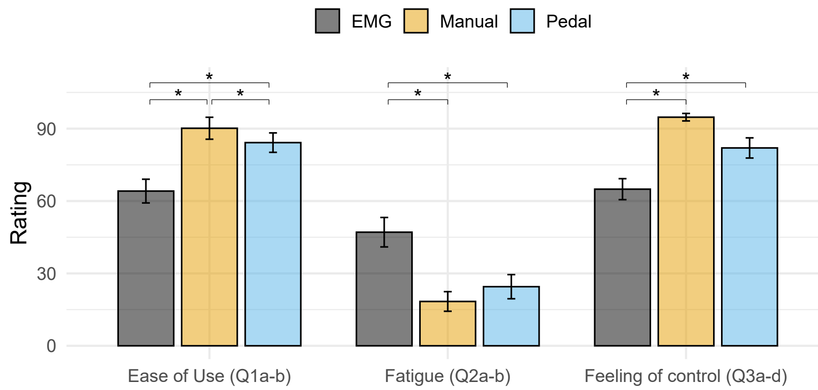

Fig. 9. Rating (averaged) for ease of use (left), fatigue (center), and perceived control (right) for each control modality as reported by our custom questionnaire (cf. Table 1, all questions were rated on a visual analog scale from 0 to 100). Error bars show standard error. Significant differences are marked with *.

5.5.2 Accuracy. For *Directive Control* only, we investigated the accuracy of the individual control modalities by analyzing the final deviation from the target position. Note that a target position was accepted when the orientation of the third hand was within ±20 deg for each angle. Overall participants were very accurate ($\bar{x} = 12.0$ deg, $s = 4.9$ deg). We found no statistical differences between the control modalities.

5.5.3 Usability and User Experience. We inquired about several aspects of usability for the different modalities in our questionnaires. Some scales were exclusively applied for the *EMG* condition, as they are not applicable for the other conditions. The purpose of this is to identify limitations of the deployment nature (electrodes, cables) of the EMG device.

On average, participants did not rate the EMG device as particularly uncomfortable to wear ($\bar{x} = 7.4$, $s = 3.5$, 0 to 20, higher values indicate higher discomfort, cf. [21]). Similarly, it was rated not significantly more creepy ($\bar{x} = 3.2$, $s = 1.2$, 7 item likert, higher values indicate higher level of creepiness, cf. [50]) than the other modalities.

Results from our custom questionnaire on ease of use (Q1a-b), the participants' fatigue (Q2a-b) when using the modality, and its perceived control (Q3a-d) are visualized in Figure 9, depicting the aggregated results for each of the three aspects. The results show that, although the measured accuracy for *EMG* was on the same level as the baseline control, participants perceived a loss of control. Similarly, fatigue and ease of use are challenges for EMG-based control. All three aspects show significant differences for the factor control modality. Significant differences from post-hoc testing are marked in Figure 9. Results from the NASA TLX confirmed these findings, as the score showed significant differences between modalities, in particular between *EMG-Pedal* and *EMG-Manual*.

5.6 Implications for Game Design

In Study I we put the focus on fine motor control, probing the precision of EMG-based input. Our results allow us to draw implications for EMG-based input control (**RQ1**), such as range of possible actions, limitations regarding usability but also identify sweet spots were its challenging nature could be ideal for game design.

While EMG inputs was the slowest of all modalities, it provided sufficient accuracy to orient the third hand. Interestingly, participants felt that the *EMG* condition was harder to control. Combining these two characteristics provides an interesting design opportunity for game elements: **EMG can be sufficiently accurate but requires increased efforts** to achieve the same results (**RQ1**). Further, increasing fatigue with prolonged use adds a natural difficulty element.

Our findings indicate that EMG-based input is most suited for coarser movements, targeted larger muscle (groups). Here, the slight impreciseness due to its challenging nature control opens up opportunities for engaging game design. In a final study, we incorporate and evaluate this concept in a flight simulation VR game.

6 STUDY II: EMG-BASED INPUT IN GAME DESIGN - VROCKETBOOTS

Through Study I, we identified constraints for EMG-based input allowing us to derive possible sweet spots for game interaction where the challenging nature of EMG can be an engaging design element. Consequently, we choose a game interaction where it would feel natural to use direct muscle input to interact in the game world, i.d., users had to exert themselves physically making use of both the design aspects of challenging muscle control as well as arising fatigue.

This makes locomotion in VR an interesting research target for EMG-based control. An active research area for decades [47], creating immersive ways of body movement is essential for a good user experience. Here, research on flight and 3D navigation surfaced interesting ways of controlling body orientation while increasing immersion in the virtual world, e.g., through bird wings in Valkyrie [27]. Other works investigated embodied interfaces [38] and the Superman pose [23] with suspended users. Leaning-based steering [1] and control via leg movements [51] focused on specific body parts.

In this study, we opted for a flight scenario with rocket boots focusing on muscle activation in the participants' leg muscles. This allowed for robust collection of EMG input and direct interaction with the game world by performing a take off jump. In our flight simulation game—VRocketBoots, participants were tasked to follow a given flight trajectory with the help of their rocket boots. Imitating the take off jump by standing on their toes activated their rocket boots, gaining altitude in the game until they returned to a normal position. We chose such a game design as it offered potential benefits to a feeling of implicit control and navigating large virtual environments in a playful manner is a common challenge in modern games. This approach follows the guidelines as presented by Nacke et al. [31], where direct physiological input should be mapped to reflect an action in the virtual world. In this case, activating the leg muscle increased flight altitude. Note that we deliberately decided on this simple interaction, as compared to a more complex interaction, such as involving roll as well by measuring both legs separately, to prevent overwhelming participants.

We conducted a mixed-method evaluation using two conditions: *EMG* and *Controller*. For the *EMG* condition, we placed electrodes on the participants' calves. In the *Controller* condition, activation was achieved through a button press. In both conditions, the hand controllers were used for flight orientation. The trajectory (350 m long) in the study was marked with 34 rings within a city scene (see Figure 10) that had to be flown through by participants.

We focused our evaluation on accuracy of control, through analyzing participants' flight paths. A concluding interview provided additional insights on their experience with the EMG-based control.

6.1 Apparatus

For measuring EMG input, we again used the recording device and EMG preprocessing steps from the previous two studies. Electrodes were attached to the participants' calves focusing on the large gastrocnemius muscle, ensuring robust input. To simplify the setup, we opted to attach electrodes only on one leg (one EMG channel). A simple threshold-based classification based on measured

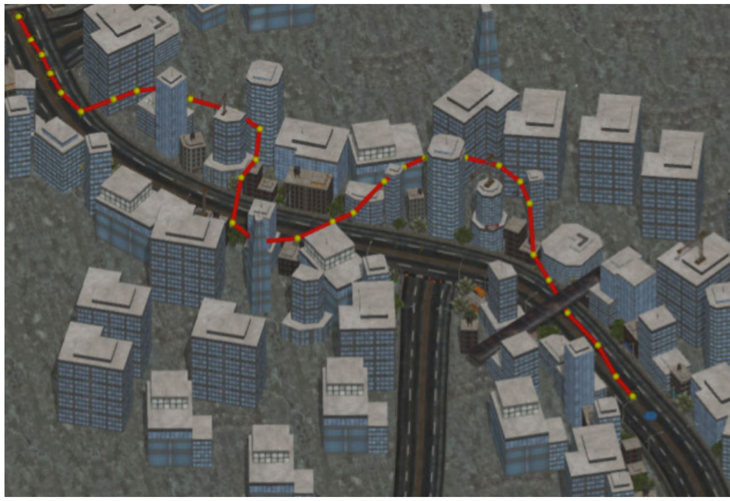

Fig. 10. Overview of the flight path consisting of 34 rings with a total distance of 350 m. Image courtesy: Magic Carpet[28].

RMS values controlled the initial activation of the rocket boost and was calibrated at the beginning of the study. During this calibration phase, participants were tasked with performing the take-off gesture by standing on their toes. Additionally, we collected EMG data when they moved around the room, allowing us to pinpoint a robust RMS value for each participant when the rocket boots should activate. Continuous flexing of the muscle would provide a continuous boost in the game. This process of collecting the calibration data was analog to Study I, guided by the program. During runtime, measured RMS values were transferred via an LSL stream and processed in the unity application. The VR scene was created using Unity, adapted from *Magic Carpet* [28], displayed on a Occulus Quest 2 to the participants (see Figure 11). During the study, we logged flight paths and EMG activation for later analysis.

6.2 Participants

We recruited 20 participants ($14m/6f$, Age: $\bar{x} = 26.3\,y, s = 2.9\,y$) for our study through university slack channels, none of whom participated in either our pilot study or Study I. The majority of participants (75 %) had some prior experience with 3D games or applications; only 40 % had regular contact with VR. The total duration of the study did not exceed 50 min, and participants were remunerated with their choice of a sweets package.

6.3 Procedure

After providing informed consents, participants were equipped with the VR headset and hand controller. Additionally, we attached the electrodes on their calves and calibrated the activation threshold for the rocket boots. The VR scene was introduced through a practice environment. We allowed ample time for the participants to familiarize themselves with the hand controllers and the EMG-based control. The practice course contained two flight rings. When participants reported feeling comfortable enough[19] with both control modalities, we started experiment. Participants were asked to perform their flights on the real track, while we measured task completion time and flight data. After completing one control condition, participants switched to the other condition

[19]No more than 5 min for any participant.

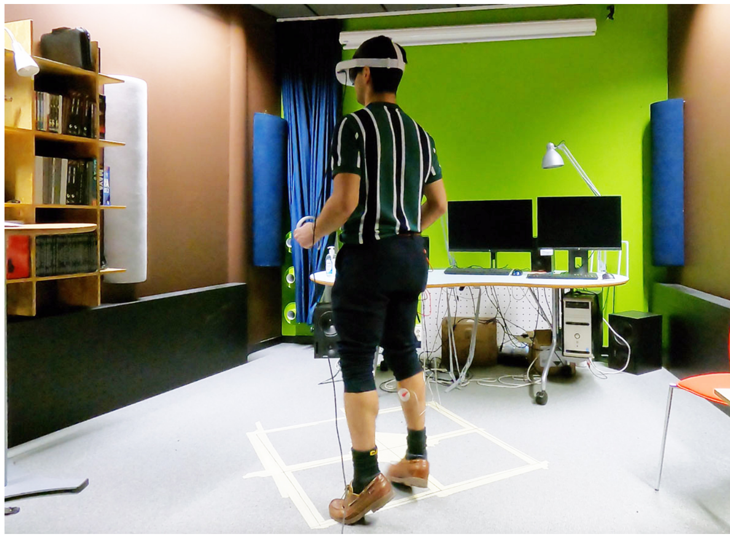

Fig. 11. Apparatus for Study II showing participant wearing the VR headset and attached electrodes on the calf.

after a short break. The order of conditions was counterbalanced using the latin square method. We concluded the study with a semi-structured interview inquiring about specific design qualities of the EMG-based control.

6.4 Findings

We report on our analysis of quantitative flight data (precision, completion times) as well as the analysis of our conducted interviews, focusing on qualitative aspects of our work.

6.4.1 Task Completion Time. Our analysis on the participants' performance in completing the given flight trajectory showed that the *Controller* condition was superior in terms on task completion times. On average, participants were faster using the *Controller* condition ($\bar{x} = 52.8\,s, s = 19.6\,s$) compared to the *EMG* condition ($\bar{x} = 85.5\,s, s = 39.9\,s$). This result was expected, as the challenging control of EMG required time to master. The high standard deviation for *EMG* also showed that this control modality was more challenging for some participants than for others.

6.4.2 Flight Path Precision. The projected flight trajectory was intended to provide a guidance for participants. To analyze the precision of the input methods, we took a look at participants' flight altitudes over time. This allowed us to identify lapses in control and estimate the difficulty in controlling the flight with a given condition. A comparison of respective flight heights is depicted for both conditions in Figure 12. Since task completion times varied across participants, we rescaled all trials to their respective median task completion time, 48.7 s for the *Controller* condition, 69.0 s for the *EMG* condition. This allowed us to visually compare the different trials at once and draw conclusions based on the mean (red line) and the standard deviation (red corridor) of the flight height over time (cf. Figure 12).

It can be observed that control via *EMG* exhibits more deviation (especially when changing flight altitude), indicating difficulties in properly controlling it. Contrarily, *Controller*-based input is more smooth. We attribute this to the more challenging nature of EMG-based control.

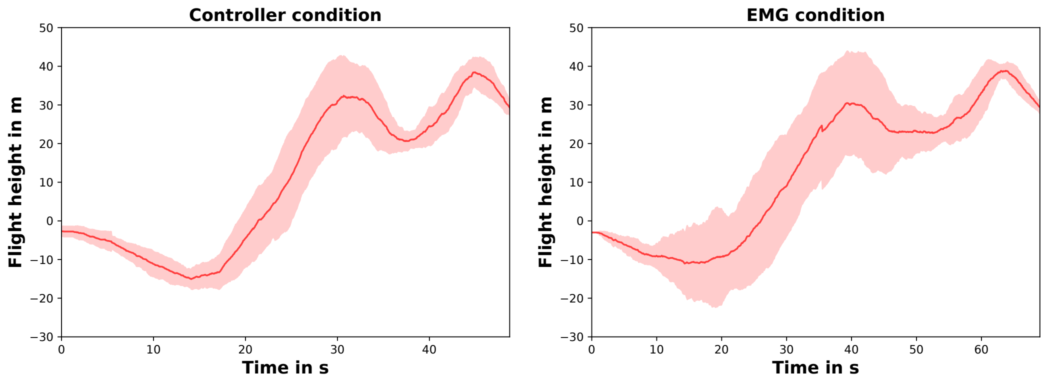

Fig. 12. Deviation of flight height over time given the two conditions (*EMG*, *Controller*). All participant trials have been rescaled to the respective median flight time. The mean over all flight trials is displayed by the red line, the red-shaded corridor shows the standard deviation. It can be observed that the *EMG* condition exhibits higher control deviation, especially for when changing the flight altitude.

6.4.3 Interviews. Our initial quantitative analysis confirmed the challenging nature of EMG-based input control. Yet, it remained unclear if this challenge would just frustrate users or if can provide more engaging experiences (**RQ2**). Through affinity diagramming, we identified positive and negative aspects of each control modality as detailed in the following section. Overall, participants preferred the EMG-based control (70%), mostly due to its challenging and immersive nature.

> *It was more challenging and immersive. A very different way of using controls, which made it more fun. (P3, m, 28y)*

Immersion. Most participants reported the *EMG* condition as being more immersive (14 out of 20) and rated it more fun (15 out of 20). While the *Controller* was easier to handle and more effective, *EMG* scored with higher immersion and a more natural feel. Some even reported that it felt like a workout.

> *It felt more like a workout. It activates more parts of my body. But it became a bit tiresome in the end. (P9, m, 23y)*

The more challenging nature allowed it to achieve higher levels of fun and immersion.

> *It was a different experience! More engaging experience, than using just your hands. You're actually moving around with the help of your body. It was positive. Because a lot of people are used to using their hands, they can be on auto mode, but now you're more invested. Gives you a better feeling. (P18, m, 28y)*

Reports from participants indicate that the increased challenge through EMG can elicit a more engaging experience (**RQ2**). Negative aspects such as frustration and fatigue are limited, but should be considered in the game design.

Control. The limits of EMG-based control were a negative aspects for participants. The imprecision at times caused a break in the VR illusion.

> *It felt quite natural to fly upwards, but when going in different directions it broke the illusion a bit. (P20, m, 28y)*

Participants provided insights into how the *EMG* control can be improved, including regression-based calibration allowing for a smoother, continuous input.

> *If it was possible to make it into a continuous movement, then it would feel like real life. (P19, m, 25)*

Our initial experiment design focused on an activation of the rocket boots, mimicking a burst of thrust in the virtual world. Comments from participants indicated that a continuous approach, where muscle activation is directly mapped to the power of the thrust, is also worth considering and could allow for a more natural interaction, similar to allowing control over the flyer's roll by individually activating each leg. Though, the technical feasibility of this approach is subject to the available recording equipment. Designers are advised that while EMG's impreciseness adds a challenging element, it warrants careful consideration to not tip over to frustration (**RQ2**).

7 DISCUSSION

Our work investigated the potential of EMG-based input for game design. In particular, we inquired whether the challenging control nature of EMG input can be beneficial in adding an engaging input control modality in games. Our investigation explored the range of movements for EMG input, thus deriving feasible game interaction, and evaluated its user experience as a game element. In this section, we discuss the implications of our findings for future systems that want to leverage playful interaction with EMG.

7.1 Imprecise but Fun

Throughout our work, the limited precision of EMG continued to be problematic for participants. As such, EMG is certainly not an adequate input modality if accuracy and task completion time are of essence (**RQ1**). Yet, based on our findings, we argue that these characteristics makes it a prime candidate for playful interaction. EMG-based input does not require an artificial layer of added difficulty. Instead, EMG creates difficulty through the inherently difficult task of controlling muscles. This also facilitates developing proficiency as there is an underlying physiological model (muscle activation yields input) that can be learned and controlled over time. This process makes EMG-based input challenging, fun and engaging. Consequently, **EMG's inherent imprecision makes it a valuable design element in playful interaction** (**RQ2**). Recent related work [7] provides additional guidance for employing limited bodily control in game design. However, the applicability of EMG to playful interfaces is likewise limited by these inherent qualities, e.g., lack of precision or signal variations for different muscles and movements.

7.2 EMG-Based Input as a Game Element

Our investigation illustrated suitable application contexts for EMG-based input (**RQ1**). While precise motor control, such as hand gestures, is less suited, coarse movements involving extremities and body movements are easy to capture and provide an active element [30] to playful interaction (**RQ2**). **EMG-based control works best using large muscle (groups) and direct mappings to game elements** [31], where the received input translates directly into an adequate reaction in the virtual world (**RQ2**). Mismatches can quickly lead to reduced immersion as evident in Study II. Similarly, use of fatigue as a design element, e.g., using it as a proxy for difficulty, should be handled with care, as overuse can lead to user frustration.

7.3 Prevalence of "EMG Controllers"

While recording accurate EMG signals may require high-quality equipment, it is best to **rely on stable input minimizing the risk of immersion loss, favoring devices that are easy to**

deploy. Available consumer products (cf. Section 2) already demonstrate ready-to-use deployment of EMG recording devices. Integrating sensing capabilities into wearables [14] or even on the skin [35] could potentially mark a paradigm shift in how we use physiological sensing for playful interaction.

7.4 Limitations

Possibilities for muscle-controlled input are as numerous as the number of muscles in our bodies. While some body locations are more favorable, it remains an open questions for game designers which muscle to use. Here, Study II and related work [31] provided insights, calling for direct input (e.g., via EMG) that is directly mapped to reflect actions in the game world. In fact, imitating an appropriate movement was beneficial for game immersion. As such, electrode positioning should rather be dictated by game design choices, albeit keeping the technical constraints of EMG in mind (cf. **RQ1**). If sufficient muscle activation can be recorded, game designers are free to explore different body locations for the EMG controller. Thus, extensive knowledge about EMG's nature or body anatomy is not required to design playful EMG experiences. A simple recording setup, such as the one shown in this work, is sufficient to experiment with EMG-based input, yet suitable body locations and associated muscles will need to be evaluated individually in terms of user perception and how challenging they are to control.

More elaborate equipment, which uses multiple recording channels, may produce better results and potentially allow to circumvent the need for individually calibrating muscle activation per user. Though, we argue that such an approach might limit the design space for using EMG input for playful interaction. Rather, we advocate straightforward recording setups, e.g., electrodes embedded in sleeves, fabric patches or VR hand controllers, offering higher versatility at the cost of increased calibration effort. It remains to be explored how calibration routines can be integrated seamlessly into game design.

The fatiguing effect of EMG input control should not be underestimated, though it can be leveraged as an additional aspect of difficulty if applied with caution. Similarly, while interesting and exciting at first, EMG as a novel input control might loose its appeal for players once they become accustomed to muscle activation. The long term effects of these limitations during prolonged game interaction still need to be investigated.

8 CONCLUSION

In this paper, we explored the potential of electromyography as a challenging input for playful interaction. We hypothesized that due to its imprecise nature, EMG-based input can serve as an engaging element in game design. To investigate our hypothesis, we conducted two studies where we derived feasible game interactions based on EMG's technical constraints, and showcased how to use EMG-based input as a game design element. Our findings highlight the opportunity of EMG's imprecision to create challenging and engaging game experiences. We provide a range of design considerations as well as pitfalls to avoid when employing EMG for playful interaction. We suggest targeting large muscles and coarse movements for robust input. Most often, limiting the game design to these coarse movements is preferred, as unintended input via EMG can negatively affect immersion. Though, if used correctly, we can create engaging game experiences with EMG that challenge users [42] in a playful way.

ACKNOWLEDGMENTS

This research is supported by the European Union's Horizon 2020 Programme under ERCEA grant no. 683008 AMPLIFY.

REFERENCES

[1] Ashu Adhikari, Abraham M. Hashemian, Thinh Nguyen-Vo, Ernst Kruijff, Markus von der Heyde, and Bernhard E. Riecke. 2021. Lean to Fly: Leaning-Based Embodied Flying Can Improve Performance and User Experience in 3D Navigation. *Frontiers in Virtual Reality* 2 (2021). https://www.frontiersin.org/article/10.3389/frvir.2021.730334

[2] 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 (CHI '15)*. ACM, New York, NY, USA, 929–938. https://doi.org/10.1145/2702123.2702501

[3] D. T. Barry, K. E. Gordon, and G. G. Hinton. 1990. Acoustic and Surface EMG Diagnosis of Pediatric Muscle Disease. *Muscle Nerve* 13, 4 (April 1990), 286–290. https://doi.org/10.1002/mus.880130403

[4] Enrico Costanza, Samuel A. Inverso, and Rebecca Allen. 2005. Toward Subtle Intimate Interfaces for Mobile Devices Using an EMG Controller. In *Proceedings of the SIGCHI Conference on Human Factors in Computing Systems (CHI '05)*. ACM, New York, NY, USA, 481–489. https://doi.org/10.1145/1054972.1055039

[5] 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 (CHI '07)*. ACM, New York, NY, USA, 819–828. https://doi.org/10.1145/1240624.1240747

[6] Kate C. Ewing, Stephen H. Fairclough, and Kiel Gilleade. 2016. Evaluation of an Adaptive Game That Uses EEG Measures Validated during the Design Process as Inputs to a Biocybernetic Loop. *Front Hum Neurosci* 10 (May 2016), 223. https://doi.org/10.3389/fnhum.2016.00223

[7] Florian 'Floyd' Mueller, Rakesh Patibanda, Richard Byrne, Zhuying Li, Yan Wang, Josh Andres, Xiang Li, Jonathan Marquez, Stefan Greuter, Jonathan Duckworth, and Joe Marshall. 2021. Limited Control Over the Body as Intriguing Play Design Resource. In *Proceedings of the 2021 CHI Conference on Human Factors in Computing Systems (CHI '21)*. Association for Computing Machinery, New York, NY, USA, 1–16. https://doi.org/10.1145/3411764.3445744

[8] Yue Gao and Regan L Mandryk. 2011. GrabApple: The design of a casual exergame. In *International Conference on Entertainment Computing*. Springer, 35–46.

[9] Nadia Garcia-Hernandez, Karen Garza-Martinez, Vicente Parra-Vega, Armando Alvarez-Sanchez, and Laura Conchas-Arteaga. 2019. Development of an EMG-based exergaming system for isometric muscle training and its effectiveness to enhance motivation, performance and muscle strength. *International Journal of Human-Computer Studies* 124 (2019), 44–55.

[10] Mohammad Ghassemi, Kristen Triandafilou, Alex Barry, Mary Ellen Stoykov, Elliot Roth, Ferdinando A. Mussa-Ivaldi, Derek G. Kamper, and Rajiv Ranganathan. 2019. Development of an EMG-Controlled Serious Game for Rehabilitation. *IEEE Trans Neural Syst Rehabil Eng* 27, 2 (Feb. 2019), 283–292. https://doi.org/10.1109/TNSRE.2019.2894102

[11] R. a. R. C. Gopura and Kazuo Kiguchi. 2012. *Application of Surface Electromyographic Signals to Control Exoskeleton Robots*. IntechOpen. https://doi.org/10.5772/26389

[12] Sandra G. Hart and Lowell E. Staveland. 1988. Development of NASA-TLX (Task Load Index): Results of Empirical and Theoretical Research. In *Human Mental Workload*. North-Holland, Oxford, England, 139–183. https://doi.org/10.1016/S0166-4115(08)62386-9

[13] A. Hernandez Arieta, R. Katoh, H. Yokoi, and Y. Wenwei. 2006. Development of a Multi-DOF Electromyography Prosthetic System Using the Adaptive Joint Mechanism. https://doi.org/10.1533/abbi.2005.0060

[14] Cedric Honnet, Hannah Perner-Wilson, Marc Teyssier, Bruno Fruchard, Jürgen Steimle, Ana C. Baptista, and Paul Strohmeier. 2020. PolySense: Augmenting Textiles with Electrical Functionality Using In-Situ Polymerization. In *Proceedings of the 2020 CHI Conference on Human Factors in Computing Systems (CHI '20)*. Association for Computing Machinery, Honolulu, HI, USA, 1–13. https://doi.org/10.1145/3313831.3376841

[15] Donny Huang, Xiaoyi Zhang, T. Scott Saponas, James Fogarty, and Shyamnath Gollakota. 2015. Leveraging Dual-Observable Input for Fine-Grained Thumb Interaction Using Forearm EMG. In *Proceedings of the 28th Annual ACM Symposium on User Interface Software & Technology (UIST '15)*. Association for Computing Machinery, New York, NY, USA, 523–528. https://doi.org/10.1145/2807442.2807506

[16] Alayna Hughes and Sergi Jorda. 2021. Applications of Biological and Physiological Signals in Commercial Video Gaming and Game Research: A Review. *Frontiers in Computer Science* 3 (2021). https://www.frontiersin.org/article/10.3389/fcomp.2021.557608

[17] Richard J. Jagacinski, Daniel W. Repperger, Martin S. Moran, Sharon L. Ward, and Betty Glass. 1980. Fitts' Law and the Microstructure of Rapid Discrete Movements. *Journal of Experimental Psychology: Human Perception and Performance* 6, 2 (1980), 309–320. https://doi.org/10.1037/0096-1523.6.2.309

[18] Jakob Karolus, Francisco Kiss, Caroline Eckerth, Nicolas Viot, Felix Bachmann, Albrecht Schmidt, and Paweł W. Woźniak. 2021. EMBody: A Data-Centric Toolkit for EMG-Based Interface Prototyping and Experimentation. *Proc. ACM Hum.-Comput. Interac.* 5, EICS (2021), 195:1–195:29. https://doi.org/10.1145/3457142

[19] Jakob Karolus, Hendrik Schuff, Thomas Kosch, Paweł W. Wozniak, and Albrecht Schmidt. 2018. EMGuitar: Assisting Guitar Playing with Electromyography. In *Proceedings of the 2018 Designing Interactive Systems Conference (DIS '18)*.

Association for Computing Machinery, Hong Kong, China, 651–655. https://doi.org/10.1145/3196709.3196803

[20] Frederic Kerber, Michael Puhl, and Antonio Krüger. 2017. User-Independent Real-Time Hand Gesture Recognition Based on Surface Electromyography. In *Proceedings of the 19th International Conference on Human-Computer Interaction with Mobile Devices and Services (MobileHCI '17)*. Association for Computing Machinery, New York, NY, USA, 1–7. https://doi.org/10.1145/3098279.3098553

[21] J.F. Knight, C. Baber, A. Schwirtz, and H.W. Bristow. 2002. The Comfort Assessment of Wearable Computers. In *Proceedings. Sixth International Symposium on Wearable Computers,*. 65–72. https://doi.org/10.1109/ISWC.2002.1167220

[22] John W. Krakauer and Reza Shadmehr. 2006. Consolidation of Motor Memory. *Trends Neurosci.* 29, 1 (Jan. 2006), 58–64. https://doi.org/10.1016/j.tins.2005.10.003

[23] Dennis Krupke, Paul Lubos, Lena Demski, Jonas Brinkhoff, Gregor Weber, Fabian Willke, and Frank Steinicke. 2016. Control Methods in a Supernatural Flight Simulator. In *2016 IEEE Virtual Reality (VR)*. 329–329. https://doi.org/10.1109/VR.2016.7504788

[24] G.M. Lyons, P. Sharma, M. Baker, S. O'Malley, and A. Shanahan. 2003. A Computer Game-Based EMG Biofeedback System for Muscle Rehabilitation. In *Proceedings of the 25th Annual International Conference of the IEEE Engineering in Medicine and Biology Society (IEEE Cat. No.03CH37439)*, Vol. 2. 1625–1628 Vol.2. https://doi.org/10.1109/IEMBS.2003.1279682

[25] Regan L. Mandryk, M. Stella Atkins, and Kori M. Inkpen. 2006. A Continuous and Objective Evaluation of Emotional Experience with Interactive Play Environments. In *Proceedings of the SIGCHI Conference on Human Factors in Computing Systems (CHI '06)*. ACM, New York, NY, USA, 1027–1036. https://doi.org/10.1145/1124772.1124926

[26] Joe Marshall, Alexandru Dancu, and Florian "Floyd" Mueller. 2016. Interaction in Motion: Designing Truly Mobile Interaction. In *Proceedings of the 2016 ACM Conference on Designing Interactive Systems* (Brisbane, QLD, Australia) *(DIS '16)*. Association for Computing Machinery, New York, NY, USA, 215–228. https://doi.org/10.1145/2901790.2901844

[27] Soroosh Mashal, Gerold Hoelzl, and Matthias Kranz. 2019. Valkyrie Project: Flying Immersion in Virtual Reality. In *2019 11th International Conference on Virtual Worlds and Games for Serious Applications (VS-Games)*. 1–4. https://doi.org/10.1109/VS-Games.2019.8864545

[28] Daniel Medeiros, Maurıcio Sousa, Alberto Raposo, and Joaquim Jorge. 2020. Magic Carpet: Interaction Fidelity for Flying in VR. *IEEE Transactions on Visualization and Computer Graphics* 26, 9 (Sept. 2020), 2793–2804. https://doi.org/10.1109/TVCG.2019.2905200

[29] Roberto Merletti and Dario Farina. 2016. *Surface Electromyography: Physiology, Engineering and Applications*. John Wiley & Sons.

[30] Florian Mueller, Stefan Agamanolis, and Rosalind Picard. 2003. Exertion Interfaces: Sports over a Distance for Social Bonding and Fun. In *Proceedings of the SIGCHI Conference on Human Factors in Computing Systems* (Ft. Lauderdale, Florida, USA) *(CHI '03)*. Association for Computing Machinery, New York, NY, USA, 561–568. https://doi.org/10.1145/642611.642709

[31] 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 (CHI '11)*. Association for Computing Machinery, New York, NY, USA, 103–112. https://doi.org/10.1145/1978942.1978958

[32] Jakob Nielsen. 1993. *Usability Engineering*. Morgan Kaufmann Publishers Inc., San Francisco, CA, USA.

[33] Anton Nijholt, Danny Plass-Oude Bos, and Boris Reuderink. 2009. Turning Shortcomings into Challenges: Brain–Computer Interfaces for Games. *Entertainment Computing* 1, 2 (April 2009), 85–94. https://doi.org/10.1016/j.entcom.2009.09.007

[34] Aditya Shekhar Nittala, Arshad Khan, Klaus Kruttwig, Tobias Kraus, and Jürgen Steimle. 2020. PhysioSkin: Rapid Fabrication of Skin-Conformal Physiological Interfaces. In *Proceedings of the 2020 CHI Conference on Human Factors in Computing Systems (CHI '20)*. Association for Computing Machinery, New York, NY, USA, 1–10. https://doi.org/10.1145/3313831.3376366

[35] Aditya Shekhar Nittala, Arshad Khan, Klaus Kruttwig, Tobias Kraus, and Jürgen Steimle. 2020. PhysioSkin: Rapid Fabrication of Skin-Conformal Physiological Interfaces. In *Proceedings of the 2020 CHI Conference on Human Factors in Computing Systems (CHI '20)*. Association for Computing Machinery, Honolulu, HI, USA, 1–10. https://doi.org/10.1145/3313831.3376366

[36] D. Peleg, E. Braiman, E. Yom-Tov, and G. F. Inbar. 2002. Classification of Finger Activation for Use in a Robotic Prosthesis Arm. *IEEE Transactions on Neural Systems and Rehabilitation Engineering* 10, 4 (Dec. 2002), 290–293. https://doi.org/10.1109/TNSRE.2002.806831

[37] Monica Perusquía-Hernández, Saho Ayabe-Kanamura, Kenji Suzuki, and Shiro Kumano. 2019. The Invisible Potential of Facial Electromyography: A Comparison of EMG and Computer Vision When Distinguishing Posed from Spontaneous Smiles. In *Proceedings of the 2019 CHI Conference on Human Factors in Computing Systems (CHI '19)*. Association for Computing Machinery, New York, NY, USA, 1–9. https://doi.org/10.1145/3290605.3300379

[38] M. Perusquía-Hernández, T. Enomoto, T. Martins, M. Otsuki, H. Iwata, and K. Suzuki. 2017. Embodied Interface for Levitation and Navigation in a 3D Large Space. In *Proceedings of the 8th Augmented Human International Conference (AH '17)*. Association for Computing Machinery, New York, NY, USA, 1–9. https://doi.org/10.1145/3041164.3041173
[39] Angkoon Phinyomark, Pornchai Phukpattaranont, and Chusak Limsakul. 2012. Feature Reduction and Selection for EMG Signal Classification. *Expert Systems with Applications* 39, 8 (June 2012), 7420–7431. https://doi.org/10.1016/j.eswa.2012.01.102
[40] Angkoon Phinyomark and Erik Scheme. 2018. EMG Pattern Recognition in the Era of Big Data and Deep Learning. *BDCC* 2, 3 (Aug. 2018), 21. https://doi.org/10.3390/bdcc2030021
[41] 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
[42] Yvonne Rogers. 2006. Moving on from Weiser's Vision of Calm Computing: Engaging UbiComp Experiences. In *UbiComp 2006: Ubiquitous Computing (Lecture Notes in Computer Science)*, Paul Dourish and Adrian Friday (Eds.). Springer, Berlin, Heidelberg, 404–421. https://doi.org/10.1007/11853565_24
[43] Wataru Sakoda, Ramin Tadayon, Yusuke Kishishita, Masataka Yamamoto, and Yuichi Kurita. 2020. Ski exergame for squat training to change load based on predicted Locomotive risk level. In *2020 IEEE/SICE International Symposium on System Integration (SII)*. IEEE, 289–294.
[44] T Scott Saponas, Desney S. Tan, Dan Morris, and Ravin Balakrishnan. 2008. Demonstrating the Feasibility of Using Forearm Electromyography for Muscle-computer Interfaces. In *Proceedings of the SIGCHI Conference on Human Factors in Computing Systems (CHI '08)*. ACM, New York, NY, USA, 515–524. https://doi.org/10.1145/1357054.1357138
[45] 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 (CHI '10)*. ACM, New York, NY, USA, 851–854. https://doi.org/10.1145/1753326.1753451
[46] E. Scheme and K. Englehart. 2014. On the Robustness of EMG Features for Pattern Recognition Based Myoelectric Control; A Multi-Dataset Comparison. In *2014 36th Annual International Conference of the IEEE Engineering in Medicine and Biology Society*. IEEE, Chicago, IL, 650–653. https://doi.org/10.1109/EMBC.2014.6943675
[47] Mel Slater, Martin Usoh, and Anthony Steed. 1995. Taking Steps: The Influence of a Walking Technique on Presence in Virtual Reality. *ACM Trans. Comput.-Hum. Interact.* 2, 3 (Sept. 1995), 201–219. https://doi.org/10.1145/210079.210084
[48] Ludger van Dijk, Corry K. van der Sluis, Hylke W. van Dijk, and Raoul M. Bongers. 2016. Learning an EMG Controlled Game: Task-Specific Adaptations and Transfer. *PLoS One* 11, 8 (Aug. 2016), e0160817. https://doi.org/10.1371/journal.pone.0160817
[49] Scott R. Vrana. 1993. The Psychophysiology of Disgust: Differentiating Negative Emotional Contexts with Facial EMG. *Psychophysiology* 30, 3 (May 1993), 279–286. https://doi.org/10.1111/j.1469-8986.1993.tb03354.x
[50] Pawel W. Wozniak, Jakob Karolus, Florian Lang, Caroline Eckerth, Johannes Schöning, Yvonne Rogers, and Jasmin Niess. 2021. Creepy Technology: What Is It and How Do You Measure It?. In *Proceedings of the 2021 CHI Conference on Human Factors in Computing Systems, Yokohama, Japan, May 08-13, 2021*. ACM, 13. https://doi.org/10.1145/3411764.3445299
[51] Yaying Zhang, Bernhard E. Riecke, Thecla Schiphorst, and Carman Neustaedter. 2019. Perch to Fly: Embodied Virtual Reality Flying Locomotion with a Flexible Perching Stance. In *Proceedings of the 2019 on Designing Interactive Systems Conference (DIS '19)*. Association for Computing Machinery, New York, NY, USA, 253–264. https://doi.org/10.1145/3322276.3322357

Received February 2022; revised May 2022; accepted June 2022