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Understanding and Enhancing Physiological Input With Multimodal Biofeedback

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Zusammenfassung

In der dynamisch wachsenden Mensch-Computer Interaktion bietet die Integration physiologischer Körpersignale eine innovative Möglichkeit zur Systemsteuerung. In Situationen, in denen herkömmliche Interaktionsmethoden aufgrund des Bedarfs an intuitiveren Kontrollmechanismen vor Herausforderungen stehen, können physiologische Signale alternative Methoden der Interaktion bieten, wenn sie von Computersystemen als Benutzerreaktionen integriert werden. Physiologische Eingaben haben das Potenzial, eine nahtlosere und direktere Steuerung innerhalb von Computerschnittstellen zu ermöglichen, insbesondere in Systemen für sitzende, freihändige Interaktion, da sie nur minimale Bewegungen erfordern. Um die Interaktion mit physiologischen Eingaben zu verbessern, können assistive Techniken aus dem Gesundheits- und Sportkontext entlehnt werden. Bei der Technik des *Biofeedback* werden die physiologischen Signale des Körpers an die Benutzenden reflektiert. Es verbessert die Interaktion, indem es den Benutzenden ermöglicht, zu lernen, ihre physiologischen Signale als Input zu kontrollieren und die Selbstregulierung fördert. Biofeedbacksysteme erfordern eine angemessene Vorbereitung, um sicherzustellen, dass die Personen die bereitgestellten Informationen bewusst verarbeiten und sie mit ihren physiologischen Eingaben in Verbindung bringen. Dieser Prozess kann durch die Unterstützung eines angemessenen *Bewusstseins* der Benutzenden über ihr Biofeedback erleichtert werden und durch die Einbeziehung von *Muskel Priming*, d.h. von Signalen vor einer Aktion oder einem

Ereignis, den Benutzenden dabei helfen ihre physiologischen Antworten kognitiv zu antizipieren. In dieser Dissertation wird die verbesserte Interaktion mit physiologischen Eingaben durch diese assistiven Techniken untersucht.

Die fünf in dieser Dissertation vorgestellten Studien bieten tiefere Einblicke in die Interaktion mit physiologischem Input von verschiedenen Körperstellen, um Leistung, Effektivität und physische Reaktionen zu verbessern und gleichzeitig die kognitive Arbeitsbelastung zu reduzieren. Wir haben herausgefunden, dass das *multimodale Biofeedback* von visuellen und taktilen Modalitäten die Interaktion in einer muskelbasierten Schnittstelle verbessern kann. Der physiologische Input ist bei den getesteten Muskelstellen vergleichbar, was die Flexibilität muskelbasierter interaktiver Systeme unterstreicht. Wir untersuchen die Rolle des *Biofeedback-Bewusstseins* der Benutzenden als Mittel zur Optimierung physiologischer Selbstregulierung. Die Ergebnisse deuten auf eine wichtige Rolle des Biofeedback-Bewusstseins hin, um die aktive Kontrolle des physiologischen Inputs zu beeinflussen und zu fördern. Die Beobachtung, dass das Berühren der Muskelstellen während der experimentellen Vorbereitungsphasen den Teilnehmern half, ihre Muskeln zu lokalisieren, regte zu weiteren Untersuchungen darüber an, wie die Vorbereitung des Benutzers physiologische Reaktionen verfeinern könnte. Aufbauend auf diesen Erkenntnissen untersuchten wir das Konzept des *Vorstimulationsfeedbacks*, das als Muskel Priming vor der Interaktion auf die Muskeln wirkt und sowohl visuelle als auch taktile Modalitäten verwendet. Um die Auswirkungen des taktilen Feedbacks weiter zu erforschen, trennten wir die taktilen Modalitäten in vibrotaktiles und elektrotaktiles Vortimulationsfeedback und untersuchten ihren Einfluss an verschiedenen Muskelstellen. Bei der Untersuchung des Konzepts der vorbereitenden Hinweise fanden wir Evidenz dafür, dass Vorstimulationsfeedback von allen Modalitäten die Interaktion mit muskelbasiertem Input verbessern kann, wobei die Wadenmuskelatur in unserem System am schnellsten reagierte. Diese Dissertation schließt mit Implikationen für physiologischen Input in Assistenzsystemen und deren Verbesserung mit multimodalem Biofeedback und Vortimulationsfeedback für die Mensch-Computer Interaktion.

Abstract

In the rapidly evolving field of human-computer interaction, the integration of input from physiological signals of the human body presents an innovative way to interact with computing systems. In situations where traditional interaction methods face challenges due to the need for more intuitive control mechanisms, physiological signals can enable alternative interaction methods when computational systems integrate them as user responses. Physiological input has the potential to enable more seamless and direct control within computer interfaces, particularly in systems for sedentary hands-free interaction because it requires minimal movement. To enhance the interaction with physiological input assistive techniques known from health and sports contexts can be adapted. The technique of *biofeedback* involves simultaneously reflecting the body's physiological signals to the user. It enhances interactions by enabling users to learn to control their physiological signals as input and fostering self-regulation. Biofeedback systems require proper preparation to ensure that individuals consciously process the provided information and accurately associate it with their physiological input. This process can be facilitated by promoting appropriate *awareness* of the users of their biofeedback and incorporating *muscle priming*, signals provided before reaction, to help users to cognitively anticipate their physiological responses. This thesis investigates the enhanced interaction with physiological input by these assistive techniques.

The five studies presented in this thesis provide deeper insights into interaction with physiological input from various body locations to enhance performance, effectiveness, and physical responses while reducing cognitive workload. We found that *multimodal biofeedback* from visual and tactile modalities can enhance the interaction in a muscle-based interface. Physiological input is comparable amongst the muscle locations tested, emphasizing the flexibility of muscle-based interactive systems. We investigate the role of *biofeedback awareness* of users as a means to optimize physiological self-regulation. Results point towards an important role of biofeedback awareness to impact and foster active control of physiological input. The observation that touching the muscle site during the experimental preparation phases helped participants localize their muscles inspired further exploration into how user preparation could refine physiological responses. Building on these findings, we investigated the concept of *prior stimulation feedback* at muscles, acting as muscle priming before the interaction, using both visual and tactile modalities. To further explore the effects of tactile feedback, we separated the tactile modalities into vibrotactile and electrotactile prior stimulation feedback and examined their influence at different muscle locations. We found evidence that prior stimulation feedback from all modalities can enhance the interaction with muscle-based input, highlighting that the calf muscles showed the fastest response in our system. This thesis concludes with implications for physiological input in assistive systems and enhancing them with multimodal biofeedback and prior stimulation feedback for human-computer interaction.

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1

Introduction

The emergence of interaction paradigms that leverage physiological signals of the human body as an input source, rather than relying solely on the motion of physical objects like mice, keys, or controllers, offers promising opportunities for human-computer interaction (HCI) [66, 198, 246, 250]. These approaches enable users to consciously modulate internal physiological processes, thereby establishing a direct and intentional link between the body and digital systems. Such interoceptive control, the focus on internal body signals, can enhance bodily awareness, improve reaction times, and refine motor performance [135, 136]. When combined with biofeedback, these systems amplify the perception of internal body signals, supporting users in learning to regulate physiological states as intentional input [131, 198, 265].

Physiological signals from the human body can not only be used to measure physiological reactions based on muscle activity (electromyography (EMG)) or skin conductivity due to the activity of the sympathetic nervous system (electrodermal activity (EDA)), but also offer a seamless and touchless alternative to interact with computational systems. Integrating input based on physiological sensing like EMG and EDA offers a novel approach to facilitate intuitive and responsive control mechanisms for HCI systems [165, 326, 327]. Ultimately, interoception-driven interaction frameworks have the potential to augment human-device communication and extend the boundaries of embodied digital interaction.

In situations where it is desired to prevent unintentional motion-based input or when movements are infeasible, e.g., for mechanical control of electric wheelchairs [195], exoskeletons [178], and remote robotic systems [10, 109, 329], traditional interaction methods like keyboards, mice, and hand-held controllers can be inefficient. Furthermore, traditional input methods can be cumbersome for untrained users [296], leading to prolonged response times [291] and frustration [262]. This makes them impractical for individuals with limited mobility [76, 85, 196]. When unobtrusive interactions are desired, e.g., for interpersonal communication in public space [193] or more subtle input interfaces for mobile computing [39], alternative input methods are needed. Input from physiological signals, e.g., from muscle contractions, can then be employed for mobile interfaces to realize unobtrusive, minimal interactions with connected devices [47, 48]. Interactions derived from physiological input channels like muscle activity, utilizing EMG, or skin conductivity as response from the sympathetic nervous system, utilizing EDA, provide a promising avenue for accessible interfaces [237, 315] while they force the users to concentrate on their bodily functions and the control of it, therefore enabling the focus on their body interoception, which consequently leads to the development of it.

Utilizing physiological input from EMG requires distinguishing between *isotonic* contractions, where muscles change length during movement [108, 203], and *isometric* contractions, where muscles exert tension without length alteration [203]. Physiological input based on isometric EMG is a promising method for hands-free interaction [208]. This technique is particularly suitable for users with mobility constraints because such systems are controllable with minimal movement, but therefore also require special tracking technology apart from motion-detection sensors [14, 82, 271]. Isometric EMG can be used to register the physiological activity of muscles at various locations on the body [165] and allows for continuous or discrete physiological input [5, 58, 237]. However, challenges remain because isometric contractions are difficult to detect [307], can lead to rapid muscle fatigue [6, 58, 91], and are not easily visible without specialized sensors with high resolution [227].

One way to gain increased control and more awareness during interactions based on physiological sensing is to display the signal back to the user via *biofeedback*. It offers great potential for enhancing interactions because the reflection of one's physiological signal during interaction fosters self-regulation and enables users to learn to control their physiological signals as input. Thus, isometric muscle contractions are often used with biofeedback to visualize EMG signals for improved awareness and body control [38, 114, 177]. Biofeedback increases body awareness by providing real-time feedback on physiological processes, enabling users to control previously unconscious responses, such as muscle tension, heart rate, or skin conductance [153, 166, 303, 322]. A key strategy involves closing the *biofeedback loop*, which facilitates neuroplasticity [102]. Users can then deliberately learn to control these responses and the related effects [11, 28, 275]. This technique is well known in psychophysiology for helping patients relax in stressful situations, often using EDA measures integrated into the biofeedback loop. EDA signals are a commonly used tool for biofeedback applications addressing relaxation, usually visually represented within these systems [138, 140, 322]. However, biofeedback systems require proper preparation because it is important to ensure the users consciously process the provided information to enable them to accurately relate it to the physiological signals from their body [87, 252, 257]. According to Gazzoni and Cerone [84], current biofeedback techniques are simplistic and not intuitive, limiting clinical effectiveness and suggesting the use of multimodal approaches. Research has explored various physiological signal feedback modalities [231]. However, combined feedback modalities to enhance physiological input remain underexplored, as such multimodal HCI experiments are resource-intensive and complex to conduct. Christopher Wickens' Multiple Resource Theory states that tasks in human attention compete for cognitive resources when they share similar characteristics [280]. Extensions to this model suggest using various modalities (visual, auditory, tactile) and processing codes (spatial, temporal) to balance the cognitive load and improve multitasking. Multimodal biofeedback in rehabilitation facilitates neuroplasticity necessary for regaining lost motor abilities [266].

This thesis aims to investigate how the biofeedback loop can be closed efficiently using different modalities to engage multiple senses simultaneously to reduce cognitive load, support multitasking, and enhance performance. It looks at how to enhance and accelerate interactions with physiological input. It sheds light on how biofeedback systems can amplify internal body signals to improve interface quality, and interoceptive awareness influences bodily control.

1.1 Research Questions

This thesis focuses on advancing HCI with input based on physiological sensing and output based on biofeedback principles. These efforts aim to develop more intuitive and efficient interfaces for a sedentary hands-free context with minimal movement. They offer practical insights for designing interactive systems with physiological input to provide developers and bioengineers with design guidelines to enhance user interfaces based on physiological input. Empirical studies are used to validate the effectiveness and practicality of the developed approaches. To inform the enhancement of applications for sedentary hands-free interaction with physiological input from EMG and EDA, we present five studies to explore the five research questions from Table 1.1.

We highlight the usefulness of isometric muscle-based input with EMG for use cases with restricted movement and as an alternative interaction method to traditional input mechanisms and to explore new ways of HCI paradigms. To refine EMG-based interaction methods for increased user performance and workload reduction, it is necessary to investigate optimal *muscle locations* for physiological input from isometric EMG. To identify optimal strategies for EMG sensor placement, we need to understand the difference among various muscle locations to optimize isometric EMG input in user interfaces (RQ1).

Isometric EMG input, derived from raw data and after signal processing, can be mapped to biofeedback modalities from multiple sensory cues. To comprehensively understand how different biofeedback modalities influence user performance and perceived workload in interactive muscle-based applications, it is necessary to investigate these modalities both individually and in full-factorial combinations. By experimental comparison of the effects of auditory, tactile, and visual feedback modalities and evaluating their impact on information throughput, it can be assessed which biofeedback modality most effectively supports isometric EMG-based interactions. To explore *multimodal biofeedback* mechanisms that relay muscle tension information back to users during interaction, it is necessary to understand which modalities enhance isometric EMG-based input performance and the effects of various biofeedback modalities on interaction (RQ 2).

Observations of participants during the previous study on isometric EMG interaction from various muscle locations revealed that they could localize their muscles faster when the experimenter touched the muscle site with the fingertip before the interaction. This supports the assumption that tactile muscle priming could speed up the recognition and interpretation of muscle activity. This priming of muscles for interaction can lead to faster and more accurate muscle contractions for input in systems with a deterministic repetitive input pattern. This applies when the system knows which muscle needs to be contracted next, and a learning effect enhances interaction. For the reduction of reaction times from relatively slow input from isometric muscle contractions, we therefore evaluate the effect of *prior stimulation feedback* on their responses. We employ visual, vibrotactile, and electrotactile cues for prior stimulation, due to their quick response timesand based on the findings from our previous study on multimodal biofeedback-enhanced interaction, which reports positive results from visual and tactile modalities. This includes the determination of the most effective modalities and muscle locations for enhancing user reaction times with *prior stimulation feedback* during isometric EMG interaction (RQ3 and RQ4).

It is currently unknown if increased or decreased *biofeedback awareness* of being in a closed biofeedback loop changes the physiological response to stress in an adaptive immersive environment. This addresses the important question in biofeedback research, whether the conscious recognition of biofeedback alters the effectiveness of physiological self-regulation to enhance the effectiveness in adaptive biofeedback applications based on physiological input (RQ5).

In summary, we integrate non-invasive physiological sensing technologies, which have firmly established their role in HCI, for interaction that we enhance through assistive techniques derived from rehabilitation and sports, such as biofeedback and muscle priming. By integrating these into comprehensive interactive methods this thesis advances the development of assistive systems with physiological input from various *muscle locations*, for *multimodal biofeedback*, introducing the concept of *prior stimulation feedback* into HCI, and investigating the role of *biofeedback awareness*. This is important for interaction designers who are interested in creating novel human-machine interfaces and bioengineers who aim to implement sedentary hands-free input techniques for real-time and responsive systems for users with and without (motor) disabilities.

Topic	**No.**	**Research Question**	**Chap.**
Muscle Interaction	RQ1	Which muscle locations are optimal for EMG-based real-time interactions considering user performance and perceived workload?	3
Biofeedback-Enhanced Interaction	RQ2	How do different feedback modalities (auditory, tactile, visual) influence the performance and workload of EMG-based interactions?	4
Enhanced Muscle Responses	RQ3	Does prior stimulation feedback enhance EMG-based interactions in reaction time tasks?	5
	RQ4	Do muscle location responses differ in EMG-based interactions with prior stimulation feedback in reaction time tasks?	
Biofeedback Awareness	RQ5	How does awareness of biofeedback, provided through EDA, influence physiological signal responses?	6

Table 1.1: Summary of research questions of this thesis.

1.2 Methodology

The improvement and enhancement of innovative interaction techniques represent a central focus within HCI. Throughout this thesis, we gathered quantitative and qualitative data in user studies to evaluate enhanced interaction techniques based on physiological sensing. The studies were conducted in laboratory environments and virtual reality (VR), mainly functioning as an experimental setup to shield participants from external influences. Immersive environments offer a non-distracting platform for engaging users in their interoception and therefore enable them to focus on their self-management of their physiological state. Such isolated environments allow interventions by providing a controlled yet dynamic setting where physiological responses can be fully monitored and modulated in real-time. The immersive nature of VR and interactive environments enhances the user's sense of presence, making the biofeedback experience more impactful [187].

Based on previous work, we developed interactive prototypes that integrated physiological signal hardware with virtual real-time environments to explore interactions based on physiological sensing and related effects. We selected simplified and easy-to-understand visual stimuli in virtual versions of well-established research methodologies in HCI like Fitts' Law Tasks (c.f., [79, 180, 181]), the Mental-Arithmetic task from the Trier Social Stress test (TSST) (c.f., [144]), and a reaction time task from the well-established Vienna Test System (VTS) approach (c.f., [103]). This was to unify the reactions of participants while the system prototypes were developed according to our research questions.

A new apparatus, consisting of software and hardware prototypes, has been developed to virtually adopt a standardized Fitts' Law target selection task setup [79, 180, 181], widely used in HCI for estimation of the information throughput from the muscle-computer interfaces in chapters 3 and 4. To adequately relate the physiological signal baselines of users a virtual version of a mental arithmetic task from the Trier Social Stress test [144] was developed in a new software prototype. alongside an immersive VR scenario that adapted to the user's biofeedback narratively by changing the theater parameters of the environment for the investigations of chapter 5. We developed a new software and hardware prototype consisting of a virtually adapted standardized response-based reaction test following the

Vienna Test System (VTS) approach (c.f., [103]), common in computer-based psychometric assessments, for muscle-computer interfacing in chapter 6. To further highlight the results, a signal database was created to classify EMG data according to muscle locations.

We took objective and subjective measures using a set of established methods and tools from the literature. Statistical analysis was performed using accepted approaches from the literature and previous work. For hypotheses testing, we used parametric and non-parametric tests at a significance level α of .05. The research in this thesis was conducted based on well-established research methodologies in HCI. This thesis investigates the proposed research questions using a combination of qualitative and quantitative methods, including questionnaires, surveys, and physiological signal analysis, across various empirical user study designs. Research techniques include controlled lab experiments, using both subjective user feedback and objective performance metrics, and observational methods. A key focus was on selecting and applying the correct algorithms for physiological signal processing, both in real-time and in post-processing. Statistical analysis was employed to interpret the complex data sets, drawing on existing models and frameworks from prior research. This thesis provides artifact and dataset contributions [312], and the source code for all applications is obtainable in an accompanying Open Science Framework (OSF) repository.

1.3 Research Context

The work in this thesis was conducted for about three years in the context of the Research Center FUTURE AGING at the Frankfurt University of Applied Sciences (FUAS), the Mixed Reality Lab of Faculty 2: Informatics and Engineering, and the Innovation Lab 5.0 in the HoST - House of Science and Transfer in Frankfurt am Main, Germany. It was supervised by Prof. Dr. Valentin Schwind at the FUAS and Prof. Dr. Niels Henze at the University of Regensburg. During this time, several collaborations with researchers have shaped this thesis, particularly with Prof. Dr. Thomas Kosch. This research was funded by the Hessian Ministry for Science and Art, Germany (FL1, Mittelbau). Beyond the scope of this thesis, several publications were produced during its preparation, contributing to related research topics and enriching the broader scientific discourse in the fields of assistive systems [234, 258, 262, 263], wearable technologies [259, 261], Mixed Reality (MR) [148], and experimental practice [255, 256].

1.4 Thesis Outline

This thesis consists of seven chapters, a bibliography, and an appendix. In the conclusion chapter, we present the results and evaluations of five empirical studies, an extensive review of related work, and a discussion and summary of the findings. We structure the work as follows:

Chapter 1 - Introduction motivates the research in this thesis and gives an overview of the research questions and the contributions of this thesis. We further introduce the concept of an innovative system for sedentary hands-free interaction based on physiological input for hands-free VR interaction using EMG and EDA multimodal biofeedback as part of an evolving system for sedentary hands-free interaction.

Chapter 2 - Background and Related Work provides an overview of the context of multimodal interaction techniques, an explanation of the physiological sensing technologies in use, and an extensive review of related work on physiological input in Virtual Reality, Augmented Reality, and beyond.

Chapter 3 - Body Locations for EMG Interaction describes the results of a study exploring the foundational question of which body locations are most effective for EMG-based interaction. It provides basic explorations of EMG interaction to lay the groundwork by exploring different body locations.

Chapter 4 - Multimodal Feedback for EMG Interaction describes the results of a study investigating how auditory, tactile, and visual feedback, as well as their combinations, can enhance sedentary hands-free interaction with minimal movement. It provides basic explorations of EMG interaction with multimodal feedback to lay the groundwork by exploring different methods and their effectiveness.

Chapter 5 - Prior Stimulation Feedback to Improve EMG Reaction Times develops how stimulation beforehand the interaction reduces EMG reaction times and enhances performance. It introduces the concept of muscle priming for prior stimulation during an EMG-based system for sedentary hands-free interaction.

Chapter 6 - Biofeedback Awareness discusses how awareness of physiological states (e.g., electrodermal activity) impacts users' control of their biosignal response. It introduces awareness as a crucial factor for effective interaction to highlight how informing users about their biofeedback can enhance the control of physiological input.

Chapter 7 - Conclusion and Future Work examines the results presented in the earlier chapters, synthesizes them, and outlines potential avenues for future research.

2

Background and Related Work

Physiological sensing has significantly evolved, transitioning from invasive methods to sophisticated non-invasive technologies integral to modern healthcare and HCI. This chapter provides an overview of the history and development of non-invasive physiological sensing with EMG and EDA, biofeedback, and human-machine interfacing. It introduces the technical foundations of physiological signal processing for biofeedback techniques used in the system prototypes for the studies of this thesis and reports on how related work integrates these methods in the context of healthcare and sports, and HCI.

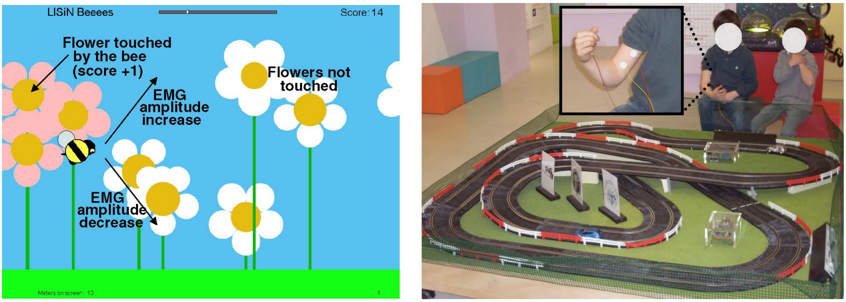
2.1 Background

Physiological sensing has its roots in medical and scientific research aimed at understanding human biology. The development of non-invasive methods, particularly for EMG and EDA, electrotechnical and computing breakthroughs, and advanced signal processing technologies marked significant milestones in this field.

Figure 2.1: First EMG recording apparatus at the Mayo Clinic Medical Sciences EMG Lab. Ervin L. Schmidt is in the chair, and Mildred Windesheim's arm is holding the electrode (1954).

2.1.1 History and Development

Physiological sensing has its roots in medical and scientific research aimed at understanding human biology. The development of non-invasive methods, particularly for EMG and EDA, electrotechnical and computing breakthroughs, and advanced signal processing technologies marked significant milestones in this field. EMG history began in 1666 with Francesco Redi's discovery of muscle-generated electricity in electric rays [229]. Galvani (1792) showed electricity induces muscle contraction and du Bois-Reymond (1849) recorded muscle activity [23, 81]. Marey coined "EMG" and made the first recording in 1890 [51]. In the 1950s, Lambert and Schmidt developed the first portable EMG machine (Figure 2.1), while EMG emerged in the 1960s with refinements by Cram and



a) EMG-driven bee touching flowers sliding on the screen.

b) EMG-controlled cars on Playmobil tracks.

Figure 2.2: Examples of two dynamic biofeedback games: (a) An EMG signal controls a bee in a video game, requiring muscle contractions to guide it to flowers or avoid danger as the background scrolls left. (b) EMG amplitude determines the speed of a slot car. (Courtesy of Compagniadi San Paolo, Torino, Italy.)

Steger in the 1980s, while Erik Stålberg led advancements in EMG analysis since 1950 [137]. From 1950 to 1973, EMG signals were recorded and analyzed manually on film or paper. Between 1973 and 1982, modular digital EMG systems emerged, enabling limited digital analysis. 1982 the first microprocessor-controlled EMG system was introduced [160]. From 1982 to 1993, EMG systems introduced new analysis methods and reporting features. Since 1993, personal computers with standard software and hardware have been used for recording, analyzing, and documenting EMG data. Similarly, EDA sensing has progressed from large galvanometers to compact, skin-mounted sensors that measure sweat gland activity, reflecting sympathetic nervous system arousal [297]. While EDA was first observed in the 19th century, the term "EDA" was adopted as a standard reference for the skin's electrical phenomena around 50 years ago [161]. EDA has become a widely used method in neuropsychiatry research to detect the skin conductance response (SCR) triggered by various sensory and psychological stimuli and, with advances in amplifiers and an understanding of its principles, is now applied in clinical disciplines [25].

The Emergence of Biofeedback Biofeedback was introduced as a technique that used physiological sensing to help individuals control involuntary bodily functions in the 1960s. Early systems employed EMG for neuromuscular disorders and EDA for stress management, showing that real-time feedback could aid recovery and performance improvement [69, 92, 313]. Neal Miller's research from the 1980s demonstrated voluntary control of autonomic functions through operant conditioning, inspiring biofeedback devices that, with advances in portable sensors, expanded from clinical therapy to broader applications [317]. Biofeedback measures physiological signals and presents them in an understandable format, helping individuals gain awareness and control of their bodily processes [87, 252, 270]. With biofeedback acting as a "sixth sense" to perceive internal functions, individuals can hear and see their physiological responses [189]. Biofeedback serves as a "psychophysiological mirror," allowing individuals to observe their body's physiological signals and use them to develop self-regulation of specific bodily responses [215].

Technological advances The acquisition of physiological signals and electrical interfacing with the human body has become significantly more accessible over time. Fifty years ago, physiological signal devices were expensive, bulky, and primarily used for medical diagnostics and sports science research. The shift from analog to digital technologies in the 1980s introduced the first consumer biofeedback devices. Recent advancements in electronic technologies have further transformed physiological sensing. Faster data transfer protocols, improved power supply, and increased storage capacity have enabled the development of handheld devices with powerful microprocessors capable of running training programs and storing user data. Wireless technologies like Wi-Fi and Bluetooth now provide greater mobility, allowing EMG signals to be transmitted wirelessly to PCs for processing and analysis.

A key milestone in this evolution was the progression from invasive to non-invasive physiological signal sensing. In the mid-20th century, the development of EMG enabled the detection of muscle electrical activity using electrodes placed on the skin, significantly enhancing the safety, comfort, and accessibility of physiological assessments in medical diagnostics and research [224]. Clinical EMG

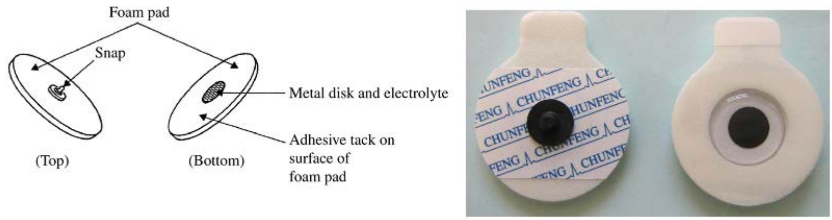


Figure 2.3: Body surface biopotential electrodes (Ag-AgCl) are often used in physiological sensing apparatus (adapted from [93]).

devices utilize invasive needle electrodes, besides adhesive electrodes, which limits their applications outside clinical settings. In the mid-20th century, advancements in electrode technology enabled EMG, allowing muscle activity to be measured non-invasively using adhesive electrodes on the skin. At the electrode interface, a charge carrier exchange occurs between dissolved ions in the electrolyte and free electrons in the metal, for accurate signal acquisition [19]. Similarly, advancements in EDA measurement techniques enabled the non-invasive monitoring of skin conductance, providing insights into autonomic nervous system activity. Figure Figure 2.3 shows the silver/silver chloride (Ag-AgCl) electrodes that are often used today in biopotential applications like EMG or EDA.

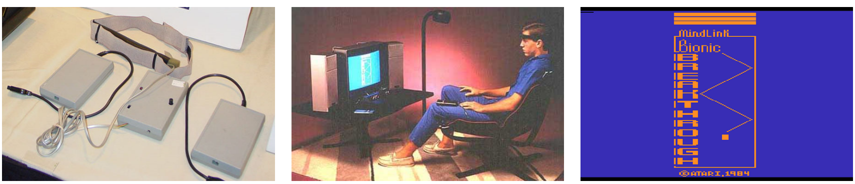


Figure 2.4: Fully working Atari Mindlink Prototypes for forehead EMG detection, shown by the Atari Museum at the 2003 Austin Gaming Expo (left), advertisement (middle), and view of the subsequent "Bionic" interface (right) (Courtesy atarimuseum[1]).

Human-Machine Interfacing The Atari Mindlink, introduced as a prototype in 1984, was one of the first HCI devices to use physiological expressions to control an interface. It functioned as a basic EMG device, measuring forehead muscle activity (e.g., frowning) to control input, contrary to its advertisement as a device for measuring EEG brain waves [249]. Demonstrated at the June CES in Chicago in 1984 (Figure 2.4), it tracked muscle signals to move screen objects left-right or up-down. Despite its innovative concept, development was canceled after Atari's Consumer Electronics division was sold to Tramiel Technologies one month later. Interestingly, the project was originally proposed in the context of the Special Olympics (Paralympics), with the Rose Kennedy Foundation offering to cover the full development cost. The plan was for Atari to develop sports software for the Special Olympics, potentially paving the way for advancements in computer interfaces for individuals with disabilities. In applications for human-machine interfacing, muscles are used as biological amplifiers of efferent nerve activity because of the one-by-one association between action potentials traveling along the axons of motor neurons and the electrical activity generated in the innervated muscle fibers [70, 74, 157]. Concerning direct nerve interfacing, muscle recordings do not necessarily need invasive techniques and provide greater signal-to-noise ratios. Therefore, the use of EMG can be seen as a general neural interface providing information on the activity of the motor neurons innervating the target muscle [76, 190].

2.1.2 Physiological Sensing and Feedback

Physiological Sensing technologies like EMG and EDA measure the electrical activity produced by skeletal muscles [105, 116] or the electrodermal activity of the hands [25, 161]. Physiological Sensing technologies can be integrated into Virtual Reality Systems to control an adaptive environment or enable new forms of interaction with the system for more intuitive, precise, or direct control within computer interfaces [145, 208, 326].

Electromyography (EMG) Skeletal muscle activity produces electrical signals that can be captured using EMG technology. A small electrical current is produced by the exchange of ions across the muscle membranes, gets amplified, and is recorded using two electrodes placed over the target muscle (typically in parallel with muscle fibers) plus a separate reference electrode on a neutral site (often a bony region) [116]. This setup is referred to as bipolar EMG or single-

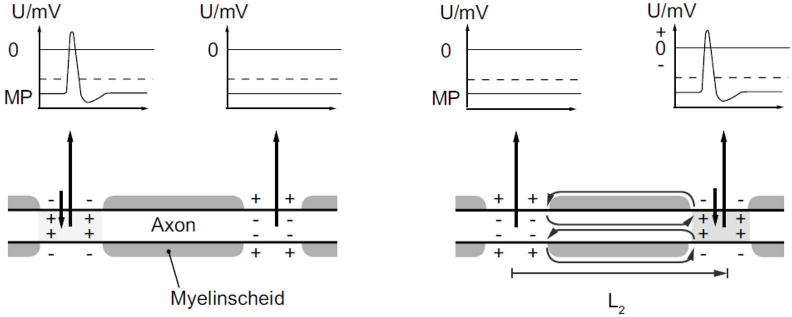


Figure 2.5: The action potential in saltatory conduction jumps between nodes of Ranvier, regenerating at each node, with a nerve conduction velocity of 10–50 m/s. The subfigures on the left and right represent different time points (reproduced from [19]).

differential configuration [30]. EMG measures the electrical activity generated by muscle fibers during contraction. This activity originates from action potentials of electrical signals that travel along nerve and muscle fibers when muscles are activated. The voltage at one electrode is compared to the voltage at another (reference electrode). The difference between the two provides the differential signal, which is what we use for analysis [19]. Surface electrodes are placed on the skin above a muscle. These electrodes detect the voltage difference between two points on the skin. The voltage difference reflects the summed electrical activity of multiple motor units (groups of muscle fibers activated by the same nerve) beneath the skin [80]. The action potential propagation in saltatory conduction of such muscle fibers is shown in Figure 2.5. Depolarization occurs in rapid jumps from one node of Ranvier of a nerve to the next, resulting in conduction speeds of 10–50 m/s. The electrical field spreads almost instantaneously along the myelinated segments of the nerve, causing the potential at the next node to rise faster than in the myelinated region, therefore moving along the nerve [19].

While using surface electromyography (sEMG) 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, however, we use the term EMG for this entire work.

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 [189]. EMG is used for medical applications and diagnostics of muscle-related disorders or diseases [282, 308]. Particularly assessing the muscle activity using EMG is indispensable for a wide range of medical, assistive, and interactive applications [5, 179, 282, 320].

The European Recommendations for Surface Electromyography (SENIAM) protocol [105] proposed common standards for assessing signals with EMG sensor technology, particularly for electrode placement instructions. Challenges affecting the EMG signal are individual tissue properties, physiological cross-talk in-between two muscles, and potential distance changes between muscle and electrode [50, 189].

Isometric Muscle Control To accurately trace back EMG signals to their source, it is essential to distinguish between signals from muscle tension based on movements, namely *isotonic* contractions [108, 203], and signals measured from muscle tension without movement, based on voluntary, namely *isometric* contractions [55, 75, 203]. Isotonic contractions are suitable for detecting movements, e.g., gestures [3, 142, 245] or locomotion [306], and can be combined with other sensors for improved recognition accuracy [326]. 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 [230].

The maximum voluntary isometric contraction (MVIC) method, where users tense their muscles with the maximum possible strength, is recommended when investigators desire no corresponding movements with cross-talking muscles, employ multiple muscle positions [45], and aim to isolate the signal of actual muscle tension from artifacts caused by movements [230, 245, 288]. A MVIC from EMG signal generally should be repeated three times to detect the highest amplitude of a muscle signal for processing physiological input from this muscle strength baseline [150].

Electrodermal Activity (EDA) The electrical conductance of the skin, which varies with sweat gland activity, can be assessed using EDA technology. This sweat secretion is controlled by the sympathetic nervous system, so it correlates with physiological arousal (e.g., stress or excitement) [25, 117, 251, 301, 321]. Instead of measuring voltage differences, as EMG does, EDA, or galvanic skin response (GSR), measures how easily current flows through the skin, which changes with the moisture level. Two electrodes are placed on the skin, typically on the palms or fingers, where sweat gland density is high. One electrode applies a very small, constant voltage (e.g., 0.5-1 V). The other measures how much current flows between the two, which depends on the skin's conductance (or resistance). EDA works with electrodes placed on the middle and ring fingers because they form a closed electrical circuit over the skin. EDA is a non-invasive, sensitive, and reliable marker of the sympathetic nervous system's activity, making it an ideal metric for biofeedback of bodily responses in the fields of healthcare and psychotherapy [194, 202, 204], and for applications in HCI [67, 96, 226, 241, 314].

Multimodal Feedback In the studies of this thesis, we consider visual, auditory, and tactile (later separated into vibro- and electrotactile) modalities in the interaction-based experiments due to their quick response times over sensations such as temperature, smell, taste, olfaction, or perceptions from organs in the vestibular system [107, 149]. Tactile stimuli are processed faster than cutaneous stimuli, such as temperature or pain [32] because their perception relies on mechanoreceptors. Mechanoreceptors typically have quicker response times compared to thermoreceptors or nociceptors (for pain, also related to very high temperature) [123, 184].

Researchers employ EMG-based visual feedback to enable subjects to increase their control over their muscle activation, e.g., for the movement of a robotic platform in real-time [42] or tend to prefer the use of visual and auditory cues for multimodal biofeedback applications for the simultaneous rendering of the physiological signal using multiple perceptual channels [84, 131, 231]. Biofeedback techniques are predominantly based on vision [273], or auditory [131, 298, 322] feedback, while some innovative applications employ biofeedback techniques rendering physiological signals using tactile [37, 131, 248].

Vibrotactile stimulation, which uses vibrations to engage skin receptors, has been applied to improve body awareness [183], with research in HCI exploring optimal placement [68], intensity [112], and user perception [316]. Vibrotactile patterns can stimulate tactile sensations in virtual reality [285], affect muscle activity [118, 119, 127, 192], and assist amputees or those with neuropathology [121, 221]. Such stimulations aid in balance rehabilitation [304], enhance EMG-controlled computing systems [168, 300], and *prior* vibrotactile stimulation (at the index finger) can increase force production, likely due to a brain response for limb stabilization and pattern memory [119].

While vibrotactile feedback stimulates skin receptors, electrotactile stimulation applies electrical currents to skin nerve endings to induce tactile sensations [127, 310]. Electrical currents with shorter pulse widths (50-125 μs) and lower intensities are known as transcutaneous electrical nerve stimulation (TENS) [176], providing electrotactile feedback without muscle contraction, in contrary to electrical currents with longer pulse widths (150-350 μs) and higher intensities, causing muscle contraction by depolarization of deeper muscle fibers, known as electrical muscle stimulation (EMS) [217, 287]. TENS can inhibit the transmission of pain signals to the brain by instead targeting dedicated sensory nerve fibers (A-beta fibers) [124, 125], responsible for transmitting tactile sensations from the location of the current [12, 26, 139, 223]. While TENS is used in the rehabilitative field for pain management [124, 147], it can be supportive for dementia [27], for tactile feedback with prosthetics [65], in VR [289], or to simulate muscle proprioception [130].

2.1.3 Signal Processing

Over the past 20 years, analog-digital converters and operational amplifiers have improved massively and become cheap. Microcontrollers and processors are widely available and can be easily integrated with the acquisition hardware. Figure 2.6 depicts the basic architecture of a physiological signal-acquisition system for EMG.

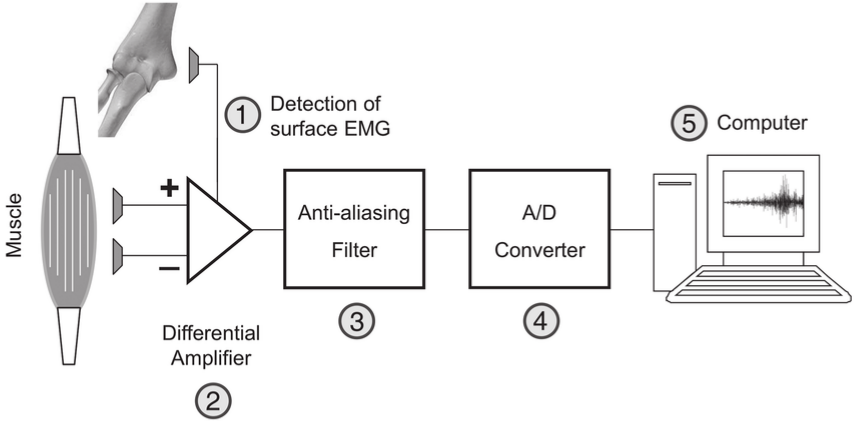


Figure 2.6: Simplified block diagram of surface electromyogram acquisition (reproduced from [31]). Block diagram illustrating the main steps involved in acquiring surface electromyograms: (1) detection of myoelectric signals using surface electrodes and a reference electrode, shown schematically on the medial epicondyle of the humerus; (2) amplification of the signals through differential amplifiers; (3) analog filtering of the amplified signals to prevent aliasing; (4) sampling the surface electromyogram into digital voltage values; and (5) storing the digital data on a computer.

Filtering We relied on the built-in pre-processing, low-noise signal conditioning, and amplification circuit designs provided by the EMG and EDA sensors of biosignalplux[1] [2]. The integrated low-noise high-speed operational amplifiers performed bandpass filtering and amplification on the basis of bitalino technology [93]. When a continuous signal is sampled, the samples represent the signal's amplitude at specific points in time. If the sample frequency is not high enough, multiple signals of different frequencies could match the same sampled points, causing aliasing, and making it difficult to accurately reconstruct the signal (step 3

[1] https://support.pluxphysiologicalsignals.com/wp-content/uploads/2021/10/physiologicalsignalsplux-Electromyography-EMG-Datasheet.pdf

[2] https://support.pluxphysiologicalsignals.com/wp-content/uploads/2021/11/Electrodermal_Activity_EDA_Datasheet.pdf

in Figure 2.6). The sampling rate should be at least double the size of the highest expected frequency of the signal according to the Nyquist-Shannon Sampling Theorem [269].

EMG-specific signal processing enhances parameter reliability and validity. Scientific guidelines (ISEK, SENIAM, c.f. [105]) recommend recording raw signals without hardware filtering, except for a bandpass filter (10–500 Hz) to prevent aliasing (step 3 in Figure 2.6). Ideally, post-hoc processing should be reversible to the raw signal. Key post-processing steps are outlined below.

Analog to Digital Conversion Electrical signals that originate from neural activity can be measured on the surface of the human body based on muscle activity, e.g., with EMG, and based on the consequences of the arousal of the sympathetic nervous system, e.g., with EDA. Different types of measurement principles can be used, which in our case are voltage potential differential principles, used for EMG measurements [19] and conductance measurements, such as those based on the basic principles of electrical current with EDA [93]. Based on their source, they differ in their measure-related amplitude and their frequency [44]. In our experiments, we followed the introductions from biosignalplux hardware datasheets, considering the specifications of an Analog-to-Digital Converter (ADC) system (step 4 in Figure 2.6). The given formula represents a process for converting an analog EMG signal to a digital format and then expressing it in millivolts (mV) (as suggested by the biosignalplux EMG sensor datasheet):

$$EMG(V) = \left(\frac{ADC}{2^n - 1} - \frac{1}{2}\right) \cdot \frac{VCC}{G_{EMG}} \tag{2.1}$$

$$EMG(mV) = EMG(V) \cdot 1000 \tag{2.2}$$

$VCC = 3V$ – Operating voltage of the system
$EMG(V)$ – EMG value in Volts (V)
n – Number of bits of the ADC channel (we use 16-bit)
$EMG(mV)$ – EMG value in millivolts (mV)
ADC – Value sampled from the channel ADC
$G_{EMG} = 1000$ – Gain of the EMG sensor system

On the contrary, the typical range of skin conductance used to measure EDA is 1 to 500 kΩ for resistance, corresponding to 0.002 to 1¯S for conductance, depending on the individual and their arousal state. To convert the raw values (ADC) into micro siemens (μS) as physical units we used the following conversion formula (as suggested by the biosignalplux EDA sensor datasheet):

$$EDA(\mu S) = \frac{\frac{ADC}{2^n} * VCC}{0.12} \tag{2.3}$$

$$EDA(\mu S) = EDA(S) \cdot 1 \cdot 10^{-6} \tag{2.4}$$

$VCC = 3V$ – Operating voltage of the system
$EDA(S)$ – EDA value in siemens
n – Number of bits of the ADC channel (we use 16-bit)
$EDA(\mu S)$ – EDA value in microsiemens
ADC – Value sampled from the channel ADC

EDA changes much more slowly than EMG. The signal's frequency range is 0.01 to 1 Hz because sweat gland activity occurs on a much slower timescale compared to muscle activation. Since EDA changes slowly, it can be sampled at a lower frequency (e.g., 10-50 Hz), sufficient to capture all relevant variations.

EMG voltage differences are tiny, typically in the range of 0.1 to 5 millivolts (mV). They are time-varying and can oscillate rapidly due to the fast firing rates of motor units. The frequency content of EMG typically ranges from 10 to 450 Hz, with most of the energy concentrated below 250 Hz. EMG signals are high-frequency and require a high sampling rate (e.g., 1000 Hz or higher) to accurately capture the details of the signal. These signals are processed following the analog-to-digital (A/D) conversion via the biosignalplux API for Unity[1], with EMG signals sampled at a high frequency (e.g., 1000 Hz) to preserve detail in rapid changes and EDA signals typically sampled at lower frequencies (e.g., 10-50 Hz) due to their slower dynamics. This provides us with the raw physiological signal measures from the corresponding signal sensors.

On-Set Detection in Real-Time The Teager-Kaiser Energy Operator (TKEO) is particularly well-suited for detecting onset periods in threshold-based interactive systems using EMG. It calculates the "instantaneous energy" of the signal and is widely used for activation detection and real-time control. A study by Solnik et al.

[1] `https://github.com/pluxphysiologicalsignals/unity-sample`

demonstrated that incorporating the TKEO into signal processing significantly improves the accuracy of EMG onset detection in EMG signals, particularly in EMG signals that originate from isometric muscle tension [278]. The Teager-Kaiser Energy Operator (TKEO) enhances the characteristic features of a signal, particularly those associated with rapid energy changes. This improves the signal-to-noise ratio and emphasizes signal components with high amplitudes, which are typically generated by muscle activity. The TKEO is commonly used for detecting muscle activation phases, extracting features like energy or frequency patterns for movement classification or prosthesis control, and filtering out baseline fluctuations or high-frequency noise to prepare signals for further analysis [277].

Rectification and Smoothing Raw EMG signals are captured as voltage differences, representing muscle activation, and require rectification, besides smoothing to extract meaningful activity levels to serve as appropriate input for interactive scenarios. Raw EDA signals are recorded as skin conductance levels (in microsiemens), reflecting physiological arousal, and typically require smoothing but not rectification.

In the rectification process, all negative amplitudes are converted to positive values through mathematical absolute value calculation, effectively "flipping" the negative signal deflections upward (Figure 2.8). This simplifies amplitude detection and enables the calculation of standard amplitude parameters such as mean, maximum, minimum, and integral. Bipolar raw signals, by contrast, have a mean or integral value of zero. Rectification ensures the EMG signal does not average to zero by eliminating its negative components. This can be done through full-wave or half-wave rectification [228]. Full-wave rectification converts the entire EMG signal to positive values, preserving all signal energy for analysis, making it the preferred rectification method [302].

To provide a reasonable level of signal smoothing, it is common to average a constant number of signal values by continuously calculating the average within a constant moving window (Figure 2.9). When applied to rectified signals and appropriately parameterized, it serves as a reliable parameter for estimating

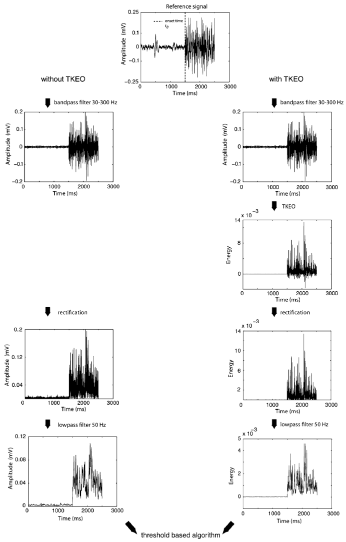


Figure 2.7: Illustration of the effect of a TKEO algorithm for onset detection of an EMG signal before it goes into rectification. On the right side, with the TKEO applied, a baseline segment and an EMG burst were extracted from a raw EMG reference signal to emphasize the characteristics of the signal (image reproduced from [278]).

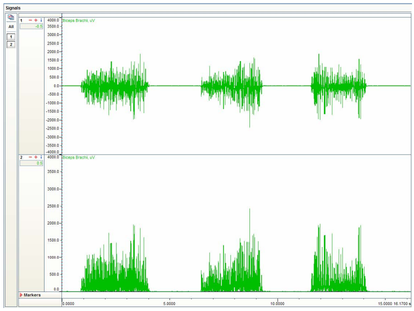


Figure 2.8: Raw EMG recording in the upper channel of a signal acquisition software and its fully rectified version in the lower channel (image reproduced from [150]).

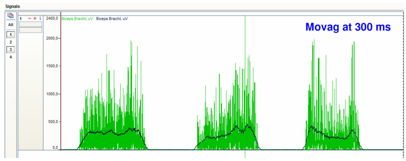


Figure 2.9: Illustration of the effect of a sliding window algorithm for signal smoothing of EMG amplitude measures shown by the black lines (image reproduced from [150]).

amplitude behavior in EMG measures [105, 150]. Using a sliding window technique with a defined length is also useful to smooth the raw EDA signal [161] for further processing.

Biofeedback Mapping Two main mapping strategies are employed in this thesis to interface the physiological signals of individuals with computing devices and

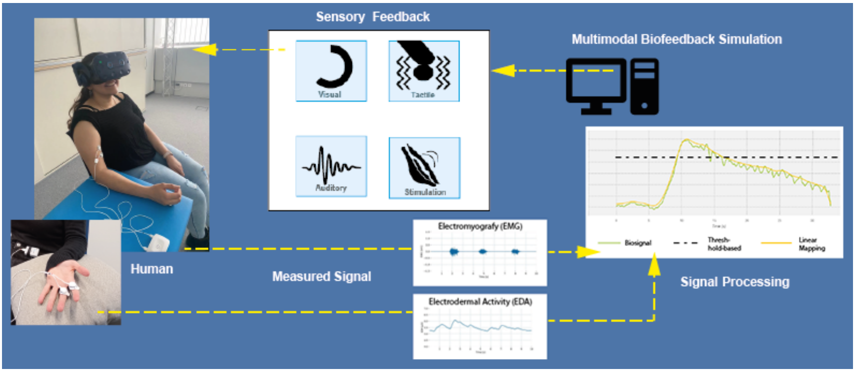


Figure 2.10: Schematic of a Biofeedback Loop: The physiological signals of the human body are displayed back during interactions, informing about the body's physiological state. Signals are recorded from EMG and EDA, processed and mapped, and transformed into multimodal biofeedback that reflects a feature (such as amplitude) or a pattern of the physiological signal as sensory feedback back at the human.

provide biofeedback: threshold-based mapping and linear mapping. Figure 2.10 illustrates the biofeedback loop, where the physiological data of the individual is sensed, processed, and displayed back in an interpretable format by the system.

Threshold-based mapping triggers events when signals exceed predefined thresholds, such as selecting a UI element by contracting and relaxing a muscle beyond set upper and lower thresholds of the EMG value. This approach is similar to up and down training of muscles known from physiological training [59, 163, 211] and can also support biofeedback mechanisms. The most common EMG indices in such contexts are signal amplitude and muscle activation timing, typically expressed as the percentage of time the amplitude exceeds a threshold. EMG biofeedback is used in the context of rehabilitation for "up-training" to increase muscle activation during tasks [163], and for "down-training" to promote muscle relaxation [63, 205] or to reduce contraction during incorrect postures [211] or spasticity [59]. We employed such techniques known from rehabilitation for interactive scenarios and applied them to facilitate the selection process of elements in VR-based user interfaces to compare different aspects that may enhance the interaction with muscle physiological signals.

Linear mapping establishes a direct proportionality between the parameters of the physiological signal and a virtual parameter, such as translating EMG values into a visual feedback parameter [42] that changes based on muscle tension intensity, or when EDA values are mapped to the intensity of a virtual parameter that guides the appearance of the VR environment, like the percentage value of a preset that influences the surrounding weather state. This mapping strategy can be employed in a multimodal biofeedback UI to reflect and inform individuals about the state of the employed physiological signal with more than visual feedback, but also vibrotactile or electrotactile feedback. Linear EMG biofeedback can be used to inform the subject on the timing of their muscle activity when translated to informative visual patterns [4, 131] and to promote the occurrence of rest periods in the case where a muscle is continuously active [104]. Similarly, linear mapping of EDA biofeedback promotes relaxation in biofeedback applications for stress reduction [117, 202].

A combination of threshold-based and linear mapping strategies was used in the studies of this thesis, where muscle tension thresholds trigger interactions while providing multimodal feedback that is then linearly mapped to muscle activity and displayed as visual, vibrotactile, and auditory parameters. In chapter 3, threshold-based mapping was used to trigger interactions, in chapter 4, threshold-based mapping was used to trigger interactions, and linear mapping was used to generate multimodal biofeedback, in chapter 5, linear mapping was used to generate visual biofeedback while signals were post-processed for reaction time evaluation, and in chapter 6 linear mapping was used to generate visual biofeedback.

Biosignal Classification Approaches for physiological signal classification from EMG data are less developed than, e.g., heart rate (HR) signal classification, utilized to assess user engagement, and cognitive load in HCI [173], or for diagnosing cardiovascular conditions [2]. This might be due to EMG signals being highly variable related to muscle location, interference, and individual physiology.

The majority of research on interactive systems with EMG signal classification employs high-density surface EMG (HD-EMG), an array of numerous electrodes to sample muscle signals at multiple points over one muscle site or around limbs, e.g., around the wrist to decode handwriting gestures [129]. The grid-like structure of HD-EMG instead of a bipolar electrode setup requires a higher data volume to be analyzed. Still, it can be appropriate for decoding input for gesture recognition and advanced prosthetic control [30, 129]. At the same time, its machine learning integration is more suitable for deep learning methods that exploit spatial correlations, similar to image detection [122].

In recent years, machine learning has enabled new biosignal processing approaches for human–computer interaction, with ensemble methods, such as random forests, playing a key role. Random forest classifiers can robustly identify patterns in bipolar EMG signals (e.g., hand gestures or muscle activation states) with high accuracy and strong noise resistance [120]. Recent studies demonstrate that random forests can decode EMG-based hand gestures to control computers or prosthetic devices with excellent performance (often >95% accuracy) [128]. Random forests have also been integrated to estimate continuous joint movements from EMG, enabling intuitive control of prosthetic limbs or wearable robots [171].

In this thesis, data from the study of Chapter 5 is used to uncover patterns in signals from different muscle locations. We present a novel approach that, instead of employing HD-EMG arrays for biosignal acquisition, uses a bipolar EMG setup and that, instead of using random forest models for real-time detection, retrospectively analyzes bipolar EMG data to demonstrate machine learning as a post-hoc analytical tool, extending beyond real-time gesture control.

2.2 Related Work

Measuring physiological signals, using those for computational input, and rendering those signals as biofeedback are subjects in multiple disciplines of related work. In this section, we built upon relevant research in the context of registering and using physiological signals as well as rendering biofeedback. We report on relevant research on EMG as physiological input as an interaction technique and the integration of biofeedback for the improvement of body perception and training in the healthcare and sports field, as well as for the enhancement of systems in HCI.

2.2.1 Interacting with Muscles

By translating muscle activity to input, EMG-based systems enable natural, hands-free interactions, crucial in muscle-computer interfaces, assistive technologies, and accessibility. For interactions with computing systems, EMG offers a promising avenue for enhancing interactions through muscle-based input methods [9, 47, 48, 175, 193, 247]. Research in HCI explores the feasibility of muscle-computer interfaces as interaction methodology between humans and devices for gesture detecting [9], remote rehabilitative exercise monitoring [151], and creating haptic full-body immersive experiences using EMG in VR [54], while early approaches showed an interest in decoding human-muscular activity rather than relying on physical device actuation [245]. Gesture recognition [245] or translating the intensity of muscle activity to select letters while typing [156] are additional use cases of EMG devices in HCI research. EMG has also been explored providing off-desktop mobile or wearable interaction systems [159] and as interactive communication tool between persons [247]. EMG input devices can enable mobile interfaces to realize unobtrusive and intimate communication based on isometric muscle contractions [47, 48] allowing subtle and minimal interactions with connected devices to stay unnoticed by observers, and integrate EMG input in applications for public space with motion-less gestures to enable private interpersonal communication [193].

In the fields of biomedical and interactive applications, physiological input was leveraged for active hardware and software control [189, 199]. It has gained popularity in non-medical research, particularly for enhancing body awareness, motion, interactive device control [38, 114, 177], and assisted control of interaction-based selections [14]. Thus, apart from its general relevance in rehabilitation and sports [15, 131, 207, 282], particularly EMG-based input mechanisms find applications in exoskeletons [178, 290], prosthetic control [29, 237], teleoperated robotic systems [10, 109, 329]. EMG feedback for active control of immersive, virtual applications has expanded into motor imagery applications, such as training for direct limb control for amputees [5, 58, 209] and post-stroke rehabilitation [111].

Research has reported different effects of EMG sensor placement at different muscle locations for interaction [45, 165]. For example, in terms of adaptive gameplay, participants in a study by Nacke et al. [198] report headaches when EMG sensors were placed on the forehead to imitate joystick input. The authors also refer to the 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 [198]. Also related to games is when EMG is connected to game mechanics to support rehabilitation and motivation. For example, Ma et al. [179] 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. [83] concluded that gamified EMG and VR therapy can lead to engagement and motivation. Supporting muscle training in multi-modal VR/augmented reality (AR) environments can also improve learning, for example, how to use a new prosthetic [197, 201] or even a virtual hand [162, 209]. The process of *muscle priming*, a phenomenon from neurophysiology, suggests that prior stimulation of muscles can enhance performance and cognitive processing [61, 62, 89, 272] and could therefore enhance EMG interaction. Similarly, muscle activation during warm-up exercises can lead to improvements in various metrics [20, 94, 293].

To interact with EMG 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 [21, 170, 233]. For target pointing or aiming in combination with EMG triggers, researchers use eye gaze [208, 242], upper and lower arm rotation [99, 233] (c.f. Thalmic Labs' discontinued Myo Gesture Control armband), hand rotation [179, 208], and head rotation [179, 208]. Related research uses pointing via head-gaze with an head-mounted display (HMD) in hands-free interaction [98, 315] with EMG-based triggers, and showed that this method works better concerning the information throughput [181] than eye-gaze pointing.

Isometric Muscle Tension Applications of isometric EMG are commonly known from systems in rehabilitation following injuries and from control mechanisms in assistive systems for users with limited mobility, with a few examples from HCI. Isometric muscle contractions are suitable for users with injuries or medical conditions that restrict movement [106] because the muscle does not change its length or position during tension. They can be employed to increase muscle stability, such as holding the weight over longer periods [164], or to address muscle stiffness and reduce blood pressure [164, 191]. After a fracture, when the arm is fixated to prevent movement, isometric contractions based on EMG-supported feedback can prevent muscle loss without destabilizing the fracture [279]. They improve control in assistive systems for users with limited movement, aiding therapists, researchers, and developers [199, 276]. These interfaces provide accessible solutions for users with physical disabilities to interact with computing devices [14]. This approach is particularly valuable for health-related applications after events like strokes, where only the intention to move a limb can be tracked [82, 271]. Isometric EMG interfaces enable a layer of motionless [39], subtle, and unobtrusive (social) interactions [48, 193, 264].

2.2.2 Biofeedback in Healthcare and Sports

Rendering a signal from a physiological activity to its user in real-time is commonly referred to as the term *biofeedback*. This allows the user to influence that signal. Biofeedback is used to increase awareness and consciousness of that physiological function [87]. Using biofeedback with EMG signals mainly emerged from the field of medical and clinical rehabilitation [15]. Actively monitoring one's physical activity of the muscles can be supportive of reacting, adapting, or understanding one's physiological-based parameters such as behavior, movements, and postures [210]. 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 [324], neuromotor [110], and stroke rehabilitation [286]. Yoo et al. [320], 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 [34, 37, 131, 248]. In particular, rendering biofeedback using multi-modal systems such as in VR or AR has been extensively investigated by previous work [174, 209, 244].

To assess stress in biofeedback applications and in real-time, medical practitioners and researchers use EDA. Closing the biofeedback loop Figure 2.10

depends on the user's awareness of consciously perceiving the biofeedback process and the extent of feeling to directly control the physiological response. For example, researchers found an increased muscle activity in high-awareness tasks using EMG and a reduced activity where participants were not fully aware of the functional control [257, 264, 281]. Thus, an increased or higher awareness of the physiological function may significantly alter the strategy to control the physiological response and could be used to enhance or decrease the effectiveness of biofeedback techniques. This is important for HCI researchers and healthcare practitioners utilizing a wide range of applications, such as in virtual reality [200]. These applications do not only comprise measuring stress in VR [67, 226, 241], but also using the signal as biofeedback modality [314] such as for anxiety [202] or phobia treatment [194], trauma coping [204], emotion-adaptive games [96], skill training [239] or architectural feedback in VR [212], or for altered appearances of one's own avatar [274]. Biofeedback for stress management with EDA is important for enhancing individual well-being and health [7, 56, 138, 167, 323]. By enabling individuals to monitor and adjust their physiological states, biofeedback offers a responsive and effective alternative to managing stress, potentially reducing the reliance on pharmacological interventions and promoting holistic health. Emerging evidence suggests that biofeedback systems can serve as a valuable adjunct to traditional therapeutic modalities, particularly for conditions like anxiety, phobias, and trauma [117].

2.2.3 Biofeedback in Human-Computer Interaction

Previous work from HCI discussed how the biofeedback loop can efficiently be closed using different modalities in EMG interfaces [131], investigating the effect of visual and auditory biofeedback for physical training exercises. However, based on their findings, the authors conclude that multimodal feedback systems should provide a choice for the user to prevent sensory overload [131]. While it appears that addressing two senses simultaneously can lead to an increased cognitive processing [222, 292, 319], there are also cognitive models predicting that combining too many external influences can increase the likelihood of information overload [13, 115, 311]. Biofeedback in VR is particularly impactful because immersive environments enhance presence and make biofeedback experiences more engaging [187] to improve sports, training, and fitness efficiency [43, 52, 299]. Here, VR has been established as a stimulating and motivating kind of application not only to support training but also multi-modal muscle control [114, 219, 232, 271].

The application of EMG in interactive systems has shown promise in enhancing user interaction from different muscle locations through biofeedback [165, 326]. EMG is widely used for various health-related interactive applications [35, 111, 145, 172, 244, 295], with biofeedback enhancing immersion and engagement [83, 162, 179, 197, 201, 209]. As these technologies provide high levels of immersion, motivation, and engagement that can be fostered by virtual, visual feedback [5, 185, 244], the usage of AR and VR is the subject of several use cases in many EMG-related disciplines such as in fitness and sports [84], for hands-free interaction [208], health [172], and rehabilitation applications [201, 209, 295]. Recent studies in HCI exploring machine learning methods, including random forests (RF), for interpreting bipolar EMG signals, have proven effective for classifying EMG-based user gestures and muscle activities. For instance, Dwivedi et al. [64] employed a Random Forest model to decode object manipulation motions in a VR setting using forearm EMG, enabling immersive muscle-computer interfaces. Similarly, Fındık et al. [268] applied a random forest classifier to multi-channel surface EMG for hand gesture recognition and muscle forces, achieving accurate classification of individual finger movements.

Body awareness, the systematic cognitive processing of sensory cues, involves both visual and tactile stimulation in HCI [60, 188] with recent research focusing on using these for biofeedback in EMG interaction with the own body [73, 131–134, 141, 264]. Similar research in HCI addressed the mechanism using isotonic contractions [152], e.g., while playing music instruments [126].

The integration of EDA into HCI, such as in Games [198, 213, 235] and immersive environments [36, 154, 187, 309], has recently gained increased interest for HCI researchers. EDA-driven systems dynamically adjust virtual environments on base of biofeedback principles to reduce stress, offering real-time interventions for relaxation training, or productivity enhancement [90, 212]. EDA with visual, narrative feedback has been increasingly recognized, e.g., for its potential in treating a variety of stress-related conditions [77, 214, 243]. Furthermore, the applications of EDA biofeedback extend beyond stress management and have been widely explored to enhance the mind-body connection, enabling users to gain greater control over psychophysiological states [11].

2.3 Summary

This chapter explores the historical development, technical foundations, and interdisciplinary applications of physiological sensing, biofeedback, and their integration into HCI systems. It explains the technical foundations and advancements in physiological sensing and signal processing for the design and implementation of interactive systems, emphasizing non-invasive techniques like EMG and EDA. Signal processing techniques enable the extraction of meaningful data from noisy physiological signals, such as EMG and EDA. Mapping strategies (threshold-based and linear) allow interactive systems to translate physiological activity into user feedback, fostering more intuitive control.

Related work has leveraged EMG for muscle-computer interfaces, gesture recognition, and assistive technologies. However, challenges like optimal sensor placement and related interaction performance remain unexplored in detail. EMG at different muscles is used in a wide number of health-related and even interactive applications [35, 111, 145, 172, 244, 295]. Therefore, we investigate the impact of different muscle locations on user performance and workload in sedentary hands-free interaction, addressing RQ1.

Biofeedback has been widely used in related research for therapeutic applications in healthcare, such as neuromuscular re-education, stroke rehabilitation, and stress management. Biofeedback measures physiological signals and presents them in an understandable format, helping individuals gain awareness and control of their bodily processes [87, 252, 270]. Related work reports on relevant aspects of the integration of multimodal feedback modalities to enhance user interaction with physiological input like EMG. Single- and multi-modal biofeedback can be presented to the user to gain control over one's own muscle contractions [15, 43, 52, 87, 131, 299] and for immersion and engagement [83, 162, 179, 197, 201, 209]. It is unknown which biofeedback modalities [131, 248, 298] can be used for optimal interaction with EMG devices. While multimodal biofeedback has shown potential, sensory overload and cognitive load are key concerns. However, no comprehensive comparison of multimodal biofeedback techniques to enhance EMG interactions has been investigated so far, therefore, we address this by investigating RQ2.

Previous work uses EMG to measure isometric contractions for various applications, including hands-free interaction in real-time systems [68, 112, 124, 125, 127, 183, 192, 285, 316]. Research indicates that vibrations as prior stimulation can affect muscle activity [118, 119]. However, it is currently unknown if this principle applies to isometric contractions and electrotactile stimulation. Additionally, the impact of these factors on muscle reaction time, vital for hands-free, real-time interactions, remains unclear. While research on muscle priming in sports and rehabilitation is established, its integration into EMG-based interactive systems remains to be explored. Related work demonstrates strong performance of random forest classification on EMG pattern recognition tasks, which is valuable for real-time control systems, but the use for post-hoc analysis of EMG data remains underexplored. This provides a foundation for addressing RQ3 and RQ4 by evaluating the effects of muscle priming with prior stimulation feedback on reaction times and muscle-specific responses.

Biofeedback acts as a "psychophysiological mirror", enhancing body awareness by visualizing internal states [11, 215]. Previous studies have demonstrated the effects of EDA biofeedback applications to improve health-related issues and report on reduced activity where participants were not fully aware of the functional control [257, 281]. How EDA-based awareness impacts physiological responses remains unclear; therefore, we investigate this by addressing RQ5.

3

Muscle Locations for EMG Interaction

This chapter explores the potential of various muscle locations for EMG input, focusing on sedentary, hands-free interaction. We investigate how isometric EMG from different muscle locations can optimize interaction performance. To study the interaction of participants targets appear on a virtual panel in front of them. The participants are asked to select the targets as fast as possible by pointing at them with their head rotation (head-gaze) tracked by the VR HMD and trigger the targets by tensioning their biceps muscle to exert a signal threshold. Understanding muscle control as an interaction technique requires distinguishing between isotonic contractions (e.g., limb movement) and isometric contractions (force exertion without movement) [39, 193]. Isometric control is essential in EMG-based systems where unintentional motion must be avoided, such as electric wheelchairs [195], exoskeletons [178], and robotic systems [10, 109, 329]. Previous research highlights the versatility of isometric EMG-based interfaces in health and interactive applications [35, 111, 145, 172, 244, 295], while it reports on isometric EMG interaction promoting muscle fatigue [91]. However, the optimal muscle locations concerning throughput and workload with isometric EMG remain unclear. To address this, we conducted an exploratory study examining the effects of isometric EMG from different muscle locations on interaction performance.

Parts of this chapter are based on the following publication:

J. Sehrt, T. Wißmann, J. Breitenbach, and V. Schwind. "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. Hamburg, Germany: Association for Computing Machinery, 2023. ISBN: 9781450394215. DOI: 10.1145/3544548.3580738

3.1 Method

As humans do not activate and use all of their muscles in the same way, we hypothesize that there are differences in the users' input performance between different muscle locations. To shield users from external influences, we conducted the exploratory user study in VR.

3.1.1 Study Design

We conducted a VR user study using a within-subjects 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 [113, 181]) as well as subjective assessments, we measured performance and workload.

Muscle Locations Research investigating EMG as muscle input uses the *upper front arm (Biceps bracchii)* [5, 273], the *upper back arm (Triceps brachii caput laterale)* [5], the *temple (Temporalis anterior)* [156, 294], the *inner calf (Gastrocnemius)* [198], or *forearm (Flexor carpi radialis)* [5, 245]. During system development, we found that EMG signals from the shoulder muscles (Infraspinatus) [328] are being compromised by the head rotation with the HMD and did not include the location. As a control condition, we included the *VR Controller (Hand)* of the headset.

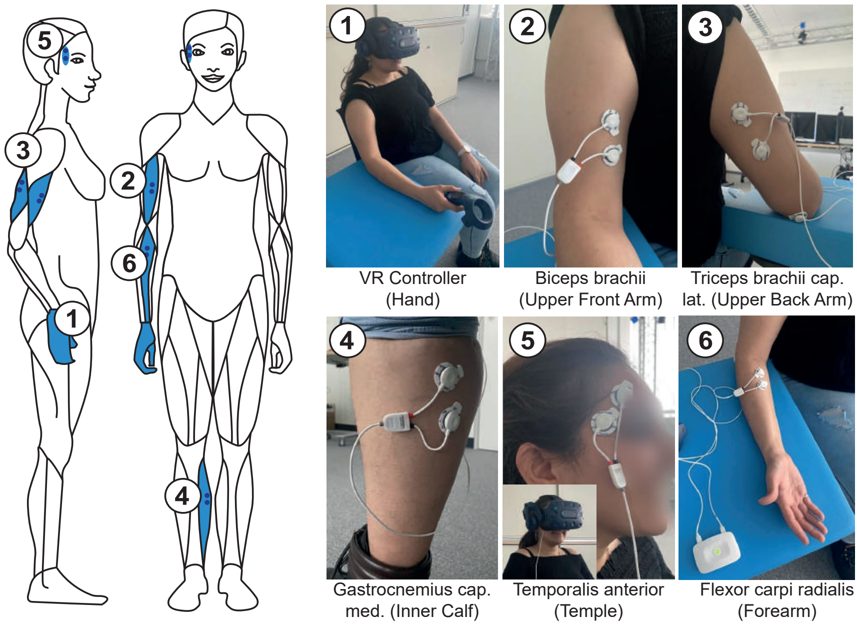


Figure 3.1: The six conditions with corresponding muscles (blue) and muscle locations (1-6) for EMG sensor placement used in the user study.

3.1.2 Apparatus

We created a virtual version of a Fitts' Law task [113, 181] using Unity Engine (Version 2019.4.1f) running on a PC with AMD Ryzen 5900X, GeForce RTX 3070, and 16 GB RAM to measure performance and workload. Targets were activated reciprocally clockwise, beginning with the uppermost target (at 12 o'clock), and were hidden until activated. The virtual scene was kept as simple as possible and contained a panel in front of the participant for calibration instructions and the display of the targets of the 2D Fitts' law target selection task right in front of the participants. 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. The 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 basis of bitalino technology [93]. Signal strength above 20% was accepted as the 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 index of difficultys (IDs) 1.5, 2.0, 2.5, 3.0, 3.5, 4.0, and 4.5.

3.1.3 Measures

As recommended by biosignalplux and in line with previous research on EMG for event detection, EMG signal was smoothed and rectified, and processed through a Taeger-Kaiser energy operator to improve onset detection [277]. The mean of all EMG values within a sliding window of 10 values (every 10 milliseconds with 1000 Hz) was calculated to provide 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-Task Load Index (raw TLX) as a widely used tool in HCI for workload assessments [101] (c.f. Appendix Section 7.3) with a digital version of the questionnaire in VR. This avoids putting off the headset and potential inconsistencies of placement of body posture and hardware [253]. Qualitative feedback was obtained by a post-VR interview and noted by the experimenter.

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

3.1.4 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 into a comfortable seated position with elbows and knees brought to 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 was consistently placed at the elbow joint bone. The experimenter put on the HMD for the participant. Lens distance was adjusted according to the participants' individual preferences. Participants were orally instructed on how to use their muscle tension as a trigger and that they should "select the targets as fast as possible". Before calibration, participants were free to ask questions.

During the calibration process, a text on a virtual panel was presented: "Please tense your muscle with effort...". The participant's physiological signal was rendered for the experimenter to ensure that the desired amplitude had been registered. In cases where participants were not able to activate their muscles 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 [105] except for the temple. Afterward, we brought the participants back into a seated position.

Before starting, the participant was explicitly instructed not to move any limbs to ensure isometric muscle activation and to "select the targets as fast as possible". Then, the participant performed the Fitts' law task with pseudo-randomized IDs and filled the raw TLX on the virtual panel. After each condition, a new set of disposable electrodes was attached to the subsequent muscle locations in counter-balanced order according to the randomization by a Latin square. During the procedure, the experimenters noted comments and suggestions from participants. After finalizing the last condition, participants were debriefed and could express individual observations about their experience.

3.1.5 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 could 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 lectures. 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.

3.1.6 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 [181]. Their model is part of ISO 9241-411 [113] 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 effective index of difficulty (IDe) and the mean time (MT) as shown in equation :

$$ID_e = log_2\left(\frac{A}{W_e} + 1\right), \quad TP_e = \frac{ID_e}{MT} \tag{3.1}$$

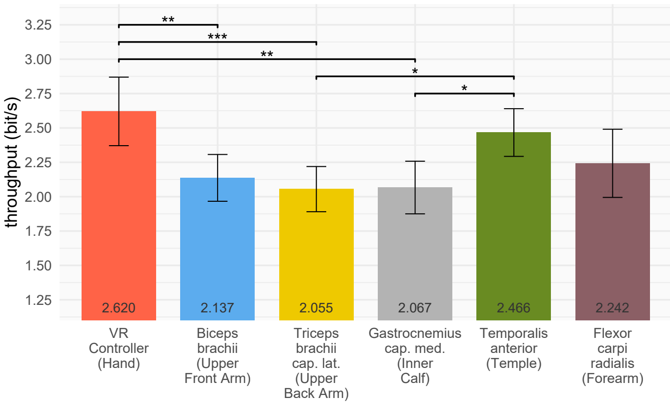


Figure 3.2: Objective performance measures of the study. The average throughput from the Fitts' law task for each condition. All error bars show 95% confidence intervals (CI95).

3.2 Results

3.2.1 Throughput

Objective performance measures of the study on the throughput measures are shown in Figure 3.2. 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 labeled following recommendations by Fields [78]. 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 3.1.) 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

Table 3.1: 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)		Gastrocn. cap. med. (Inner Calf)		Temporalis ant. (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						
Gastrocn. cap. med. (Inner Calf)	**.001***	1.000	.995	1.000	1.000	1.000				
Temporalis ant. (Temple)	.862	1.000	.150	.092	**.034***	**.024***	.042	.657		
Flexor carpi rad. (Forearm)	.065	1.000	.969	1.000	.730	1.000	.780	1.000	.558	.229

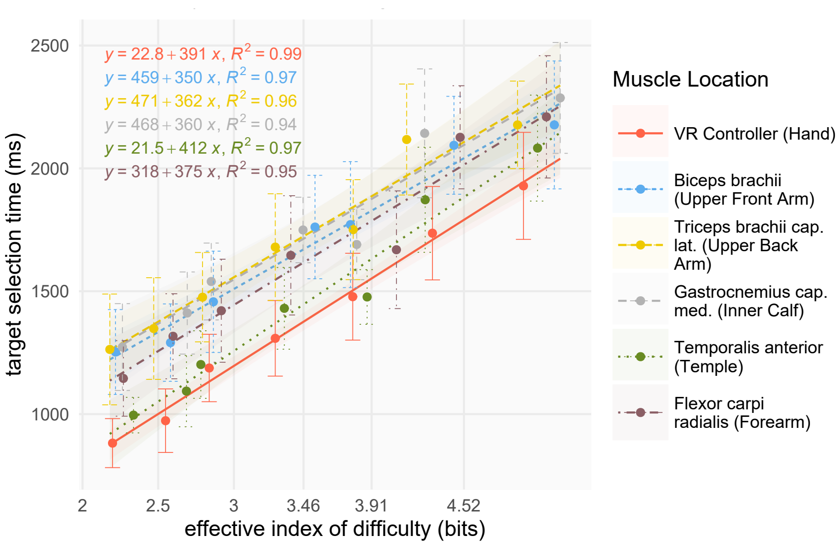


Figure 3.3: The regression slopes show the target selection time of each condition as a function of the IDe. All error bars show 95% confidence intervals (CI95).

Temporalis anterior. Moreover, the *VR Controller* was significantly faster than the *Biceps brachii*. Any significant differences between *Flexor carpi radialis* and the other MUSCLE LOCATIONS or between other condition pairs could not be found (all with $p \geq .065$). No gender-related effects or interactions were found (all $p > .05$).

3.2.2 Target Selection Time

The regression fits for the mean target selection time of the individual MUSCLE LOCATIONS based on the IDe and the resulting slope parameters (constants *a* and *b* from the Fitts' task) can be found in Figure 3.3. We further analyzed the log-transformed mean target selection time on the participant level and included the ID as co-variate in a repeated measures analysis of covariance (RM-ANCOVA) to understand if the difficulty during 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 ($\varepsilon = 0.892$) 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 target selection time of the EMG device is independent of the difficulty during target selection.

3.2.3 Subjective Workload

Subjectively perceived workload was assessed using the raw TLX questionnaire with results shown in Figure 3.4. 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

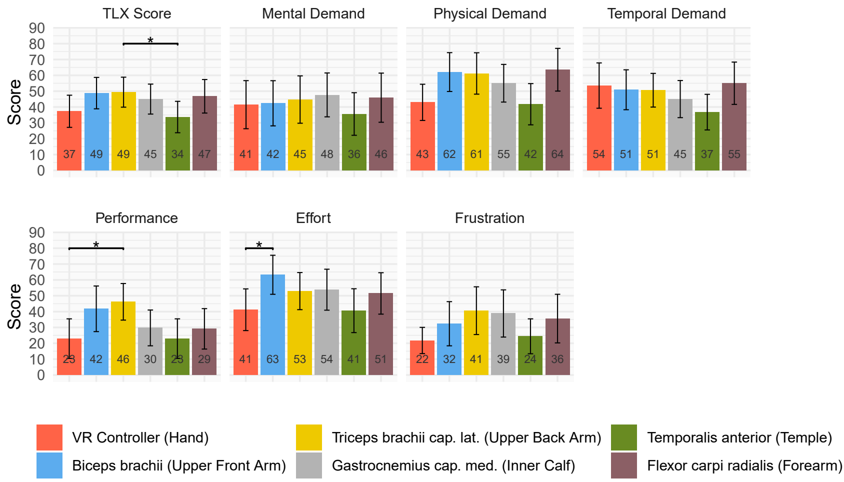


Figure 3.4: Bar charts of the raw TLX task workload score and subscales in the study. Regarding the main score, the triceps received a significantly higher workload rating than the muscle at the temple. The VR controller received significantly lower ratings for perceived performance than the triceps and also significantly lower ratings for effort than the biceps.

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 95% confidence intervals (CI95) are shown in Figure 3.4.

3.2.4 Qualitative Results

After the experiment, we asked participants which body location (without a VR controller) they finally preferred based on overall comfort. The post-experimental semi-structured 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 muscles 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 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). Many participants particularly highlighted that the 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 made by two participants, who stated that a connection to a muscle, was "helpful when an external person touched the body region".

3.3 Discussion

We compared the ability of participants to control their muscle tension at different muscle locations in their body and to interact with the EMG system in a target selection task with the headset as a directional pointer. The 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 forced to move their temple muscles as long as the weight of the headset put pressure on their heads. However, the finding was informative insofar as it was previously unclear whether the electrodes can be used under the HMD and could be of interest to manufacturers of such headsets, who could build 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 the 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 muscle locations independent from the level of difficulty. Related research has reported different effects of EMG sensor placement at different muscle locations for interaction [45, 165] and investigated EMG as muscle input from various muscle locations with differing results [5, 156, 198, 245, 273, 294], highlighting flexibility of employing EMG input as interaction technique, which is in line with our results. Participants in our exploratory study reported difficulty in sustaining isometric contractions due to muscle fatigue, aligning with previous research [6, 91].

3.3.1 Limitations and Future Research Directions

Future research could also explore additional muscle locations, such as the shoulders or back muscles, and compare feedback modalities (e.g., visual vs. tactile). In this foundational exploratory study, the aim was to keep the setup simple with a limited set of muscle locations in the arms and the easily accessible calf muscle. The upper leg muscle was not included, as it posed practical challenges due to its proximity to sensitive areas. A more conservative approach was taken to ensure participant comfort and maintain procedural ease. In subsequent studies, as methodological confidence increased, the thighs at the upper leg were integrated into the setup to broaden the experimental scope.

The integration of signal classification techniques (e.g., machine learning) could further improve interaction accuracy in dynamic settings. Advancements in signal processing using machine learning classifiers could enhance isometric muscle signal detection and processing. Such methods could mitigate interference from voluntary and continuous muscle activity.

3.4 Summary

Chapter 3 explores the foundational question of optimal sensor placement for EMG-based real-time interaction, addressing RQ1 "Which muscle locations are optimal for EMG-based real-time interactions considering user performance and perceived workload?". Using a standardized Fitts' Law task in VR, we evaluated the performance of isometric muscle contractions at various muscle locations, focusing on user performance and perceived workload. Results indicated no significant difference in input performance between muscle locations with isometric muscle contractions. However, participants reported challenges in controlling isometric contractions due to muscle fatigue, emphasizing the importance of feedback mechanisms in interaction design. Qualitative feedback highlighted that tactile cues (e.g., touching the muscle site) facilitated muscle localization and improved ease of use during the initial setup. Exploring alternative biofeedback visualizations (e.g., rendering audio, visual, or tactile cues) and their combinations could further refine interaction designs. These findings establish a foundation for designing EMG-based systems in VR, underscoring the need to accommodate the physical and cognitive demands of isometric muscle control. The findings are relevant for designing games, wearable devices, and therapeutic applications that use EMG input.

3.4.1 Lessons Learned

From the investigation into EMG-based interaction at various muscle locations, the following insights were derived:

Isometric Interactions Across Muscle Locations Are Feasible The study demonstrated that isometric muscle contractions can be used effectively for real-time interaction in VR, with no observed differences in input performance between tested muscle locations. This indicates the robustness of EMG-based systems for diverse muscle sites.

Challenges with Isometric Control Participants reported fatigue from sustaining isometric muscle tension for interaction. This finding highlights the need for systems that minimize prolonged muscle use and support users with fatigue-aware feedback mechanisms.

Tactile Cues (from touch) Facilitate Muscle Localization Tactile feedback during the initial setup and calibration procedure improved participants' ability to locate and activate the target muscle. This suggests that tactile cues could enhance usability and reduce the learning curve for EMG-based systems.

3.4.2 Data Sets

To enable replication and further exploration, we provide the dataset and source code used in this study. The data and source code are publicly available on GitHub `https://github.com/JessicaSehrt/EMG-VR-biofeedback.git` This resource supports reproducibility and encourages further research into optimal muscle locations for EMG-based interactions.

4

Biofeedback Modalities for EMG Interaction

Closing the biofeedback loop using EMG enables users to gain control over muscle activity, supporting motor functions in applications such as rehabilitation [38, 177, 220]. 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 [82, 271].

This chapter builds on the previous chapter by choosing a muscle location amongst the results of the previous exploratory study that showed a relatively low throughput with means of enhancement. We use the biceps muscle location and examine how combining visual, auditory, and tactile feedback can enhance user interaction. We compare the effects on performance and perceived workload in the same Fitts' law task from the apparatus of the previous chapter to enhance interactions in isometric EMG-based interactions for sedentary hands-free systems. Vision, audio, and tactile senses are perceived faster compared to senses like smell, taste, olfaction, or senses from the vestibular system [107, 149]. Tactile stimuli are processed faster because they rely on mechanoreceptors with quicker sensory processing than thermoreceptors or nociceptors related to cutaneous stimuli, such as temperature or pain [123, 184]. Therefore the study of this chapter explores how high-paced visual, auditory, and tactile cues can be used to effectively render biofeedback [32].

While previous research demonstrates that EMG biofeedback helps users focus on muscle tension and gain control over it [38, 177, 220], given the limitations of human cognitive resources [311], multimodal feedback could pose challenges in sensory processing and task performance. Researchers tend to prefer the use of multiple perceptual channels for simultaneous rendering of physiological signals [84, 131, 231]. However, the optimal biofeedback modalities for EMG-based interaction remain unknown [131, 248, 298]. To address this, we conducted an empirical user study to investigate the effects of different modalities on users' interaction performance.

Parts of this chapter are based on the following publication:

J. Sehrt, T. Wißmann, J. Breitenbach, and V. Schwind. "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. Hamburg, Germany: Association for Computing Machinery, 2023. ISBN: 9781450394215. DOI: 10.1145/3544548.3580738

4.1 Method

To answer the research questions on which multimodal sensory cues for biofeedback modalities improve interaction with an isometric EMG device, we conducted a user study in VR, shielding users from external sensory influences.

4.1.1 Study Design

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. We conducted a Fitts' law target

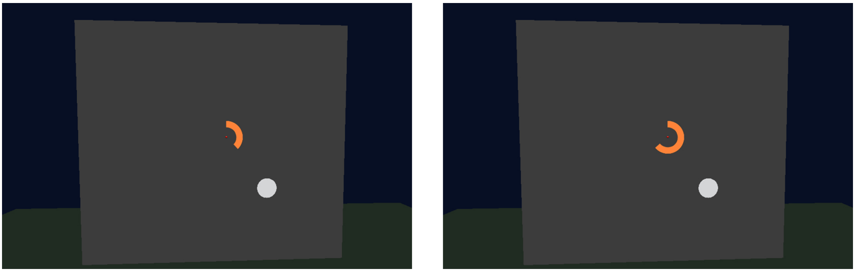


Figure 4.1: Screenshot of the user's view in VR during the visual feedback modality performing the Fitts' law task. Left: 30%, right: 60% muscle strength amplitude.

selection task [113, 181] to measure performance and workload. Due to the low variance of the throughput in the first experiment, its observability during the experiment to ensure isometric contractions, and its prominence in related literature [5, 35, 172, 320, 328], we only used the *Biceps brachii* (at the front of the upper arm) for EMG input.

4.1.2 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 [49, 186] 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 participant's field of view (see Figure 4.1). A concept of how the modalities closed the biofeedback loop in our experiment is shown in Figure 4.2.

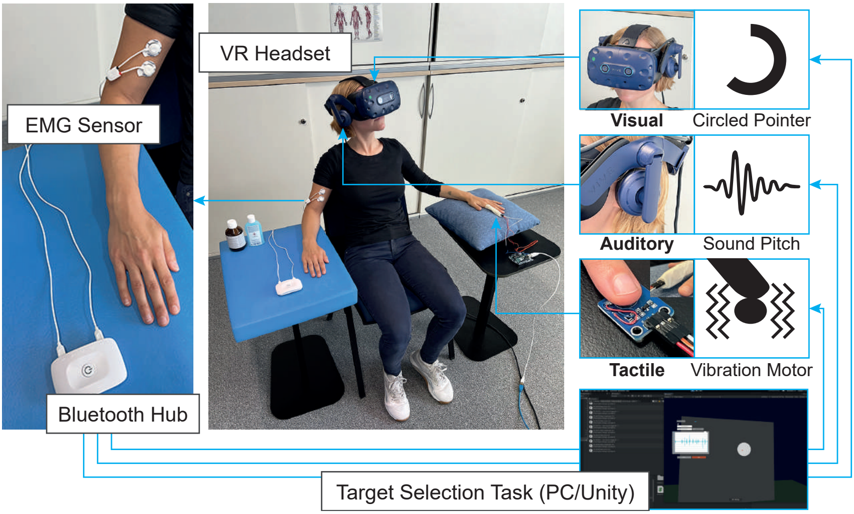


Figure 4.2: User in the apparatus in VR experiencing the three feedback modalities. The system renders the EMG signal from the user with visual, auditory, and tactile cues. A circled pointer in the shape of a partial torus renders the visual feedback. A pitched sound is used as an auditory cue from the EMG device. A vibration motor fixated under the index finger renders tactile feedback.

4.1.3 Apparatus

Calibration and task ran in a Unity3D application running on a PC with AMD Ryzen 5900X, GeForce RTX 3070, and 16 GB RAM. We reused the virtual version of a Fitts' Law task [113, 181] from the study of chapter 3 to measure performance and workload, and the same scripts for the integration of the biosignalplux 4-Channel Hub[1] with EMG sensors for isometric muscle tension detection and HMD display (HTC Vive Pro) for head-gaze pointing. Additionally, edge detection was implemented with 20% upper and 10% lower trigger thresholds. 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

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

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 the maximum speed capacity possible, modulated by PWM with a frequency of 490 Hz in linear mapping relation to the amplitude of the muscle strength tension. An audio source in Unity was a looped A-major chord[1] with a pitch value starting at 0 % pitch to 100% pitch. The 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 was also linearly mapped using the amplitude of the muscle strength tension.

4.1.4 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 raw TLX (c.f. Appendix Section 7.3). To gain a deeper understanding of how participants perceived 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 focused on the participants' opinions (positively and negatively) on the modalities and their combinations, the system, and the task. The subjects were also asked about any other remarks they might have regarding the experiment.

4.1.5 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 were tested. Additionally, the non-dominant arm was identified and placed on a pillow beside it 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

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

received and adjusted the HMD. To ensure the 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 physiological signal was visible for the experimenter to ensure that the desired amplitude had been registered correctly. Maximum muscle strength was 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 asked 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 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 raw TLX within the virtual environment. After the VR experience and removal of the headset and electrodes, we collected the participants’ qualitative feedback in a semi-structured interview.

4.1.6 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’s course in computer science and were compensated using credit points for their lectures. They were informed that they could 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

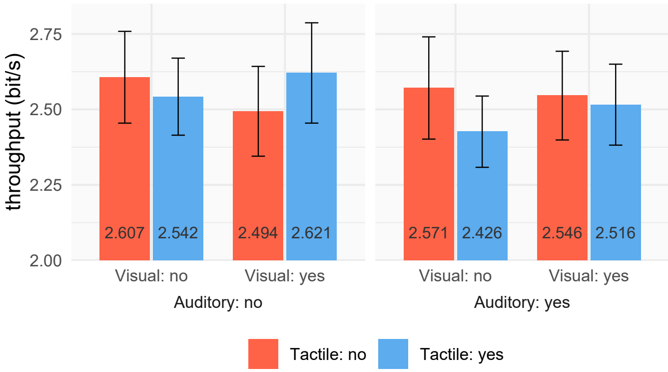


Figure 4.3: Bar charts of the throughput performance measures for each biofeedback modality used in the study. The highest throughput was achieved using visual and tactile feedback simultaneously as well as when no feedback was rendered. A main effect for the auditory feedback indicates that the average throughput was significantly lower when auditory cues were present compared to when not. All error bars show CI95.

Table 4.1: Summary of the RM-ANOVA results of throughput and workload for 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

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.

4.1.7 Data Analysis

For data analysis of the recorded data samples from the target selection task, we performed simple outlier filtering (Q1/Q3 $\pm$ 1.5 IQR rule) and included 17105 from a total of 18179 samples (94.1%). The 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 [79, 113, 181].

4.2 Results

4.2.1 Throughput

Shapiro–Wilk's test among all conditions (all with $p > .203$) indicated a normal distribution of the throughput measures. We conducted a three-way RM-ANOVA to investigate the effect of AUDITORY, TACTILE, and VISUAL feedback modalities on throughput. There were statistically significant effects for AUDITORY and TACTILE $\times$ VISUAL biofeedback modalities. The statistical power for the TACTILE $\times$ VISUAL interaction was 83.9%, indicating a strong likelihood of correctly rejecting the null hypothesis. No gender-related effects or interactions were found (all $p > .05$).

Individual throughput results of all conditions are shown in Figure 4.3. The lack of 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. The interaction effect between TACTILE $\times$ VISUAL modalities suggests that throughput performance was higher when both cues were present simultaneously, compared to conditions where only tactile or only visual feedback was provided, or when both were absent. An overview of the results is shown in Table 4.1.

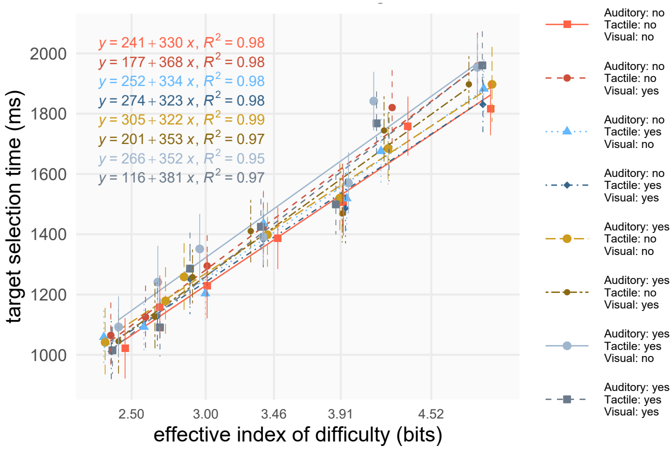


Figure 4.4: Target selection time for each biofeedback modality as a function of the IDe. All error bars show CI95.

4.2.2 Mean Target Selection Time

The target selection time as a function of difficulty and the condition-wise regression equations can be found in Figure 4.4. We performed an RM-ANCOVA of the log-transformed mean time adding the ID as a 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 $\times$ TACTILE, $F(1,269) = 8.950$, $p = .003$, $\eta_p^2 = 0.032$ (medium), AUDITORY $\times$ VISUAL, $F(1,269) = 3.993$, $p = .047$, $\eta_p^2 = 0.015$ (medium), and TACTILE $\times$ VISUAL, $F(1,269) = 8.367$, $p = .004$, $\eta_p^2 = 0.030$ (medium). Interestingly, there was no three-way interaction AUDITORY $\times$ TACTILE $\times$ VISUAL, $F(1,269) = 0.010$, $p = .919$, $\eta_p^2 = 0.000$ (undetectable). The analysis further revealed a significant main effect of the covariate ID, $F(6,269) = 61.579$, $p < .001$, $\eta_p^2 = 0.579$ (large), however, showed no interaction effect with the other factors (all with $p > .136$), indicating that the target selection time is independent of the difficulty during target selection with the modalities. Considering the absence of an overarching three-way interaction, the analysis of the target selection time revealed that the time independent from the difficulty is always affected by two modalities.

4.2.3 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 shown in Figure 4.5. 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.

4.2.4 Subjective Workload

Shapiro-Wilk test on all conditions did not show any evidence of non-normality on the raw TLX score (all with $p > .15$). The results of the analysis are summarized in Table 4.1. All raw TLX scores and subscales results are shown in Figure 4.6. 6.1 A three-way RM-ANOVA revealed a significant interaction main effect of

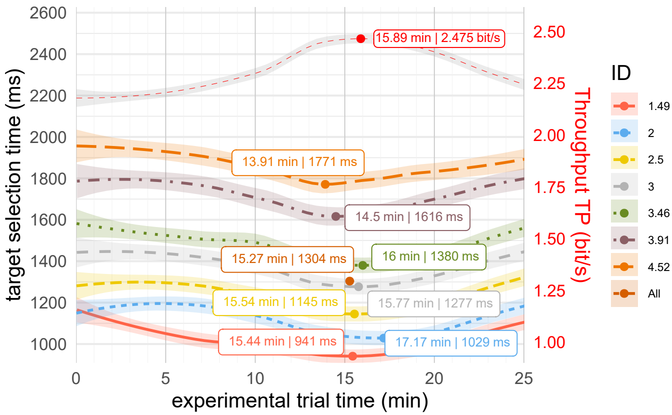


Figure 4.5: Target selection time throughout the experiment. The fitted curves indicate a decrease in target selection time due to learning effects and a decrease after potential fatigue. Difficulty-dependent inflection points were found between 13.907 mins (ID=4.52) and 17.173 mins (ID=2). Colored areas indicate the standard error of the loess fit.

AUDITORY feedback. An analysis of the raw TLX 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 $\times$ VISUAL, $F(1,39) = 9.145$, $p = .004$, $\eta_p^2 = 0.190$ (large), no further main or interactions were found between those and other raw TLX subscales. Thus, perceived performance was higher with visual cues. Frustration was lower when audio was on, and higher when tactile and visual cues were rendered compared to when the modalities were off.

4.2.5 Subjective Modality Preferences

We also asked participants, which feedback they finally preferred and did 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

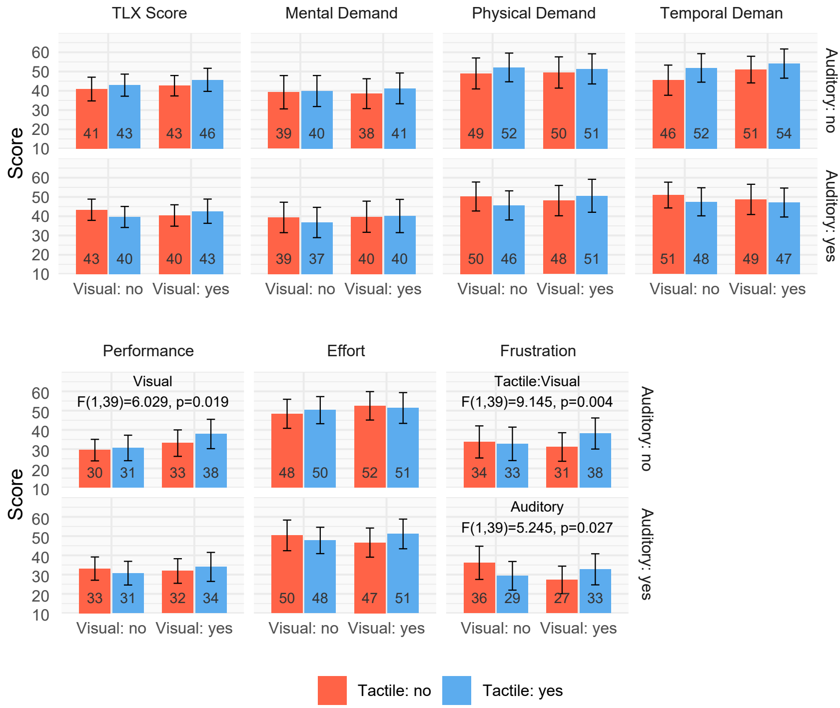


Figure 4.6: Score and subscale ratings of the NASA Raw-TLX questionnaire of the study. All error bars show CI95.

(2.1%) desired no feedback. 12.5% ($N = 5$) 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, and three (6.4%) were not sure or remained vague.

4.2.6 Qualitative Results

Inductive thematic analysis was used to build a structure and deeper understanding of the qualitative assessments after verbatim transcription [22]. 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.

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).

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 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 to be supportive, one of them acknowledged "the coherence of the required 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 single modality feedback compared to multi-modal feedback, indicating that more cues provide more *informativeness* about the state of the muscle.

Information overload, obtrusiveness, and repetitive patterns distract. P20 highlighted that the "combination of all feedback methods stressed me", and saw an effect on the 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*.

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.

Summary of Qualitative Results 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.

4.3 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 in the meantime 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 that 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 is 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 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 time, but also that the muscles then began to tire after a short time. 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.

Related Work addresses that two senses simultaneously can lead to an increased cognitive processing [222, 292, 319], but there is no strong evidence that combining modalities increases workload in our system. Authors of related research conclude that multimodal feedback systems should provide different modalities for feedback, but not simultaneously, to prevent sensory overload [131], while we found that only simultaneous visual and tactile feedback had the highest throughput in our system compared to single modalities, while too many modalities received complaints on sensory overload during qualitative feedback.

Researchers employ EMG-based visual feedback to enable subjects to increase their control over their muscle activation, e.g., for the movement of a robotic platform in real-time [42], while the visual modality did not significantly reduce perceived workload compared to the other modalities in our system. The visual modality by itself does not significantly improve throughput. However, interaction effects, such as tactile $\times$ visual, might indicate that combining visual feedback with other modalities (like tactile) could enhance performance in specific scenarios. Some innovative applications employ biofeedback techniques rendering physiological signals using tactile [37, 131, 248]. In our system, the tactile modality alone does not significantly improve throughput or reduce perceived workload while provided as biofeedback. Researchers tend to prefer the use of visual and auditory cues for multimodal biofeedback applications for the simultaneous rendering of the physiological signal using multiple perceptual channels [84, 131, 231]. While in our system frustration from perceived workload results were lower when audio was on, the throughput while interacting with auditory feedback was the lowest.

Related work from HCI [60, 188] argues that both visual and tactile modalities contribute to the development of body awareness, with recent research focusing on using these modalities for biofeedback in EMG interaction with the own body [73, 131–134, 141, 264]. That underpins our results, that tactile and visual modalities in combination have significantly improved the throughput of our system, and even though the tactile and visual modalities together do not significantly reduce perceived workload, they show a potential trend toward reduced workload, even if it was not significant in this study.

4.3.1 Limitations and Future Directions

The subject of future work should be an investigation of alternative biofeedback visualizations rendering visual, but importantly also different tactile feedback modalities, like vibrotactile and electrotactile. Combined EMS and EMG (c.f. [147, 206]) or comparison of different body locations for visual, vibrotactile, and electrotactile feedback should be investigated as complementing research.

4.4 Summary

Chapter 4 addresses RQ2: "How do different feedback modalities (auditory, tactile, visual) influence the performance and workload of EMG-based interactions?". Using a standardized Fitts' Law task in VR, the study evaluated the role of multimodal biofeedback in enhancing interaction performance during isometric muscle contractions. Results revealed that a combination of tactile and visual feedback significantly improved performance, while auditory feedback negatively affected it. Participants noted that tactile cues enhanced their ability to direct muscle contractions, suggesting the potential of multimodal biofeedback to improve EMG-based interaction ease and effectiveness. However, qualitative feedback highlighted challenges such as muscle fatigue and learning effects.

4.4.1 Lessons Learned

From the study, the following key insights were derived:

Combined tactile and visual feedback improves performance The combination of tactile and visual biofeedback significantly enhanced the throughput during EMG-based interactions, while participants stated enhanced control with tactile biofeedback modalities. This suggests that multimodal biofeedback can effectively support hands-free interactions, particularly in complex target selection tasks.

Auditory Feedback May Hinder Control Auditory feedback negatively impacted participants' ability to control their muscles, indicating that it may be less effective or even counterproductive in EMG-based systems. This finding highlights the importance of selecting appropriate feedback modalities based on the interaction context.

Challenges of Muscle Fatigue and Learning Effects in Isometric Interactions Muscle fatigue impacts performance over time in sustaining isometric contractions, as evidenced by qualitative feedback and turning points in response times. Future designs should consider fatigue and include measures to mitigate its effects during prolonged use. Learning effects were also noted, emphasizing the need for designs that account for physical and cognitive demands during prolonged interactions.

4.4.2 Data Sets

The dataset used in this study is publicly available to support replication and further exploration. The dataset and resources can be accessed on GitHub `https://github.com/JessicaSehrt/EMG-VR-biofeedback.git`.

5

Prior Stimulation Feedback to Improve EMG Reaction Times

Results from the study of the previous chapter 4 of this thesis on multimodal biofeedback in a Fitts' law study demonstrated modest improvements in user performance when visual and tactile modalities were combined with isometric EMG interaction [264]. Additionally, finger tapping on the muscle site before interaction facilitated muscle localization and activation. Building on these findings, the study of this chapter investigates whether automatically provided tactile or visual interventions can reduce reaction times in isometric EMG-based responses.

The technique of muscle priming, known from sports and physiotherapy, is a concept in which stimulation before, rather than during interaction, is used to enhance neuromuscular response times [62, 89] and related cognitive processing [61]. Similarly, muscle warm-up exercises have demonstrated performance benefits across various domains [20, 94, 293]. This chapter examines how different prior stimulation feedback mechanisms, inspired by muscle priming techniques, can be used to refine sedentary hands-free interaction systems. To explore the concept of prior stimulation, we employed visual, vibrotactile, and electrotactile modalities, while we excluded auditory because it resulted in overall lower throughput across conditions in the previous studies from chapter 3 and 4 of this thesis [264], and findings on its disruptive nature from related studies [72]. Electrotactile feedback, delivered via TENS, was hypothesized to enhance the development of an internal body map through repeated muscle priming [100]. Mechanoreceptors in the skin, crucial for tactile perception [46, 225], significantly influence body awareness [57]. Visual cues, alongside tactile stimulation, also play a critical role in body localization, as shown in studies on the virtual and rubber hand illusions [24, 216, 254].

The system design explored in this chapter relies on predetermined patterns, allowing the system to anticipate which muscle has to be activated next. This design is particularly suitable for applications with repetitive interaction patterns, such as gaming [198], driving assistance [8], multi-channel prosthetic training [1, 143, 236], and remote learning scenarios for industrial workers [18] with limited range of motion. Priming muscles can prepare an individual to respond appropriately because they help them anticipate the physiological response and therefore speed up the reaction. Feedback given *prior* to muscle actuation sharpens the user's awareness of upcoming actions and maintains the user's sense of agency by allowing the cognitive association between movement initiation and intent. This contrasts with stimulation *during* muscle actuation [135] and may be particularly advantageous for applications in such training or learning contexts.

While prior research has used EMG to measure isometric contractions for hands-free, real-time systems [68, 112, 124, 125, 127, 183, 192, 285, 316], the impact of prior stimulation on isometric contractions and electrotactile feedback remains underexplored.

Parts of this chapter are based on the following publication:

J. Sehrt, L. Ferreira, K. Weyers, A. Mahmood, T. Kosch, and V. Schwind. "Improving Electromyographic Muscle Response Times through Visual and Tactile Prior Stimulation in Virtual Reality." In: *Proceedings of the 2024 CHI Conference on Human Factors in Computing Systems*. CHI '24. Honolulu, HI, USA: ACM, Jan. 1, 2024. ISBN: 979-8-4007-0330-0/24/05. DOI: 10.1145/3613904.36420

5.1 Method

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

5.1.1 Study Design

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

5.1.2 Independent and Dependent Variables

The four levels of the independent variable PRIOR STIMULATION were *no*, *visual*, *vibrotactile*, and *electrotactile* stimulation. PRIOR STIMULATION was presented before the signal for the reaction test. The *visual* conditions consisted of a schematic anatomical line drawing with the corresponding muscle highlighted in red (see Figure 5.3). The *vibrotactile* conditions consisted of a vibration applied at the center of the corresponding muscle, and the *electrotactile* conditions consisted of a TENS impulse at the corresponding muscle. Each PRIOR STIMULATION was presented for the same duration of 3 seconds during the trial procedure (see Figure 5.3).

With the paradigm of hands-free interaction in mind, we tested four levels of the independent variable MUSCLE LOCATION frequently used by related work: the *upper front arm (Biceps brachii)* [5, 273], the *upper back arm (Triceps brachii caput laterale)* [5, 264], the *upper leg (Vastus medialis)* [151], and the *calf (Gastrocnemius caput medialis)* [151, 198] (see Figure 5.1). To ensure reproducibility and comparability, we tested the four limb muscles exclusively on the right side of the body. The EMG and TENS electrodes were positioned uniformly with enough space for the vibration motors. Thus, the EMG signal was not influenced by any movements (e.g., head movements at the shoulder), breathing, or talking (e.g., by natural movements of the chest).

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

5.1.3 Subjective Measures

We conducted a subjective muscle assessment both before and after the experiment by asking participants to rate the ability to tense each MUSCLE LOCATION using a visual analog scale (VAS) ranging from 0 to 10. Post-Experiment, participants completed the raw TLX, a standard tool in HCI for workload assessments [101] (c.f. Appendix Section 7.3) with two additional questions on perceived pain and fatigue. They also responded to a questionnaire using a 7-point Likert scale on the item "To which extent do you agree with the statement that [stimulation] helped me to locate my [muscle]?", evaluating the extent to which various PRIOR STIMULATIONS aided in identifying the tested MUSCLE LOCATIONS (subjective survey on muscle localization and reaction time), and whether they perceived any changes in their reaction time during the experiment. Finally, we conducted semi-structured interviews to gain further insights into the participant's exhaustion, positive and negative experiences, preferences, and overall impression of the experiment.

5.1.4 Task

Participants' reaction times were measured using a modified Vienna Test System (VTS) adapted for VR according to Prieler et al. [103]. In its setup, participants responded to alternating red and green lights, with the green light and a beeping tone serving as the stimuli. They reacted by tensing specific muscles, indicated by text and highlighted on a schematic anatomical drawing. Each trial began with 2 seconds of rest, followed by a 3-second prior stimulation phase, and then the green light stimuli appeared randomly after a period from 3 to 13 seconds,

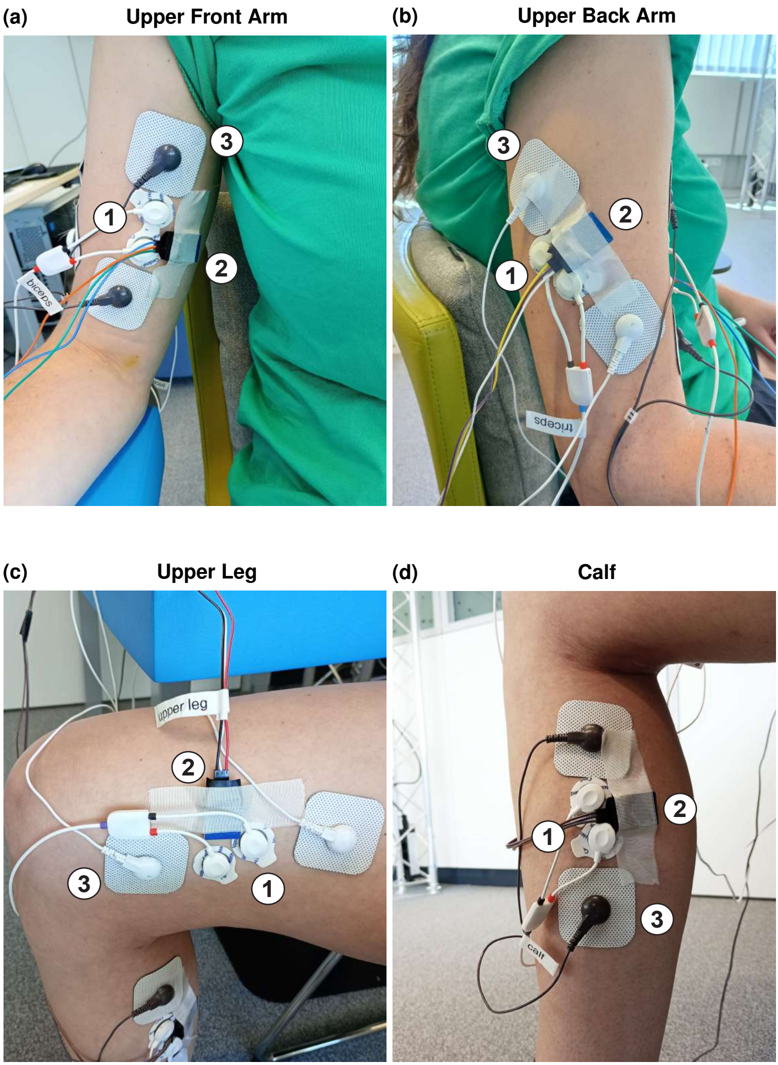


Figure 5.1: The placement of EMG electrodes [1], vibration motors [2], and TENS electrodes [3] at the four tested muscle locations: Biceps brachii (upper front arm)a, Triceps brachii caput laterale (upper back arm) b, Vastus medialis (upper leg) c, and Gastrocnemius caput medialis (calf) d.

lighting up for 2 seconds duration to indicate that the muscle now has to be tensed (green light phase). Trials were 20 seconds each, with varying combinations of PRIOR STIMULATION, MUSCLE LOCATION, and stimuli timing, presented twice in random order (see Figure 5.3). The whole experimental procedure resulted in 192 conditions and a total duration of 64 minutes. The fixed duration of the experiment, with variable timeframes for employing prior stimulation and considering the muscle location, enables the reliable determination of both reaction times and muscle fatigue effects.

5.1.5 Apparatus

A virtual 3D environment for the simple reaction test was created using Unity Engine (Version 2021.3.5f1) running on a PC with AMD Ryzen 5900X, GeForce RTX 3070, and 16 GB RAM. The minimalistic scene contained a 3D panel for displaying test instructions and stimuli. An HTC Vive Pro with 90 fps was used as HMD and tracked using four lighthouse boxes for high accuracy. Muscle activity was monitored using a biosignalplux 4-Channel Hub[1] with EMG sensors at 1000 Hz sampling rate with 16-bit resolution and Kendall H124SG electrodes. The integrated low-noise high-speed operational amplifiers performed bandpass filtering and amplification on the base of bitalino technology [93]. Two Sanitas SEM 47 EMS/TENS devices were used with self-adhesive electrodes according to the manual (see Figure 5.2).

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

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

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

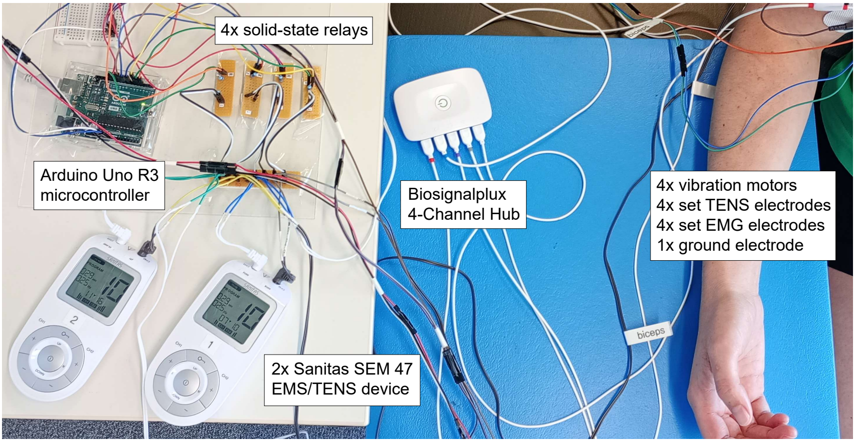


Figure 5.2: Apparatus with the hardware components, consisting of two EMS/TENS devices, an Arduino R3 microcontroller, and four solid state relays, connected to the participant by four pairs of TENS electrodes on the one hand and a biosignalplux 4-Channel Hub, connected to the participant by four pairs of EMG electrodes (and a ground electrode).

made with opaque rendering mode and green-colored (RGB: 0,255,43) and red-colored (RGB: 255,76,52) spot-type light sources. The system featured real-time monitoring of EMG signals and participant VR view.

5.1.6 Study Procedure

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

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

Phase 2: Body/Electrode Preparation We calibrated the TENS device for electrotactile stimulation by presenting incrementing values for the impulse intensity until the participants until a very light muscle tension was observable, keeping it then just under this threshold. To not compromise any of the muscle locations tested on the dominant body half of the participants, we initially attached the TENS electrodes to other, non-dominant body half to avoid priming effects. The participants preferred TENS impulse intensities ranging from 8-52 mA for the biceps, 20-56 mA for the triceps, 20-80 mA for the upper leg, and 28-100 mA for the calf. To keep the applied electrotactile stimulation suitable for all muscle locations the two digital Sanitas EMS/TENS SEM 43 devices were set to 25 Hz impulse frequency with a TENS program function that automatically moved the pulse widths from 50 to 250 μs continuously. This ensured a greater suitability to various muscle anatomy and facilitated the calibration procedure. Placement of the TENS electrodes followed the manufacturer's manual [1], with skin preparation involving alcoholic pads and shaving, if necessary. We also calibrated the TENS strength for all muscle locations by asking if a stinging or burning sensation or any discomfort was felt. If necessary, electrodes were re-positioned and the intensity was adjusted. We mirrored the electrode placements to the right side of the participant's body using rulers and visual estimates for accuracy. Participants sat with elbows and knees at 90°, hand palm up, and feet positioned using a stencil drawing. One participant desired to reduce the TENS signal strength after mirroring.

EMG electrodes were attached to the right side of the body, with adjustments for strong EMG signal, following SENIAM guidelines [105]. Due to limited space on the muscle bulges, we prioritized the signal strength over adhering strictly to the guidelines. We monitored EMG physiological signal for correct amplitude registration placing electrodes according to anatomical landmarks. Two electrodes were placed at a distance of 0.5 cm on each muscle bulge and

[1] `https://sanitas-online.de/media/download/752-907-0416_sem43_de.pdf`

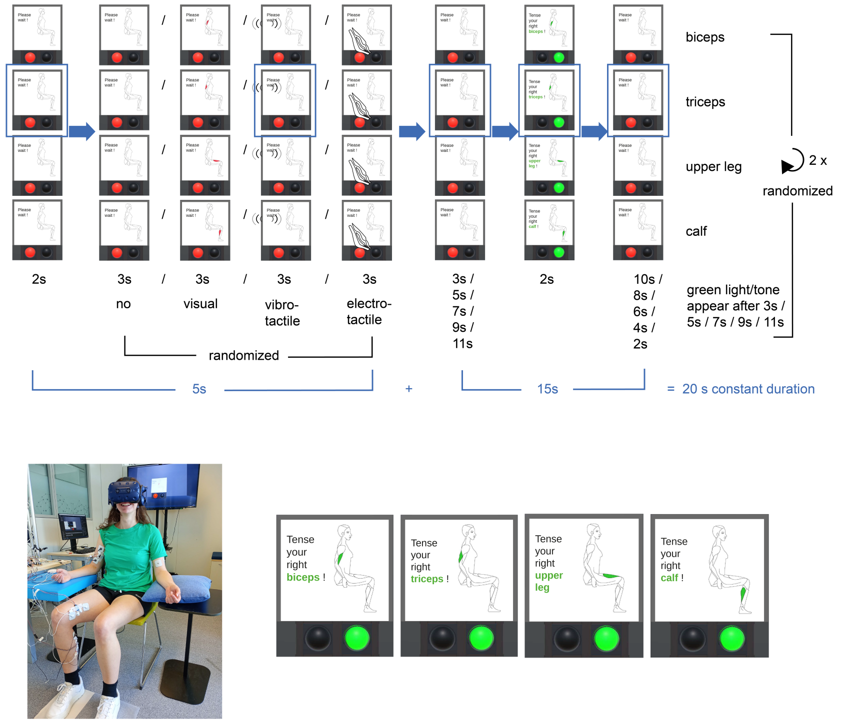


Figure 5.3: *Up*: The illustration shows the trial procedure scheme of all tested conditions with an example trial framed in blue. The trial procedure started with 2 seconds of resting. A 4 × 4 factorial design, combining four stimulation types (no, visual, vibrotactile, electrotactile) and four muscle locations (biceps, triceps, upper leg, calf) resulted in 16 conditions. The presented stimuli of a condition were randomized and presented for 3 seconds. Then 15 seconds followed in which a 2-second green light and sound (green light phase), randomly appeared at a certain moment after 3, 5, 7, 9, or 11 seconds. Thus, all participants experienced the same experimental trial length (64 min). Each prior stimulation, muscle location, and duration until the green light/tone were presented twice and in a fully randomized order.

Down: Participant sitting in the apparatus with the hardware components attached, with the control monitor in the background (left). The four stimuli of the green light phase as of the presented virtual Panel (right).

a reference electrode consistently to the elbow joint bone. We stuck vibration motors with adhesive tape next to the electrode arrangements at the center or a maximum of 1 cm apart from the center of the muscle on each muscle location. The setup is detailed in Figure 5.1.

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

5.1.7 Participants

Participants were recruited via institutional email lists, social media, and referrals, excluding those with cardiac issues, metallic implants (e.g., screws), cardiovascular complications, recent infections, or surgeries, by the explicit advisory. Six interested participants were pre-excluded from the study due to heart problems ($N = 4$) or metallic implants ($N = 2$). All participants had the option to withdraw without penalty.

Twenty-four participants were initially recruited. Student volunteers ($N = 14$) from computer science or mechanical engineering were rewarded with credit points for their study participation. Institutional employees ($N = 7$) were reimbursed for their working hours. External participants ($N = 3$) were remunerated with [1]. One participant withdrew, and the data of two were unusable due

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

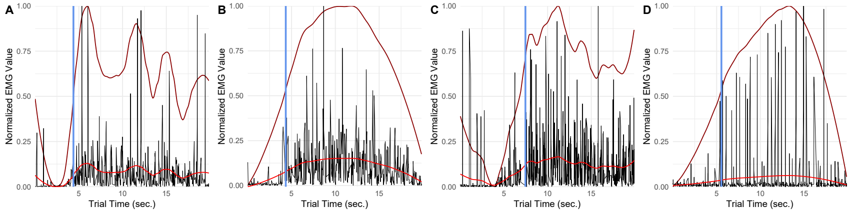


Figure 5.4: Four randomly selected trial data sets of the 2-second onset periods (A-D) illustrating the data processing. The absolute value of the raw signal (black line) was processed using the Teager-Kaiser Energy Operator and signal smoothing (red line). The individual reaction time of each trial was then determined using a Bisection Extremum Distance Estimator (BEDE) operator based on the normalized signal (dark red line). BEDE determines the inflection point at the curve incline (vertical blue line) and the final reaction time (RT) measurement.

to technical issues. Thus, the final analysis included twenty-one participants (7 self-identified as female, 14 self-identified as male), mean age was 26.76 ($SD = 4.5643$), ranging from 18 to 37. The study received ethical clearance according to our institution's regulations and hygiene protocols for user studies.

5.1.8 Data Analysis

We recorded the EMG signal as raw data and in a frame-based format, including the conditions, timestamps, and metadata. In line with previous research on EMG event detection, a Taeger-Kaiser energy operator (TKEO) [53, 169, 277] using the seawave package for R[1] was applied for EMG signal processing and smoothing with parameters according to biosignalplux. As recommended by the Vienna test system (VTS), [103], the mean reaction times (RTs) of all trials and repetitions were aggregated for each subject. The actual RT was calculated using the Bisection Extremum Distance Estimator (BEDE) method [40, 41] on the TKEO processed EMG signal during the 2 seconds onset period (green light phase) provided by the inflection package[2] for R.

[1] https://rdrr.io/cran/seewave/man/TKEO.html
[2] https://rdrr.io/cran/inflection/

BEDE is an algorithmic method used for efficiently estimating the extremum of a function by iteratively bisecting the interval and evaluating distances to identify the point of extremum. The BEDE method [40, 41] does not require a functional hypothesis for the data, therefore its utility lies in its ability to provide a fast and reliable determination of the inflection point, representing the moment of highest signal increase. This approach eliminates the subjectivity and potential inaccuracies associated with threshold-based criteria, with no need for an initial calibration phase that potentially biases the participants' muscle performance. Based on the BEDE method we calculated the mean and the fastest (and minimal) average reaction time in each condition. Examples of data processed are shown in Figure 5.4.

Additionally, we analyzed the maximum value of the smoothed EMG signal to pinpoint when the highest amplitude occurred. For this, we employed polynomial regressions with locally estimated scatterplot smoothing fit (loess) using an automatic parameter selection (auto span) identified by generalized cross-validation (GCV). The same method was used to evaluate how the reaction times varied throughout the experiment. The whole data set included 3,838,041 samples and is available at GitHub[1].

5.2 Results

For statistical analysis, all RTs, with means shown in Figure 5.5, were log-transformed to remove any skewness from the data and ensure normal distribution. If Mauchly's assumption of sphericity was not confirmed, we applied Greenhouse-Geisser correction for the degrees of freedom on the factor using the rstatix package[2] in R.

Normality was confirmed for all conditions ($p > .118$) except one (*biceps-vibration* with $p = .042$) using Shapiro Wilk's tests. However, visual inspection of the QQ plot and histogram showed that the data followed a normal distribution. A RM-ANOVA revealed a significant effect of PRIOR STIMULATION, $F(3,60) = 7.868$, $p < .001$, $\eta_p^2 = 0.282$, and MUSCLE LOCATION,

[1] https://github.com/JessicaSehrt/ReactionTest_EMG-V_vT_eT_priorStim
[2] https://rdrr.io/cran/rstatix/

$F(2.00, 39.91) = 8.324$, $p = .001$, $\eta_p^2 = 0.305$, however, there was no interaction effect of PRIOR STIMULATION × MUSCLE LOCATION, $F(9, 180) = 1.616$, $p = .146$, $\eta_p^2 = 0.075$. We performed a pairwise t-test post hoc comparison using Bonferroni corrected p-values based on the two main effects. Among the modalities, we found a significant difference between *electrotactile* and *no* ($p = .014$, $d = -0.341$), *vibrotactile* and *no* ($p = .002$, $d = 0.405$), and *visual* and *no stimulation* ($p < .001$, $d = 0.442$). Regarding the muscles, the analysis also revealed a significant difference between *biceps* and *calf* ($p < .001$, $d = 0.622$), *biceps* and *triceps* ($p = .047$, $d = 0.297$), *triceps* and *calf* ($p = .002$, $d = -0.401$), as well as between *upper leg* and *calf* ($p < .001$, $d = -0.557$). Other combinations were not significant. The results indicate that the RT depends on MUSCLE LOCATION and PRIOR STIMULATION. The participants showed the fastest muscle responses when a prior location stimulation was used. As we had no interaction effect, this finding is independent of the muscles tested. The fastest power was the calf.

5.2.1 Minimum RT

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

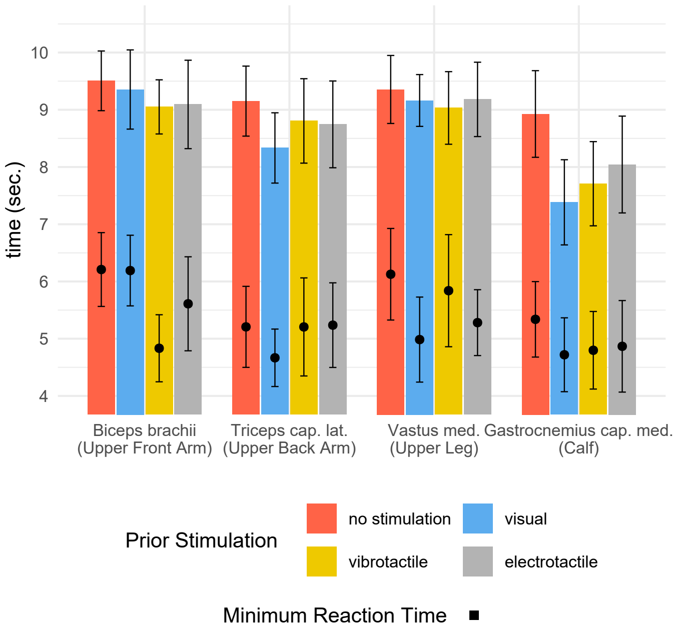


Figure 5.5: Mean reaction times of the tested prior stimulation and muscles of the reaction test. The faster muscle responses were found for all prior stimulations. The fastest muscle was the *Gastrocnemius cap. med. (Calf)*. The point indicates the mean RTs with the fastest of each participant. Error bars show 95% confidence intervals.

the *biceps*, the minimum reaction times were lower using *vibrotactile* than with *visual stimulation* or *no stimulation*. All means of the minimum RTs are shown as points in Figure 5.5.

5.2.2 Time of Highest Amplitude

We also determined the inflection points on the saddle of the first EMG signal bulge to understand when the strongest voluntary muscle contraction occurred. The log-transformed times' normality violation test was insignificant, except in one condition (biceps and electrotactile, $p = .002$, all other conditions $p > .107$). However, visual inspection of the QQ plot and histogram showed that the data

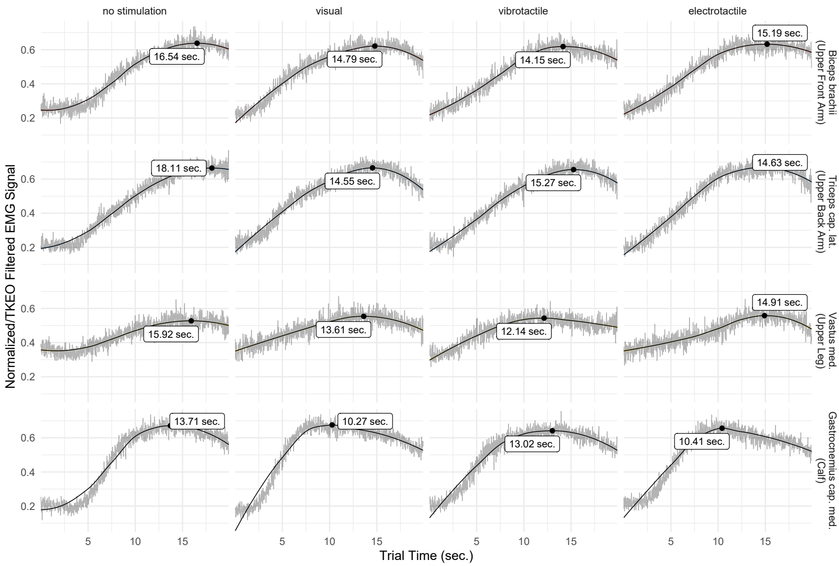


Figure 5.6: Grid plot of all participants' aggregated EMG signal curves separated by muscles and modalities. The plots illustrate the individual characteristics of the raw data and the loess fit and show the time of the highest amplitude of the EMG signal.

follows a normal distribution. Thus, we performed parametric tests. A RM-ANOVA revealed a significant effect of PRIOR STIMULATION, $F(3,60) = 3.069$, $p = .035$, $\eta_p^2 = 0.133$, MUSCLE LOCATION, $F(2.31, 46.3) = 13.628$, $p < .001$, $\eta_p^2 = 0.405$, however, there was no interaction effect of PRIOR STIMULATION $\times$ MUSCLE LOCATION, $F(9,180) = 1.661$, $p = .101$, $\eta_p^2 = 0.077$. Pairwise post hoc t-test comparisons using Bonferroni correction showed significant differences among the modalities between *vibrotactile* and *no* ($p = .015$, $d = 0.286$), and *visual* and *no stimulation* ($p = .006$, $d = 0.319$). Regarding the muscles, the analysis also revealed significant differences between all comparisons (all with $p < .001$), except between *biceps* and *triceps* as well as *upper leg* and *calf* (both $p = 1$). The results generally support the findings of the effects of MUSCLE LOCATION and PRIOR STIMULATION. The aggregated signals with the times of the maximal amplitude are shown in Figure 5.6.

5.2.3 Reaction Time vs Signal Strength

As the experiment lasted the same duration of all participants and all conditions were performed in fully randomized order, we analyzed how the reaction times and the amplitude of the EMG signal evolved. We were interested in the increase/decrease of the muscles' activity and analyzed the *reaction times* and *max. EMG amplitude* as a function of time using a generalized mixed-effect regression model with EXPERIMENTAL TIME and MUSCLES as predictors. The regressions for reaction times ($R^2 = 0.083$, $AIC = 12283.82$) and max. EMG amplitude ($R^2 = 0.082$, $AIC = -3936.437$) were significant (both $p < .001$). The scatterplots (not illustrated) of standardized residuals indicated that the data met the assumptions of homogeneity of variance, linearity, and homoscedasticity for both regression analyses. All regression equations can be found in Figure 5.7 and fits of reaction time and EMG amplitude are shown in Figure 5.7. For reaction times, the slopes for the *calf* significantly ($p = .002$) tend towards a negative value, indicating the reaction times for that muscle decreased over time. No effects were found for the normalized values of the amplitudes. However, the correlations between both variables were significant (all with $p \leq .001$) and negatively and weakly correlated for the biceps ($\rho = -0.20$), triceps ($\rho = -0.19$), upper leg ($\rho = -0.14$), and moderately for calf ($\rho = -0.38$). This indicates that the calf was getting faster during the experiment, however, moderately at the cost of signal strength.

5.2.4 Subjective Assessments

Support of Stimulation After the experiment, we asked participants to rate to which extent they agreed that a stimulation helped them locate a muscle. An Aligned Rank Transform (ART) RM-ANOVA revealed a significant effect of PRIOR STIMULATION, $F(3,300) = 160.704$, $p < .001$, $\eta_p^2 = 0.616$, and MUSCLE LOCATION, $F(3,300) = 2.792$, $p = .041$, $\eta_p^2 = 0.027$, without an interaction effect between PRIOR STIMULATION $\times$ MUSCLE LOCATION, $F(9,300) = 0.537$, $p = .847$, $\eta_p^2 = 0.016$. Post hoc pairwise comparisons using Wilcoxon signed rank using Bonferroni correction showed significant differences between all modalities ($p < .038$). Among the muscles, we found a significant difference between *upper*

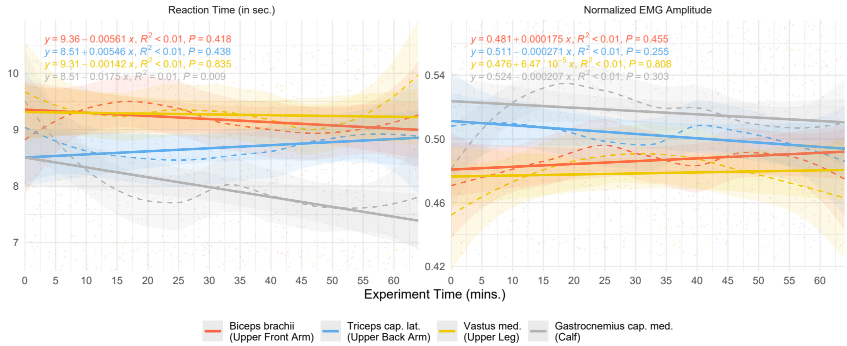


Figure 5.7: Regression fits of the reaction time and the EMG amplitude in the course of the experiment. The slope parameter for the calf was significantly decreased during the experiment. No signal strength trends were observed, but correlation analysis revealed a potential negative relationship between reaction time and amplitude. Straight solid lines show the linear trends; the dashed curve is the smoothed loess fit.

leg and *triceps* ($p = .011$); however, not between the other pairs ($p > .052$). The results (see Figure 5.8) indicate that the participants tend to agree that best location accuracy could be achieved using *electrotactile* stimulation and that all prior stimulation modalities were preferred over none. Interestingly, the participants noticed that mainly the upper leg and not the calf, such as in the objective measure, benefited from stimulation.

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

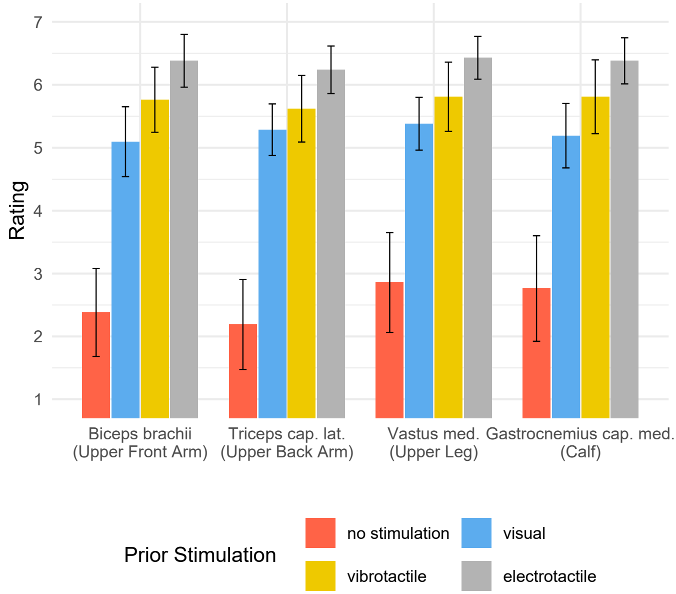


Figure 5.8: Subjective ratings from a 7-point Likert Scale questionnaire on the item "To which extent do you agree with the statement that [stimulation] helped me to locate my [muscle]?", evaluating the helpfulness of each prior stimulation and localization to isometrically tense a muscle. Electrotactile stimulation was perceived as the most helpful among the prior stimulation modalities. The highest ratings among the muscles were found for the upper leg and calf. Error bars show 95% confidence intervals.

Task Difficulty VAS ratings of task difficulty were significantly affected by the experiment with an effect of PRE-POST, $F(1,140) = 7.863$, $p = .006$, $\eta_p^2 = 0.053$, and MUSCLE LOCATION, $F(3,140) = 5.137$, $p = .002$, $\eta_p^2 = 0.099$, but without an interaction effect of PRE-POST $\times$ MUSCLE LOCATION, $F(3,140) = 0.661$, $p = .577$, $\eta_p^2 = 0.014$. Post hoc pairwise comparisons using Wilcoxon signed rank using Bonferroni correction showed significant differences between biceps and calf ($p = .007$), biceps and triceps ($p = .011$), as well as between biceps and upper leg ($p = .009$) indicating that the workload on the biceps ($M = 2.286$, $SD = 2.361$) was significantly lower compared to calf ($M = 3.643$, $SD = 2.694$), triceps ($M =$

3.452, $SD = 2.530$), or upper leg ($M = 3.357$, $SD = 2.685$). Perceived difficulty of tensing was significantly greater after the experiment ($M = 3.452$, $SD = 2.604$) than at its beginning ($M = 2.917$, $SD = 2.589$).

NASA-TLX and Subjective Performance The mean score of the NASA-TLX Score was 53.056 ($SD = 17.170$), which can be considered a high workload for the assessment [97] of the task. The majority of the participants (9/21) tend to agree with the statement that the modalities increased their reaction times (7/21 neutral, 5/21 disagree). This contrasts the finding that the majority (8/21) tend to agree that it also decreases their reaction times (6/21 neutral, 7/21 disagree). The majority (14/21) tend to disagree with the statement that the modalities did not affect their reaction times (3/21 neutral, 4/21 disagree). Thus, the subjective metrics indicate that most of the participants assumed that their performance changed in the course of the experiment. This is supported by the non-linear measures (see Figure 5.6) of, e.g., calf and triceps and the qualitative statements.

5.2.5 Qualitative Results

We used inductive thematic analysis to structure participant feedback from post-experiment interviews and relate it to experimenter notes [22]. Two researchers independently coded the statements to identify common categories and patterns, then merged these into overarching themes, resolving any discrepancies through discussion.

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

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

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

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

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

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

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

5.2.6 EMG Classification

Our analysis revealed distinct EMG signal shapes (Figure 5.6) in the physiological signals of the muscles. To further highlight the results, we investigated how well a standard machine-learning algorithm could classify muscle activation, location, and modality. We performed EMG signal classification in a sliding window approach (0.5 sec./500 samples). This examination allows us to understand our EMG data set from the prior stimulation study, determine if the findings can be incorporated into future applications, and learn the nuances of data differentiation. As all EMG recordings in our data set were labeled by our software, we were able to train our models based on ground truth. We used a standard feature extraction of the 24 most commonly used feature metrics stated by the literature [16, 318]: mean, median, standard deviation, minimum, maximum, root mean square (RMS), number of slope sign changes (SSC), waveform length (WL), skewness, kurtosis, Willison Amplitude (WAMP), Absolute Temporal Moment (TM), average amplitude change (AAC), variance, LOG Detector (LOD), integral absolute value (IAV), mean frequency (MNF), median density frequency (MDF), my pulse percentage rate (MPR), signal-to-noise ratio (SNR), and four auto-regressive coefficients using ARIMA (ARC1-4). The data was divided into 70% of the data for training the model and 30% used as test sets. To ensure the validity of muscle classification, we did not use the four input streams from the EMGs in parallel but only took the signal of the corresponding trial. For classification, we used a random forest[1] classifier, which is more robust against overfitting, can handle

[1] `https://rdrr.io/cran/randomForest/`

large feature spaces more effectively, provide importance measures, which can be helpful for feature selection, and generally faster and more scalable in training compared to other approaches such as SVMs [95, 158, 240].

Muscle Location Prediction The most fruitful attempt during the performance analysis of the classifiers was the accuracy of the muscles' location prediction. Determining the location of the EMG signal can help to automatically classify the forces and their movements in a wide range of future applications and wearable devices. We found an overall accuracy of 80.70%, a sensitivity from 78.83% to 82.59%, and a high specificity from 91.84% to 95.76%. The detection rate among all muscles ranged from 19.89 to 20.75% ($\kappa = 0.742$, Mcnemar's Test $p < .001$). The confusion matrix of the result can be found in Figure 5.9.

Muscle Tension Prediction While the overall prediction accuracy (94.56%), sensitivity (98.79%), and detection rate (88.82%) of the classifier for detecting muscles were tensing were high, the specificity and ability of the model ($\kappa = 0.650$, Mcnemar's Test $p < .001$) to correctly identify negative cases where there was no muscle tension were relatively low (56.90%). The visual exploration of the data (cf. Figure 5.4) suggests that this limitation was primarily due to the late response times of participants and the time required for them to tense their muscles.

Prior Stimulation Feedback Modality Prediction The overall accuracy in predicting the feedback modality (27.06%) used for prior stimulation, the sensitivity of the model (from 26.15% to 27.82%), and the detection rate (from 6.56% to 7.09%) was very low ($\kappa = 0.650$, Mcnemar's Test $p < .001$). The results indicate that the EMG signal is not a reliable predictor of the muscle activation modality. As the classifier could not differentiate between the modalities, we also assume that the prior stimulation did not significantly interfere with the signals.

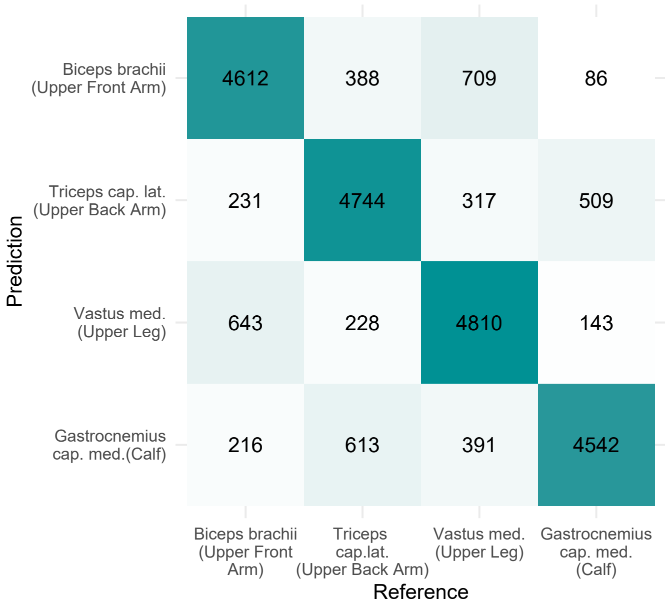


Figure 5.9: Confusion matrix of the EMG muscle location prediction based on 24 features and a 0.5-sec sliding time window (500 samples per entry) for data sampled at 1000 Hz frequency. The matrix was determined by random forest machine learning classification.

5.3 Discussion

In a VR user study, we compared visual, vibrotactile, and electrotactile prior stimulation modalities to no prior stimulation at the biceps, triceps, upper leg, and calf muscles, measuring reaction times with EMG. Our results indicate that the reaction times depend on both the prior stimulation modality and muscle location. All proposed prior stimulation modalities (visual, vibrotactile, electrotactile) significantly improved muscle response compared to no prior stimulation modality, with no notable differences among them. Notably, vibrotactile stimulation significantly enhanced reaction times in the biceps, a slower muscle. This means that vibrotactile feedback could significantly support the participants in cases where the interaction was particularly "challenging." Surprisingly, the calf muscle showed the fastest response, aligning with existing research on its high information throughput [264]. However, our experimental investigation is the first one, to our knowledge, to uncover significant differences in calf muscle performance.

We hypothesize that improvements in reaction times observed across both visual and tactile modalities are due to a mental representation of the body schema (c.f. [17]) in the primary somatosensory cortex [216, 267], rather than just activation of local nerve cells. The calf's faster response might be due to lower nerve sensitivity (or density) [182], suggesting multisensory integration prioritizes less variable stimuli [71]. The low nerve sensitivity in the calf leads to a more reliable, "noise-free" signal, aiding the somatosensory cortex in effectively localizing that muscle. This could mean muscles in more sensitive areas are harder to discriminate, warranting further research.

The main effects and lack of interaction effects in our experiment indicate that the findings could apply to more body muscles. The calf's quick response and its negative correlation with EMG signal strength might relate to its role in postural control and locomotion, which often requires a fine-tuned balance between quick responses and adequate force. An effect of the EMG amplitude would be in line with related work on increased EMG amplitude with prior vibrotactile stimulation [119]. However, the lack of significant parameter slopes remains unknown, and it is unclear if this is the case among other muscles. The results from subjective quantitative assessments revealed a significant preference for prior stimulation modalities, especially electrotactile over no stimulation. While the calf showed the fastest reaction time objectively, participants subjectively rated that the upper leg benefited most from prior stimulation. Both quantitative and qualitative data indicated that participants found tactile prior stimulation, particularly electrotactile, useful for muscle localization and favored the electrotactile cues. Participants reflected on the relation of our apparatus to their body awareness in their qualitative comments. This diverse feedback suggests our apparatus could have a highly versatile utility in assisting both able-bodied and disabled individuals in physical and cognitive aspects.

These insights are valuable for EMG developers and interaction designers, suggesting that prior stimulation using visual and tactile modalities can enhance interaction accuracy and speed across various muscle locations. This has implications for EMG-based user interfaces [242] and therapeutic VR applications requiring isometric muscle control [5, 58, 237]. Systems in VR working with EMG currently only provide visual and tactile cues in closed-loop feedback settings *simultaneously* to the EMG interaction and not *before*. Our system introduces an additional feedback layer for enhancing communication patterns in VR systems using EMG.

Enabling precise muscle classification and accurate placement of EMG electrodes is crucial for future assistive devices with integrated electrodes [146] and automated setup [147]. Our machine learning analysis demonstrates fine-grained EMG classification from recorded interaction data, enabling devices to autonomously identify the correct muscle without requiring explicit calibration procedures. This post-hoc approach lays the foundation for smarter, *self-learning wearables* that can automatically adapt to a user's unique muscle patterns.

Self-calibrating EMG wearables could enhance skill training and rehabilitation by automatically adapting to each user's muscle signals. In manual fabrication, they could compare muscle activity to expert reference patterns, giving real-time feedback on effort, grip, and coordination without manual calibration, accelerating skill transfer from experts to non-experts [18]. For rehabilitation, those wearables could guide home exercises, adjust to recovery stages, and ensure proper muscle engagement, improving technique, adherence, and enabling remote clinician monitoring [151]. Removing explicit calibration reduces setup complexity, supports non-expert use, and enables scalable tele-rehabilitation and remote mentoring through shared muscle activation feedback.

5.3.1 Implications

Our study's findings indicate that visual and tactile prior stimulation can enhance muscle reaction times, with tactile prior stimulation modalities being subjectively favored. Prior stimulation patterns in EMG-based interaction offer a more accessible approach to learning deterministic input commands. On-body cues could prompt which muscles to activate next, offering EMG-interfaces as an affordable, easy way to interact with computing devices beyond traditional hand-based controllers such as for games [198].

The approach of using prior stimulation can support on-body notifications in VR, which are preferred over visual ones [238, 325], offering new possibilities of assistive systems with EMG response-based commands, e.g., to enhance gamers' VR experiences [198], or supportive systems using tactile alerts, e.g., while driving [8]. Users of prosthetic systems can benefit from shortened training of functional mapping by prior stimulated on-body feedback [1, 143, 236]. Learning scenarios with goal-oriented tasks and repetitions can be improved by muscle priming to (re)gain motor control of dedicated muscle sites for researchers, therapists and their patients in the field of neurophysiology and telemedicine [151, 304], or for (industrial) workers during remote instructions [18].

Electrotactile prior stimulation could enhance supportive driving scenarios [305] and visual prior stimulation could correct industrial machine use [18] by assisting faster adjustments and facilitating learning of motor control. Tactile prior stimulation could enable physical therapists to remotely stimulate patient muscles, substituting for direct touch. This could facilitate clearer guidance on which muscle to activate next during (tele-)medicine sessions, enhancing neurorehabilitation [151] by promoting quicker adaptation to therapy movements. Visual, vibrotactile or electrotactile prior stimulation could aid patients in regaining balance in MR-based assisted-training systems that capture the body motion and provide tilt feedback [35, 304].

Tactile prior stimulation in simulated training environments may enhance muscle localization and mental body schema integration, potentially speeding up the adaptation to prosthetic limbs [5, 58, 310] and facilitating quicker movement response in impaired limbs during mirror therapy for stroke rehabilitation [174, 218, 295]. Systems of EMG dexterous prostheses with precise control systems are capable of sending and receiving signals to mimic natural sensations [1, 65]. These devices could benefit from additional tactile prior stimulation, which simulates the sensation of contact against the prosthetic finger to provide feedback comparable to a natural touch. This would then prompt the muscle responsible for controlling the prosthesis' finger movement to adjust its tension, thereby preventing excessive pressure on grasped objects [33, 236].

As one of the main implications of our study, we recommend using the calf for EMG input if low reaction times are desired and there is no necessity for a specific body location for the EMG acquisition (c.f. [198, 242]). Our research paves the way for more responsive and accurate EMG-based user interfaces [242] for various applications, including assistive, therapeutic, and hands-free applications [5, 14, 58, 198, 237].

Limitations Our system is limited to sedentary hands-free interaction scenarios that require quick responses and are designed with a predetermined pattern, allowing the system to anticipate which muscle needs to be activated next. This limits its application to prosthetics with multichannel control mechanisms, where the system can benefit from direct stimulation of an antagonist muscle that needs to be activated, e.g., grab with a complex finger pattern movement or in virtual training scenarios where the system anticipates the next muscle that has to be to be tensed [1, 143, 236]. The applicability of our system design is limited to enhancing and speeding up repetitive sequences during remote instructions [18, 305] or telemediated applications [151, 304]. The system cannot be applied to interactive systems for controlling a user interface with isometric EMG because it would not be able to determine early enough when the user intends to interact via isometric EMG input to stimulate the corresponding muscle location in advance.

Future Research Motor learning research demonstrated rapid neuroplastic changes through activities like juggling or playing musical instruments [62, 86]. We observed that participants often activated incorrect muscles despite knowing the correct muscle-to-computer mappings, hinting at the possibility of intentional "mistaken" activations. Related work has suggested the integration of visual and tactile cues in VR to augment sensory perception, including compensatory mechanisms for deficits in visual perception, proprioception, and spinal cord function [283, 284]. Our system, inspired by these studies, aims to speed up the training of new neuro-muscular pathways, especially from the sensorimotor cortex to the motor cortex, using novel visual and tactile interactions in an EMG-integrated VR framework. We suggest further research on non-linear pre-stimulation modalities to improve EMG response times in target muscles and their relation to cognitive workload [155].

Future research could explore additional muscle locations, such as the butt, back, or stomach muscle locations, and extend to isotonic contractions and movements. Given the effectiveness of tactile prior stimulation, we propose comparing mechanical tactile approaches with vibrotactile and electrotactile modalities as additional *mechanotactile* modality, including intensity variations. Our research demonstrates that prior stimulation modalities enhance muscle response in EMG-based reaction tests in VR, subsequently, future studies could explore threshold-based EMG interactions in VR, examining metrics beyond reaction time to gain further insights into muscle activation variations across different locations. The key benefit of using prior and multiple muscle stimulations lies in these applications and in providing tactile feedback before threshold-based control. Future research should focus on integrating more advanced machine learning models, such as deep learning, to enhance classification accuracy and scalability. Expanding the feature set and incorporating real-time processing capabilities would further improve the system's utility in dynamic environments.

5.4 Summary

Chapter 6 investigates the concept of muscle priming with prior stimulation feedback modalities and their impact on EMG-based interactions, addressing RQ4 "Does prior stimulation feedback enhance EMG-based interactions in reaction time tasks?" and RQ5 "Do muscle locations differ in EMG based interactions with prior stimulation feedback in reaction time tasks?" It focuses on prior stimulation to reduce EMG reaction times and enhance performance by connecting biofeedback awareness to actionable user interactions. We demonstrated that prior stimulation significantly enhances reaction times and performance across various muscle groups.

Our research evaluated visual, vibrotactile, and electrotactile stimulation modalities compared to no stimulation, showing that all modalities significantly improved reaction times. Vibrotactile stimulation was particularly effective for slower muscles like the biceps, while the calf muscle exhibited the fastest reaction times, aligning with its high information throughput [264]. These findings emphasize the utility of prior stimulation to prime muscles, enabling the somatosensory cortex to efficiently integrate multisensory feedback and enhance response accuracy. Subjective assessments also revealed a preference for electrotactile stimulation, which participants found helpful for muscle localization and interaction, while having effects on learning and muscle fatigue. We highlight how prior stimulation not only enhances reaction times but also influences user perception and body awareness. They connect the mental representation of the body schema [17, 267] with practical enhancements in VR interaction design, demonstrating an adaptive system for sedentary hands-free interaction for more responsive and precise EMG-based systems.

5.4.1 Lessons Learned

From the investigation of muscle priming with prior stimulation feedback and their impact on EMG interactions, we derive the following insights:

Prior Stimulation Feedback Improves Reaction Times Prior stimulation feedback—whether visual, vibrotactile, or electrotactile—proved to be an effective preparatory mechanism for improving reaction times in a response-based test with isometric EMG. This demonstrates the potential to enhance EMG-based interactions, particularly in hands-free scenarios where rapid and precise responses are required, e.g., for prosthesis control [29, 237].

Muscle-Specific Insights The calf muscle emerged as the fastest responder, highlighting its suitability for scenarios where minimal reaction times are critical. Conversely, vibrotactile feedback was notably effective for slower muscles like the biceps. These results guide the design of adaptive EMG-based systems, suggesting muscle-specific configurations for optimizing interaction performance [198, 242] with prior stimulation feedback.

Subjective Preferences of Electrotactile Modality Participants favored electrotactile stimulation for muscle localization, indicating its potential for training and rehabilitation applications. Systems could improve muscle response times while enhancing user understanding of body dynamics. This dual benefit positions tactile stimulation as a versatile tool for assistive, therapeutic, and interactive systems.

Feasibility of EMG Signal Classification Machine learning methods, such as random forest classifiers, are effective for classifying muscle activation and location using EMG physiological signal data. The demonstrated classification framework has the potential to scale across various applications, including assistive technologies, telemedicine, and remote healthcare.

5.4.2 Data Sets

As an outcome of chapter 6, we provide a comprehensive dataset EMG-based reaction times testing under different prior stimulation modalities, and the whole dataset for classification of the EMG-based muscle prediction publicly available on GitHub `https://github.com/JessicaSehrt/ReactionTest_EMG-V_vT_eT_priorStim` By fostering reproducibility, this resource supports the development of EMG-based systems for sedentary hands-free interactions, enhanced with prior stimulation feedback.

6

Biofeedback Awareness

The multimodal biofeedback investigations presented in the previous chapters of this thesis demonstrated that providing users with information about their physiological states can significantly enhance interaction. Visual, narrative biofeedback mapped from physiological input through EDA contributes to a deeper understanding of multimodal systems. This approach informs users about their physiological responses, particularly those related to stress and relaxation. It is beneficial in biofeedback applications and related research in various forms. EDA biofeedback is extensively in use for individual well-being and health [7, 56, 138, 167, 323], but also for applications in HCI [67, 96, 226, 241, 314], emotion-adaptive games [96], skill training [239], and reflected in adaptive environments in VR [67, 226, 241], e.g., for virtual architectural feedback [212]. While EDA-based interaction differs from EMG in that it is not directly voluntary, it still actively informs and influences how users interact with their physiological input. Although the benefits of biofeedback are well-documented, the influence of user awareness on its effectiveness remains unexplored. Consciously understanding that physiological responses directly influence the system by enhanced awareness of biofeedback can create more comprehensive and effective interaction mechanisms. Research suggests that heightened awareness can amplify control over physiological states and increase perceived efficacy [257, 281]. However, its impact on physiological outcomes, particularly in immersive VR settings, remains unclear. This chapter explores the role of awareness in influencing user responses during a sedentary hands-free biofeedback application related to their physiological input from EDA.

Parts of this chapter are based on the following publication:

J. Sehrt, U. Yilmaz, T. Kosch, and V. Schwind. "Closing the Loop: The Effects of Biofeedback Awareness on Physiological Stress Response Using Electrodermal Activity in Virtual Reality." In: *Extended Abstracts of the CHI Conference on Human Factors in Computing Systems*. CHI EA '24. Honolulu, HI, USA: Association for Computing Machinery, 2024. ISBN: 9798400703317. DOI: 10.1145/3613905.3650830

6.1 Method

Participants' EDA levels were used to control the virtual environment in a linear mapping from their physiological signals to the parameters of the VR scene of an immersive weather simulation as visual biofeedback. Two groups were compared in a between-subject user study, both groups experienced the same mapping in the same scene, and both groups could control the weather with their physiological input. The only difference was that one group was informed about the fact that they could control the weather by their EDA level, and the other was not.

6.1.1 Study Design

To understand if biofeedback awareness affects the physiological response during stress management, we conducted a VR user study in which the EDA was used to control the weather in an immersive environment. Participants were either informed about their ability to control or not (INFORMED CONTROL), resulting in a between-subject study in which the participants (and experimenter) were blind to the conditions. In addition, we were interested in whether the participants felt control over the weather (CONTROL-AWARE), which was assessed posterior to the VR experience. As all participants experienced the same amount of time, we used

TIME as a within-subject variable, assuming an interaction effect with INFORMED CONTROL or CONTROL-AWARE, indicating that the EDA will change during the biofeedback phase.

6.1.2 Apparatus

The key biofeedback parameter in our study is the EDA. We used a biosignalplux OpenBan one-channel hub[1] kit with skin conductance electrodes to measure the EDA. The electrodes were attached to the index and middle finger of the left hand. The sampling rate was 1000 Hz with 16-bit resolution.

We used the Unity game engine (2021.3.6f1) and the biosignalplux API for Unity[2] to implement the VR application. For the visual representation of the animated weather in the biofeedback scene, we used the WeatherMaker asset[3] by Digital Ruby. The asset provides a realistic and smooth transition between volumetric cloud profiles with fluid animations. Animation transitions were set in 10 seconds using linear interpolation. The asset also included suitable sound effects for the respective weather conditions. By leveraging the minimum and maximum values of the participant's EDA, each received value was transformed into a single weather variable transitioning between different weather profiles. Thus, the weather variable could take on values ranging from 0% to 100%, where 0% represented a very relaxed state on a sunny day, and 100% indicated a state of high stress using stormy cloud profiles. This enabled a linear mapping between the participants' calibrated EDA and the weather parameters of the VR scene.

The Unity application ran on an XMG Fusion 15 Laptop with Intel Core i7-9750H, GeForce RTX 2070 Max-Q, 16GB RAM, and Windows 10. While targeting frames per second (FPS) in Unity was set to 90, the application's average FPS was around 52 Hz. As VR HMD we used the HTC Vive Pro and SteamVR. The VR controller in the participant's right hand was only visible during the mental arithmetic task. We used the meadow environment from the Dynamic Nature

[1] `https://www.pluxphysiologicalsignals.com/products/solo-kit`

[2] `https://github.com/pluxphysiologicalsignals/unity-sample`

[3] `https://assetstore.unity.com/packages/tools/particles-effects/weather-maker-volumetric-clouds-and-weather-system-for-unity-60955`

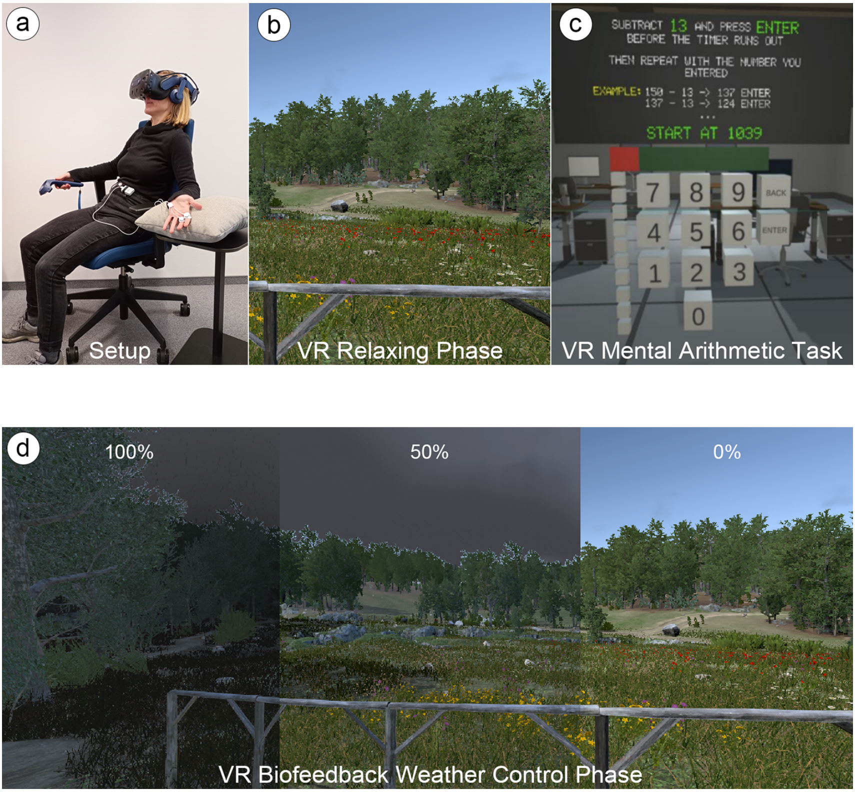


Figure 6.1: Photo of the experimental setup (a) and screenshots of the three phases in VR: Seven minutes in the Relaxation Phase (b) ensured a decreased EDA level as a minimum baseline for calibration. Maximal EDA levels were obtained in the Mental Arithmetic Task (c) based on the Trier Social Stress Test (TSST) paradigm to induce cognitive stress. In the biofeedback phase (d), the participants were able to control the weather activity from stormy (100% EDA) to sunny (0% EDA).

Asset[1] from the Unity Asset Store for vegetation and animations in the nature scene during the relaxation and biofeedback phases. The system automatically calibrated the participant's skin conductance value during the relaxation and stress tasks for a (possible) full-range weather transition during the biofeedback phase. The application ran fully automatic to prevent any intervention from the experimenter.

6.1.3 Procedure

After signing the informed consent and being briefed on the experimental setup, each participant was seated in our laboratory. Before launching the Unity application, the openBan device was attached to the fingers of the participant's left hand, and they were equipped with the HMD. The Unity application automatically assigned participants to an experimental condition, with the experimenter and the subject initially unaware of the condition. During the application's operation, participants received no further instructions other than those provided. The application's procedure was divided into three phases: Relaxation Phase, Stress Phase, and Biofeedback Phase (see Figure 5.1.). The entire experimental procedure in VR lasted 24 minutes for all participants and was planned using the HCI studies toolkit [255].

Relaxation Phase Participants were instructed to relax using a visual prompt (the panel was visible for 20 sec). In this scene, a serene environment with natural sounds was displayed. This phase lasted exactly seven minutes (420 sec) to ensure full relaxation of the participants. The minimum EDA recorded in this phase was used to calibrate the weather conditions in the Biofeedback Phase.

Stress Phase In this phase, participants solved a mental arithmetic challenge within seven minutes, based on the serial subtraction task from the Trier Social Stress Test (TSST) [144]. They were placed in a stressful office environment with loud noise and flickering lights. Participants had to continuously subtract thirteen from 1,039 and enter the result into a numerical field using a VR controller.

[1] `https://assetstore.unity.com/packages/3d/vegetation/meadow-environment-dynamic-nature-132195`

Correct entries were acknowledged with a rewarding sound and a green cube lighting up. If time ran out or an incorrect entry was made, a loud horn sounded, and the number reset to 1,039. The remaining time was reduced by one second after each successful entry to increase stress. Additionally, at certain checkpoints, a false attempt was falsely attributed to the participant, resulting in the horn sounding and progress resetting. The participants' maximum EDA values were determined in this phase.

Biofeedback Phase In the experimental phase, participants controlled the weather as biofeedback using their EDA levels. Through the relaxation and stress phase, we calibrated the user's response to map it linearly onto the weather conditions from stormy (maximal EDA) to sunny (minimal EDA). A task panel in the field-of-view (FoV) (visible for 20 sec) prompted the participants to relax while only the informed group additionally received the information that they could control the weather by their relaxation-related EDA values. An explanatory panel was shown in the participants' HUD at the beginning of the biofeedback phase showing either the instruction to just relax or to relax by controlling the weather of the scene. High EDA levels were visualized by a fierce storm tossing trees and plants. The sky was covered with dark thunderclouds, heavy rainfall prevailed, and nature was shrouded in darker light. The more the participants relaxed and therefore lowered their EDA values, the less rain fell, the clouds dissipated, the wind animations calmed down, and the sun illuminated nature again, thus returning to the calm state of the relaxation phase. The biofeedback phase lasted ten minutes.

6.1.4 Participants

Thirty participants were recruited via our institution's social networks and mailing lists. The mean age of the participants was 23.333 ($SD = 3.613$), ranging from 18 to 34 years (6 female, 24 male). Twenty-one were computer science or mechanical engineering faculty students, and nine were staff members or in vocational training. Students were compensated with credit points for their lectures, and staff members were compensated with working hours. The study received ethical clearance according to our institution's guidelines and hygienic instructions.

6.1.5 Data Analysis

Raw data were recorded throughout the experiment. We only considered the EDA for hypothesis testing in the biofeedback phase where participants controlled the weather (840 - 1440 seconds after application start). To reduce the noise in the data, we aggregated the raw values within each second using their median.

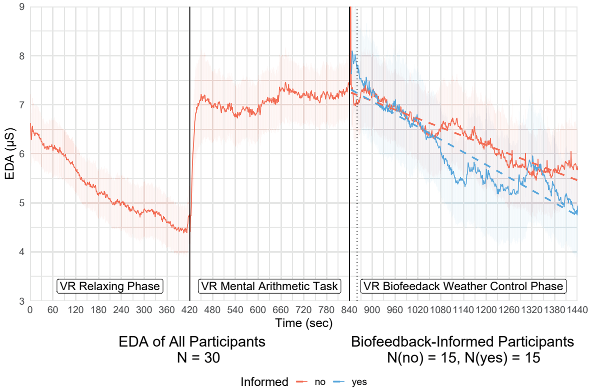
6.2 Results

Interestingly, the responses from the participants were markedly distinct. Among the informed participants, 8 out of 15 (53.3%) correctly surmised that they could control the weather. In contrast, 7 out of the 15 participants (46.6%) who were not informed also believed that they had control over the weather. Pearson Chi-squared test of independence was conducted to assess the relationship between the variables INFORMED CONTROL and CONTROL-AWARE, which was not significant, $\chi^2 = 0$, $p = 1$. Therefore, we considered both groups independently and analyzed them separately using linear mixed model analysis. Linear regressions are shown in Figure 6.2

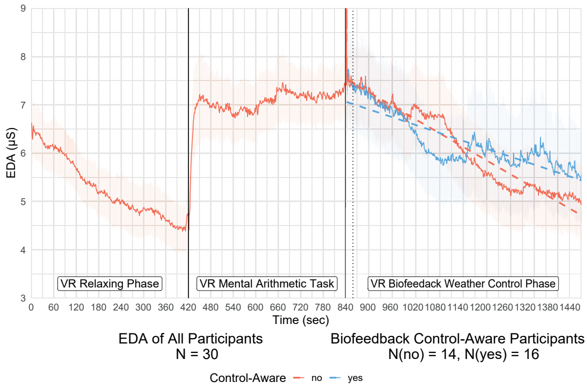
6.2.1 Biofeedback Informed

We fitted a linear mixed model using restricted maximum likelihood (REML) and nloptwrap optimizer of the lme4 package[1] for R to predict the EDA (in μS) with INFORMED CONTROL and TIME as independent variables (IVs). Since all participants were in the VR for exactly the same amount of time, the time was treated as a within-subject variable. The model included the subject as a random factor. The model showed substantial explanatory power, with a conditional R^2 of .91. The contribution from fixed effects alone (marginal R^2) is .03. The intercept of the model, representing the scenario of *non-informed* and *time* = 0, is at 9.78 ($CI95 = [8.040, 11.510]$), $t(17976) = 11.04$, $p < .001$. The main effect of being INFORMED CONTROL is positive but statistically non-significant, $\beta = 1.170\,(CI95 = [-1.280, 3.620])$, $Std.\beta = -0.090\,(CI95 = [-1.280, 3.620])$, $t(17976) = 0.930$, $p = .350$. The effect of TIME is statistically significant and

[1] `https://cran.r-project.org/web/packages/lme4/index.html`



(a) 15 participants were informed that their EDA would control the weather, while the other 15 were not (the info panel disappeared at the dotted vertical line).



(b) Post-experiment inquiries revealed that 16 participants realized their EDA influenced the weather (control-aware), whereas 14 participants did not.

Figure 6.2: EDA of 30 participants during the VR Biofeedback Phase, evaluated in two ways. Linear regression model fit (dashed lines) using REML estimation at the participant level showed significant interaction effects ($p < .001$). Informed participants showed significantly lower EDA measures at the end of the phase than those who were not informed (a). Participants who were aware that their EDA controls the weather exhibited elevated measures until the end of the phase (b). Graphs include standard error bars.

negative, $\beta = -0.003$ ($CI95 = [-0.003, -0.003]$), $Std.\beta = -0.150$ ($CI95 = [-0.150, -0.140]$), $t(17976) = -45.400$, $p < .001$. However, also the interaction effect of INFORMED CONTROL × TIME is statistically significant and negative, $\beta = -0.001$ ($CI95 = [-0.002, -0.001]$), $Std.\beta = -0.060$ ($CI95 = [-0.070, -0.060]$), $t(17976) = -14.050$, $p < .001$. Standardized parameters were derived by fitting the model to a standardized version of the dataset. The 95% CIs and p-values were calculated using a Wald t-distribution approximation. Thus, that analysis confirmed the assumption that the EDA of participants being informed at the beginning of the biofeedback phase were significantly lower at the end of the phase than those who were not informed.

6.2.2 Biofeedback Control-Aware

For CONTROL-AWARE, we fitted a second linear mixed model with the subject as a random effect factor. The model's total explanatory power is substantial (conditional $R^2 = 0.91$) and the part related to the fixed effects alone (marginal R^2) is 0.03. The model's intercept, corresponding to *not aware* and TIME = 0, is at 11.51 ($CI95 = [9.710, 13.310]$), $t(17976) = 12.55$, $p < .001$. The main effect of CONTROL-AWARE is negative but statistically non-significant, $\beta = -2.150$ ($CI95 = [-4.610, 0.310]$), $Std.\beta = 0.04$ ($CI95 = [-0.660, 0.730]$), $t(17976) = -1.71$, $p = 0.087$. The effect of CONTROL-AWARE is statistically significant and negative, $\beta = -0.005$ ($CI95 = [-0.005, -0.005]$), $Std.\beta = -0.23$ ($CI95 = [-0.240, -0.220]$), $t(17976) = -69.56$, $p < .001$. The interaction effect of CONTROL-AWARE × TIME is statistically significant and positive, $\beta = 0.002$ ($CI95 = [0.002, 0.002]$), $Std.\beta = 0.10$ ($CI95 = [0.090, 0.110]$), $t(17976) = 21.48$, $p < .001$. Thus, participants who believed in their ability to control the weather showed higher EDA values until the end of the biofeedback phase. We also analyzed the data under one single model and considered the hypothesis if there is a three-way interaction between INFORMED CONTROL × CONTROL-AWARE × TIME, which was, however, not significant ($p = .914$). Due to rank deficiency from the limited sample size, while the null hypothesis might be rejected, the reasons for the rejection may not accurately reflect the true underlying patterns, increasing the risk of Type III errors. This limits valid conclusions regarding differences in EDA values for informed and control-aware participants (or other combinations). The same limitation applies to potential gender effects.

6.2.3 Subjective Feedback and Observations

As already mentioned, only eight participants from the group that was informed about having biofeedback believed that it was the changes in their physiological signals, e.g., their biofeedback, that caused the weather change. After the experiment, seven participants believed that the weather had been controlled by their stress level, even though they were not informed. Consequently, 14 participants, almost evenly distributed in both groups, were strongly convinced that the weather was not manipulated by their stress or relaxation obtained from their EDA. While all of them observed that the weather changed over time, only ten of them reported on explicit reasons why they had not been convinced that the weather was being manipulated by them, and did not feel stressed or relaxed at all. However, a decrease in the EDA data of all participants was noticed.

The participants who believed that their bodies controlled the weather stated that they felt connected with the environment. "When I breathed in and out, the weather improved. When I was getting excited, the weather worsened." (P20). Every third participant experienced boredom during the relaxation scene. However, most of them reported positive feelings, including relaxation or a state of serenity during that first phase. Only two participants were annoyed during the experiment due to restricted movement caused by the sensor attached. In total, 25 participants described in their own words that they felt particularly stressed, frustrated, or angry during the arithmetic task. Three stated that they felt challenged, one felt competent enough, and only one participant (P8) reported feeling good after the task. Indeed, his EDA reflected this, as despite a significant increase during the transition from relaxation to the stress scene, his EDA quickly decreased when he started the mental arithmetic task. Generally, most participants praised the VR environment, even though the graphics and resolution were criticized. Generally, the biofeedback itself was positively received by the participants. The arithmetic task, however, was mostly negatively recognized as being too stressful.

We explored the impact of biofeedback awareness on physiological responses during stress management in VR. Thirty participants were involved in a between-subject design, where they were either informed or not informed about their ability to control the weather using EDA. The VR application allowed participants to control the weather based on their EDA levels, with a range from sunny (low EDA) to stormy (high EDA) conditions. After the experiment, we surveyed the participants to assess their perceived control over the weather. Two linear mixed models revealed significant interaction effects between group and time during the biofeedback experience, confirming that the biofeedback mechanism functioned identically for all participants. The EDA of informed participants was significantly lower at the end of the biofeedback phase than that of participants who were not informed. This suggests that knowing their stress levels could influence the environment enhanced relaxation, which aligns with prior research on biofeedback using EDA [202, 212, 226, 239, 314]. However, higher EDA values of participants who recognized that they also gained control were probably higher due to their ability to test and "play around" with their influence on the weather in the biofeedback phase. Participants who were not able to control it showed lower values, indicating that they just waited and relaxed until the end of the experiment. This finding indicates that being informed about the biofeedback loop does promote relaxation, but not necessarily due to their ability to control the weather. Glass and Singer's classic studies showed that even a modest perception of control, such as believing one could stop loud noise, significantly reduced stress responses and improved task performance [88] and concluded that perception of control can buffer stress, even when actual control is limited or illusory Our findings parallel this effect, suggesting that the biofeedback benefit observed in our study may partly stem from perceived rather than actual control. Biofeedback activeness may partly derive from users' perceived control, not just physiological feedback loops. This raises the question of whether physiological effects observed in biofeedback contexts are always attributable to actual functional control or may also emerge from a placebo-like mechanism based on perceived control. Similar to findings in other biofeedback research [257], participants' belief in a functional system—even when its influence is absent or limited—may itself modulate physiological states. Future studies could explicitly manipulate actual versus perceived control, for example, by varying the degree to which biofeedback signals truly influence the environment, for example by adjusting the responsiveness or sensitivity of the system. Subjective measures of perceived control and relaxation, complemented with physiological markers such as heart rate (HR), heart rate variability (HRV), breathing, or cortisol, could further clarify the mechanisms underlying these effects. Beyond the role of control, the observed variability in responses highlights the importance of exploring individual differences and temporal patterns. Time-series analysis and pattern recognition approaches could help identify predictors of how individuals respond to biofeedback, such as initial stress levels, personality traits, or engagement with the VR environment. Such approaches could inform adaptive biofeedback systems that tailor interventions to individual needs, potentially increasing effectiveness.

Limitations and Future Directions The sample primarily consisted of young, healthy individuals, limiting the generalizability of our findings. The relatively short duration of the VR intervention may not capture long-term effects or potential habituation to biofeedback mechanisms. Moreover, our focus on a single physiological marker (EDA) limits the scope of interpretation, as multimodal measures could reveal richer insights into stress responses [251]. Future research should therefore (1) examine varying degrees of actual and perceived control, for example by adjusting the responsiveness or sensitivity of the biofeedback system, to disentangle belief-driven from function-driven effects, (2) incorporate additional physiological markers (HR, HRV, breathing, cortisol) to better capture stress and relaxation processes, (3) analyze individual response patterns using time-series and machine learning approaches, and (4) recruit more diverse participant groups to improve external validity and to refine these systems further.

6.3 Summary

Chapter 6 investigates the role of awareness in shaping physiological responses during stress management in VR. Addressing RQ1 "How does awareness of biofeedback, provided through EDA, influence physiological signal responses?". This study examined how informing participants about their ability to control the environment using EDA impacts the effectiveness of physiological input and stress levels. In a between-subjects design involving 30 participants, the VR application allowed participants to influence the weather (e.g., sunny to stormy) based on their EDA levels. Participants who were informed about their biofeedback control exhibited significantly lower EDA levels at the end of the session compared to those who were not informed, suggesting enhanced relaxation. Interestingly, informed participants who believed they had control also showed higher EDA levels during the session, possibly due to engagement and experimentation with the biofeedback mechanism. These findings highlight the importance of biofeedback awareness in reducing stress and promoting user engagement in immersive environments, with implications for healthcare, interactive systems, and game design.

6.3.1 Lessons Learned

From this investigation into biofeedback awareness, the following insights were derived:

Awareness Promotes Physiological Response Participants informed about their ability to control the environment using EDA exhibited lower stress levels, as indicated by reduced EDA at the end of the session. This finding aligns with the principle of biofeedback and its potential for stress management.

Belief in Control Influences Engagement Participants who believed they had control over the environment, regardless of being informed, displayed higher EDA during the session. This indicates that perceived control fosters engagement and experimentation, even in the absence of explicit instruction.

Complexity of Subjective and Objective Responses A disparity between subjective feedback and physiological responses was observed, suggesting that participants may not always accurately assess their stress or relaxation levels. This highlights the need for a nuanced understanding of cognitive and physiological factors in biofeedback systems.

6.3.2 Data Sets

To enable further exploration, the data and source code are publicly available on GitHub `https://github.com/JessicaSehrt/EDA_VR_biofeedback.git` This resource supports reproducibility and encourages further research into EDA-based biofeedback applications in VR.

7

Conclusion and Future Work

This thesis begins by describing physiological sensing as an interaction technique in HCI, presenting the technical foundations and related research trends, and introducing challenges and solutions for isometric muscle-based interactions enhanced by multimodal biofeedback, prior stimulation feedback, and biofeedback awareness. Each study provides unique insights into the processes and implications of utilizing physiological signals for virtual interactions, revealing shared patterns and complementary findings that advance our understanding of systems that enable the improvement of interoceptive focus on one's physiological signals as an input mechanism in sedentary, hands-free interaction with minimal movement. The following summarizes the research contributions, answers the research questions, and concludes with shared insights and an outlook on future research directions.

7.1 Summary of Research Contributions

This thesis ties together the following investigations to enhance hands-free HCI systems with physiological input. We report on two studies based on a VR Fitt's Law task investigating how muscle-based interactions and multimodal biofeedback with EMG input can be improved, addressing RQ1 and RQ2. The first study investigates the efficacy of EMG-based interaction from various muscle locations in VR, pointing towards high flexibility for EMG interaction in interactive applications. Building on this, the second study explores the impact of combining multimodal biofeedback and its impact on enhancing EMG-based interaction, demonstrating that combining tactile and visual feedback enhances EMG interaction performance. This multimodal approach not only augments interaction with isometric

This thesis further investigates the impact of multimodal prior stimulation modalities on reaction times in EMG-based input, revealing a significant improvement of visual, vibrotactile, and electrotactile modalities. *Prior stimulation feedback* refers to cues provided before an action to help prepare the users. The study‘s investigation, inspired by the assistive technique of muscle priming into prior stimulation feedback, showed reduced reaction times and enhanced isometric EMG-based interaction, providing insights into learning and fatigue. This study enhances the overall contributions of this thesis by demonstrating how prior stimulation feedback can improve muscle response, adding another dimension to optimizing interactions with physiological sensing technologies.

This highlights the importance of user awareness and readiness in sedentary hands-free interactions. Visual, vibrotactile, and electrotactile prior stimulation feedback modalities were used to prime muscles, all reducing the time needed to respond. The electrotactile prior stimulation modality was particularly favored in subjective ratings on the improvement of the localizability of all muscles. The calf muscle exhibited the fastest reaction times when prior stimulated, aligning with its high information throughput from the second study of this thesis [264]. The results emphasize that prior stimulation at specific muscle sites improves reaction times and interaction fidelity with physiological sensing. The results were further highlighted by the investigation into the potential for accurate muscle location classification using the acquired EMG data.

Furthering the approach, this thesis investigates the impact of *biofeedback awareness* on the user's physiological response. We present the study's results exploring the effects of awareness on the efficacy of biofeedback in stress management, using EDA as a primary measure and biofeedback control using a VR weather control system. This third study revealed that when researchers do not just take care of informing users of their biofeedback control but also ensure that users are aware of their biofeedback control, their interaction within the VR environment becomes significantly more nuanced and effective.

Together, these findings, studies, and investigations culminate in a sophisticated framework for hands-free interaction design with physiological sensing technologies, offering great potential for applications aiming to transform EMG and EDA measures as input into biofeedback mechanisms as output, offering innovative ways to design adaptive and intuitive interactions that provide innovative ways to connect humans with computers. Improved human interoception of physiological functions as input mechanisms can be beneficial in various fields. These include healthcare for rehabilitation, fitness training, accessibility in HCI for individuals with limited mobility, and gaming, where sedentary hands-free interactions can create novel experiences, with potential to be useful for deterministic learning in industrial or rehabilitative training scenarios.

In the following, we revisit the research questions addressed in this thesis:

- **RQ1:** *Which muscle locations are optimal for EMG-based real-time interactions considering user performance and perceived workload?*

  We compared user performance and perceived workload using different muscle locations for isometric EMG input in a virtual Fitt's Law Task. We found similar performance across all tested muscle locations and that input performance does not significantly differ among isometric-controlled muscle contractions. While the forearm shows slightly higher throughput, other muscle locations are equally viable for interaction.

- **RQ2:** *How do different biofeedback modalities (auditory, tactile, visual) influence the performance and interactions of EMG-based interactions?*

  We compared how different feedback modalities and their combinations affect the performance and workload in a virtual Fitt's Law Task. Results showed that combining tactile and visual biofeedback significantly improved performance, while auditory feedback negatively impacted performance. The findings highlight the robustness of EMG-based systems for target selection, regardless of target size or distance. The qualitative feedback revealed the importance of addressing challenges such as muscle fatigue.

- **RQ3:** *Does prior stimulation feedback enhance EMG-based interactions in reaction time tasks?*

  We tested the prior stimulation modalities on four key muscles, finding that prior stimulation in a Virtual Reaction Time Test with visual, vibrotactile, and electrotactile modalities shortened isometric EMG reaction times in isometric EMG-based interaction with all muscle. The electrotactile modality was subjectively favored.

- **RQ4:** *Do muscle location responses differ in EMG-based interactions with prior stimulation feedback in reaction time tasks?*

  The Gastrocnemius cap. med. muscle in the inner calf responded significantly faster than the other muscles. The calf muscle had the shortest reaction times in a Virtual Reaction Time Test during prior stimulation with isometric EMG-based interaction.

- **RQ5:** *How does awareness of biofeedback, provided through EDA, influence physiological signal responses?*

  We showed that biofeedback awareness can impact physiological responses. Participants with perceived control over their EDA to control the environment fostered engagement and experimentation, even in the absence of explicit instruction.

7.2 Implications

Our research advances the understanding of EMG-based systems and biofeedback by synthesizing insights from multiple studies into a cohesive framework. Across the studies, we explored isometric muscle contraction, biofeedback modalities, and prior stimulation mechanisms, emphasizing their implications for improving user performance and interaction design. A central theme across all studies is the transformation of physiological signals into actionable biofeedback loops that influence user states and system behavior. By focusing on different contexts, the studies converge on a critical insight into how adaptive systems can enhance user engagement and performance by aligning multimodal biofeedback mechanisms with physiological and cognitive processes.

Linking all of this thesis's insights together, we emphasize how different feedback modalities and prior stimulation feedback can collectively enhance the effectiveness and responsiveness of interactions based on physiological sensing. We highlight these systems' adaptability and enhanced responsiveness and demonstrate their potential in hardware and software prototypes.

Multimodal Feedback Enhances EMG-Based Interaction Through these investigations, we identified an innovative way to enhance biofeedback technology systems with multimodal biofeedback. Simultaneously integrating *tactile and visual biofeedback loops* in EMG-based interfaces, we identified that such multimodal feedback significantly improves performance. This work showcases the potential of multimodal biofeedback to address key challenges in EMG-based interaction systems. We demonstrated that muscle-based inputs using isometric contractions from various muscle locations are robust for target selection tasks in VR, independent of target size or distance. However, extensive muscle usage and user fatigue necessitate future investigation into dynamic and sustainable designs. We extended these findings by illustrating that combining visual and tactile biofeedback significantly enhances control over muscle activity.

We introduced the concept of *prior stimulation feedback* modalities as a preparatory mechanism to enhance isometric muscle responses. Importantly, reaction times improved significantly across visual, vibrotactile, and electrotactile modalities compared to no prior stimulation. Notably, the calf muscle consistently showed the fastest responses, likely due to its relatively high information throughput [264] and lower nerve sensitivity [182, 216].To our knowledge, this is the first research to systematically examine the impact of prior stimulation modalities on response times with isometric EMG from various muscle locations. Our research paves the way for more responsive and accurate EMG-based user interfaces [242] for various applications, including assistive, therapeutic, and hands-free applications [5, 14, 58, 198, 237].

By integrating visual, vibrotactile, and electrotactile modalities in simultaneous and prior stimulation feedback loops, this research offers a scalable and adaptive approach to EMG-based interactions. These findings collectively establish a foundation for the future of multimodal biofeedback systems. A hypothetical explanation for the high effectiveness of the tactile modality is that it leverages the user's awareness of the apparatus being in direct contact with their skin, thereby potentially enhancing somatosensory engagement and spatial focus. This heightened body awareness has been reported by users in our results. Visual modalities are the dominant sensory input for humans and may have been further leveraged by spatial and contextual cues amplified within the immersive VR environment. Together, these modalities not only improve interaction efficiency but also increase the user's awareness of their physiological responses, which has been identified as an important factor for successful EMG-based interactions and during the EDA-based biofeedback experiment.

User-Oriented Feedback Design Both EDA and EMG studies reveal that the effectiveness of biofeedback depends on contextual factors, such as task demands and the user's cognitive state, making the consideration of individual variability in feedback design important.

In the EMG experiments, we calibrated each muscle location's threshold to the individual capacity, building a multimodal apparatus that could enhance throughput in interaction and reduce response times. In the EDA study, we calibrated the individual stress and relaxation baseline values, building an apparatus that ultimately assisted in enhanced control of users' physiological states. Together, these findings underscore the importance of tailoring biofeedback systems to both user-specific and task-specific factors. This adaptability emerges as a shared requirement for systems that transform physiological signals into meaningful control inputs. While multimodal feedback (visual, tactile) can improve interactions and interaction performance, excessive sensory inputs may overwhelm users. Overloading feedback modalities should be avoided. Designers should allow customizable feedback settings to prevent cognitive overload, particularly for sensitive users.

The versatility of biofeedback systems, from gaming and hands-free interfaces to prosthetic training, highlights their potential for broader adoption. Systems that adapt to individual physiological and psychological profiles could provide inclusive, user-centered solutions for diverse populations. Biofeedback systems should calibrate signal thresholds and feedback intensities based on user preferences and capabilities to ensure comfort and effectiveness, as well as resistance to stimuli, e.g., stress resistance. Adapting feedback modalities to individual differences in physiology and cognitive processing abilities, especially for users with disabilities or the elderly, improves their accessibility.

A machine learning-based analysis of the EMG physiological signal data that was acquired during the prior stimulation experiment enabled precise muscle classification, paving the way for adaptive and self-calibrating EMG-based systems. These insights are particularly valuable for wearable assistive devices, where accurate placement and feedback are critical for usability and could further contribute to the personalization of isometric EMG-based applications.

Awareness of Biofeedback Enhances Physiological Responses Our research identified a significant innovation in biofeedback systems research by demonstrating the profound effect of user *awareness of biofeedback loops* on stress regulation, emphasizing the psychological and behavioral impact of perceived control in biofeedback systems. Informing users about their control in biofeedback systems. Awareness of their ability to influence VR environments (e.g., through weather changes via stress levels) experiences caused more pronounced physiological responses in participants, and cueing them for interaction increased the speed of their reaction times in their physiological interaction. This suggests that explicit awareness enhances engagement and efficacy.

Across all studies, the belief in control played a critical role in shaping user outcomes. This underscores the need for systems that not only respond to physiological markers but also address psychological dimensions. By integrating multimodal feedback with mechanisms that enhance user awareness and preparation, systems can bridge the gap between physical signals and subjective experience.

Critical Role of Muscle Fatigue Fatigue during muscle-computer interactions, with a non-linear progression, was characterized by initial improvements from learning and habituation, followed by declines as fatigue set in. The effects of fatigue vary across muscles, highlighting the importance of designing systems that balance the benefits of learning with strategies to mitigate fatigue, ensuring optimal and sustained interaction performance. To address muscle fatigue in muscle-computer interactions, tasks should be limited to durations of around 15 minutes or include structured breaks to allow recovery. Redistribution of interaction tasks to less fatigue-prone muscles, such as the calf, or alternating between muscle groups, can prevent overuse. Adaptive biofeedback systems that dynamically adjust intensity and responsiveness based on real-time muscle activity can reduce cognitive strain. Progressive training protocols can enhance endurance and efficiency, while real-time monitoring of signal strength can help detect early fatigue and prompt timely interventions.

7.3 Future Work

The convergence of findings points to an insight that physiological signals like EMG and EDA are not merely passive markers of user states, but are dynamic inputs that, when integrated with adaptive feedback mechanisms, enable transformative interaction paradigms. While EDA is a powerful indicator of stress and emotional arousal, other physiological sensing offers complementary insights. Heart rate variability (HRV) and respiratory patterns are frequently used alongside EDA to provide a holistic view of autonomic nervous system activity [275]. EMG-based systems augmented with prior stimulation modalities offer precise control for therapeutic and assistive applications. For example, tactile or electrotactile feedback could aid in neurorehabilitation by guiding muscle activation, facilitating quicker motor adaptation [151, 236]. Prior stimulation feedback may facilitate neuroplastic changes, offering a promising approach for training new neuromuscular pathways [62]. Future studies could explore the impact of non-linear prior stimulation modalities and their role of cognitive workload in shaping EMG responses.

Toward Unified Adaptive Biofeedback Systems Combining the physiological input mechanisms from enhanced awareness of stress management through EDA with enhanced body awareness through EMG prior stimulation could lead to innovative interactive systems that focus on augmenting users' interoception and ability to focus on their physiology. Future research should investigate how physiological signals that are more indirectly controllable, e.g., EDA (HR, electroencephalography (EEG)), can be integrated into interactive systems with EMG and how related feedback mechanisms could work next to each other. Additionally, exploring the long-term effects of biofeedback and its role in fostering user learning and adaptation is critical for advancing these technologies. Biofeedback loops, with EDA and EMG, can be seen as two systems for sedentary hands-free interactions for static sedentary hands-free interaction Future work could combine with different sensing modalities to create a richer, more informative system for sedentary hands-free interaction.

As we move forward, we envision that user awareness and prior stimulation feedback are seamlessly integrated into practical applications, advancing the design of sedentary hands-free applications. Future development could enable automated calibration and customization for training programs that enhance skill acquisition through real-time biofeedback interaction, which adapts to users. Additionally, understanding individual differences in perceptual thresholds, particularly among diverse populations, remains an important area for investigation. This holistic approach not only enriches the virtual experiences but also opens new avenues for interactive and adaptive technologies. Adaptive physiological signal mapping strategies could further refine the approaches by adjusting parameters dynamically based on user profiles, e.g., adjusting biofeedback intensities for less resilient users.

The studies collectively reveal that transforming physiological signals into biofeedback mechanisms is not just about system responsiveness — it's about creating systems that actively shape the interactions. By closing the loop between user intention, physiological feedback, and system adaptation, these technologies enable a new generation of interactive systems that are more intuitive, effective, and accessible.

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List of Acronyms

AR augmented reality

ART Aligned Rank Transform

BEDE Bisection Extremum Distance Estimator

CI95 95% confidence intervals

EDA electrodermal activity

EEG electroencephalography

EMG electromyography

EMS electrical muscle stimulation

FoV field-of-view

FPS frames per second

GSR galvanic skin response

HCI human-computer interaction

HD-EMG high-density surface EMG

HMD head-mounted display

HR heart rate

HUD heads-up display

ID index of difficulty

IDe effective index of difficulty

IV independent variable

MR Mixed Reality

MT mean time

MVIC maximum voluntary isometric contraction

PWM pulse-width modulation

raw TLX raw NASA-Task Load Index

REML restricted maximum likelihood

RM-ANCOVA repeated measures analysis of covariance

RM-ANOVA repeated measures analysis of variance

RT reaction time

sEMG surface electromyography

SENIAM European Recommendations for Surface Electromyography

TENS transcutaneous electrical nerve stimulation

TKEO Taeger-Kaiser energy operator

TPe effective throughput

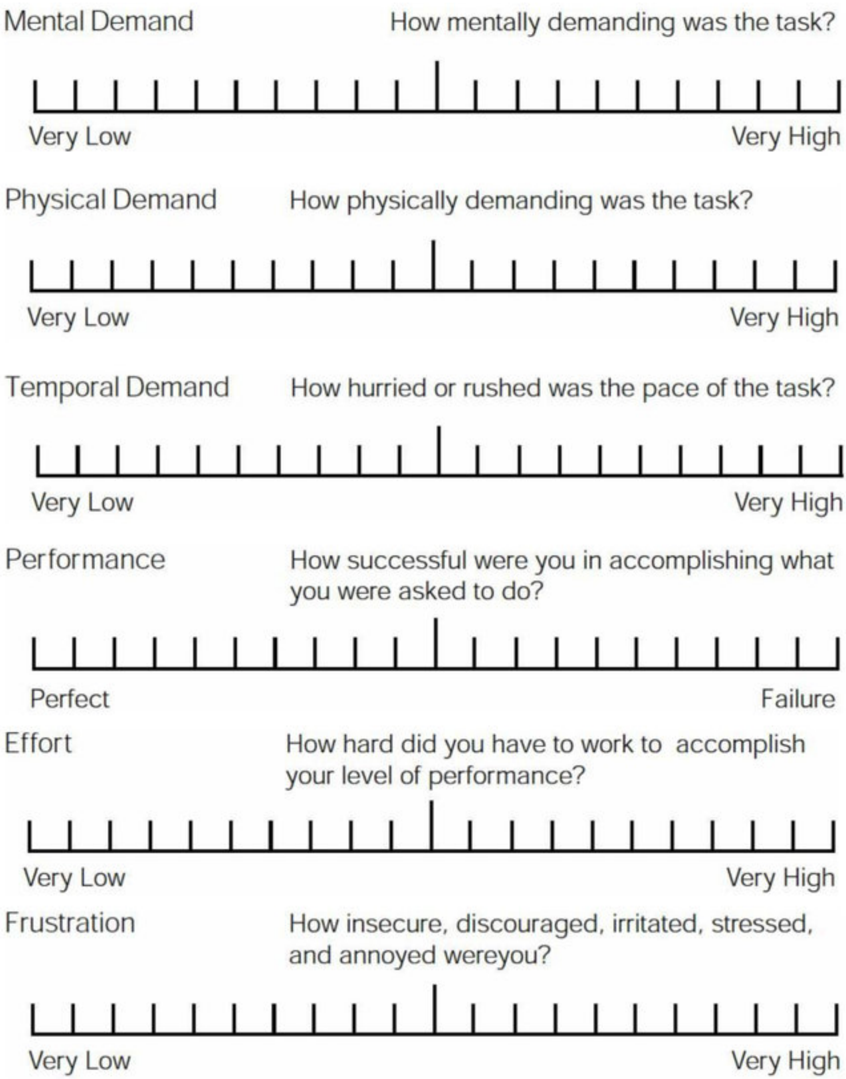
TSST Trier Social Stress Test

VAS visual analog scale

VR virtual reality

VTS Vienna test system

Appendix



Mental Demand How mentally demanding was the task?

Very Low Very High

Physical Demand How physically demanding was the task?

Very Low Very High

Temporal Demand How hurried or rushed was the pace of the task?

Very Low Very High

Performance How successful were you in accomplishing what you were asked to do?

Perfect Failure

Effort How hard did you have to work to accomplish your level of performance?

Very Low Very High

Frustration How insecure, discouraged, irritated, stressed, and annoyed wereyou?

Very Low Very High

Raw NASA-TLX questionnaire.