# Facilitating Bodily Insights Using Electromyography-Based Biofeedback during Physical Activity


Jakob Karolus
jakob.karolus@ifi.lmu.de
LMU Munich
Munich, Germany

Felix Bachmann
bachmann@bchmn.de
LMU Munich
Munich, Germany

Thomas Kosch
thomas.kosch@tk.informatik.tu-darmstadt.de
TU Darmstadt
Darmstadt, Germany

Albrecht Schmidt
albrecht.schmidt@ifi.lmu.de
LMU Munich
Munich, Germany

Paweł W. Woźniak
p.w.wozniak@uu.nl
Utrecht University
Utrecht, the Netherlands



## ABSTRACT

Physical exercises can benefit our health, but avoiding improper form and overexertion is essential. Facilitating bodily insights can encourage learning about exercise form, allowing users to gain a deeper understanding of their physiology. To investigate this, we conducted a lab experiment where amateur users performed bicep curls, and interviews with sports coaches. Participants were provided with FitBack—a system that monitors muscle activity during exercises via electromyography (EMG) and offers real-time biofeedback. Amateurs reported that they were successful in improving their exercise form and could acquire deeper bodily insights. Coaches reflected on how understanding muscle activity through EMG could be effectively used for increasing body awareness during coaching, highlighting that EMG-based biofeedback is beneficial for a diverse set of users. Our work contributes insights into using bodily sensing to help users understand their bodies. We contribute guidelines for designing systems that use EMG biofeedback effectively in physical activity.



## CCS CONCEPTS

• **Human-centered computing → Interaction techniques**; *Ubiquitous and mobile computing systems and tools.*

## KEYWORDS

electromyography; HCI for sports; physical activity; fitness; body awareness

**ACM Reference Format:**
Jakob Karolus, Felix Bachmann, Thomas Kosch, Albrecht Schmidt, and Paweł W. Woźniak. 2021. Facilitating Bodily Insights Using Electromyography-Based Biofeedback during Physical Activity. In *23rd International Conference on Mobile Human-Computer Interaction (MobileHCI '21), September 27-October 1, 2021, Toulouse & Virtual, France.* ACM, New York, NY, USA, 15 pages. https://doi.org/10.1145/3447526.3472027





*MobileHCI '21, September 27-October 1, 2021, Toulouse & Virtual, France*





ACM ISBN 978-1-4503-8328-8/21/09…$15.00
https://doi.org/10.1145/3447526.3472027


## 1 INTRODUCTION

Physical activity is an increasingly important part of our lives. The number of people exercising regularly is on the rise [19, 21], as is the number of interactive systems that accompany exercise every day. However, while regular physical exercise offers mental and physical health benefits, these come at the price of the hard work needed to master the forms and techniques required for a given sport. The difficulties in reaching the required body awareness to achieve the desired proficiency may lead to dissatisfaction and even abandonment, reducing or losing the accrued health benefits [62] altogether. While coaching experts are widely available, physically active users cannot be constantly accompanied while exercising. Past research in Human-Computer Interaction (HCI), e.g. [42, 70] showed that interactive technologies can effectively build body awareness for certain exercise scenarios. Yet, it remains a challenge to develop methods that would enable generic, exercise-agnostic methods of better understanding one's body when exercising. Thus, there is a need for developing ways in which users can monitor their bodies to better understand their sports practice.

While professional sportspeople use a wide array of sensors to improve their performance, e.g. [6], these technologies are too complex for everyday users. In this paper, we explore the means for users to become more aware of their muscle activity through electromyography (EMG). EMG offers additional insight into muscle physiology to facilitate motor memory consolidation. Users desire a better insight into their bodies [15]. Yet, it remains a challenge to understand how complex physiological data streams, such as EMG, can be effectively used to foster insight.

EMG in current commercial products offers highly customized feedback about muscle strain, exertion, and training effect, optimizing for individual exercises and performance metrics. In contrast, our work investigates if and how visualized EMG data can provide insight into one's own body physiology and how to provide an encouraging—yet challenging—way for users to access knowledge about their muscles. We believe that current tools undervalue the potential of EMG as a visualization of exercise form. As muscle activity differs significantly among users, no algorithm can offer

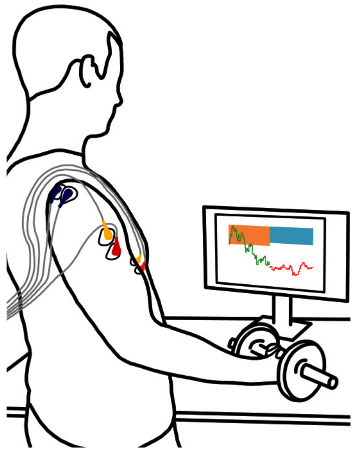

**Figure 1: A user monitoring their biceps curl exercise via electromyography. Respective feedback is shown on the monitor screen (biceps on the left, deltoid on the right). Electrode pairs (red/yellow) are attached on the biceps and deltoid. Reference electrodes are marked in dark blue.**

an effective automated interpretation of the signals, which considers the individual context of the exercise. Our work explores how interactive technology can facilitate this user-driven process of interpretation as an opportunity for monitoring physical activity, empowering users to understand their bodies better.

Consequently, this paper investigates user attitudes and performance when interacting with muscle activity data. We first confirmed the technical feasibility of our low-cost, mobile prototype FitBack (see Figure 1) to record and visualize EMG data and examined first impressions and performance of amateur users when supported via EMG-based biofeedback while performing bicep curls. Users reported that having access to their muscle activity through visualizations supported them in gaining an understanding of their own body movements. Amateur users mostly preferred abstract feedback that did not include rich EMG data during the exercise. Additionally, feedback preferences were primarily related to the exercise's context, such as supervising daily workouts vs. perfecting exercise form. Interestingly, for the latter, users reported that they preferred detailed feedback.

To further investigate how to design for rich physiological feedback in the context of coaching and supervision during physical activity, we conducted a set of interviews with experienced professional sportspeople and coaches, during which they experimented with the detailed view of FitBack and considered its possible use in their practice. The professionals remarked that the detailed EMG data was easy to interpret for a variety of exercises and that it offered a way towards a more informed exercise form and increased body awareness. They recognized its potential to support coaches in confirming correct execution and providing tangible evidence to present to students.

This paper contributes to the HCI for sports area by reporting on two studies of how users interpret rich bodily signals: (1) a lab study with amateur users and (2) interviews with professional sportspeople. Our results indicate that amateur and professional users can gain deeper insights into their own physiology through interpreting EMG signals. The users could immediately grasp the properties of the EMG signal, and they appreciated its information value. Based on our findings, we conclude with a set of design recommendations about building engaging and informative EMG-based biofeedback systems for physical activity, which facilitate interpretation.

## 2 RELATED WORK

HCI has investigated modalities and exercise forms suitable for tailored feedback. In this section, we introduce relevant research projects in the context of physical activity and feedback. We additionally take a closer look at biofeedback modalities and EMG as input for HCI applications.

### 2.1 Biofeedback

Biofeedback is a type of physiological-driven feedback, where physiological responses of a user are voluntarily measured and communicated with the user at the same time to create a feedback loop [10, 23]. Biofeedback has recently been extensively used in rehabilitation and treatment of disorders such as stroke rehabilitation [13], anxiety [53], or substance abuse [64]. A typical biofeedback session exposes the user to a visualization of a physiological signal that is correlated to a disorder. Users are instructed to proactively act towards a desired signal, where the physiological signal is usually visualized in a simplified form. In contrast to raw signals such as brain activity [17, 43] or heart rate variability [74], simpler visualizations are easier to understand by laymen. Results from previous work showed that biofeedback has a strong influence over physiological functions and offers users several advantages over traditional treatments, including a visible metric for reflection, progress, and ongoing involvement of the treatment process [58]. For example, biofeedback has been successfully employed for stroke rehabilitation [13], posture corrections [57], treatment of neurological impairments [65], and substance abuse [51]. Apart from medical treatments, biofeedback has shown potential to improve training efficiency, as highlighted in the following section.

### 2.2 Fitness and Feedback

The HCI field has recognized possibilities for interactive artifacts to build increased body awareness and thus contribute to a better experience and skill development in sports. Being more aware of the relative position of one's body has been shown to benefit those practicing yoga [68] or swimming [42]. However, gym exercises, perhaps due to their static nature, received more extensive attention. A number of projects proposed using different sensing modalities for recognizing exercise execution such as inertial measurements [47, 54, 71], pressure sensors [18, 66] or cameras [9, 41]. Also, the now discontinued Myo[1] armband could effectively differentiate between various gym exercises [45]. While these systems offered effective ways to count execution or assess the correctness of the motion, they did not enable the user to determine if the correct muscles were used in their exercise. Our work examines the possibilities of direct muscle monitoring and investigates the opportunities of the user possessing that knowledge.

[1] https://support.getmyo.com/hc/en-us

Another strain of HCI work recognized the benefits of helping users understand their own bodies through additional feedback. Turmo Vidal et al. [70] built wearable lights that could be customized to enhance the perception of relative body position, improve exercise technique and facilitate instruction [69]. They showed that additional insight during activities can lead to skill development. Earlier, Hämäläinen [34] suggested using the mirror metaphor, which is particularly suited to gym exercises as fitness clubs usually feature mirrors. Anderson et al. [4] developed an Augmented Reality (AR) mirror system which tutored users in gym exercises. Past work shows many opportunities for possible interventions at the gym and a need for users to understand their bodies better in order to train better. However, it remains an open question what sensing and feedback offers the most benefits to users and how it can be adopted into exercise environments. Our work is different from past research as it specifically investigates what happens when users are aware of their muscle activity and how they can benefit from this knowledge.

## 2.3 EMGxHCI

Contracting specific muscle groups of our body allows us to position ourselves and direct our extremities. This muscle contraction happens along the muscle fibers and generates an electric field. Using surface electromyography (sEMG), this field can be measured and quantized. As a result, electromyography provides excellent access to a person's muscle exertion. Already in the early 20th century, researchers investigated the interplay between neural activity and muscle contraction [1]. While EMG has its main area of application in clinical settings for diagnostics and prosthetic control [5, 30], the last two decades have shown the feasibility of interactive systems leveraging EMG-based interaction in the domain on human-computer interaction (HCI). Important research includes work by Costanza et al. [12] highlighting properties of isometric muscle activation for intimate interaction as well as a seminal work by Saponas et al. [59] showcasing the potential of EMG for muscle-computer interfaces, detecting gestures using a circular array of electrodes around the forearm. In more recent work, Karolus et al. confirmed these findings in particular for fine gestures in a guitar tutoring [39] and piano playing scenario [37]. An inherent challenge of EMG-based interfaces is engineering user-independent classification algorithms. Works by Kerber et al. [40] and Huang et al. [33] showcase possible solutions to this issue. While the first one relies on a robust classification approach, the latter work leverages implicit calibration to collect data samples without interrupting the user. Similarly, advances for electromyographic sensing with low-cost, mobile devices are essential, such as follow-up work from Saponas et al. [60] and most recently printable electrodes for rapid fabrication of on-skin interfaces [55].

In the form of biofeedback, EMG has proven to be effective for behavioral change and rehabilitation [2, 31, 52] as well as strength acquisition [14, 22]. Work by Toader et al. [67] showed that users adapted their exercise form after receiving visual EMG-based biofeedback compared to a control group with no feedback. With FitBack, we extend their work and investigate the influence of different feedback modalities on performance and the users' perceived awareness of their body posture and movements.

On the consumer market, readily available products which use EMG-based biofeedback for physical activity, such as Athos[2], Myontec[3], and Mpower[4] are primarily aimed at sports professionals and competitive athletes. Athos relies on post-hoc reports and Myontec reports on exertion over the course of the whole training session. In FitBack, we rely on displaying live muscle activity allowing users to grasp timings of exercise forms, similar to the activation curves provided in Mpower. All commercial systems rely on pre-configured smart clothing and tailored algorithms, limiting the set of exercises that can be monitored. Lastly, these devices provide very specific feedback, designed for professional athletes and post-exercise analysis with professional coaches. While the technology is available, albeit, for a high price, it remains to be investigated how everyday users can benefit from detailed biofeedback. As one solution to allow for more scalable solutions for exercise monitoring, our work envisions user-driven interpretation of collected data with the aim to provide deeper bodily insight. Consequently, this work examines if and how EMG-based biofeedback can foster reflection on exercise form to further the users' understanding of their body physiology.

# 3 METHOD

Our investigation is informed by previous research, including technical and design requirements. Commercial systems and research probes established that EMG is an effective method to support fitness exercises. However, there still a need to understand the design principles for interactive technologies which empower users to understand muscle activity. In this work, we evaluate if the access to detailed muscle activity can facilitate an improved understanding of one's own body physiology. With increased insight into how their body reacts to exercise, users will experience more health benefits [50] and develop expertise [46].

To explore this, we replicated existing feedback methods as a baseline, but opted for a low-cost mobile prototype, which makes EMG-supported sports exercises accessible for amateurs. Accordingly, we chose an exploratory approach by first building a mobile prototype capable of recording electromyograms via adhesive electrodes. We used this system to explore requirements and resulting technical constraints, asking how feedback should be conveyed, what is the optimal temporality, and what audience can benefit from such a system. For the latter, we identified two main audiences, namely novice to experienced independent users who engage with the feedback directly, and fitness coaches who aim to gain deeper insights into their student's exercise form.

Thus, we employed a mixed-method inquiry consisting of a user study with 18 novice to experienced participants (Study I) and interviews with sports professionals and coaches (Study II). This allowed us to capture opportunities, requirements, and constraints for using interactive muscle sensing and biofeedback during physical activity. We structured this investigation into two main research questions:

[2]https://www.liveathos.com/
[3]https://www.myontec.com/
[4]http://www.mpower-bestrong.com/index.html

### RQ1: Is supporting users via EMG-based biofeedback during physical activity technically feasible with a low-cost EMG device?

This research question investigates technical constraints that arise from mobile electromyograms. Existing research [39, 60] and commercial products (Section 2.3) have already demonstrated the feasibility of EMG for recognizing body movements, highlighting the importance of mobility for such systems and focusing on data-intensive post hoc analysis. Consequently, we provide a technical evaluation of a mobile, low-cost EMG device (FitBack) with regard to (1) recognizing the correct form of fitness exercises and (2) the feasibility to accurately and effectively visualize muscle activity of users in our experimental investigation (Study I). We used the bicep curl as an example exercise, suitable for beginners and experienced sportspeople. Besides the technical evaluation, we evaluate user experience, perceived workload, and flow experience during the exercises when interacting with FitBack.

### RQ2: How can we design EMG-based biofeedback to facilitate bodily insights during physical activity?

Here, we look at different feedback modalities (visual and auditory) and granularities for a broader audience (amateurs and coaches). The system should provide easy access to bodily insights both for novices and more experienced practitioners while providing necessary details for experts and coaches to find the perfect form. We compare existing designs with detailed EMG feedback through rankings and evaluate opportunities (Study I). We additionally conducted semi-structured interviews to gain further insights into how participants in this first study perceived their body awareness. Further, we conducted interviews with sports coaches (Study II) to finalize a design suitable for a variety of exercises. The interviews also enabled us to explore how EMG feedback can be leveraged in a coaching scenario. We focus our analysis on the collected qualitative data and derived themes from the interviews for this research question.

## 4 STUDY I: EXPERIMENTAL INVESTIGATION OF EMG-BASED BIOFEEDBACK

In this first evaluation, we focus on one particular fitness exercise and test different feedback types and granularities using FitBack. Hence, we first confirm that EMG-based biofeedback is technically feasible using a low-cost recording device, before finalizing design requirements for physical activities in Study II. This section first introduces our implementation of FitBackand reports on the employed study design, used measures, procedure and participants.

### 4.1 Apparatus

FitBack is an integrated system that records and processes EMG data. The system is closely adapted from EMBody [38], a toolkit for EMG-based interface prototyping. In fact, the hardware is identical, only the software components were adapted as outlined below. FitBack was developed with requirements for physical exercises in mind, such as mobility, allowing users to freely move around. Different feedback modalities and granularities allow FitBack to cater to a broad audience of users, while a simple but robust detection algorithm is used to recognize exercise repetitions. The following section provides an overview of the implementation of FitBack.

*4.1.1 Hardware.* FitBack's hardware is based on an ESP32 microcontroller[6], which is a low-cost and low-power system on a chip with integrated WiFi. We measure EMG using a bipolar measurement technique [52] including a reference electrode and two sensing electrodes to minimize noise artifacts. Amplification is realized through an existing design[7] that we adapted for our purposes. The amplified signal for each channel gets processed by the ESP's Analog Digital Converter (ADC) yielding a 12 bit resolution. Measurements are broadcasted over the network via UDP at a sampling rate of 200 $Hz$, which is sufficient for the following filtering steps (see Section 4.1.2). The whole hardware system can be powered by powerbank and fits in a 3D-printed case allowing it to be carried around by the user. Please refer to EMBody's [38] github[5] for a complete overview and all resources.

*4.1.2 Software.* To process incoming EMG data, FitBack includes an accompanying software application that receives the data samples and extracts important EMG indices (see Section 4.2) to generate biofeedback. First, a bandpass filter between 2 $Hz$ and 100 $Hz$ is applied [59], reducing long-term drifts and high-frequency noise. A follow-up bandstop filter between 49 $Hz$ and 51 $Hz$ removes interference from power line noise. Secondly, FitBack calculates epoched root mean square (RMS) features with a window size of 40 samples[8]. RMS values can be seen as a proxy for the amplitude of the EMG signal, hence increasing when muscular activity increases [52]. To counteract fluctuations that might be confusing to users, a Savitzky-Golay filter [61] was used. After these processing steps, the signal is visualized (see Section 4.2).

To detect individual exercises, FitBack further cross-correlates the RMS signal with a target signal which is acquired for each participant during the calibration phase before the experiment. A large correlation coefficient indicates an alignment between the target signal and the incoming signal during the experiment. The correlation value is used to determine whether individual trials were correctly performed by aggregating the values for all muscle groups that were measured (see Section 4.3).

### 4.2 Design

We chose the bicep curl as a reference fitness exercise. This simple exercise is suitable for beginners as well as popular among experienced practitioners [8]. Additionally, it involves only a few selected muscle groups (biceps and deltoid) allowing for easy electrode placement [16]. Despite its simplicity, the bicep curl still leaves a certain margin for error, such as performing curls too fast or using the deltoid to aid in lifting the weight. This significantly reduces the training effect and can lead to injuries [8, 16]. Figure 2 shows two examples from filtered EMG signals including the bicep as well as the deltoid. The left side illustrates a correct execution involving

[6]https://www.espressif.com/en/products/socs/esp32
[7]www.github.com/BigCorvus/2-Channel-Biopotential-Amp
[5]https://github.com/HCUM/embody
[8]Corresponds to 200 $ms$; a hop size of 0.5 times the window size was used. Parameters are based on preliminary tests.

exclusively bicep activation, while the right side shows a bad example using the deltoid during the repetition. Focusing on a simple exercise with a clear sequence allowed us to evaluate the suitability of EMG-based biofeedback with a special focus on different needs from a diverse audience (novices vs experienced sportspeople).

Design decisions for feedback modality and granularity are informed by past work on EMG-based biofeedback [52] and self-reflection [49] (cf. *six kind of questions*). Visual feedback enables detailed and concise feedback and allows users to observe different muscles [48] or different muscle regions [31]. Varying temporal granularity additionally enables users to capture the timing of their muscle activation [2]. However, visual feedback can be problematic where users are required to visually observe and control their actions. Hence, we introduce auditory feedback as another modality. For both modalities, we implement the most commonly used indices [52]: EMG *amplitude* and *timing* of muscle activation as detailed in the following sections. We employed a mixed design that used the visualizations as within-subject and the sound cues as between-subject factor. All participants were instructed to exercise with each visualization while the presence of the sound cues was varied per participant. We note, that the employed modalities and indices are predominantly used in the introduced commercial products as well. While there are other viable feedback modalities (e.g. vibrotactile), the investigation of this work is primarily focused on visual feedback, due to the high bandwidth constraints of conveying rich EMG data.

*4.2.1 Visual Feedback.* FitBack implements three different feedback visualizations that change according to the measured muscle activity: *Bars*, *Circles*, and *Lines* as illustrated in Figure 3. *Bars* and *Circles* present an abstracted EMG signal to the user based on the EMG *amplitude*. In contrast, the *Lines* visualization shows a smoothed version (see Section 4.1.2) of the raw EMG signal to the user over time Here, we hypothesize that abstract visualizations can increase the understanding of laymen of the complex signal [11]. Direct representations of the signal, such as the *Lines* representation, provide deeper insights into the training efficiency, offering a finer granularity for *amplitude* and *timing*. While this visualization is potentially more difficult to understand for novices, it offers most details and the biggest potential for user-driven interpretation.

All visual representations provide a target zone that needs to be reached during the execution of an exercise, such as high bicep activation marked by an orange area at the far end of the respective visualization. An avoid zone is implemented for the deltoid in analog fashion.

*4.2.2 Auditory Feedback.* In addition to visual feedback, FitBack utilizes auditory feedback to communicate correctly executed repetitions of an exercise. Apart from their use in biofeedback [52], auditory cues have been verified as a suitable modality for successful actions [24], warnings [25], or errors [44] in various research projects. FitBack plays a positive auditory cue when a repetition has been executed correctly, while faulty exercise form is reported by a negative cue. In our case, the respective sound is played when the measured signal reaches the target or avoid zone.

## 4.3 Measures

For our data collection, we focused on the following aspects in relation to our research questions: (1) participant performance of the executed bicep curls, (2) usability and perceived workload when exercising with FitBack and (3) impact of feedback type on exercise form.

*4.3.1 Participant Performance.* For our analysis, we collected a total of three performance metrics detailing how accurate participants executed the biceps curls. These include a binary coach rating, the binary rating from FitBack, and a post hoc rating (7-item Likert), as detailed below.

*Coach rating.* During the experiment, we collected performance assessments by the experiment instructor (a sports professional), who judged (silently) each execution as correct or incorrect. Contrary to the calibration phase (cf. Section 4.5), the instructor relied solely on the visual inspection of each execution and had no access to the EMG signal. This constellation mimics a standard practice session where the coach can only observe the disciple.

*FitBack rating.* Additionally, we logged FitBacks' assessments of the trial. Here, preliminary tests have shown that a correlation value of greater than 0.5 for both the bicep and the deltoid signal indicated correct execution of the exercise. Details on the correlation algorithm are provided in Section 4.1.2.

*Post hoc rating.* Lastly, we conducted post hoc reviews of the collected EMG data. The three reviewers are researchers who use EMG-based systems daily and are familiar with the fitness exercise. They were presented with the EMG signals (cf. Figure 2) of each execution after the experiment and rated them on a 7-item Likert scale. A set of example executions (covering correct and incorrect trials during the study) served as orientation. Correct execution was rated highest, while points were deducted for bad form, such as lifting with momentum or using excessive deltoid activation[9]. We additionally confirmed the inter-rater agreement of the three reviewers using the $r_{WG(J)}$ agreement index [35]. A value of $r_{WG(J)} > .99$ confirmed high agreement. We subsequently transformed the averaged post hoc ratings into a binary scale by categorizing all executions rated 4 and higher as correct. Executions with this rating only exhibited minor flaws and could be considered correct. This allowed us to compare all three assessments in our results (cf. Section 4.6).

*4.3.2 Questionnaires.* We measured the Usability Metric for User Experience (UMUX) [20] to identify FitBack's user experience and detect potential flaws when exercising with it. To assess perceived workload during the exercise, we employed the NASA Task Load Index (NASA-TLX) [27] in its raw form without the weighting process [26]. We further used the flow experience questionnaire [63] to measure the participants' engagement in the training exercises. Finally, we asked custom questions[10] which addressed feedback ranking its perception and influence during the exercise.

[9]The rating form and examples are provided as supplementary material.
[10]Measured on a visual analog scale (VAS): 0 to 100.

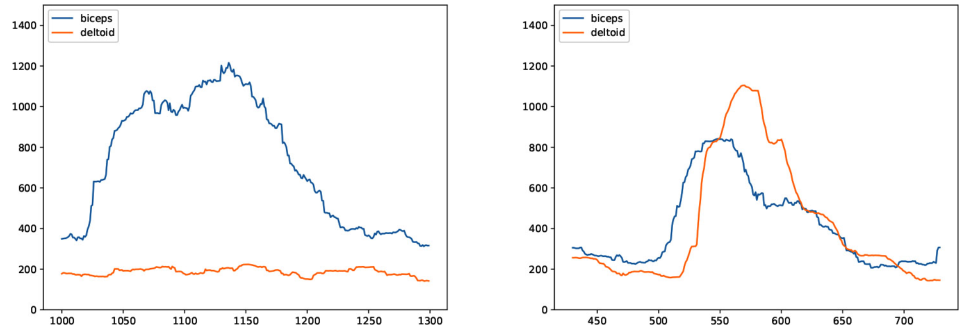


**Figure 2: Example EMG data for a correct (left) and incorrect (right) bicep curl. The incorrect example clearly shows excessive deltoid use (orange) compared to bicep use (blue). Time (in samples) on the x-axis; muscle activation (as RMS values) on the y-axis.**

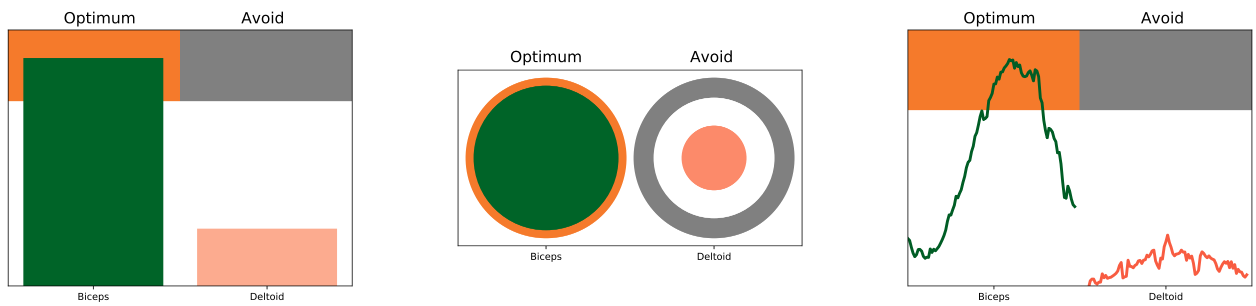


**Figure 3: FitBack visualizations showing the same EMG data. Abstract representations *Bars* (left) and *Circles* (middle), and the detailed representation *Lines* (right).**

*4.3.3 Interviews.* We conducted semi-structured post-hoc interviews with all participants. Interviews took approximately 10 minutes each. We made sure to cover relevant topics including technical elements such as influence of electrodes and perceived latency of the shown feedback. Additionally, we inquired about their perceived confidence in the feedback and had them enumerate some of the advantages and disadvantages of different feedback types from their view, including auditory feedback if applicable. Lastly, we investigated possible application scenarios with FitBack.

## 4.4 Participants

For our first study, 18 participants (four female, 14 male) with a mean age of $M = 25.6\,y$ ($SD = 3.24\,y$) were recruited from university mailing lists. The average self-reported general fitness experience was 59.3 ($SD = 22.77$) and 42.3 ($SD = 29.81$) for experience in weight training[10]. Participants trained $3.2\,h$ per week on average ($SD = 1.54\,h$). Each participant was compensated with an equivalent of USD 12 in the local currency.

## 4.5 Procedure

The experimenter welcomed each participant and explained the intention of the study. After providing informed consent, participants stated their fitness background and demographic data. Next, they received an introduction on how to perform a correct bicep curl and were made aware of common mistakes. Electrodes were placed on the participant's dominant arm on the bicep and deltoid muscles (see Figure 4). The experimenter then picked weights that were appropriate to the participant's fitness level. Afterward, the calibration started in which a visualization dictated the rhythm for the bicep curl repetitions. The experimenter verified the correctness of the bicep curls during the calibration phase, both visually and via the EMG data. After successfully calibrating a target signal (cf. Section 4.1.2) for the participant, the experiment started. Participants were given some time to familiarize themselves with each visual condition before starting ten bicep curl repetitions for each condition, yielding a total of 30 repetitions per participant. Note that sound cues were used as a between-subject variable, hence each participant either saw all three visualizations with sound cues or completely without sound cues. Participants filled out the questionnaires for each condition during short breaks. The experiment was concluded by removing the electrodes and conducting the short interview. In total the experiment lasted approximately one hour.

## 4.6 Results

We report on the statistical analysis of measured usability measures as well as feedback ranking and perception. For each measure, we conducted two-way (*visualization* and *sound*) mixed ANOVAs. If the data deviated from normality, we first aligned rank transformed [72]

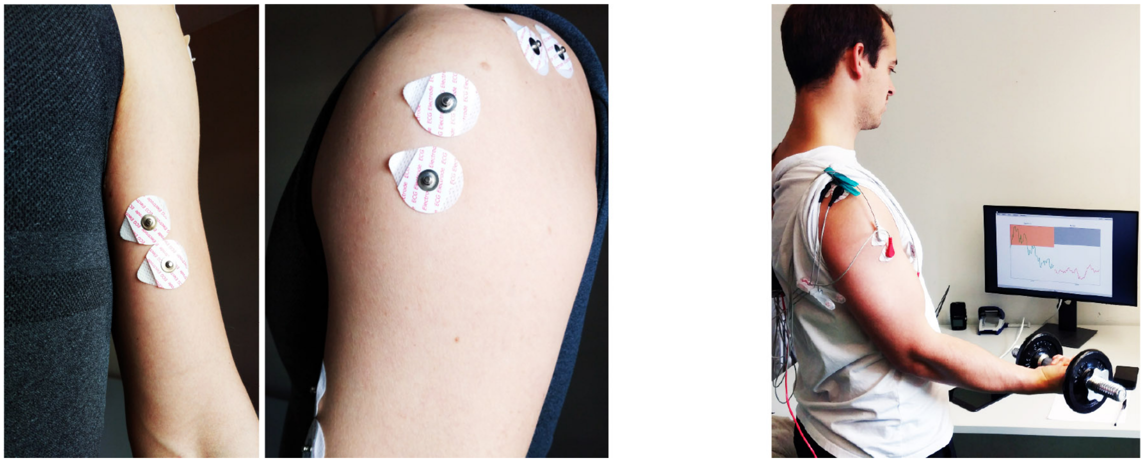

**Figure 4: Electrode placement on biceps (left) and deltoid (middle) muscles. Reference electrodes can be seen close to the scapula. On the right side: participant during the study.**

it. Scripts and raw data are provided in the supplementary materials for additional details. Further, we present an analysis of FitBack's accuracy in detecting correct exercise form and include a qualitative analysis based on the interviews.

*4.6.1 Judging Exercise Form.* To evaluate the validity of the presented performance ratings (cf. Section 4.3), we compare the ratings against each other. Here, the coach rating provides a gold standard for feedback in a standard training session, while the post hoc rating allowed us to acquire a more accurate look at involved muscle activity. The rating of FitBack demonstrates the feasibility of a simple detection mechanism for this type of exercise. We provide an overview of all comparisons in Figure 5.

On the left side (Figure 5), the confusion matrix between the coach rating and the FitBack rating shows a good degree of consensus. In 76% of executed trials, the coach and FitBack issue the same rating. It is noteworthy that the class distribution (as rated by the coach) is unbalanced[11]: the GOOD (correct execution) class contains 519 samples, while the BAD (incorrect execution) class only contains 21. In approximately a quarter of cases for each respective class[12], the rating by the coach and FitBack's assessment differ.

While the coach only relied on a visual inspection of the exercise, FitBack had access to the EMG signal but uses a simple algorithm to predict correctness. Here, we introduce our post hoc rating. It allowed us to further utilize the EMG signal through manual inspection of the exercises, providing a much more fine-grained analysis than FitBack. Consequently, we considered these ratings to be most conclusive when rating the exercise form of the participants.

The confusion matrix in the middle and on the right (Figure 5) shows the respective comparison of the coach rating and the FitBack rating with the post hoc ratings. The class distribution is slightly less unbalanced: 469 for GOOD and 71 for BAD. The comparison with the coach rating shows near-perfect unison for correct executions (GOOD class), yet the coach fails to recognize up to 87% of BAD executions. This highlights that having access to the actual EMG data improves the judgment of exercise form, as involved muscle activity can be observed accurately, and false activation (e.g., deltoid usage) cannot be masked by the participant. This also explains the high degree of consensus for GOOD executions, as correct muscle activation inevitably results in the correct visual manifestation of the exercise.

The comparison with FitBack on the far right side (Figure 5) illustrates that the system is generally stricter than our post hoc rating, only recognizing 77% of correct executions. However, the system correctly predicts nearly half of the BAD executions, outperforming the coach in this regard. We attribute the mixed predictions of FitBack to its simple algorithm. While more elaborated algorithms may yield better performance, we note that recognizing correctness is not the main purpose of FitBack but rather visualizing their own EMG signal to users. This added information has already shown insightful for versed practitioners (cf. post hoc rating). In the following, we evaluate if this is also the case for laymen users of EMG.

*4.6.2 User Performance.* We further tested the performance of the participant with regard to correct exercise form as judged by the post hoc rating, given *visualization* and *sound* in Figure 6. We found a significant effect of *visualization* ($F(2, 518) = 3.93, p < .05$) and a two-way interaction effect of *visualization* and *sound* ($F(2, 518) = 3.80, p < .05$). Post-hoc pairwise comparison using tukey-adjusted p-values showed a significant difference between the visualization *Bars* and *Lines* as well as between *Bars* and *Circles*. We found one significant two-way interaction effect between *Lines* and *Circles* for the factor *sound* (*No* - *Yes*).

*4.6.3 Questionnaires.* We did not observe any significant differences for either the NASA-TLX, the UMUX nor the flow experience questionnaire. Descriptive statistics for each condition are listed in the supplementary material. Our analysis of the custom questions polling feedback ranking and perception did not show any significant differences. A graphical representation and the complete data is provided in the supplementary material.

[11] An artifact of the experiment, as participants were generally good at performing the exercise.
[12] 124 for GOOD, 5 for BAD.

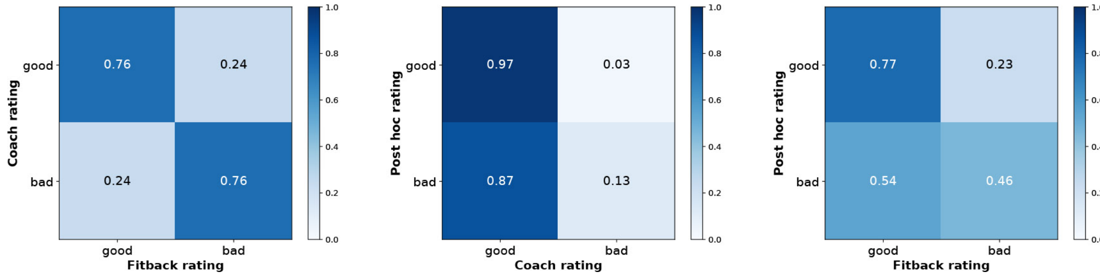


**Figure 5: Confusion matrices (associated truth labels on the y axis) between coach—system (left), post hoc—coach (middle), post hoc—system (right). Note that percentages are based on within-class instances (per row), as class distribution is highly skewed.**

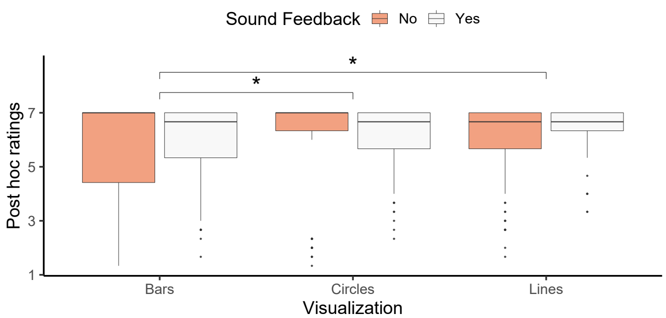


**Figure 6: Post hoc ratings given the shown visualization and sound feedback. Significant differences are marked with *.**

*4.6.4 Interviews.* All interviews (1:39 hrs of recording) were transcribed verbatim. We opted to conduct a focused analysis based on the pragmatic approach by Blandford et al. [7]. To do so, three researchers open coded a representative 17% of the material. In a discussion, the researchers agreed on an initial coding tree. The rest of the material was evenly split between the three coders and coded separately. A concluding discussion refined the coding tree and surfaced a code hierarchy with four themes: Feedback Type and Granularity, Cognitive Effort, Gaining Insights and User Acceptance. The following section presents the content of each theme and associated quotes.

*Feedback Type and Granularity.* Participants commented extensively on advantages and disadvantages of the different feedback types and granularities. All visualizations were understandable for the participants, but there were clear favorites in terms of when and how to use them. For example, the abstract visualizations (*Bars*, *Circles*) were perceived as straightforward and easy to interpret:

> *It was evident what needed to be done. When the [deltoid] was red, one had to correct one's shoulder movement. (P3)*

The detailed *Lines* feedback allowed for a more detailed analysis of the executed exercise. Additionally, participants remarked that *Lines* provided them with a more profound temporal component, as it displayed a history of values that was not present for the abstract visualizations.

When asked about the sound feedback, some participants commented that they felt it was more discreet than the visualizations allowing them to focus on the exercise, while others preferred the visual feedback. Interestingly, the additional sound feedback provided some participants with a feeling of accomplishment whenever they perceived positive sound feedback:

> *It was a short feeling of accomplishment. That motivated me. (...) that could be integrated well into one's training. (P17)*

*Cognitive Effort.* Participants reported that the level of cognitive effort they needed to invest into understanding and interpreting the feedback varied. Abstract visualizations (*Bars*, *Circles*) are less cognitively demanding, while the detailed *Lines* feedback was more demanding and required additional concentration, occasionally interfering with exercise execution:

> *To just do one exercise; the lower fidelity is more pleasant and less cognitively demanding. (P13)*

*Gaining Insights.* Participants commented on how FitBack helped them to understand their muscle activity during the exercise and supported them in finding mistakes and incorrect form. It helped them to establish an understanding of their own exertion:

> *If you are not that familiar with muscles, then the system shows this quite well and you get better awareness for specific muscles, especially those that one has not used. (P15)*

By doing so, FitBack facilitated their learning process, making them aware of their movements and supporting correct exercise execution. Participants remarked that it was straightforward to map their movements to feedback provided by FitBack.

*User Acceptance.* Participants relied on the feedback from the system when correcting their exercise form. They appreciated that mistakes were transparent for them and could be rectified immediately:

> *If I know that I do something wrong and that this is visualized, I can clearly imagine how to get rid of it. (P9)*

On a more technical side, we also investigated whether the electrode setup and the induced latency for the abstract feedback posed any issue for participants. Most participants reported that neither influenced their exercise rhythm. It was noted however, that the required setup needed to be kept minimal for FitBack to be feasible in a daily workout.

Another idea mentioned by the interviewees was the integration of electrodes into wearables such as sport shirts and trousers. This would minimize setup time and would make FitBack much more accessible for short daily workouts, also reducing social stigma as remarked by a few participants:

> *If there could be a wearable that includes the device and cables, e.g. a shirt with electrodes inside, that you can just wear, that would be different. Then you would just need to wear the shirt. (P6)*

## 4.7 Summary

While the results from our quantitative analysis showed that *Lines* and *Circles* outperformed *Bars* in terms of actual user performance (as measure by the post hoc ratings), *Bars* was ranked highest by participants. In our follow-up interviews we found that detailed feedback was more favored by experienced practitioners[13] and in situations where the user wants to perfect exercise form. Abstract feedback, such as *Bars*, was preferred by less experienced users and for daily workout scenarios. In general, all forms of feedback were noticed by the participants and used to adapt their exercise form to a large degree as confirmed by our custom questionnaire, highlighting the viability of EMG-based feedback to facilitate bodily insights.

While usability and perceived workload metrics showed no significant differences for feedback type, interviewees reported that *Lines* required higher cognitive effort, mostly to understand the complex signal. This might have been masked by the fact that users were always monitored by the system, hence implicitly forcing them to concentrate more as stated in the interviews.

Further, our experimental investigation with FitBack demonstrated that low-cost EMG sensing devices are suitable to monitor exercise form. While accurate detection of correct form is not possible with the employed algorithm, this analysis showcased that having access to detailed EMG data is beneficial to judge exercise form for both laymen and versed practitioners. Hence, in this next evaluation step with sports professionals, we put emphasis on this aspect by allowing them to monitor the EMG signal in detail to explore a variety of exercises.

# 5 STUDY II: INTERVIEWS WITH COACHES

Our initial study confirmed the feasibility of building an EMG-based exercise assistance system and showed the breadth of the design space. In order to further understand the requirements and constraints involved in using EMG systems for physical activity in general, we conducted a series of interviews with sports professionals in which participants used FitBack in an open-ended exercise session.

## 5.1 Participants

We recruited four experts who were career sports coaches with different backgrounds and varying levels of experience, see Table 1. We recruited the experts through contacts at sports clubs whose members had participated in previous studies conducted by the research team. None of the participants had used EMG systems before, but they had all tried Electrical Muscle Stimulation (EMS) as part of their profession. The interviews took place at locations chosen by the participants. We provided shopping vouchers for the equivalent of USD 12 for participating in the study.

**Table 1: Information about the participants in our study. The sports professionals specialized in different sports and had different levels of experience.**

| Participant ID | Age | Gender | Expertise | Experience |
|---|---|---|---|---|
| P1 | 32 | M | Personal trainer | 8 y |
| P2 | 27 | F | Yoga | 4 y |
| P3 | 36 | M | Martial arts | 15 y |
| P4 | 33 | M | Martial arts | 15 y |

## 5.2 Procedure

The interview session began by obtaining written consent for participation and recording. Next, the researcher prepared the FitBack system in a location chosen by the participant. A voice recorder and a video camera were used to record the session. We then conducted the initial part of the interview, which concerned the participant's background and experience with EMG/EMS. Afterwards, we asked them to choose a movement form that was particularly difficult for their students and indicate which key muscles were involved in that movement. Upon choosing the exercise, the researcher attached electrodes to the key muscles. FitBack was started and muscle activity was visible. We then asked the participant to perform the motion correctly and incorrectly. We encouraged them to explore different possible mistakes and to examine how FitBack reacted to changes in movement (see Figure 7). We also answered any questions the participant may have had while exploring the system. When they indicated that they were done experimenting with the motion, we conducted the next interview part. These questions explored the participant's interpretation of the EMG signal, differences between signals from different muscles, the suitability of the feedback for everyday coaching and identifying mistakes in movement. We then allowed the participant time to rest and repeated the same procedure for another type of motion. Finally, we conducted an interview where we inquired about the differences in feedback between the two exercises, the possible target user groups for EMG systems, the use of EMG for professional development and requirements for everyday integration. The entire session was recorded on video, and additional voice recording was used when asking interview questions. We also recorded the FitBack screen.

## 5.3 Data analysis

All interviews (2:16 hrs of recording) were transcribed verbatim. Given the volume of the data, we again followed the pragmatic approach to qualitative analysis as recommended by Blandford et al. [7, 53]. In an initial analysis step, two researchers open-coded one interview to identify key concepts. We then conducted a discussion,

[13] As indicated by their weight training experience.

**Figure 7: Participants during the exploration phase performing different exercises.**

which resulted in an initial coding tree. The remaining material was then evenly split between the researchers. Afterwards, all authors refined the coding tree in iterative discussions, finally creating a code hierarchy with four themes. These themes represent the key aspects of using EMG in sport coaching practice discussed by the experts.

## 5.4 Findings

Here, we present the results of the interviews with the sports professionals. We identified four themes in the accounts of using EMG provided by the experts: Assessment, Body Awareness, Exercise Form and Interpretability. Quotes from the interviews are accompanied by the participant ID and, if applicable, the exercise which they were describing.

*Assessment.*
This theme describes how the coaches used EMG feedback to assess the correctness of a given body position and how they identified issues with posture. We observed that the experts quickly reflected on EMG data and related the reading to their current movement. Interestingly, low EMG signal was as interesting as high muscle activation, because some exercises required relaxing muscles:

> *This is very easy to apply when I'm in a static position, which I want to hold. When I'm doing this correctly, I am more or less relaxed. (P4, cadeira)*

The experts also described another way to effectively use EMG to assess correctness which was to determine if the right muscles were active during a specific movement. P1 explicitly addressed how specific muscles should work during push-ups.

> *I can see if I'm activating the deltoid when moving up, as I should. [FitBack] tells me if I'm beginning the movement by raising my shoulder and using the descending part of the trapezius. (P1, push-ups)*

Finally, he also reflected on the impact that being able to objectively assess an exercise would have on fitness instruction. Being able to confirm one's professional opinion with objective data was seen as an opportunity for proving the coach's credibility.

*Body Awareness.*
EMG was perceived as a way to see beyond what they could perceive using their professional insight. P2 remarked that FitBack could be used to determine what muscles were targeted in new exercises, previously unknown to the coach and their students:

> *You often see those things online: "100 best planks" etc... but you never fully know what these exercises do. With [FitBack], you can see what's inside, check if [the muscle] is even contracting. (P2)*

EMG also allowed the experts to better understand the transitions between different body postures and movement forms. While they knew what muscles were to be active (or inactive) during defined exercises, EMG allowed investigation into what happened in the intermediate stages of the movement. P3 analyzed how his body worked while adjusting his posture in a complicated handstand:

> *When I changed the alignment of my body, moved my legs, you could ideally see where I contracted the muscle very hard and where it was weaker. (P3, queda de rins)*

*Exercise Form.*
This theme describes how EMG was used to reflect different exercise styles and different ways of understanding physical activity by coaches and their students. The coaches were eager to speculate on how different types of their class attendees may have perceived the feedback. In contrast to assessment, here, the experts described implicit, less defined qualities that can be inferred from EMG data. The need to place EMG electrodes implicitly required reflecting about the key muscles involved in the exercise:

> *Figuring out where to place the electrodes is interesting by itself. If I were to do this myself, I would experiment with this, stick it somewhere, check it out. (P4)*

The additional information provided by FitBack facilitated exercising while being aware of the benefits of the exercise. P1 commented extensively on how past philosophies of training promoted maximum exertion, while more modern methods preferred targeting specific muscles and avoiding injury. He saw EMG as a way to facilitate this transition from simple exertion to informed practice:

> *All the way, just to get super tired and feel pain. If you can't push through the pain, then you're weak. (...) But, the modern school of training is not about lifting very heavy bars. You're supposed to slowly learn how to activate specific muscles. I think that most people appreciate that in the long run. (P1)*

The coaches provided many comments on the temporal aspect of EMG data. They reflected that timing was differently important in various exercises and requested more control over the time scale. Especially P3 and P4 (martial arts specialists) remarked that a change of tempo and thus change of the speed of muscle activation was a key aspect of their practice:

> *It can be used for all the static exercises. I imagined that for dynamic things, it might be different. Capoeira has the full spectrum of exercises and thus paying attention to relaxing muscles is important. (P3)*

*Interpretability.*
The coaches commented extensively on how they interpreted the output produced by FitBack. They wondered about the form and timing of the feedback and anticipated possible deployment in their exercise classes. The experts anticipated how their students would understand EMG data and how FitBack could benefit the training process. The coaches remarked that EMG in the form presented by FitBack would be too difficult to monitor for larger fitness classes:

> *It would be tough for classes where we have a lot of people. One coach won't be able to interpret the muscle behavior of many people. But, for personal training, this would be very suitable. (P3)*

The experts remarked that EMG had the potential for changing achieving proper form in exercises from a vague pursuit of correctness to a tangible goal. P4 reflected on how a well-known exercise was a challenge when FitBack provided detailed feedback:

> *It was very stimulating because I was trying to do the exercise better so that it was more visible on the screen, (...) because I like tangible challenges. (P4, primera)*

Our experts underlined the importance of associating specific EMG responses with proprioceptive perception, i.e. 'how a movement felt'. As most fitness classes focused on mastering specific forms and limiting the use of incorrect forms, quantifying how far one was from an ideal movement was key to interpreting the EMG data and one's body. One participant saw FitBack as a tool for iteratively developing more precise movements and fine-tuning one's performance. EMG data enabled minuscule changes to posture which would be visible in the measurement data, but hard to perceive with one's senses.

> *In functional training, where the key goal is developing correct movement patterns, the basic movements are key. Here, [FitBack] can be very useful, guiding you to find the ideal ratio, the perfect movement. You can then copy the movement and master its execution (P3).*

## 6 DISCUSSION

Our investigation showed the potential of EMG-based biofeedback to facilitate bodily insights during physical activity. In this section, we draw implications and present opportunities for future systems. We conclude with a list of guidelines for designing for EMG-based biofeedback that allows users to increase their own body awareness.

*EMG-Based Biofeedback is Feasible with Wearable Recording Devices.*

Our quantitative analysis in the first study showed that both FitBack and the coach rating perform less accurately than post hoc reviewers who have access to the EMG data when it comes to recognizing exercise form (**RQ1**). In the current version, FitBack's movement analysis is based on correlation coefficients of the respective muscle groups. We believe a more elaborated classification approach, e.g., using multiple features to describe relevant characteristics of the EMG curve, allows one to identify execution more accurately. However, this results in a **trade-off between the amount of customization needed for a specific exercise** (e.g., training the model to detect common errors of biceps curls) **and the ability to generalize feedback for a wide array of fitness exercises** (**RQ1**), as illustrated in Study II. Our findings also suggest that EMG-based feedback can be effectively used to build both prescriptive and reflective feedback in HCI for sports. EMG-based systems which support exercise can give users explicit instructions (e.g. as in Gymsoles [18]) or present the signal to be interpreted by the user or coach. This emerges as a key design choice for future technologies which support amateur athletes.

In this work, we intentionally refrained from building a sophisticated data processing model to keep the amount of required domain knowledge that informs the model training process to a bare minimum. Building a fully automatic system to supervise specific fitness exercises is outside of the scope of this paper. We already know from related work that it is feasible to build accurate detection systems using EMG [3, 39, 59]. In contrast, FitBack is designed to be an aid for amateurs and coaches alike by **presenting data about muscle activity in a comprehensible manner and letting the user reflect on their data** (**RQ1**), thus contributing to their own body awareness.

*EMG-based Biofeedback Increases Body Awareness.*
We observed that FitBack provided expressiveness and supported users in gaining bodily insights about their own muscle activity and exertion, cf. Gaining Insights, Interpretability. Both studies revealed that FitBack was able to accurately depict transition between body posture, clearly showing active and inactive muscle groups. As a result, participants perceived which muscles were used. This finding was not only evident for experienced users but also present for novices. Through increasing one's own body awareness, **FitBack was able to facilitate a tangible learning process that minimized erroneous execution** (**RQ2**). An area for future research is to investigate whether such feedback can help maintain correct form over time, which can contribute to reducing injury risk. This is particularly relevant as experts in our study remarked that FitBack supported informed practice, allowing users to track their own fitness progress and presenting them with visible achievements that might otherwise have been hard to grasp or require personal supervision by coaches. Hence, biofeedback supports users in judging their own progress as well as empowering coaches to provide better feedback (**RQ2**).

*Access to Detail is Beneficial for Practitioners and Coaches Alike.*
In our analysis, the detailed feedback was favored mostly by experienced sportspeople. Our interviews with professionals revealed that the additional temporal component allowed them to analyze their movements in greater depth and supported them in perfecting their exercise form. Often, minuscule improvements where only visible in the EMG data, allowing **coaches to monitor otherwise invisible muscle activity and curate an appropriate training response** (**RQ2**). This finding implies that systems in HCI for sports which feature a prominent temporal component are likely to benefit from EMG-based feedback, which can allow for a high level of fidelity and potential for interpretation. For example, in golf, an EMG-based system could not only indicate that the user's body is misaligned (as in the Subtletee system [73]), but also help the user understand how to alter the movement to achieve the desired posture.

Additionally, both studies highlighted that the detailed temporal feedback was especially useful for dynamic exercises where the correct sequencing of muscle movements is crucial. Accordingly, an EMG-based biofeedback system should always provide a feedback view that allows to examine historic data. Future systems can improve the interaction with this view, by providing exercise markers within the view and even a corresponding recording functionality (**RQ1, RQ2**). As a consequence, designers of future technolgies for sports should consider providing detailed feedback for reflection-based technique improvement as an alternative to systems which provide automated corrections through on-body input such as FootStriker [28].

*Required Setup for EMG-Based Biofeedback Needs to be Minimal.*
To record electromyograms, FitBack requires the user to attach electrodes on respective muscle groups. This is a major limitation of not only our system but every EMG-based system. While participants reported that the attached electrodes and cables did not hinder their exercise execution, the required time for setting up the system was deemed acceptable only for continued workouts or when one wanted to gain additional insights. For daily workouts, the required effort was rarely deemed acceptable. In this work, we explicitly focused on user requirements and constraints with regard to the suitability of EMG-based biofeedback to increase body awareness during physical activity (**RQ2**). We envision that more **biofeedback systems will be integrated into affordable wearable artifacts and clothing** in the near future (cf. PhysioSkin [56], PolySense [32]), enabling easy and fast setup routines as is already possible with commercial products for professionals.

## 6.1 Design Guidelines for EMG-Based Biofeedback

During our work, we identified opportunities, requirements, and constraints of EMG-based biofeedback for physical activity. In this section, we provide a list of design guidelines for EMG-based biofeedback systems to inspire and aid in the design of future EMG systems for sports.

*Offer Feedback Customization.*
The different user groups in our study had differing requirements in terms of feedback. FitBack offers two different feedback modalities (visual and auditory) as well as abstract and detailed representations of the visual feedback. In our evaluation, we found that while the *Bars* visualization was most preferred, our interviews and quantitative results have also shown that access to multiple types allows the system to tailor to a broad audience. There was no feedback form that would not affect exercise form or was ignored by the participants (**RQ1, RQ2**). Novice users preferred abstract feedback that was less cognitively demanding and easy to interpret, cf. Cognitive Effort. On the other hand, switching to more detailed feedback should always be possible for more experienced sportspeople (**RQ2**). In the interviews with coaches, we observed that the understanding of feedback can be different for different movements within the same sport. Thus, **an EMG feedback system for physical activity must offer output that dynamically changes based on the current activity**. This finding is in line with past research in HCI for sports, which showed that customization and allowing fine tuning was also effective for less complex sensing modalities from accelerometers [73] to note taking [29].

Users exhibited varying preferences with regard to audio feedback. While some participants reported that it helped them keep their focus during a continued workout without having to look at the visual feedback, others strongly preferred visual cues, cf. Feedback Type and Granularity. Thus, **multi-modal feedback systems should provide a choice for the user to prevent sensory overload** (**RQ2**).

*Allow for Temporal Control.*
While our experimental study used only immediate feedback, the interviews with professionals revealed that EMG data was meaningful for understanding motion in different time horizons. The experts commented on their need to experiment and establish thresholds of correctness for different exercises, cf. Exercise Form. They also wanted to establish baselines and be able to review past exercises to draw comparisons, similarly to existing commercial products. They recognized the benefits of EMG data both in intantaneous use and over entire exercise session. As a consequence, **future EMG systems for exercise should offer a high degree of control in terms of the time intervals used to aggregate and display EMG data** (**RQ2**).

*Design for Social Context.*
Both of our studies showed that participants were eager to consider using FitBack in contexts associated with everyday exercise. What became apparent in the interviews was that these contexts were primarily social and possible social interaction impacted possible interpretations of EMG data. As we observed in the Interpretability theme, experts reported that feedback modalities for individual sessions should be very different from the feedback in group fitness classes (**RQ2**). Further, they also noted that the use of EMG could be dependent on a certain fitness philosophy or mental approaches to a given exercise. Participants in both studies reported that they often changed the social contexts of their physical activity. Thus, we recommend that **the granularity of EMG feedback be adjusted to allow for adequate interpretation**. Producing detailed EMG feedback in a context where it cannot be effectively interpreted is likely to cause frustration. Future systems should offer detailed data for individual classes and self-monitoring and ambient and/or summary feedback that would enable coaches in group exercises

to monitor the activity of multiple users (**RQ2**). Thus, future systems should strive to find a balance between optimally using the expertise of the user and providing coaches an optimal experience of understanding one's body. Our research shows that coaches can include the interpretation of rich feedback in their coaching practice. This is in contrast to past studies, where the role of the system was primarily to provide a replacement for the coach [39, 73] or cases where coaches identified issues in systems [36].

## 6.2 Enabling Alternative Use Case Scenarios for EMG-Based Biofeedback

While EMG-based biofeedback is already employed in professional sports to achieve maximum performance, amateur sportspeople cannot readily benefit from such technologies. In this paper, we showed how EMG-based biofeedback can support a wide range of users in gaining deeper insights into their own physiology through interpreting the EMG signals. To further illustrate this aspect, we describe two use case scenarios that highlight how systems like FitBack integrate into existing training regimes.

*6.2.1 Facilitating Body-Awareness for Physical Activities.* Jasha recently started to conduct basic strength exercises. However, Jasha has no insights into the correct execution of the activities. He decides to buy "MusclePower", a wearable that recognizes curls via the built-in accelerometer. During the first weeks, he is pleased with his performance as MusclePower tells him that his exercise form is optimal. However, a friend of his remarks on the excessive tension in his shoulders during a joint training session and recommends him to try FitBack. Jasha already had a hunch that he was doing something wrong, as he noticed periodical back pain in the last weeks, but he did not know what he was doing wrong. With FitBack's live visualization, he finally recognizes that he uses the muscles around the deltoid too much and adjusts his exercise form over time. Jasha realizes that the exercise feels different now. He needs to put much more effort into the movement, and he is finally confident in his exercise form.

*6.2.2 A Complementary Tool for Coaches.* Maxime is a coach who is training amateur athletes. However, due to training centers and the accompanied sessions being distributed, Maxime invests a considerable amount of time traveling to her clients. She is spending most of the time analyzing her clients' postures, correcting exercise routines. Maxime hears of FitBack, a system that collects and visualizes muscular activity, which can be viewed remotely. Maxime decided to give it a try as she can invest the saved travel time to improve her clients' overall training quality. Maxime is impressed by how she can correct the athletes' training postures by viewing the live EMG visualization while providing instructions using a video conference system. Additionally, FitBack allows her to record and annotate the visualizations, which is helpful for post hoc analysis to optimize the training sessions further. By gaining additional insights into her students' exercise form, Maxime can give more direct feedback and has objective evidence of the correct form.

# 7 CONCLUSION

In this paper, we investigated how EMG-based biofeedback can facilitate bodily insight during physical activity. Our two-fold evaluation, consisting of a lab study with amateur users and interview sessions with sports coaches, highlights the feasibility of this approach. We present implications and design guidelines for future EMG-based systems, allowing users to gain deeper insights into their own physiology by leveraging user-driven interpretation of bodily signals. Our work showed that feedback about one's muscle activity and exertion is beneficial for a broad audience, from novices to fitness professionals. Here, we found no necessity for complex algorithms preparing the signal for users to ease understanding. All of our participants were capable of interpreting their own EMG recordings, leveraging them to benefit their exercise form. We believe that these findings will inspire further research in understanding how users access and reflect on provided feedback, a key element to creating interactive systems beneficial to our wellbeing.

# REFERENCES


[1] E. D. Adrian and D. W. Bronk. 1929. The Discharge of Impulses in Motor Nerve Fibres. *J Physiol* 67, 2 (March 1929), i3–151.

[2] E. Aiello, D. H. Gates, B. L. Patritti, K. D. Cairns, M. Meister, E. A. Clancy, and P. Bonato. 2005. Visual EMG Biofeedback to Improve Ankle Function in Hemiparetic Gait. *Conference proceedings: ... Annual International Conference of the IEEE Engineering in Medicine and Biology Society. IEEE Engineering in Medicine and Biology Society. Annual Conference* 2005 (2005), 7703–7706. https://doi.org/10.1109/IEMBS.2005.1616297

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

[4] Fraser Anderson, Tovi Grossman, Justin Matejka, and George Fitzmaurice. 2013. YouMove: enhancing movement training with an augmented reality mirror. In *Proceedings of the 26th annual ACM symposium on User interface software and technology (UIST '13)*. Association for Computing Machinery, New York, NY, USA, 311–320. https://doi.org/10.1145/2501988.2502045

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

[6] Marco Belloli, Stefano Giappino, Fabio Robustelli, and Claudio Somaschini. 2016. Drafting Effect in Cycling: Investigation by Wind Tunnel Tests. *Procedia Engineering* 147 (2016), 38–43. https://doi.org/10.1016/j.proeng.2016.06.186

[7] Ann Blandford, Dominic Furniss, and Stephann Makri. 2016. Qualitative HCI research: Going behind the scenes. *Synthesis lectures on human-centered informatics* 9, 1 (2016), 1–115.

[8] W. Boeckh-Behrens and Buskies W. 2000. *Fitness-Krafttraining*. Rowohlt-Taschenbuch-Verlag.

[9] Anargyros Chatzitofis, Nicholas Vretos, Dimitrios Zarpalas, and Petros Daras. 2013. Three-dimensional monitoring of weightlifting for computer assisted training. In *Proceedings of the Virtual Reality International Conference: Laval Virtual (VRIC '13)*. Association for Computing Machinery, New York, NY, USA, 1–7. https://doi.org/10.1145/2466816.2466820

[10] Christopher Gilbert and Donald Moss. [n.d.]. Biofeedback and Biological Monitoring. In *Handbook of Mind-Body Medicine for Primary Care*. Thousand Oaks, CA: SAGE Publications, Inc. http://dx.doi.org/10.4135/9781452232607.n8

[11] Sunny Consolvo, David W. McDonald, and James A. Landay. 2009. Theory-driven design strategies for technologies that support behavior change in everyday life. In *Proceedings of the SIGCHI Conference on Human Factors in Computing Systems (CHI '09)*. Association for Computing Machinery, New York, NY, USA, 405–414. https://doi.org/10.1145/1518701.1518766

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

[13] CD Cozean, William S Pease, and SL Hubbell. 1988. Biofeedback and functional electric stimulation in stroke rehabilitation. *Archives of physical medicine and rehabilitation* 69, 6 (1988), 401–405.

[14] Ronald V. Croce. 1986. The effects of EMG biofeedback on strength acquisition. *Biofeedback and Self-regulation* 11, 4 (Dec. 1986), 299–310. https://doi.org/10.1007/BF01000166

[15] Claudia Daudén Roquet and Corina Sas. 2020. *Body Matters: Exploration of the Human Body as a Resource for the Design of Technologies for Meditation.* Association for Computing Machinery, New York, NY, USA, 533–546. https://doi.org/10.1145/3357236.3395499

[16] F. Delavier. 2010. *Strength training anatomy.* Human Kinetics. tex.lccn: 2009045227.

[17] John N Demos. 2005. *Getting started with neurofeedback.* WW Norton & Company.

[18] Don Samitha Elvitigala, Denys J.C. Matthies, Löic David, Chamod Weerasinghe, and Suranga Nanayakkara. 2019. GymSoles: Improving Squats and Dead-Lifts by Visualizing the User's Center of Pressure. In *Proceedings of the 2019 CHI Conference on Human Factors in Computing Systems (CHI '19).* Association for Computing Machinery, New York, NY, USA, 1–12. https://doi.org/10.1145/3290605.3300404

[19] Eurostat. 2017. How much do Europeans exercise? https://ec.europa.eu/eurostat/web/products-eurostat-news/-/DDN-20170302-1

[20] Kraig Finstad. 2010. The Usability Metric for User Experience. *Interacting with Computers* 22, 5 (05 2010), 323–327. https://doi.org/10.1016/j.intcom.2010.04.004 arXiv:https://academic.oup.com/iwc/article-pdf/22/5/323/1992916/iwc22-0323.pdf

[21] Center for Disease Control and Prevention. 2019. Early Release of Selected Estimates Based on Data From the 2018 National Health Interview Survey. https://www.cdc.gov/nchs/nhis/releases/released201905.htm

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

[23] IV Gartha. 1976. What is biofeedback? *Canadian Family Physician* 22 (1976), 105.

[24] Stavros Garzonis, Simon Jones, Tim Jay, and Eamonn O'Neill. 2009. Auditory Icon and Earcon Mobile Service Notifications: Intuitiveness, Learnability, Memorability and Preference. In *Proceedings of the SIGCHI Conference on Human Factors in Computing Systems* (Boston, MA, USA) *(CHI '09).* Association for Computing Machinery, New York, NY, USA, 1513–1522. https://doi.org/10.1145/1518701.1518932

[25] Christiane Glatz, Stas S. Krupenia, Heinrich H. Bülthoff, and Lewis L. Chuang. 2018. *Use the Right Sound for the Right Job: Verbal Commands and Auditory Icons for a Task-Management System Favor Different Information Processes in the Brain.* Association for Computing Machinery, New York, NY, USA, 1–13. https://doi.org/10.1145/3173574.3174046

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

[27] Sandra G. Hart and Lowell E. Staveland. 1988. Development of NASA-TLX (Task Load Index): Results of Empirical and Theoretical Research. In *Human Mental Workload*, Peter A. Hancock and Najmedin Meshkati (Eds.). Advances in Psychology, Vol. 52. North-Holland, 139 – 183. https://doi.org/10.1016/S0166-4115(08)62386-9

[28] Mahmoud Hassan, Florian Daiber, Frederik Wiehr, Felix Kosmalla, and Antonio Krüger. 2017. FootStriker: An EMS-Based Foot Strike Assistant for Running. *Proc. ACM Interact. Mob. Wearable Ubiquitous Technol.* 1, 1, Article 2 (March 2017), 18 pages. https://doi.org/10.1145/3053332

[29] Hayati Havlucu, Aykut Coşkun, and Oğuzhan Özcan. 2019. Designing the Next Generation of Activity Trackers for Performance Sports: Insights from Elite Tennis Coaches. In *Extended Abstracts of the 2019 CHI Conference on Human Factors in Computing Systems* (Glasgow, Scotland Uk) *(CHI EA '19).* Association for Computing Machinery, New York, NY, USA, 1–7. https://doi.org/10.1145/3290607.3312945

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

[31] A. Holtermann, P. J. Mork, L. L. Andersen, H. B. Olsen, and K. Søgaard. 2010. The use of EMG biofeedback for learning of selective activation of intra-muscular parts within the serratus anterior muscle: a novel approach for rehabilitation of scapular muscle imbalance. *Journal of Electromyography and Kinesiology: Official Journal of the International Society of Electrophysiological Kinesiology* 20, 2 (April 2010), 359–365. https://doi.org/10.1016/j.jelekin.2009.02.009

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

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

[34] Perttu Hämäläinen. 2004. Interactive video mirrors for sports training. In *Proceedings of the third Nordic conference on Human-computer interaction.* Association for Computing Machinery, New York, NY, USA, 199–202. https://doi.org/10.1145/1028014.1028044

[35] Lawrence R. James, Robert G. Demaree, and Gerrit Wolf. 1984. Estimating within-group interrater reliability with and without response bias. *Journal of Applied Psychology* 69, 1 (1984), 85–98. https://doi.org/10.1037/0021-9010.69.1.85 Place: US Publisher: American Psychological Association.

[36] Mads Møller Jensen, Majken Kirkegaard Rasmussen, and Kaj Grønbæk. 2014. Design Sensitivities for Interactive Sport-Training Games. In *Proceedings of the 2014 Conference on Designing Interactive Systems* (Vancouver, BC, Canada) *(DIS '14).* Association for Computing Machinery, New York, NY, USA, 685–694. https://doi.org/10.1145/2598510.2598560

[37] Jakob Karolus, Annika Kilian, Thomas Kosch, Albrecht Schmidt, and Paweł W. Wozniak. 2020. Hit the Thumb Jack! Using Electromyography to Augment the Piano Keyboard. In *Proceedings of the 2020 ACM Designing Interactive Systems Conference (DIS '20).* Association for Computing Machinery, New York, NY, USA, 429–440. https://doi.org/10.1145/3357236.3395500

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

[39] Jakob Karolus, Hendrik Schuff, Thomas Kosch, PawełW. Wozniak, and Albrecht Schmidt. 2018. EMGuitar: Assisting Guitar Playing with Electromyography. In *Proceedings of the 2018 Designing Interactive Systems Conference (DIS '18).* ACM, New York, NY, USA, 651–655. https://doi.org/10.1145/3196709.3196803 event-place: Hong Kong, China.

[40] Frederic Kerber, Michael Puhl, and Antonio Krüger. 2017. User-independent real-time hand gesture recognition based on surface electromyography. In *Proceedings of the 19th International Conference on Human-Computer Interaction with Mobile Devices and Services (MobileHCI '17).* Association for Computing Machinery, New York, NY, USA, 1–7. https://doi.org/10.1145/3098279.3098553

[41] Rushil Khurana, Karan Ahuja, Zac Yu, Jennifer Mankoff, Chris Harrison, and Mayank Goel. 2018. GymCam: Detecting, Recognizing and Tracking Simultaneous Exercises in Unconstrained Scenes. *Proc. ACM Interact. Mob. Wearable Ubiquitous Technol.* 2, 4, Article 185 (Dec. 2018), 17 pages. https://doi.org/10.1145/3287063

[42] Francisco Kiss, Paweł W. Woźniak, Felix Scheerer, Julia Dominiak, Andrzej Romanowski, and Albrecht Schmidt. 2019. Clairbuoyance: Improving Directional Perception for Swimmers. In *Proceedings of the 2019 CHI Conference on Human Factors in Computing Systems (CHI '19).* Association for Computing Machinery, New York, NY, USA, 1–12. https://doi.org/10.1145/3290605.3300467

[43] Thomas Kosch, Mariam Hassib, and Albrecht Schmidt. 2016. The Brain Matters: A 3D Real-Time Visualization to Examine Brain Source Activation Leveraging Neurofeedback. In *Proceedings of the 2016 CHI Conference Extended Abstracts on Human Factors in Computing Systems* (San Jose, California, USA) *(CHI EA '16).* ACM, New York, NY, USA, 1570–1576. https://doi.org/10.1145/2851581.2892484

[44] Thomas Kosch, Romina Kettner, Markus Funk, and Albrecht Schmidt. 2016. Comparing Tactile, Auditory, and Visual Assembly Error-Feedback for Workers with Cognitive Impairments. In *Proceedings of the 18th International ACM SIGACCESS Conference on Computers and Accessibility* (Reno, Nevada, USA) *(ASSETS '16).* Association for Computing Machinery, New York, NY, USA, 53–60. https://doi.org/10.1145/2982142.2982157

[45] Heli Koskimäki, Pekka Siirtola, and Juha Röning. 2017. MyoGym: introducing an open gym data set for activity recognition collected using myo armband. In *Proceedings of the 2017 ACM International Joint Conference on Pervasive and Ubiquitous Computing and Proceedings of the 2017 ACM International Symposium on Wearable Computers (UbiComp '17).* Association for Computing Machinery, New York, NY, USA, 537–546. https://doi.org/10.1145/3123024.3124400

[46] Ralph La Forge. 2005. Aligning mind and body: Exploring the disciplines of mindful exercise. *ACSM's Health & Fitness Journal* 9, 5 (2005), 7–14.

[47] Sih-Pin Lai, Cheng-An Hsieh, Yu-Hsin Lin, Teepob Harutaipree, Shih-Chin Lin, Yi-Hao Peng, Lung-Pan Cheng, and Mike Y. Chen. 2020. StrengthGaming: Enabling Dynamic Repetition Tempo in Strength Training-Based Exergame Design. In *22nd International Conference on Human-Computer Interaction with Mobile Devices and Services* (Oldenburg, Germany) *(MobileHCI '20).* Association for Computing Machinery, New York, NY, USA, Article 7, 8 pages. https://doi.org/10.1145/3379503.3403529

[48] B. F. LeVeau and C. Rogers. 1980. Selective training of the vastus medialis muscle using EMG biofeedback. *Physical Therapy* 60, 11 (Nov. 1980), 1410–1415. https://doi.org/10.1093/ptj/60.11.1410

[49] Ian Li, Anind K. Dey, and Jodi Forlizzi. 2011. Understanding my data, myself: supporting self-reflection with ubicomp technologies. In *Proceedings of the 13th international conference on Ubiquitous computing (UbiComp '11).* Association for Computing Machinery, New York, NY, USA, 405–414. https://doi.org/10.1145/2030112.2030166

[50] Rachel Martin, Ivanka Prichard, Amanda D Hutchinson, and Carlene Wilson. 2013. The role of body awareness and mindfulness in the relationship between exercise and eating behavior. *Journal of Sport and Exercise Psychology* 35, 6 (2013),

655–660.

[51] Timothy Horrell MEng, Ayman El-Baz PhD, Joshua Baruth MS, Allan Tasman MD, Guela Sokhadze, Christopher Stewart MD, and Estate Sokhadze PhD. 2010. Neurofeedback Effects on Evoked and Induced EEG Gamma Band Reactivity to Drug-Related Cues in Cocaine Addiction. *Journal of Neurotherapy* 14, 3 (2010), 195–216. https://doi.org/10.1080/10874208.2010.501498

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

[53] Norman C. Moore. 2000. A Review of EEG Biofeedback Treatment of Anxiety Disorders. *Clinical Electroencephalography* 31, 1 (2000), 1–6. https://doi.org/10.1177/155005940003100105

[54] Dan Morris, T. Scott Saponas, Andrew Guillory, and Ilya Kelner. 2014. RecoFit: Using a Wearable Sensor to Find, Recognize, and Count Repetitive Exercises. In *Proceedings of the SIGCHI Conference on Human Factors in Computing Systems* (Toronto, Ontario, Canada) *(CHI '14)*. Association for Computing Machinery, New York, NY, USA, 3225–3234. https://doi.org/10.1145/2556288.2557116

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

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

[57] Se-yeon Park and Won-gyu Yoo. 2012. Effect of EMG-based Feedback on Posture Correction during Computer Operation. *Journal of Occupational Health* 54, 4 (2012), 271–277. https://doi.org/10.1539/joh.12-0052-OA arXiv:https://onlinelibrary.wiley.com/doi/pdf/10.1539/joh.12-0052-OA

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

[59] T Scott Saponas, Desney S. Tan, Dan Morris, and Ravin Balakrishnan. 2008. Demonstrating the Feasibility of Using Forearm Electromyography for Muscle-computer Interfaces. In *Proceedings of the SIGCHI Conference on Human Factors in Computing Systems (CHI '08)*. ACM, New York, NY, USA, 515–524. https://doi.org/10.1145/1357054.1357138

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

[61] Abraham. Savitzky and M. J. E. Golay. 1964. Smoothing and Differentiation of Data by Simplified Least Squares Procedures. *Analytical Chemistry* 36, 8 (1964), 1627–1639. https://doi.org/10.1021/ac60214a047

[62] Greg W. Schmidt and Gary L. Stein. 1991. Sport Commitment: A Model Integrating Enjoyment, Dropout, and Burnout. *Journal of Sport and Exercise Psychology* 13, 3 (Sept. 1991), 254–265. https://doi.org/10.1123/jsep.13.3.254 Publisher: Human Kinetics, Inc. Section: Journal of Sport and Exercise Psychology.

[63] Seth J. Schwartz and Alan S. Waterman. 2006. Changing interests: A longitudinal study of intrinsic motivation for personally salient activities. *Journal of Research in Personality* 40, 6 (2006), 1119 – 1136. https://doi.org/10.1016/j.jrp.2005.12.003

[64] William C. Scott, David Kaiser, Siegfried Othmer, and Stephen I. Sideroff. 2005. Effects of an EEG Biofeedback Protocol on a Mixed Substance Abusing Population. *The American Journal of Drug and Alcohol Abuse* 31, 3 (2005), 455–469. https://doi.org/10.1081/ADA-200056807

[65] Leena Subramanian, John V. Hindle, Stephen Johnston, Mark V. Roberts, Masud Husain, Rainer Goebel, and David Linden. 2011. Real-Time Functional Magnetic Resonance Imaging Neurofeedback for Treatment of Parkinson's Disease. *Journal of Neuroscience* 31, 45 (2011), 16309–16317. https://doi.org/10.1523/JNEUROSCI.3498-11.2011 arXiv:https://www.jneurosci.org/content/31/45/16309.full.pdf

[66] Mathias Sundholm, Jingyuan Cheng, Bo Zhou, Akash Sethi, and Paul Lukowicz. 2014. Smart-mat: recognizing and counting gym exercises with low-cost resistive pressure sensing matrix. In *Proceedings of the 2014 ACM International Joint Conference on Pervasive and Ubiquitous Computing (UbiComp '14)*. Association for Computing Machinery, New York, NY, USA, 373–382. https://doi.org/10.1145/2632048.2636088

[67] Laurentiu Toader, Nicolai B. K. Jensen, and Michael B. Holte. 2018. The Influence of Biofeedback on Exercise Correctness and Muscle Activity. In *Interactivity, Game Creation, Design, Learning, and Innovation (Lecture Notes of the Institute for Computer Sciences, Social Informatics and Telecommunications Engineering)*, Anthony L. Brooks, Eva Brooks, and Nikolas Vidakis (Eds.). Springer International Publishing, Cham, 139–150. https://doi.org/10.1007/978-3-319-76908-0_14

[68] Laia Turmo Vidal, Elena Márquez Segura, Christopher Boyer, and Annika Waern. 2019. Enlightened Yoga: Designing an Augmented Class with Wearable Lights to Support Instruction. In *Proceedings of the 2019 on Designing Interactive Systems Conference (DIS '19)*. Association for Computing Machinery, New York, NY, USA, 1017–1031. https://doi.org/10.1145/3322276.3322338

[69] Laia Turmo Vidal, Elena Márquez Segura, and Annika Waern. 2018. Movement Correction in Instructed Fitness Training: Design Recommendations and Opportunities. In *Proceedings of the 2018 Designing Interactive Systems Conference (DIS '18)*. Association for Computing Machinery, New York, NY, USA, 1041–1054. https://doi.org/10.1145/3196709.3196789

[70] Laia Turmo Vidal, Hui Zhu, and Abraham Riego-Delgado. 2020. BodyLights: Open-Ended Augmented Feedback to Support Training Towards a Correct Exercise Execution. In *Proceedings of the 2020 CHI Conference on Human Factors in Computing Systems (CHI '20)*. Association for Computing Machinery, New York, NY, USA, 1–14. https://doi.org/10.1145/3313831.3376268

[71] Eduardo Velloso, Andreas Bulling, Hans Gellersen, Wallace Ugulino, and Hugo Fuks. 2013. Qualitative activity recognition of weight lifting exercises. In *Proceedings of the 4th Augmented Human International Conference (AH '13)*. Association for Computing Machinery, New York, NY, USA, 116–123. https://doi.org/10.1145/2459236.2459256

[72] Jacob O. Wobbrock, Leah Findlater, Darren Gergle, and James J. Higgins. 2011. The Aligned Rank Transform for Nonparametric Factorial Analyses Using Only Anova Procedures. In *Proceedings of the SIGCHI Conference on Human Factors in Computing Systems (CHI '11)*. ACM, New York, NY, USA, 143–146. https://doi.org/10.1145/1978942.1978963

[73] Mikołaj P. Woźniak, Julia Dominiak, Michał Pieprzowski, Piotr Ładoński, Krzysztof Grudzień, Lars Lischke, Andrzej Romanowski, and Paweł W. Woźniak. 2020. Subtletee: Augmenting Posture Awareness for Beginner Golfers. *Proc. ACM Hum.-Comput. Interact.* 4, ISS, Article 204 (Nov. 2020), 24 pages. https://doi.org/10.1145/3427332

[74] Bin Yu, Mathias Funk, Jun Hu, and Loe Feijs. 2017. StressTree: A Metaphorical Visualization for Biofeedback-Assisted Stress Management. In *Proceedings of the 2017 Conference on Designing Interactive Systems* (Edinburgh, United Kingdom) *(DIS '17)*. Association for Computing Machinery, New York, NY, USA, 333–337. https://doi.org/10.1145/3064663.3064729