Fourfolds: Enhancing Proprioception through Visual Electromyography Biofeedback and Camera-Based Motion Tracking

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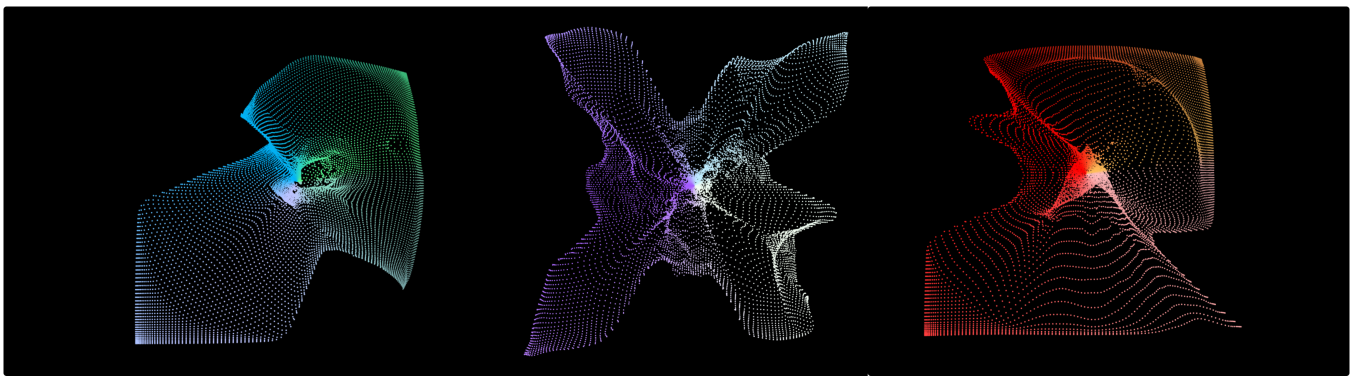

Figure 1: Fourfolds: Fostering personal sense of proprioception through biofeedback visualization. From left to right, the user's muscle state gradually transitions from relaxed to tense, corresponding to different color tones in a deformable field.

Abstract

Proprioception is the body's ability to sense the position and movement of its parts without relying on vision. It is essential for everyday actions, motor control, and injury prevention. However, HCI systems that solely concentrate on proprioception are still quite rare. This paper presents *Fourfolds*, a system that visualizes body movements and triggers proprioceptive awareness using visual biofeedback centered on Electromyography (EMG). By combining EMG with camera-based motion tracking, the system converts inner muscular efforts to more perceivable external visual stimuli. Interactive deformable fields transform the principle of Active Movement Extent Discrimination Assessment (AMEDA) into an intuitive visual challenge, enabling users to perceive their own proprioceptive states directly. Our work contributes to the field with a system that bridges psychophysical testing with embodied interaction design, offering a framework for proprioceptive training through EMG-driven interactive experiences.

CCS Concepts

• **Human-centered computing** → **Human computer interaction (HCI)**; **Interaction design**; *Visualization techniques*.

Keywords

Proprioception, Electromyography (EMG), Biofeedback, Camera-based Motion Tracking, Interactive Experience

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1 INTRODUCTION

In our fast-paced world, the connection to our bodies is weaker than ever. It is essential to stop and recognize the importance of

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nurturing this bond for our overall well-being. Daily movements of our body often occur unconsciously, causing subtle proprioception, the body's internal sense of position, movement, and force exertion [27], to be overlooked. This disconnection can trigger multiple negative consequences, including poor posture and chronic tension in areas like the neck and shoulders [18], diminished coordination and spatial awareness that make even simple actions seem clumsy [31], and emotional numbness or anxiety stemming from a weakened mind-body connection [4, 22]. Long-term lack of bodily awareness may even lead to injury; the damage often builds up over time, and it can be hard to notice.

The decline in proprioception has led to mind-body practices such as the Feldenkrais Method, which guides participants through mindful movement to help them reconnect with subtle bodily [7, 13]. In these practices, participants are guided to explore minute changes in movement, pause to perceive bodily responses, and reflect on shifts in balance, breathing, or muscle tension. Research in HCI similarly reveals the potential for interactive technologies to enhance such proprioception. When systems make implicit physiological processes perceptible, they create opportunities for users to reconnect with their bodies, thereby enhancing proprioceptive awareness in daily life.

Electromyography (EMG) presents unique opportunities in this context. While early HCI research primarily employed EMG for gesture recognition and hands-free interaction, recent studies have explored its application as a biofeedback system. For instance, the *FitBack* system [14] demonstrated that visualizing EMG signals during strength training helps users to more clearly identify activated muscle groups, thereby promoting more standardized movements. Signals during strength training help users gain clearer insight into which muscles are being activated [35], promoting reflection [15] and enhancing technical proficiency. This series of studies indicates that when EMG is combined with interactive visualization technology, it not only enables movement correction but also serves as a medium to stimulate deeper proprioception.

Building upon this research, we propose a system that fosters proprioceptive awareness by integrating surface EMG with camera-based motion tracking technology and translating feedback into interactive deformable fields. This translation allows for mapping internal muscle activity and body posture and transferring this into a visual stimulus that provides users with an intuitive means to perceive and enhance their sense of proprioception.

2 BACKGROUND AND RELATED WORK

2.1 Visual Feedback for Physical Activity

Biofeedback refers to a form of physiological-driven feedback in which the bodily responses of a user are measured and communicated back in real time, thereby forming a closed feedback loop [9, 24]. Over the past decade, researchers have increasingly recognized its value in rehabilitation and treatment, with applications ranging from stroke rehabilitation [32] to the management of anxiety disorders [40] and substance abuse [6]. What makes biofeedback particularly effective is the way it transforms complex physiological signals into perceivable visualizations that ordinary users can easily interpret. Compared with raw data such as EEG traces or Heart Rate Variability [33], these features minimize participant requirements and encourage broader participation.

Accumulating evidence shows that such feedback can positively influence physiological functions while providing advantages that extend beyond those of conventional treatments. Users not only gain visible metrics for reflection, but also benefit from progress tracking and sustained engagement [30]. Consider, for example, its successful use in stroke therapy [32], posture correction [9], neurological impairments [25], and even interventions for substance abuse [6]. These cases highlight biofeedback's versatility across clinical domains.

Beyond medical or therapeutic settings, biofeedback has also begun to reshape the way physical training is approached. Athletes and everyday users alike can rely on these systems to gain intuitive insights into their own movement patterns, using the feedback to refine exercise form and improve efficiency [38]. This raises an important question: if biofeedback can strengthen both rehabilitation and training, how might its principles be extended to cultivate a deeper sense of proprioception? This question motivates our exploration of biofeedback not only as a corrective tool but also as a medium for enhancing embodied experiences.

2.2 Electromyography as an Input in HCI

Muscle contractions generate electric fields. Surface Electromyography (sEMG) can detect them and give direct access to muscular exertion [21]. EMG was first used for diagnostics and prosthetic control [25]. In the past two decades, researchers have shown more interest in using EMG for interactive systems in HCI. Costanza et al. [3] showed that isometric muscle activation can be used for intimate interaction. Saponas et al. [28] used forearm-based electrode arrays for gesture recognition and built early muscle-computer interfaces. Later work used EMG in fine-motor cases, for example, musical instrument tutoring in guitar [17] and piano [16]. One challenge is to design classifiers that work well for all users. Kerber et al. [19] made stable algorithms, and Zheng [42] made implicit calibration methods to get training data without much effort from users. Low-cost sensing, like printable electrodes [41], also made EMG more scalable and accessible for daily use.

EMG is also used in biofeedback for behavioral change, rehabilitation [10, 23], and strength training [5]. Toader et al. [35] showed that visual EMG feedback improved exercise form more than no feedback. The *FitBack* system studied how feedback modalities change both performance and awareness of posture [14]. Some commercial products like *Athos*, *Myontec*, and *Mpower* put EMG feedback into smart clothing [1]. These are mainly for professional athletes. However, they are expensive, limited to fixed exercises, and often used for post-session analysis by coaches. Hence, there is still a lot of potential in exploring EMG feedback systems that are cheaper, easier to use, and can be understood by everyday users to build bodily insight [14].

2.3 Visual Mapping, Bodily Insights, and Proprioception in HCI

A growing body of HCI work explores how visual mappings of physiological signals can facilitate bodily insight. Turmo Vidal et al. [36] developed *BodyLights*, a wearable light-feedback system that enhances users' perception of limb alignment during exercise. Earlier, Hämäläinen [11] introduced the idea of interactive video mirrors for sports training, later extended by Anderson et al. [2] through the *YouMove* augmented reality fitness mirror. Together, these approaches suggest that mapping physiological signals to accessible sensory channels can deepen user understanding of movement. However, the design space remains insufficiently explored, and it is not yet well understood which types of visual or multimodal mappings are most effective in eliciting and enhancing proprioception.

Research in interactive sonification and visualization has shown that EMG features can be transformed into graphical or auditory representations, enabling users to reflect on their bodily states beyond task performance [26]. Collectively, these studies demonstrate that mapping physiological signals onto accessible sensory channels can support awareness, reflection, and correction in movement practices. However, despite these advances, existing systems still emphasize external task performance over the cultivation of proprioception itself [15], highlighting the need for approaches that explicitly foreground proprioceptive awareness as a design and evaluation goal.

Several prototypes already leverage either Kinect-based kinematic feedback or EMG-only biofeedback to guide movement quality. For instance, Taylor et al. provide posture training with real-time visual feedback using Kinect depth sensing [34], and Wang et al.'s *SomaTech* encourages users to expand their awareness of everyday movements via a Kinect-based somatic training experience [37]. On the EMG side, *FitBack* investigates how EMG-based visualizations facilitate bodily insights during physical activity [14]. Our implementation differs in three concrete ways: (1) we fuse *internal* muscle activity (sEMG) with *external* body kinematics (camera-based tracking) to align sensed exertion with visible posture in one coupled representation; (2) we make *proprioception enhancement* the primary design and evaluation target rather than a secondary outcome behind performance metrics; and (3) our visualization adopts a *theory-inspired* deformable-field metaphor (Section ??) to elicit intuitive, goal-directed correction beyond mirror- or gauge-like cues.

This multimodal, theory-grounded mapping extends Kinect-only mirrors and EMG-only dashboards by explicitly coupling perception of muscle recruitment with the felt sense of position and movement, thus enabling interactions that prior single-modality systems do not support.

2.4 Proprioception: Testing Methods

Researchers have often studied proprioception with psychophysical methods that look at different dimensions of body awareness [12]. The Threshold to Detection of Passive Motion (TTDPM) method finds the smallest angular change that a participant can detect during passive joint movement. This method shows kinesthetic sensitivity; it [12]uses the Method of Limits, and the angle or speed is slowly changed until the participant detects it. This method focuses on the sensory threshold of mechanoreceptors such as muscle spindles and joint receptors. The Joint Position Reproduction (JPR) method measures how well a participant can reproduce a joint position that they have memorized. This method shows the accuracy of the sense of position. JPR uses the Method of Adjustment, and the participant moves their limb until it matches the target position. This method focuses on the memory and reproduction of proprioceptive information. The Active Movement Extent Discrimination Assessment (AMEDA) [12]method tests how well a participant can tell apart different ranges of active movement. This method shows proprioceptive sensitivity during functional motion. AMEDA uses the Method of Constant Stimuli, and it relies on absolute judgments with ROC/AUC analysis. The main point of AMEDA is that it has high ecological validity, and it combines perceptual sensitivity with decision-making under active control.

Among these methods, we selected AMEDA to further design the interactive experience and translate its principles into design insights. Unlike TTDPM and JPR, AMEDA emphasizes active, functional movement under natural load-bearing conditions. This aligns with our design goal to foster proprioception enhancement in everyday contexts. AMEDA requires participants to make categorical judgments (e.g., distinguishing between five movement extents), linking proprioceptive perception with cognitive evaluation. This dual demand of sensation and judgment makes it particularly suitable for interactive feedback systems.

In summary, past work shows that biofeedback, EMG interaction, and visual mappings can help improve performance. However, systems that focus only on proprioception are still rare. Most EMG-based designs try to improve visible outcomes and do not support or leverage users' inner proprioception. Our work builds on this concept and combines EMG, camera-based motion tracking, and real-time visual feedback based on design insights driven by AMEDA. By linking inner muscle activity and body posture in one interactive visualization, we want to help users perform better and also reflect on and strengthen their sense of proprioception.

3 FOURFOLDS

3.1 System overview

Our system integrates EMG sensing with camera-based motion tracking into a unified workflow, translating physical activity into dynamic visual feedback (Figure 2). At the input stage, EMG sensors capture the user's muscle activity. The raw signal undergoes preprocessing via an Arduino circuit board to generate an EMG signal spectrum. Kinect 2.0, a camera-based motion sensor, tracks body posture in real time, extracting coordinates, relative joint angles, and acceleration values reflecting the user's movements.

Raw data are processed through TouchDesigner (TD). Body posture is mapped onto deformable fields geometries, generating stretching or compression effects through physical simulation. EMG peak values are mapped to visual parameters (such as color and saturation), allowing muscle activity states to be intuitively visualized through tonal shifts. These two data streams ultimately merge into a unified field that responds to the user's internal and external physical states, dynamically deforming and altering its form and color.

From a macro-perspective, the system works as a signal-to-vision process. Biological electrical signals and kinematic signals are collected and processed, and they are then mapped into visual elements given back to the user. This feedback loop allows participants to

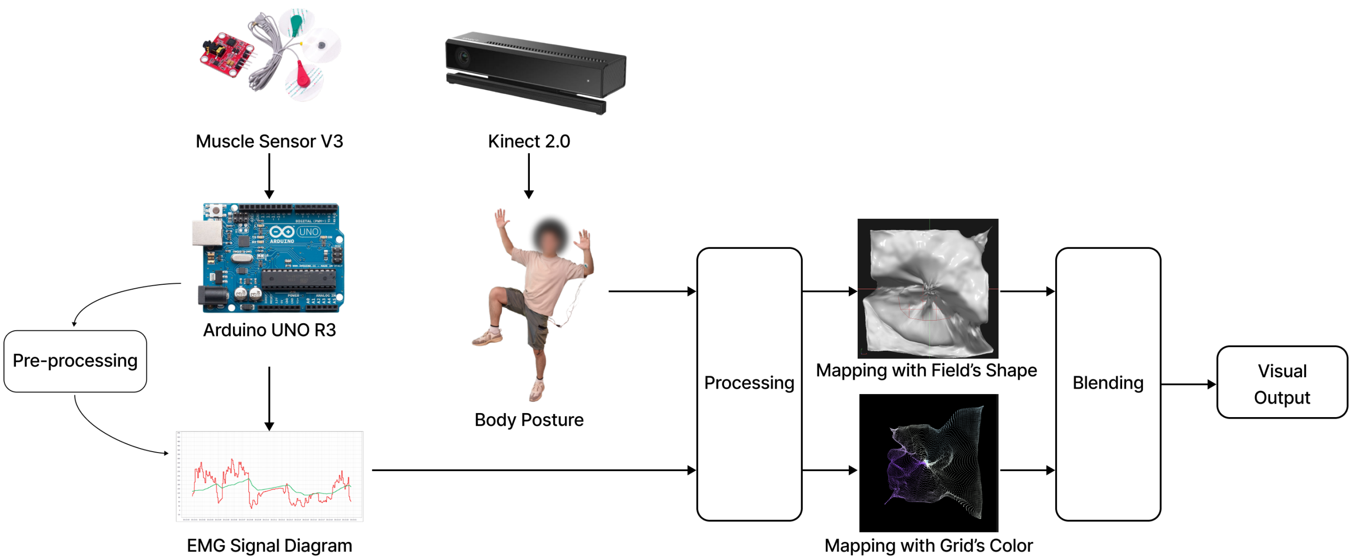

Figure 2: System overview diagram.

see muscle activation and body posture through changes in the visual field, attempting to trigger reflection on their own bodies and improve their sense of proprioception.

3.2 System Design

The system is designed as an interactive experience. A projector faces one wall and shows interactive, deformable fields at a large scale. A Kinect 2.0 sensor is placed near the center to track body posture. One participant stands in front of it with EMG electrodes attached to the head and upper body. The electrodes connect to an Arduino on a pedestal. The Arduino sends the signals to a computer, which processes the data and drives the projection.

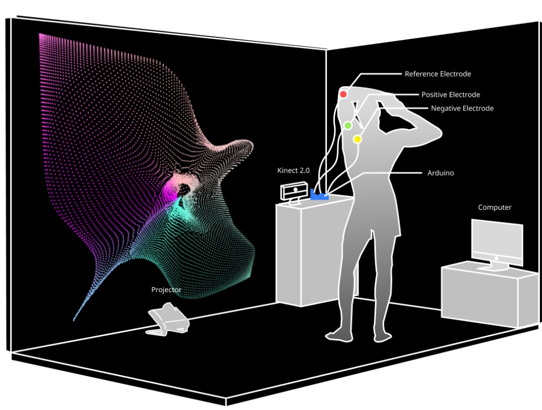

Figure 3: Interactive experience set up.

3.2.1 Theoretical Insights for Visual Feedback and Interactive Experience. Our system leverages a natural psychological tendency for individuals to instinctively seek to smooth irregularities in a deformation. This tendency can be interpreted through the lens of embodied cognition, which posits that perceptual and cognitive processes are grounded in bodily action and sensorimotor experience [20, 39]. In our case, the deformable field functions as a continuous error landscape: users perceive local curvature or "tension" and act to minimize it, aligning with error-based motor adaptation and closed-loop correction. The act of "smoothing a deformation" exemplifies a universal embodied schema, transforming an abstract proprioceptive judgment into a tangible, goal-directed action. Unlike angle reproduction, which requires conscious memorization and cognitive matching, smoothing a deformation instead elicits an intuitive perceptual-motor response [29], thereby reducing cognitive load and fostering deeper bodily engagement. From a design perspective, this affordance-driven interaction [8] situates proprioception within an ecological frame, highlighting how natural deformable fields can inspire theory-grounded interactive systems.This mapping generalizes across joints and tasks, reduces reliance on verbal instruction, and supports self-paced exploration—conditions favorable for cultivating proprioception beyond mere performance compliance.

3.2.2 Interactive Visualization Based on AMEDA. In conventional AMEDA, proprioceptive acuity is shown through numerical judgments of joint angles. Our system keeps the principle but changes its form. The visual target is a simulated deformable grid that flutters in random directions. The system sets its movement to go against the target action of the user's limb. This setting makes sure that the user cannot depend on easy cues but must use proprioception to fight the disturbance. The action requirement is that each limb controls one edge of the grid. The user must coordinate all four limbs to flatten the grid. This task makes the user produce graded muscular engagement that is similar to AMEDA's multiple motion extents. The perceptual feedback is also different from numbers. The degree of flattening directly shows how well the user can make range discrimination. The user can see the state of the fabric and feel how small bodily adjustments change the visual result. We translate AMEDA principles into a visual, interactive experience. It keeps the core principle of multi-extent discrimination so that users need to distinguish between several levels of movement. At the same time, the system provides an accessible and immediate feedback loop, and this loop connects the task with users' intuitive psychological operation.

3.3 EMG Biofeedback and Camera-based Tracking

Fourfolds adopts a dual-modality input combining surface EMG and camera-based motion tracking, rather than relying on a single physiological signal. Conventional biofeedback systems often use heart rate or respiration, which are stable and easy to measure but primarily reflect broader bodily states such as stress, arousal, or relaxation. These autonomic signals lack spatial resolution to capture limb-specific proprioceptive information and cannot reveal how particular muscle groups contribute to fine-grained movement.

Camera-based tracking complements this by capturing posture, extremity position, and kinematic trajectories, yet it misses internal muscular efforts behind these visible movements. Two users may perform the same trajectory with different exertion levels or muscle recruitment, leading to diverse and distinct proprioceptive experiences that motion data alone cannot differentiate.

The complementarity of EMG and camera-tracking is therefore central: EMG provides direct information about muscle activation, effort intensity, and subtle motor adjustments often invisible externally, while camera tracking anchors these signals to spatial coordinates, situating them in physical space. Together, they align inner muscular effort with outer posture, forming a feedback loop that integrates hidden and observable aspects of movement.

This dual-modality setup is particularly suited for fostering a sense of proprioception through an interactive experience. Proprioception emerges not from a single physiological dimension, but from the integration of effort and position. By mapping EMG to color saturation and posture data to grid deformation, our system offers users an immediate, embodied way to perceive how muscular engagement and spatial movement co-evolve. Compared to single-modality biofeedback, this approach provides richer, more accurate insights into the embodied experience of movement.

3.4 System Implementation Based on Touch Designer (TD)

3.4.1 Data Processing. TouchDesigner acquires the Motion capture data streamed by Kinect 2.0 via the Kinect SOP node. Among the extensive set of skeleton nodes, only the positional information of four key nodes—left hand, right hand, left foot, and right foot—is filtered and extracted. This selected data serves as the foundational input for subsequent grid-shape manipulation.

For the EMG signal detection module, TD receives the serial port data output via EMG through the Serial In component, with the communication parameters configured as follows: baud rate of 115200 bps, 8 data bits, 1 stop bit, and no parity check. Raw EMG signal data is an analog quantity ranging from 0 to 1023, which corresponds to the intensity of the myoelectric signal. TD directly normalizes this raw data into myoelectric intensity values within the range of 0 to 1. Concurrently, a Timer component is employed to set a sampling interval of 100 ms, enabling real-time recording of the EMG signal peak value in each sampling cycle. The collected peak values are organized into a peak sequence dataset, which is dedicated to supporting subsequent grid color control.

3.4.2 Grid Deformation Module. The core of the grid deformation simulation is implemented using TD's built-in Grid component, where both the number of Rows and Columns is set to 100. The high-density arrangement of rows and columns enhances the fineness and smoothness of grid deformation, thereby achieving a more accurate simulation of fabric texture.

The grid deformation simulation uses the Grid component in TD. The number of rows and columns is set to 100. This high-density arrangement increases the fineness and smoothness of the grid. The system can then produce a more accurate simulation of fabric texture. The grid shape is regulated by several factors, and this forms the core logic of the limb-controlled grid.

The positional information of the four nodes, including the left hand, right hand, left foot, and right foot, comes from the Kinect SOP. This information is sent to four independent Metaball nodes. Each Metaball node connects to a Force node and then to a Transform node. The positional data of the limb nodes goes through the Transform node, which changes the spatial positions of the four Force nodes.

At the same time, the Grid node connects to a Noise node. In the default state, the Noise node adds random perturbations to the grid. These perturbations create arbitrary deformation and free contraction behaviors.

The Noise node and the four Force nodes processed by the Transform node are then sent to the Spring node. The Spring node connects back to the Grid node. This process lets the system combine forces from limb position data and noise-induced effects. The combined effect produces synergistic control of the grid, which acts as a deformable field.

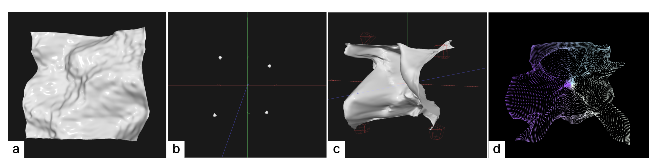

Figure 5: Deformable fields implementation and processing in Touchdesigner. (a): Fields deformation (b): Body mapping (c): Force mapping (d): Color mapping.

3.4.3 Visual Rendering and Color Control Module . Visual rendering is implemented through TD's Render TOP component, which combines the grid data output by the grid deformation simulation module with color mapping data to generate real-time visualizations. The base color of the grid is not a single hue but rather a randomly distributed multicolor pattern achieved through the

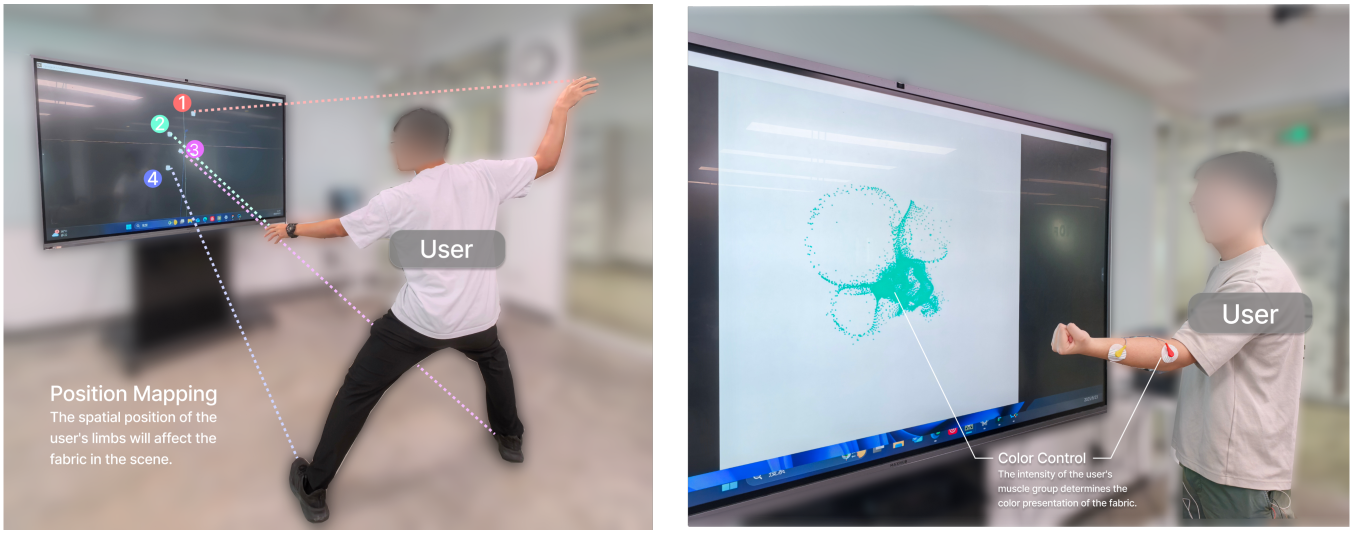

Figure 4: Visual-biofeedback and raw data mapping. Left: posture position mapping (1. Right Hand 2. Left Hand 3. Left Foot 4. Right Foot) Right: mapping EMG signals to color change

superposition of Noise TOP components. This establishes an initial dynamic color base, providing a foundation for contrast and transition in subsequent color changes.

The core logic of dynamic color adjustment is directly linked to the peak values of EMG signals. The peak values define the tension level of the user's corresponding muscle groups, which in turn synchronously control the noise level and overall color tone. The specific implementation pathway is as follows:

Noise level regulation: A Math CHOP component establishes a mapping relationship between EMG peak values and the "Detail" parameter of the Noise TOP component. When the peak value ≤ 0.3, a "cyan-green tone mapping" is triggered (indicating the user is in a relaxed state with low muscle group tension), the "Detail" parameter of the Noise TOP is reduced to below 0.2, significantly decreasing the disorder of random colors and resulting in a more regular color distribution across the grid. When the peak value ≥ 0.7(indicating the user is in a tense state with excessive muscle exertion), the "Detail" parameter is increased to above 0.8, increasing the superposition layers of random colors and creating a distinctly disordered color distribution. When the peak value falls in the 0.3–0.7 range, the "Detail" parameter increases linearly with the peak value, achieving a smooth transition in color disorder.

Overall color tone switching: A Color Correct TOP component and a Lookup TOP component work in conjunction to trigger color tone shifts based on EMG peak values. When the peak value ≤ 0.3, a "cyan-green tone mapping" is triggered. The Lookup TOP calls a preset cyan-green color table (with main tones ranging from RGB: 22, 163, 74 to RGB: 56, 189, 248), which is superimposed on the base random colors, giving the grid an overall fresh and unified cyan-green texture. When the peak value ≥ 0.7, it automatically switches to "red tone mapping," calling a red color table (with main tones ranging from RGB: 239, 68, 68 to RGB: 252, 165, 165), making the grid overall lean toward a warning red system. When the peak value is in the 0.3–0.7 range, a Lerp CHOP component enables a linear color transition from cyan-green to red, avoiding the abruptness of color jumps.

In addition, light is used to add ambient light (intensity 0.5) and directional light (intensity 0.8, direction along the negative Z-axis). The lighting parameters are fine-tuned synchronously with the color tone: for cyan-green tones, the ambient light intensity is increased to 0.6 to highlight the transparency of the colors; for red tones, the shadow depth of the directional light is enhanced to strengthen the visual warning effect, further improving the user's perception of their own state.

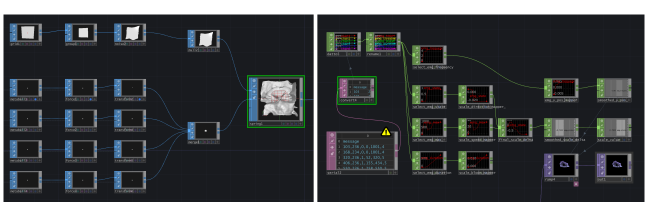

Figure 6: Left: Logic for grid deformation. Right: Logic for color mapping.

4 Evaluation Metrics

To assess the effectiveness of our system in enhancing proprioception, we consider both objective metrics and subjective metrics. For the objective, we examine task performance accuracy, defined as the degree of success in flattening the cloth, where lower residual deformation in the simulated fabric indicates better proprioceptive control. We also analyze EMG signal variability, focusing on peak amplitude and variance across trials to determine whether the system encourages more consistent muscle activation. In addition, we calculate a coordination index, derived from Kinect motion tracking, to capture the temporal synchronization of four-limb movements as a reflection of overall bodily coordination.

For subjective dimensions, we include a proprioception questionnaire, adapted from established body awareness scales, to capture participants' perceived ability to sense and regulate their muscle activity. We also administer a user experience survey in which participants rate the clarity, intuitiveness, and engagement of the interactive deformable field using 7-point Likert scales. Finally, we measure perceived workload through the NASA-TLX in order to assess whether the system imposes additional cognitive demands beyond natural proprioceptive engagement.

5 DESIGN POTENTIALS FOR PROPRIOCEPTION

The design of our system highlights several implications for interaction research. First, the use of a deformable grid can show how intuitive visual representations can render otherwise invisible proprioceptive processes perceivable, giving users a direct way to engage with bodily feedback. This design choice emphasizes the role of deformable fields in making abstract physiological signals meaningful in everyday interaction.

Moreover, the integration of EMG and camera tracking underscores the value of combining modalities. EMG captures inner muscular effort while camera data situates this activity within observable posture, showing that multi-modal alignment can reveal aspects of proprioception that neither signal alone can convey. Furthermore, embedding AMEDA principles within the interactive cloth task illustrates how psychophysical tests may evolve into training experiences that cultivate proprioception. Finally, the project embodies a dual role: it functions as a research prototype for validating proprioceptive visualization and simultaneously as a public installation that bridges scientific exploration with artistic engagement.

6 LIMITATIONS AND FUTURE WORK

Evaluations to date have been conducted solely within the design team. While the team confirmed the system functions correctly and is ready for immediate deployment, no systematic user research has been conducted.

We aim to run a user study to test if the system can enhance proprioception through interactive tasks. We will recruit participants to engage in the proprioceptive interaction with and without EMG-driven visual feedback. We will collect objective measures such as task performance and EMG activation patterns, and subjective questionnaires on proprioception. We expect that the deformable fields will give feedback that is more intuitive and more immediate than abstract angle-based tasks. This result will support the value of visualizing proprioception for future applications.

The system has only been designed for short single sessions. Users interact with the deformable fields for a short time, and the effect of long-term use is still unknown. It is not clear if repeated use can build stronger proprioception, if motivation stays high over time, or if learning moves into daily movement.

Surface EMG is easy to use and does not require invasive methods; however, it can only capture signals from muscles close to the skin. It cannot measure deeper muscles well, so some muscle groups are harder to be detected. The signals are also sensitive to electrode placement and skin condition, which could affectresults between different users.

In summary, this system demonstrates that visualizing proprioception through visual feedback is feasible, yet current research remains limited; on another side, this work sets grounds for precious future applications and research directions.

7 CONCLUSION

This study proposes an interactive system that visualizes proprioception by mapping Electromyography (EMG) signals and camera-based motion tracking onto interactive deformable fields. Distinct from most biofeedback designs, this system focuses on proprioception rather than visual representation. It translates psychophysical testing principles into user-engaging interactive tasks. The deformable fields intuitively display muscle activation and postural states, reducing cognitive load while fostering individual reflection on bodily experience.

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Ethics. No formal user study with human participants was conducted at this stage; all evaluations were performed internally by the authors.

Conflicts of Interest. The authors declare no competing interests.

References

[1] 2015. Athos: Smart Fitness Apparel for EMG Tracking. https://www.liveathos.com.

[2] 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)*. ACM, 311–320. doi:10.1145/2501988.2502045

[3] 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, 819–828. doi:10.1145/1240624.1240747

[4] A. D. Craig. 2009. How do you feel—now? The anterior insula and human awareness. *Nature Reviews Neuroscience* 10, 1 (2009), 59–70. doi:10.1038/nrn2555

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

[6] F. Dehghani-Arani, R. Rostami, and H. Nadali. 2013. Neurofeedback training for opiate addiction: Improvement of mental health and craving. *Applied Psychophysiology and Biofeedback* 38 (2013), 133–141. doi:10.1007/s10484-013-9218-5

[7] Moshe Feldenkrais. 1972. *Awareness Through Movement: Health Exercises for Personal Growth.* Harper Row, New York.

[8] James J. Gibson. 1979. *The Ecological Approach to Visual Perception.* Houghton Mifflin, Boston, MA.

[9] Owen M. Giggins, Ulrik M. Persson, and Brian Caulfield. 2013. Biofeedback in rehabilitation. *Journal of NeuroEngineering and Rehabilitation* 10 (2013), 60. doi:10.1186/1743-0003-10-60

[10] Marc Haab, Benjamin Maire, Hugo Bothorel, Frédéric Noë, Franck Brocherie, and François Fourchet. 2024. Role and effectiveness of surface EMG feedback in sports and orthopedic rehabilitation. *Exploration of Musculoskeletal Diseases* 2, 2 (2024), 100765. doi:10.37349/emd.2024.00065

[11] Perttu Hämäläinen. 2004. Interactive Video Mirrors for Sports Training. In *Proceedings of the 2004 ACM SIGCHI International Conference on Advances in Computer Entertainment Technology (ACE '04)*. ACM, 193–202. doi:10.1145/1067343.1067369

[12] Jia Han, Gavin Waddington, Roger Adams, Judith Anson, and Yu Liu. 2016. Assessing Proprioception: A Critical Review of Methods. *Journal of Sport and Health Science* 5, 1 (2016), 80–90. doi:10.1016/j.jshs.2014.10.004

[13] Susan Hillier and Amanda Worley. 2015. The effectiveness of the Feldenkrais Method: A systematic review of the evidence. *Evidence-Based Complementary and Alternative Medicine* 2015 (2015), 752160. doi:10.1155/2015/752160

[14] Jakob Karolus, Felix Bachmann, Thomas Kosch, Albrecht Schmidt, and Paweł W. Woźniak. 2021. Facilitating Bodily Insights Using Electromyography-Based Biofeedback during Physical Activity. In *Proceedings of the 23rd International Conference on Mobile Human-Computer Interaction (MobileHCI '21)*. ACM, 1–15. doi:10.1145/3447526.3472027

[15] Jakob Karolus, Thomas Kosch, Hendrik Schuff, Albrecht Schmidt, and Paweł W. Woźniak. 2020. FitBack: Exploring Feedback Modalities for Exercise Reflection. In *Proceedings of the 2020 CHI Conference on Human Factors in Computing Systems (CHI '20)*. ACM, 1–14. doi:10.1145/3313831.3376271

[16] Jakob Karolus, Thomas Kosch, Paweł W. Woźniak, and Albrecht Schmidt. 2019. EMG-Supported Piano Tutoring to Enhance Feedback and Self-Assessment. In *Proceedings of the 2019 CHI Conference on Human Factors in Computing Systems (CHI '19)*. ACM, 1–13. doi:10.1145/3567719

[17] Jakob Karolus, Hendrik Schuff, Thomas Kosch, Paweł W. Woźniak, and Albrecht Schmidt. 2018. EMGuitar: Assisting Guitar Playing with Electromyography. In *Proceedings of the 2018 Designing Interactive Systems Conference (DIS '18)*. ACM, 651–655. doi:10.1145/3196709.3196803

[18] F. P. Kendall, E. K. McCreary, and P. G. Provance. 2005. Muscles: Testing and Function with Posture and Pain. *Lippincott Williams & Wilkins* (2005).

[19] Frederic Kerber, Michael Puhl, and Antonio Krüger. 2017. User-Independent Real-Time Hand Gesture Recognition Based on Surface Electromyography. In *Proceedings of the 22nd International Conference on Intelligent User Interfaces (IUI '17)*. 163–174. doi:10.1145/3098279.3098553

[20] George Lakoff and Mark Johnson. 1999. *Philosophy in the Flesh: The Embodied Mind and Its Challenge to Western Thought*. Basic Books, New York, NY.

[21] Carlo J. De Luca. 2006. Electromyography. In *Encyclopedia of Medical Devices and Instrumentation* (2 ed.), John G. Webster (Ed.). John Wiley & Sons, Hoboken, NJ, 98–109. doi:10.1002/0471732877.emd097

[22] Wolf E. Mehling, Judith Wrubel, Jennifer J. Daubenmier, Cynthia J. Price, Catherine E. Kerr, Theresa Silow, Viranjini Gopisetty, and Anita L. Stewart. 2011. Body Awareness: a phenomenological inquiry into the common ground of mind–body therapies. *Philosophy, Ethics, and Humanities in Medicine* 6, 1 (2011), 6. doi:10.1186/1747-5341-6-6

[23] Roberto Merletti and Dario Farina. 2016. *Surface Electromyography: Physiology, Engineering, and Applications*. Wiley-IEEE Press.

[24] Anton Nijholt. 2015. Brain–Computer Interfaces and HCI. In *Foundations of Augmented Cognition*. Springer, 325–334. doi:10.1007/978-3-319-20816-9_32

[25] M. A. Oskoei and Huosheng Hu. 2007. Myoelectric control systems—A survey. *Biomedical Signal Processing and Control* 2, 4 (2007), 275–294. doi:10.1016/j.bspc.2007.07.009

[26] Sandra Pauletto and Andy Hunt. 2006. The Sonification of EMG Data. In *Proceedings of the 2006 International Conference on Auditory Display (ICAD '06)*. 1–8.

[27] Ulrich Proske and S. C. Gandevia. 2012. The proprioceptive senses: their roles in signaling body shape, body position and movement, and muscle force. *Physiological Reviews* 92, 4 (2012), 1651–1697. doi:10.1152/physrev.00048.2011

[28] 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, 515–524. doi:10.1145/1357054.1357138

[29] Reza Shadmehr and Steven P. Wise. 2005. *The Computational Neurobiology of Reaching and Pointing: A Foundation for Motor Learning*. MIT Press, Cambridge, MA.

[30] Leslie H. Sherlin, Martijn Arns, Joel Lubar, and Estate Sokhadze. 2011. Neurofeedback and physiologically driven feedback. *Journal of Neurotherapy* 15, 1 (2011), 68–85. doi:10.1080/10874208.2011.545764

[31] Anne Shumway-Cook and Marjorie H. Woollacott. 2012. Motor Control: Translating Research into Clinical Practice. *Lippincott Williams & Wilkins* (2012).

[32] Rosalyn Stanton, Louise Ada, Catherine Dean, and Elisabeth Preston. 2017. Biofeedback improves performance in lower limb activities more than usual therapy in people following stroke: a systematic review. *Journal of Physiotherapy* 63, 1 (2017), 11–16. doi:10.1016/j.jphys.2016.11.006

[33] Zhida Sun, Manuele Reani, Qiong Li, and Xiaojuan Ma. 2020. Fostering engagement in technology-mediated stress management: A comparative study of biofeedback designs. *International Journal of Human-Computer Studies* 140 (2020), 102430. doi:10.1016/j.ijhcs.2020.102430

[34] Brett Taylor, Max Birk, Regan L. Mandryk, and Zenja Ivkovic. 2013. Posture Training with Real-time Visual Feedback. In *CHI '13 Extended Abstracts on Human Factors in Computing Systems*. ACM, 3135–3138. doi:10.1145/2468356.2479629

[35] 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: 6th International Conference, ArtsIT 2017, and Second International Conference, DLI 2017, Heraklion, Crete, Greece, October 30–31, 2017, Proceedings (Lecture Notes of the Institute for Computer Sciences, Social Informatics and Telecommunications Engineering, Vol. 229)*. Springer, Cham, 139–150. doi:10.1007/978-3-319-76908-0_14

[36] 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)*. ACM, 1–12. doi:10.1145/3313831.3376268

[37] Qian Wang, Kristina Höök, Pedro Sanches, Thecla Schiphorst, George Poonkhin Khut, Özge Subasi, Alissa Nolden, and Jarmo Laaksolahti. 2014. SomaTech: Sensitizing the Design of Somatic Technology. In *CHI '14 Extended Abstracts on Human Factors in Computing Systems*. ACM, 1771–1776. doi:10.1145/2559206.2581339

[38] Brenda K. Wiederhold, Ahmad Soomro, Giuseppe Riva, and Mark D. Wiederhold. 2014. Future Directions: Advances and Implications of Virtual Environments Designed for Pain Management. *Cyberpsychology, Behavior, and Social Networking* 17, 6 (2014), 414–422. doi:10.1089/cyber.2014.0197

[39] Margaret Wilson. 2002. Six views of embodied cognition. *Psychonomic Bulletin & Review* 9, 4 (2002), 625–636. doi:10.3758/BF03196322

[40] Bing Yu, Mathias Funk, Jun Hu, and Loe Feijs. 2018. Unwind: a musical biofeedback for relaxation assistance. *Behaviour & Information Technology* 37, 8 (2018), 800–814. doi:10.1080/0144929X.2018.1484515

[41] Lei Zhang, Kirthika Senthil Kumar, Hao He, Catherine Jiayi Cai, Xu He, Huxin Gao, Shizhong Yue, Changsheng Li, Raymond Chee-Seong Seet, Hongliang Ren, and Jianyong Ouyang. 2020. Fully organic compliant dry electrodes self-adhesive to skin for long-term motion-robust epidermal biopotential monitoring. *Nature Communications* 11 (2020), 4683. doi:10.1038/s41467-020-18503-8

[42] Nan Zheng, Yixin Yin, Junhao Liu, Yunsong Mi, and Yong Sun. 2022. User-Independent EMG Gesture Recognition Method Based on Adaptive Learning. *Frontiers in Neuroscience* 16 (2022), 847180. doi:10.3389/fnins.2022.847180