Towards EMG-Driven Pseudo-Haptic Feedback for VR Surgical Training

[Wei Lan]*
[Keio University, Yokohama, Japan]

[Danyang Peng]†
[Keio University, Yokohama, Japan]

[Zicheng Xia]‡
[Keio University, Yokohama, Japan]

[Tobias Langlotz]§
[Aarhus University, Aarhus, Denmark]

[Stefanie Zollmann]¶
[Aarhus University, Aarhus, Denmark]

[Kai Kunze]‖
[Keio University, Graduate School of Media Design, Yokohama, Japan]

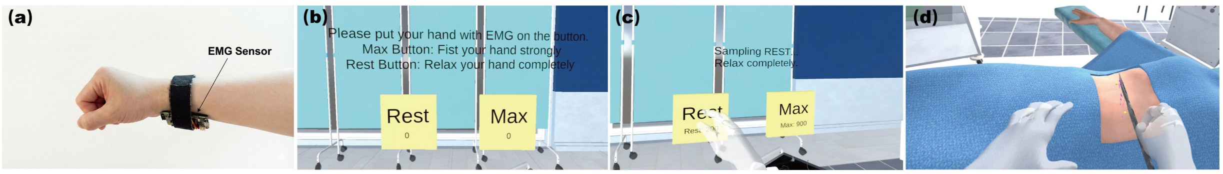


Figure 1: Overview of the EMG-driven pseudo-haptic feedback system for VR surgical training. (a) An inner wrist surface EMG sensor is used to capture muscle activity. (b–c) Participants calibrate EMG signals by recording rest and sustained target-effort contractions. (d) Participants then perform a straight-line incision task in VR while receiving effort-adaptive visual, audio, and vibrotactile pseudo-haptic feedback.

Abstract

Haptic feedback is prevalent in virtual reality applications, but replicating effort-dependent sensations required for surgical incision practice remains difficult without dedicated force-feedback devices. This work explores whether surface electromyography (EMG) can drive an effort-adaptive pseudo-haptic alternative for VR-based incision training.

Our system streams forearm EMG to estimate users' muscular effort in real time and adaptively modulates visual, audio, and vibrotactile cues when effort deviates from a predefined target range, fostering force awareness and self-correction without physically grounded haptics.

We implemented the system on a VR platform and conducted an exploratory within-subject study comparing three feedback conditions: visual-only feedback, a non-adaptive pseudo-force baseline, and EMG-adaptive pseudo-force feedback.

Initial results suggest that EMG-adaptive feedback improves perceived force awareness and self-correction tendencies without a disproportionate increase in perceived workload. Although limited in scale, these findings indicate the potential of EMG-driven pseudo-haptics as a lightweight approach for early-stage surgical skill training and motivate larger-scale evaluations.

Index Terms: H.5.1 [Information Interfaces and Presentation]: Multimedia Information Systems—Artificial, augmented, and virtual realities; H.5.2 [Information Interfaces and Presentation]: User Interfaces—Haptic I/O; J.3 [Computer Applications]: Life and Medical Sciences—Medical information systems

*e-mail: [lanwei@kmd.keio.ac.jp]
†e-mail: [pengdanyang@keio.jp]
‡e-mail: [xiazicheng@keio.jp]
§e-mail: [tobias.langlotz@cs.au.dk]
¶e-mail: [stefanie.zollmann@cs.au.dk]
‖e-mail: [kai.kunze@keio.jp]

1 Introduction

Virtual reality (VR) simulators are increasingly used for surgical skills training, offering repetitive practice and controlled assessment without patient risk [20, 24]. However, many surgical training systems rely on grounded force-feedback devices to convey cutting resistance and tissue interaction forces, which are often bulky, expensive, and difficult to deploy at scale [5, 7, 19]. This raises the open question if there are lightweight options that can provide an alternative for supporting force-related learning without physical haptics.

In this research, we explore whether light-weight surface electromyography (EMG) can drive effort-adaptive pseudo-haptic feedback to provide such an alternative. Specifically, we aim for VR surgical incision practice. Rather than simulating physical interaction forces, our approach estimates users' muscular effort from forearm EMG and modulates visual and audio feedback when effort deviates from a target range. Our goal is to foster force awareness and self-correction during incision cutting, without requiring force-feedback hardware.

We present an EMG-driven pseudo-haptic system implemented on a standalone VR platform and report findings from an exploratory within-subject study with novice users (no surgical training). We compare three feedback conditions: visual-only (baseline), non-adaptive pseudo-force (fixed feedback mapping), and EMG-adaptive pseudo-force. Although our study is initial and limited in scale, observed trends and qualitative feedback suggest that EMG-adaptive feedback can enhance perceived force awareness and encourage self-regulation without a disproportionate increase in perceived workload, motivating further investigation of EMG-based pseudo-haptics for surgical training.

Accordingly, we frame this work as an exploratory pre-study that aims to surface early trends and design insights, rather than to establish statistically conclusive performance claims. The novelty of this work lies in explicitly integrating users' own muscular effort, captured via EMG, as a control variable for adaptive pseudo-haptic feedback, shifting pseudo-haptics from scripted interaction cues toward physiology-driven effort awareness in motor skill training.

2 Related Work

Our work touches on different aspects, namely Surgical training using VR, pseudo haptics and EMG-based feedback. In the following a brief discussion on key works for each of these directions.

2.1 VR Surgical Training and Cutting Tasks

VR-based surgical simulators have been shown to support skill acquisition and transfer to the operating room, particularly when combined with objective performance metrics and structured training tasks. Early work demonstrated that VR training with haptic feedback can improve real surgical performance, establishing simulation as a viable training modality [24]. Subsequent systems have explored both physically grounded and shared haptic environments for fine motor surgical skills, including dental and cutting-related procedures [14, 27]. More recent clinical studies further support the effectiveness of VR simulation for minimally invasive surgical training, highlighting its potential for scalable and accessible education [25].

Virtual implementations of these tasks enable scalable deployment and automated assessment. Systems such as VBLaST report comparable performance trends between physical and virtual trainers while discriminating between novice and expert users [2, 6]. However, reproducing realistic force feedback remains challenging, motivating alternative feedback strategies that emphasize learning-relevant cues rather than high-fidelity physical simulation.

2.2 Pseudo-Haptic Feedback

Pseudo-haptic feedback refers to techniques that evoke haptic sensations through visual or multimodal manipulation, without relying on physically grounded force feedback. Lécuyer formalized the concept by showing that visual interaction dynamics alone can induce perceptions of stiffness, friction, and resistance [15]. Subsequent surveys describe pseudo-haptics as a practical design space when mechanical haptics is limited or unavailable [26, 29].

Recent work extends pseudo-haptics beyond vision-only cues by combining visual, audio, and cutaneous feedback. In the HCI community, lightweight pseudo-haptic techniques have demonstrated that convincing sensations of resistance and inertia can be rendered through perceptual manipulation alone, such as exploiting visual drag or undetectable control-display mappings [10, 30]. Audio-based pseudo-haptics and vibrotactile or electrotactile stimulation have further been shown to shape perceived material properties and compliance, particularly in motor learning and training contexts [1, 21]. These approaches suggest that meaningful force-related impressions can be conveyed without physical force rendering, making pseudo-haptics attractive for portable surgical training systems.

2.3 EMG-Based Biofeedback in XR

Electromyography (EMG) provides a direct measure of neuromuscular activation and has been increasingly integrated into XR systems for interaction and training. In rehabilitation and motor learning, EMG-based real-time feedback has been used to quantify user effort, encourage engagement, and support adaptive feedback loops [?, 17]. Recent VR systems leverage EMG to shape motor behavior by coupling muscle activation to visual or task-level feedback [3, 18].

These findings motivate our work and specifically the exploration of using EMG not merely as an input modality, but as a principled signal for effort-aware adaptation with the potential to drive adaptive pseudo-haptic feedback. Related work in VR surgical training has shown that automated real-time technical feedback can effectively support learning, and that simpler feedback designs may be sufficient or even preferable during early stages of skill acquisition [28].

3 Methods

The key idea of our work is to explore if EMG-driven feedback offers a potential pathway to support force regulation and self-correction without direct force sensing or actuation. The specific context for our exploration is surgical training, where excessive or insufficient force can compromise performance and safety. Our work takes inspiration from earlier work that uses EMG to couple muscle activation to visual or task-level feedback [3, 18] but instead integrates EMG-driven pseudo-haptics into a VR incision task and examining its subjective impact on novice users.

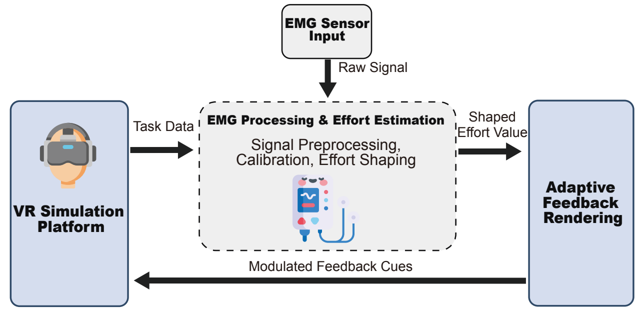


Figure 2: High-level system architecture of our approach of VR with EMG driven pseudo-haptic feedback.

3.1 System Architecture

Our system integrates three main components (shown as Fig.2): (1) VR surgical simulation, (2) surface EMG acquisition and processing, and (3) adaptive pseudo-haptic feedback rendering.

EMG Placement Surface EMG electrodes were placed on the volar (inner) side of the dominant wrist, targeting the forearm flexor muscle group involved in grip stabilization and fine force modulation during tool manipulation [4, 13, 16, 22]. This placement was selected to capture effort-related activation associated with maintaining contact and applying pressure during cutting-like motions, while remaining compatible with lightweight, wearable deployment. Although this location does not isolate a single muscle, prior work suggests that wrist and forearm flexor EMG provides a reliable proxy for overall exertion during precision manipulation tasks.

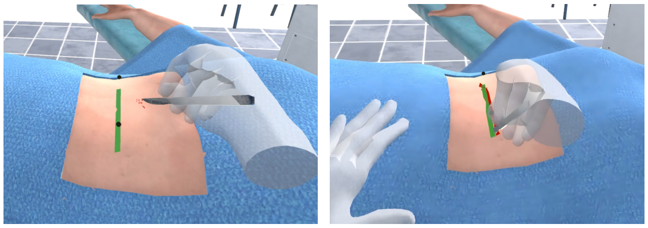
VR Simulation Platform We developed a straight-line incision task in Unity that was tested on the Meta Quest 3 standalone VR headset. In this environment, users can manipulate a virtual scalpel using the controller held like a pen grip, with the blade oriented perpendicular to a virtual tissue block. Cutting progress is determined by blade penetration depth and velocity along a marked target path.

EMG Acquisition Surface EMG was acquired using an oRion EMG sensing module and streamed in real time to the VR application through a lightweight relay pipeline. EMG samples were updated at approximately 30 ms intervals and used to estimate muscular effort for adaptive feedback.

EMG Processing Pipeline The incoming EMG stream provided a stable muscle activation level produced by the oRion sensing pipeline. Within the Unity VR application, we performed 1) calibration, 2) normalization, 3) temporal smoothing, and 4) effort shaping to obtain a real-time estimate of user effort suitable for feedback control. In the following, we provide a high-level overview of these key steps.

1. Calibration: Before the experimental trials, participants completed a two-step calibration to record (i) a relaxed baseline (REST) and (ii) a sustained target-effort contraction (MAX). For each step, EMG samples were collected for a fixed time window and summarized by their mean, yielding a rest level and a reference maximum level for normalization.

2. Normalization and noise gating: During interaction, each sample was baseline-corrected using the calibrated rest level and



(a) Off-line contact / insufficient effort. (b) On-line cutting within the valid segment.

Figure 3: **Visual feedback states for adaptive pseudo-haptics in EMG-adaptive mode. Red cut line** is rendered *exclusively* when (i) the blade trajectory is aligned with the predefined cutting line, (ii) the contact occurs within the valid segment (between the two endpoints), and (iii) the normalized EMG effort falls within the target effort range (i.e., sufficient exertion for cutting), indicating effective cutting progression. When the user merely touches the surface, exerts insufficient effort (normalized EMG below the target range), or moves off the valid segment, no cut line is shown; instead, **blood speckles** are displayed to convey frictional contact without meaningful incision, which can still occur under nonzero EMG activity (e.g., grasping or light pressing) that does not meet the cutting criterion.

a small margin to suppress low-level noise. The corrected signal was normalized by the calibrated span and clamped to the range $[0, 1]$, producing a normalized effort intensity.

3. Temporal smoothing and control mapping: To reduce jitter in real-time feedback, the normalized intensity was smoothed using exponential smoothing (first-order low-pass filtering). The resulting effort estimate was then mapped to multimodal pseudo-haptic feedback intensities in the adaptive condition.

4. Effort shaping for feedback control: For pseudo-haptic control, we additionally applied an effort-shaping stage. First, a dead-zone was applied so that low-level activation around baseline did not trigger feedback. Second, the remaining range was mapped through a power-law curve (e.g., quadratic) to emphasize higher-effort deviations. We also support scaling the effective control range (`targetRangeScale`) to tune sensitivity under sub-maximal calibration, and optional soft saturation above 1.0 when needed. The shaped effort value (`EmgEffort`) was used to modulate multimodal pseudo-haptic feedback intensity in the adaptive condition.

3.2 Adaptive Pseudo-Haptic Feedback

Our feedback system provides multimodal cues based on real-time comparison between normalized EMG effort and a target effort range. The target range is intended to represent appropriate cutting effort in a given training setup (e.g., reflecting different blade sharpness profiles or instructor-defined effort strategies), without requiring physically grounded force rendering. Although the incision task is performed in mid-air, users' muscular effort is influenced by visually induced resistance cues and task semantics. Prior work on pseudo-haptics shows that visual slowing, deformation, and effort-contingent feedback can elicit compensatory increases in motor effort. In our system, depth- and effort-dependent feedback encourages users to exert greater muscular effort to "push through" deeper layers, despite the absence of physical resistance.

Visual Feedback A color-coded effort indicator displays current effort level (green = optimal, yellow = approaching limits, red = overshoot/undershoot). The scalpel blade changes opacity when effort exceeds limits, creating a visual–motor conflict between the user's exerted effort and the visually perceived cutting effectiveness.

Audio Feedback Cutting sounds are triggered when effort enters the target range, while overshoot produces a warning tone.

4 Exploratory Study and Experimental Setup

To test our approach for EMG driven pseudo-haptic feedback, we ran a preliminary study based on a within-subject study. Besides providing initial feedback on our approach, this study also served the purpose of testing the study setup and protocol. The study was approved by the ethics committee of Keio University.

4.1 Experimental Conditions

We designed three different experimental conditions:

Visual-Only (Baseline) Participants receive only visual rendering of the cutting task (tissue deformation, blade penetration, layer transitions). No pseudo-haptic effects or EMG integration.

Non-Adaptive Pseudo-Force Pseudo-haptic feedback (visual, audio, vibrotactile) followed a fixed mapping that did not depend on EMG effort. Feedback intensity was driven by the interaction state (e.g., contact and cutting progression) but remained the same regardless of the user's muscular activation.

EMG-Adaptive Pseudo-Force Pseudo-haptic feedback was continuously modulated by real-time EMG effort relative to a target range. Users received immediate feedback when the effort deviated from the target range, enabling closed-loop self-correction during cutting.

4.2 Apparatus

The experiment was conducted within a head-mounted VR system with hand-based interaction. Participants wore a standalone VR headset and interacted within the virtual environment using a virtual surgical knife responding to the position of the tracked hands. The system integrated visual feedback, audio cues, and pseudo-haptic force modulation based on EMG input. For the latter, EMG signals were collected from the dominant forearm using the EMG sensing module, streamed in real time to the VR application via a TCP connection where it was processed as described earlier. Depending on the experimental condition, EMG signals were used to modulate cutting resistance and efficiency through a software-based pseudo-force model. All experimental conditions were implemented within the same virtual environment and interaction pipeline to ensure consistency.

4.3 Task and Procedure

The participants performed a straight-line incision task on a virtual surface representing a generic cutting scenario. A target cutting line was displayed on the surface, and participants were instructed to cut along the line as accurately and smoothly as possible using the virtual knife. The task consisted of three phases: initial contact, continuous cutting along the target trajectory, and completion of the incision. Participants were instructed to prioritize precision and smooth force application rather than speed. No explicit instruction regarding force magnitude was provided during the task, allowing participants to rely on system feedback to regulate their actions. Fig.4 shows the main steps for each session.

4.4 Measures

The study design focuses on using mainly quantitative measures assessing subjective workload and combining it with specific subjective measures to asses the efficacy of the pseudo-haptics force feedback as outlined below:

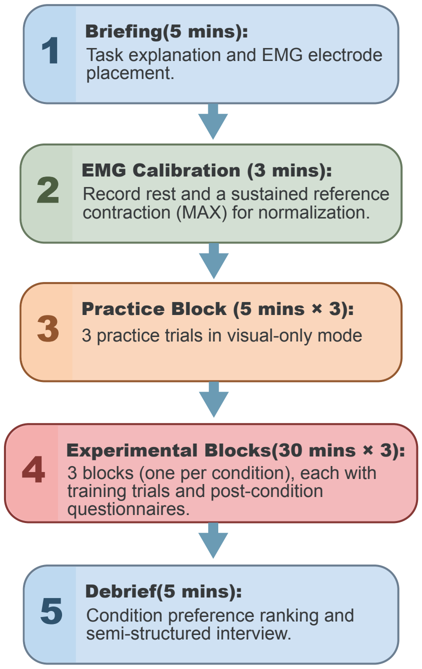


Figure 4: The experimental process, timeline, and content.

4.4.1 Subjective Workload

To assess perceived workload, we employed a shortened version of the NASA Task Load Index (NASA-TLX), also referred to as the Raw TLX [11]. Participants rated five dimensions on a 7-point Likert scale (1 = very low, 7 = very high). The dimensions included Physical Demand, Temporal Demand, Performance, Effort, and Frustration. The Mental Demand dimension was omitted, as the task primarily involved continuous sensorimotor control rather than complex cognitive decision-making.

Consistent with the original NASA-TLX formulation, higher scores on the Performance item indicate worse perceived task performance. No pairwise weighting was applied; an overall workload score was computed as the unweighted mean of the five subscales.

4.4.2 System-Specific Subjective Measures

To capture participants' subjective experience with the proposed system, we designed a system-specific questionnaire consisting of three items. All items were rated on a 7-point Likert scale (1 = strongly disagree, 7 = strongly agree).

The items assessed (1) force awareness, i.e., whether the system helped participants become more aware of the amount of force they were applying; (2) self-correction, i.e., whether the feedback encouraged participants to adjust their force and motion without explicit instruction; and (3) perceived usefulness, i.e., whether the feedback would be beneficial for learning or improving the target skill.

For each condition, a composite system-specific score was calculated as the unweighted mean of the three items.

4.5 Data Analysis

All statistical analyses were conducted using SPSS (IBM SPSS Statistics). For each experimental condition, composite scores were computed for subjective workload and system-specific subjective experience. The workload score was calculated as the unweighted mean of the five NASA-TLX (Raw) subscales (Physical Demand, Temporal Demand, Performance, Effort, and Frustration). The system-specific subjective score was calculated as the unweighted mean of the three custom questionnaire items assessing force awareness, self-correction, and perceived usefulness.

As the study employed a within-subject study with a small sample size and ordinal Likert-scale data, non-parametric statistical tests were used. Given the very small sample size, formal statistical testing was conducted only to provide descriptive context. We therefore focus our interpretation on relative ordering and trend-level patterns rather than statistical significance. For each measure, mean ranks are reported to indicate the relative ordering of conditions. The significance level was set to $\alpha = .05$.

All questionnaire scores were analyzed at the condition level. No post-hoc pairwise comparisons were conducted due to the exploratory nature of the study and the limited sample size.

4.6 Participants

We recruited 3 participants (N = 3, F = 1, M = 2), age (M = 26.3, SD = 1.5) with no prior surgical training. All participants provided informed consent.

5 Initial Results

We report descriptive and trend-level comparisons across the three conditions. Given the exploratory nature of the study and the limited sample size (N = 3), statistical analyses are reported only to contextualize observed patterns rather than to support confirmatory claims.

System-specific subjective score. We report trend-level comparisons of the system-specific ratings (control, force awareness, self-correction, and usefulness). Across participants, rank ordering showed a consistent tendency favoring the EMG-adaptive condition (C; mean rank = 2.83) over the non-adaptive pseudo-force baseline (B; 1.67) and visual-only feedback (A; 1.50). Although the small sample size limits inferential claims (Friedman test: n.s.), this ordering is consistent with the interpretation that effort-contingent feedback may better support users' awareness of their own force output and encourage self-regulation during the incision task.

Subjective workload (NASA-TLX Raw). Overall workload exhibited a trend toward increasing from the visual-only condition (A; mean rank = 1.50), to the non-adaptive pseudo-force condition (B; 1.83), and the EMG-adaptive condition (C; 2.67). While this ordering should be interpreted cautiously given the exploratory sample size (Friedman test: n.s.), it suggests a plausible trade-off: effort-adaptive cues may require additional attentional resources for monitoring and regulating exertion, even as they support force awareness. This interpretation aligns with the intended training mechanism, in which participants actively engage with effort monitoring rather than relying on purely scripted cues.

Table 1: Subjective workload (NASA-TLX Raw) and system-specific ratings reported as median [min–max] (N=3).

Condition	NASA-TLX Raw	System-specific
A	2.20 [1.80–2.80]	1.00 [1.00–4.33]
B	2.80 [2.20–3.20]	3.00 [1.33–4.67]
C	3.40 [2.20–5.80]	4.33 [4.00–6.33]

Objective performance and movement stability metrics. In addition to subjective ratings, we analyzed objective performance and movement quality metrics computed from system logs. Given the exploratory nature of the study and the limited sample size, these measures are reported descriptively to contextualize the subjective trends rather than as confirmatory statistical outcomes.

Across conditions, participants achieved similarly high task completion (latched progress ≈ 0.94–0.96), indicating that all feedback

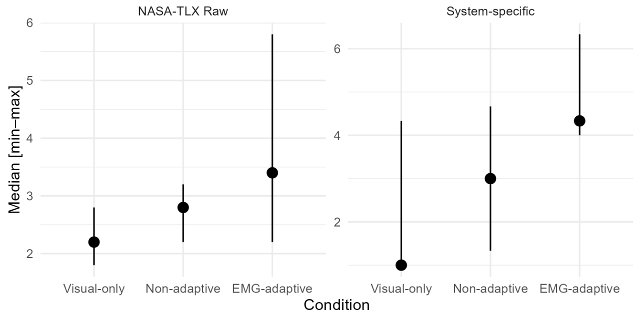


Figure 5: Subjective outcomes summarized as median [min–max] across participants (N=3). Left: NASA-TLX Raw workload. Right: system-specific ratings.

Table 2: Completion and performance (mean±SD).

Cond.	Prog.	Time (s)	Speed (mm/s)
A (Visual)	0.96±0.04	2.57±1.85	66,402±6,853
B (NonAd)	0.94±0.04	3.14±2.28	53,557±24,497
C (EMGAd)	0.95±0.04	3.93±1.41	69,449±298

Prog. denotes latched completion progress.

regimes supported successful execution of the task. EMG-adaptive feedback was associated with longer contact time and higher movement speed, consistent with a more deliberate yet dynamically engaged interaction strategy rather than premature termination.

As shown in Table 3, the EMG-adaptive condition exhibited the lowest mean deviation and RMSE, along with reduced variability, suggesting a tendency toward improved movement stability compared to both visual-only and non-adaptive pseudo-force conditions. While non-adaptive feedback also reduced deviation relative to visual-only feedback, its stability metrics remained more variable than those observed under EMG adaptation. Path length showed substantial dispersion across all conditions, likely reflecting heterogeneous corrective strategies and trial-to-trial differences in contact duration.

Objective effort measures indicated higher and more variable EMG activation in the EMG-adaptive condition, consistent with participants actively engaging in effort modulation when adaptive cues were present. In contrast, the non-adaptive condition exhibited greater dispersion in alignment relative to the surface normal, suggesting less consistent spatial control in the absence of effort-contingent feedback. Taken together, these objective trends complement the subjective findings by illustrating how EMG-adaptive pseudo-force feedback may reshape the coupling between effort regulation and movement stability, even when overall task completion remains comparable across conditions.

Qualitative feedback. Participants also provided brief design-oriented comments. P2 suggested that *"adding additional EMG sensor to alternative muscle sites (e.g., triceps brachii) could better capture effort-related activation during cutting, potentially improving sensitivity to exertion."* P3 reported that *"the current setup still lacked a convincing sensation of "holding" a tool, and suggested pairing the experience with a physical controller to increase grip realism and strengthen the coupling between effort cues and perceived manipulation."*

6 Discussion

Although our statistical analyses did not reveal significant differences across the three feedback conditions due to the small sample size and exploratory nature of the study, several consistent trends emerged that offer insight into the role of EMG-driven pseudo-haptics in VR surgical incision training. Importantly, this preliminary work was designed not only to probe the feasibility of an effort-adaptive pseudo-haptic approach, but also to evaluate the suitability of the study protocol itself for future, larger-scale investigations.

6.1 Perceived Workload in Effort-Adaptive Pseudo-Haptics

Across participants, the EMG-adaptive pseudo-force condition (C) was associated with the highest mean workload rank, whereas the visual-only baseline (A) was consistently rated as the lowest. This pattern is consistent with prior pseudo-haptics literature, which shows that feedback techniques relying on perceptual conflict or effort regulation often introduce additional cognitive or attentional demands [15, 26]. In such systems, increased workload does not necessarily indicate poorer usability; rather, it may reflect deeper engagement with task-relevant perceptual cues.

In our case, the elevated workload in the EMG-adaptive condition likely reflects participants' active monitoring and regulation of their own muscular effort in response to feedback. This interpretation aligns with earlier findings in force visualization and biofeedback-based training, where users must learn to interpret additional feedback channels while performing motor tasks [8,12]. Notably, despite this increase, workload in the EMG-adaptive condition did not increase markedly relative to the non-adaptive pseudo-force condition, suggesting that effort-aware pseudo-haptic cues can be integrated without overwhelming users when appropriately calibrated.

6.2 Force Awareness and Relation to Pseudo-Haptics Research

Participants' system-specific subjective ratings showed a consistent trend favoring the EMG-adaptive condition in terms of force awareness, self-correction, and perceived usefulness. Although these effects did not reach statistical significance, they resonate strongly with the core claims of pseudo-haptics research. Lécuyer's seminal survey emphasizes that pseudo-haptic illusions are particularly effective when visual or multimodal feedback is coupled to user action in a way that creates meaningful sensorimotor contingencies [15]. More recent surveys further highlight that pseudo-haptics is most successful when feedback adapts to user behavior rather than remaining purely scripted [26, 29].

Our findings suggest that EMG provides a promising internal signal for such adaptation. By tying pseudo-haptic feedback to users' own muscular effort, the system creates a closed-loop coupling between intention, action, and perceptual consequence. Qualitative feedback supports this interpretation: one participant proposed relocating the EMG sensor to alternative muscle sites (e.g., triceps brachii or inner wrist) to better capture exertion, while another suggested pairing the system with a physical controller to strengthen the sensation of holding a tool. These comments indicate that participants actively reflected on how their bodily effort related to the perceived resistance, a key mechanism underlying effective pseudo-haptic experiences.

6.3 Implications for VR Surgical Training

Straight-line incision tasks serve as foundational exercises for visuomotor precision and force modulation in surgical skill curricula. While grounded force-feedback devices can effectively convey tool–tissue interaction forces, they substantially increase system complexity and are often bulky and difficult to deploy in scalable training settings [8, 19]. Our results suggest that EMG-driven pseudo-haptics offers an alternative pathway that, while not physically grounded, can still communicate meaningful information about force-related aspects of the task.

Table 3: Path stability (mean±SD; lower is better).

Condition	Mean dev. (mm)	RMSE (mm)	Max dev. (mm)	Path len. (mm)
A (Visual)	9.29±2.69	13.12±4.97	42.51±18.26	250±229
B (Non-adaptive)	7.58±1.28	9.60±1.89	30.45±10.09	178±170
C (EMG-adaptive)	6.71±0.63	8.44±0.53	26.79± 6.25	271±276

Table 4: Effort and alignment-related metrics (mean ± SD).

Condition	EMG	Angle to surface normal (deg)
Visual-only	0.25 ± 0.29	122.39 ± 11.46
Non-adaptive	0.25 ± 0.29	119.09 ± 26.19
EMG-adaptive	0.61 ± 0.43	125.21 ± 9.94

By adapting feedback intensity to user effort rather than relying solely on scripted depth- or contact-based cues, the system introduces an additional dimension of realism: the sense that "pushing too hard" or "too lightly" has perceptual consequences. This form of effort realism is consistent with pseudo-haptics principles and may be particularly valuable for early-stage learners who lack an internalized model of appropriate cutting force. Even with minimal hardware, effort-adaptive pseudo-haptics can encourage safer force application and more reflective motor control, both of which are widely recognized as markers of developing surgical expertise.

Based on our experience, EMG-driven pseudo-haptics appears particularly well suited for early-stage motor training scenarios where effort awareness, self-monitoring, and scalability are prioritized over high-fidelity force rendering.

6.4 Limitations and Reflections on the Study Protocol

The primary limitation of this study is the small sample size (N=3), which limits statistical power and precludes strong inferential claims. However, an important outcome of this work is the validation of the overall study protocol. The within-subject study, calibration procedure, questionnaire measures, and analysis pipeline functioned as intended, and participants were able to meaningfully differentiate between the three feedback conditions.

Several protocol-level insights emerged that inform future studies. First, the current single-channel EMG configuration provides only a coarse estimate of exertion. Participant feedback and prior EMG research suggest that multi-channel sensing or alternative muscle placements could better capture distinct force-generation strategies (e.g., grip stabilization versus pushing). Second, the absence of a physical gripping artifact may have limited perceived tool embodiment; integrating a passive prop or controller could strengthen the coupling between effort, grip sensation, and perceived resistance.

Also,there is lack of evidence regarding transfer of learning to real-world surgical tasks. While this work focuses on effort regulation and force awareness within VR, future studies must evaluate whether such training effects generalize to physically grounded or real surgical contexts.

Another limitation of the present study is the absence of a comparison with grounded force-feedback systems, which are commonly regarded as the gold standard for rendering tool–tissue interaction forces in VR surgical training. While such devices can provide high-fidelity physical resistance, their bulk, cost, and deployment constraints pose challenges for scalability and accessibility. As a result, this exploratory work intentionally focused on a lightweight, effort-adaptive pseudo-haptic approach rather than attempting to replicate physically grounded force rendering.

Importantly, this design choice reflects a trade-off rather than a replacement claim. A direct comparison between EMG-driven pseudo-haptics and grounded force-feedback systems in a future, larger-scale study would help clarify the conditions under which effort-adaptive cues can provide sufficient training benefit, and where physically grounded feedback remains indispensable. Such comparisons may be particularly informative across different stages of skill acquisition, for example contrasting early-stage learners, who may benefit from scalable effort-awareness cues, with advanced trainees, who may require higher-fidelity force rendering.

If extended to a full-scale study with a larger sample (e.g., $N \approx 30$), we would retain the core protocol while introducing objective performance measures (e.g., path deviation, EMG-derived effort variability), refining the calibration process, and potentially stratifying participants by learning stage. Stratification by learning stage is motivated by established differences in how novices and advanced learners utilize feedback during motor skill acquisition [9, 23]. Because effort-adaptive pseudo-haptics emphasizes self-monitoring and force awareness rather than precise force rendering, its effects are likely to vary across training stages. Stratifying participants would therefore help disentangle stage-specific benefits that may be masked in aggregated analyses.These adjustments would allow for a more rigorous assessment of learning effects and the long-term impact of effort-adaptive pseudo-haptics.

Overall, this exploratory study demonstrates both the feasibility of EMG-driven pseudo-haptic feedback and the suitability of the proposed experimental framework, laying the groundwork for future investigations into scalable, effort-aware VR surgical training systems.

7 Conclusion

We introduced an EMG-driven pseudo-haptic feedback system for VR surgical incision training that adapts visual and audio feedback based on users' real-time muscular effort. By linking surface EMG to an effort-based control signal, the system provides a form of "effort realism" without requiring force-feedback hardware. Findings from our exploratory within-subject study suggest that adaptive pseudo-force cues increase users' awareness of their applied effort and encourage self-correction during incision, while maintaining a manageable level of subjective workload. Although statistical differences were not significant due to the small sample size, consistent trends indicate that EMG-adaptive feedback may promote more engaged and force-aware cutting behavior compared to visual-only or non-adaptive pseudo-haptic conditions.

These initial results support the feasibility of EMG-based adaptation as a lightweight and portable alternative to traditional haptics for early-stage surgical skill training. Future work will expand participant numbers, incorporate objective performance metrics, and investigate the long-term learning effects of effort-adaptive feedback. We see this approach as a promising pathway toward scalable VR surgical training systems that emphasize safe force regulation, stable motion control, and embodied skill acquisition without reliance on specialized force-feedback equipment.

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