The Interplay of Vision and Referred Haptic Feedback in VR Environments

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Abstract. As virtual reality environments evolve, users should be able to interact with real objects while also receiving artificially designed sensory cues – such as those from haptic devices. Our research examines wearable haptic devices that provide feedback at the wrist, enabling free fingertip movement. Limited prior work has studied how the shift in feedback location (from fingertips to wrist), called referred haptics, affects perception in a multisensory context. To explore this effect under visual and haptic sensory integration, we ran a within-subjects 2I-2AFC study. Participants chose what they perceived to be the stiffer of two springs in virtual reality while receiving haptic feedback at the wrist through squeezing. We tested three different sets of spring stiffness and five levels of visual manipulation. Two different discrimination strategies were observed among participants – haptic-focused and visual-focused. Notably, the visual-focused participants showed reduced accuracy with greater stiffness differences and more pronounced visual cues. Interaction times also varied according to the study conditions and post-fact groups. Our insights underscore the importance of considering sensory priors in multisensory integration research, particularly for referred haptic feedback.

Keywords: referred haptics · stiffness · perception · multisensory · wearable · virtual reality · interaction

1 Introduction

To interact in virtual reality environments, people must combine multisensory signals from the real world and programmatic signals from artificial sensors, e.g., haptic feedback. As people use haptic devices more, it will be necessary to understand how they perceive haptic cues, especially in the presence of additional sensory inputs such as vision. Wearable devices can use *sensory substitution*, in which one sense stands in for another. One type of sensory substitution is referred haptic feedback, such as when a wearable wristband provides fingertip sensations at the wrist, enabling those fingertips to be free for other interactions and expanding the range of possible sensory signals.

A large body of work has explored multisensory perception at the fingertips with congruent sensory information but referred haptic feedback has not been studied extensively in a multisensory context [13]. Prior work has explored vision and haptic integration for compliance discrimination and found that vision dominated in cases of sensory mismatch [15, 2]. We seek to understand how findings from such prior literature, specifically those considering fingertip contact and kinesthetic devices, extend to the referred haptic feedback setting. By learning how people integrate such referred feedback with visual information to form higher-level perceptions, we can build new multisensory virtual reality interactions with all their benefits.

We adapted a study from Srinivasan et al., which considered participants' perception of stiffness between two springs [15]. While the original work had an admittance-based device, we used an impedance-based approach. Our haptic wristband, the Tasbi [12], provides both vibrotactile and squeeze feedback at the wrist. In this study, we focused on squeeze as it has a direct analog to force, which users would feel while compressing virtual springs. The study explored three stiffness values for the comparison spring (all closer to the reference spring than previously studied) and a range of five visual manipulations. We found two distinct groups of participants from the results: haptic-focused and visual-focused. The haptic-focused group almost always relied on the physical squeezing force provided, while the visual-focused group used a combination. We also examined interaction time, to find that each group had different strategies and trends for making perceptual decisions.

2 Related Work

Integrating vision and haptics has long been explored in the haptics community, especially in the context of stiffness. Tan et al. considered the effect that work and terminal force have on compliance discrimination – determining that they both play a large role [16]. In related work, Srinivasan et al. explored human perception of two springs with an admittance-type haptic device [15]. They simulated two springs, a reference and a comparison, where the latter was always stiffer. The visual feedback was augmented such that the relative visual stiffness values were the inverse of the relative haptic stiffness. They found that people had visual dominance when completing this task, i.e., that they used visual information more than haptic information. Follow-up work considered the role of perspective on perceived object size, finding that haptic information can reduce innate visual bias [17]. It also studied compliance, finding that farther objects were perceived as softer with haptic feedback, but this perception was reset when visual information was introduced. Furthermore, some researchers have recently extended their work on stiffness perception in virtual environments by developing a new device for grasping with the thumb and index finger [2]. They support their earlier finding that visual information is dominant compared to haptic hand position – and suggest using vision to expand the range of perception available with haptic devices.

These early works contributed to expanding the range of haptic interactions through sensory illusions, such as pseudo-haptic illusions – where adjusting visual information can lead to the "feeling" of something, without any physical devices [9]. One highly relevant idea in this work is the Control to Display (C/D) ratio. In this paradigm, small physical movements result in large visual displacements and vice versa. Dominjon et al. demonstrated that adjusting the C/D ratio of on-screen motion affected participants' ability to discriminate weight using a haptic device [4]. Others have utilized programmatic delays to alter stiffness perception. When the visuals are provided on time, but haptic signals are temporally delayed, people perceive objects to be less stiff [11, 14]. However, when visual delays are increased (relative to haptic information), objects are perceived as being stiffer [8]. These works demonstrate the need to understand how multisensory information is perceived, especially when different sensory sources are not temporally or physically congruent.

More recent work has considered combining both pseudo-haptic illusions and haptic feedback. Pezent et al. found significant effects to adding haptic feedback to a pseudo-haptic illusion [13]. Through a haptic bracelet that provides both vibration and squeezing forces to the wrist, they showed that utilizing both vision and haptics expands the range of physical stiffness perceived to be associated with a virtual button press. Further exploration of this technology in new scenarios could enable low-cost or lower-fidelity devices that improve user experiences and accessibility.

3 Methods

3.1 Hardware

Participants wore a first-generation Oculus Quest headset and held a controller in their right hand for tracking and input. To mask any motor sounds, users listened to pink noise through noise-canceling headphones (Figure 1).

To implement referred haptic feedback at the wrist, we used the Tasbi haptic wristband [12], which has a custom tensioning mechanism that produces controllable force around the wrist (Figure 1a).

Parameter Choice We chose our reference stiffness ($K_o = 50\ N/m$) and smallest comparison stiffness ($K_\Delta = 0.2$, $K_c = K_o(1+K_\Delta) = 60\ N/m$) to be difficult to distinguish – below the pre-determined tactile-only just noticable difference of 15 N/m [13]. The Tasbi can produce a maximum stiffness of 161 N/m for pure tactile information [13], which is smaller than the original study values ($K_o = 330\ K/m$ and $K_{max} = 660\ K/m$) [15]. However, we found that even using Tasbi's more limited maximum range was too salient and highly encouraged pilot participants to choose the haptic output (rather than incorporating visual information). Thus, we used smaller values of K – and reduced the difference between the reference and comparison stiffness.

While the Tasbi can be controlled with torque, position, or force – we found that the most reliable feedback for this study was position-based control. In this mode, the device will spool to a set position, based on extents determined in

Fig. 1. Study Setup: A participant is seated with no obstruction to movement. They see two virtual springs in front of them. They have the Tasbi haptic device (a) tightened onto their right wrist, an Oculus controller in their right hand, an Oculus headset on their head, and noise-canceling over-ear headphones.

a tightening calibration function we administered before the study. Relative to force-based control, position-based control does not provide consistent results if people are flexing and extending at the wrist; however, in this work, people maintained their hand position while reaching to compress the spring.

3.2 Software

Using virtual reality for the study ensures that participants only see visual information that we intend – specifically allowing for control over the locations of the hand while compressing the virtual springs. We implemented the study using the Unity Game Engine (Version 2022.3.15f1).

3.3 Rendering

We used an impedance-type device, in contrast to the admittance control of the original study. Therefore, we adjusted the force output and visual displacement to conform to the following equations:

$$x_{ov} = \frac{x_{oh}\ K_o\ \frac{1}{1+\epsilon}}{(1-\lambda)\ K_o + \lambda\ K_c} \quad F = x_{ov}\ K_o \tag{1}$$

$$x_{cv} = \frac{x_{ch}\ K_c\ (1+\epsilon)}{(1-\lambda)\ K_c + \lambda\ K_o} \quad F = x_{cv}\ K_c, \tag{2}$$

where o is the reference spring and c is the comparison spring (that always has a higher stiffness than the reference). In Equation 1, x_{ov} is the visual displacement of the virtual reference spring, x_{oh} is the physical movement of the hand into that spring (measured using the headset and controller), K_o is the reference stiffness, K_c is the comparison stiffness, λ indicates the distribution of visual stiffness between the springs ($[0, 1]$), and F is the force output to the haptic device. Equation 2 uses similar values for computing force and displacement for the virtual comparison spring. This slightly deviates from the original paper, which used x_{rh} and y_{rh} as the output parameters [15].

Additionally, based on pilot testing, we conditionally increased the scale of the visual displacement with ϵ, defined here:

$$\epsilon = \begin{cases} 0 & \text{if } \lambda = 0 \\ 0.25 & \text{if } \lambda \neq 0 \text{ \& } K_o < K_c \end{cases} \tag{3}$$

The above conditional rescaling ensured that visual displacements were still perceivable for the smaller range of K_o and K_c used in this study.

Force corresponded to x_v, rather than x_h, as this resulted in a more realistic interaction. If $F = K_r\ x_h$ when $\lambda \neq 0$, participants would receive more force feedback while their finger is stuck at the virtual spring's surface, or stop feeling additional force feedback while still compressing it.

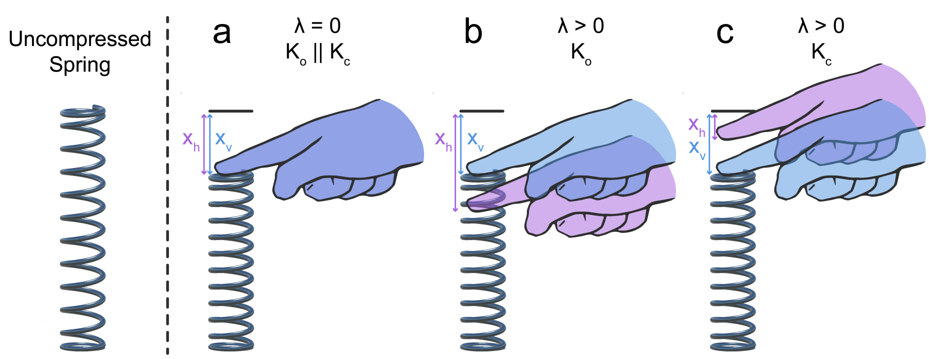

Fig. 2. Visual Rendering of Virtual Springs: physical hand shown in purple and proxy hand shown in blue; (a) when $\lambda = 0$ the two hands move identically; (b) when $\lambda > 0$ and the user interacts with the reference spring (K_o), the physical hand moves more than the proxy hand; (c) when $\lambda > 0$ and the user interacts with the comparison spring ($K_c > K_o$), the physical hand moves less than the proxy hand

Varying λ effectively changes the control-to-display (C/D) ratio and thus requires some retargeting of the visual (proxy) hand in virtual reality [1], so as not to break the illusions by having the finger penetrate through the spring. When $\lambda \neq 0$, the hand and spring locations are offset. The reference spring, K_o, visually appears stiffer – meaning that as users move their physical hand down in space, the proxy hand will compress for some percentage less (Figure 2b). The comparison spring visually appears softer, so as they move their physical hand down, the proxy spring compresses more quickly (Figure 2c).

4 Hypotheses

We have two main hypotheses. First, based on the original study, which found that as λ increased, accuracy decreased [15]:

(H1) *Participants will be less accurate in discriminating object stiffness as visual discrepancy (λ) increases.*

Given the smaller difference in stiffness selected for this study, participants should be more uncertain about the information from the haptic source. People may try to integrate [5] more across sources when there is more uncertainty in each source. We hypothesize that visual dominance will result when there is more uncertainty with the haptic information, but that the influence of visual information will decrease as the haptic cues become more certain and salient.

(H2) *Participants will be more accurate in discriminating object stiffness as stiffness (K_Δ) increases.*

As the differences in stiffness increased, we expect that participants will perform better – selecting the stiffer object regardless of the visual information.

5 Study

Sixteen participants (age: $\mu = 24$, $\sigma = 2.6$; sex: 7 female, 9 male; 14 right-handed, 2 left-handed) completed the study under IRB-FY2019-49 and were compensated $15.

5.1 Experimental Setup

Design The study is a within-subjects, repeated measures design with two factors: spring stiffness delta (K_Δ, 3 levels: 0.2, 0.4, 0.6) and visual difference (λ, 5 levels: 0, 0.25, 0.5, 0.75, 1). It uses a two-interval two-alternative forced choice paradigm (2I-2AFC). We selected this method to enable direct comparisons to related work. The task is also simple, and one that participants can complete after an unlimited time for interaction. In each trial, the virtual left and right springs were assigned to either the reference stiffness ($K_o = 50\ N/m$) or the comparison stiffness ($K_c = K_o(1 + K_\Delta)$). Each spring (left/right) was the reference stiffness 50% of the time, and this was equally distributed amongst the different visual conditions.

Trials were grouped into three blocks. During each block, K_Δ was held constant, per the method of constant stimuli [7]. Each visual difference was repeated 10 times within the block (50 trials) – for a total of 150 trials per participant. The trial order within each block was randomized. The block order was also randomized to reduce any learning effects.

Procedure Participants were seated with no obstructions in front of them. After an introduction to the controller and headset, participants were fitted with the Tasbi. We ran a pre-developed Tasbi function that uses torque-based control to determine the resting position of each user's wrist size as well as the maximum amount of spooling (due to the maximum torque of the device). The Tasbi was tightened to their right wrist holding an Oculus controller. Both an Oculus Headset and noise-canceling headphones were used (Figure 1). Participants were able to adjust the height of the virtual table and springs to be at a comfortable location for study and used the chair's armrest as a resting location.

Then, participants began a practice trial to familiarize them with the input devices and the task. In practice, the stiffest K_c was presented with the reference stiffness, K_o, and $\lambda = 0$ (no visual changes). This was to give users the example of force and visual combination that is easiest to discriminate. After this, participants began the study.

During each trial, participants touched both virtual springs with their right index finger. They were instructed to avoid poking the springs laterally (as there would be no feedback) and to allow the spring to return to its fully uncompressed state before removing their finger (to reduce spurious feedback). Participants could interact with both springs as many times as desired, with a minimum requirement of one interaction per spring. Once ready to make a choice, participants pressed a button, and this question appeared:

Which spring was stiffer? [1]

Then participants selected either *Left* or *Right* using the controller.

Between each block, the system required participants to pause for a 30-second break before allowing them to move on to the next block. After all blocks, participants completed a survey with demographic information and an open-ended question about how they made their decisions. All participants completed the study within 60 minutes.

6 Results

Response accuracy was the main dependent variable of the study, with the selection of the stiffer spring resulting in a 1 and the less stiff spring (incorrect) as 0. Participant's accuracy was affected by controlled values of λ and K_Δ.

Generalized linear mixed-effects models were fit to the data with the appropriate family and with a probit link function (for the binary response data). We fit the models using Bayesian methods with the *brms* package in R [3]. To determine which model best predicts participant accuracy, we used approximate leave-one-out cross-validation via the *loo* function. Our inference criterion was that the 95% credible interval (CrI) excludes zero.

[1] This question was modified from prior work [15], which used the verb *felt* rather than *was*, to reduce the chances that people would rely solely on haptic feedback – ignoring any visual cues relating to stiffness.

6.1 Exploratory Analyses

We did not predict that people would have strong differences in responses. However, from our participant-level results, a *group* emerged with two clear levels based upon behavior: haptic-focused and vision-focused. We define the *haptic group* as those with accuracy $\geq 97\%$ (9/16 participants). This was confirmed by participants' open survey responses (see Discussion) and comments to the experimenter. Thus, we present the following as exploratory, rather than confirmatory, analyses.

To address our hypotheses, we compared two statistical models – one simple and one more complex (with additional interaction effects). These include main and random effects of λ, K_Δ, and *group*, as well as a random effect for participant *id*. Both λ and K_Δ were treated as continuous variables, while *group* was coded as a factor.

M1: single-trial accuracy $\sim 1 + \lambda + K_\Delta + \text{group} + (1 + \lambda + K_\Delta + \text{group} \mid \text{id})$

M2: single-trial accuracy $\sim 1 + \lambda * (K_\Delta + \text{group}) + (1 + \lambda * (K_\Delta + \text{group}) \mid \text{id})$

M2, which accounts for interaction effects between λ & K_Δ and λ & *group*, better predicts the data compared to M1. Moving forward, all analyses use M2.

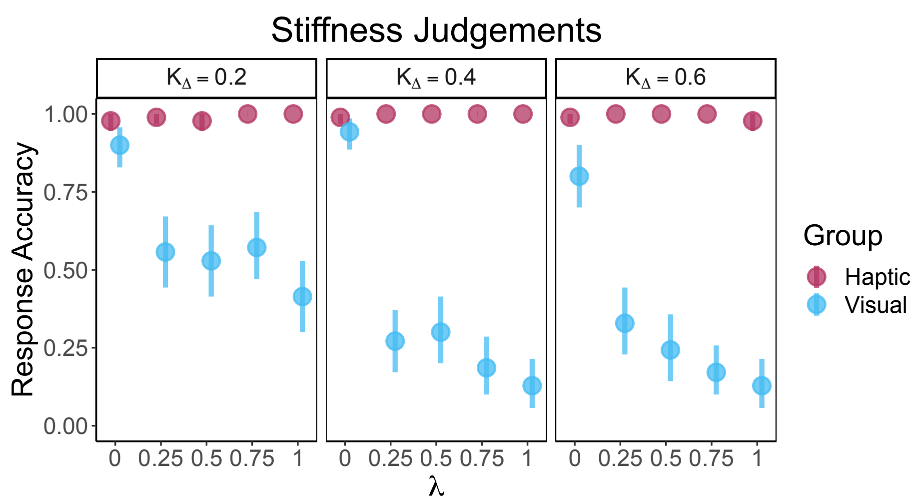

Fig. 3. Stiffness Judgement Results: collated into three columns by increasing K_Δ. The x-axis shows λ increasing from 0 to 1. The y-axis shows response accuracy, where 1 indicates 100% accuracy in selecting the stiffer spring. The *group* is denoted by color: Haptic (pink) and Visual (blue). Circles mark the mean, and lines show the 95% CI

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First, *group* was an important factor in predicting accuracy. The *haptic group* was more accurate ($\beta = -2.71$, 95% CrI [-5.12, -0.45]).

H1: Decreasing Accuracy With Increasing $\boldsymbol{\lambda}$ There was an *inverse relationship between accuracy and* λ for the *visual group* as determined by an interaction effect between λ & *group* ($\beta = -10.12$, 95% CrI [-18.53,-3.15]), represented by the decreasing values of the blue data within each column in Figure 3. There is also a main effect of λ ($\beta = 8.07$, 95% CrI [1.92,15.39]).

H2: Increasing Accuracy With Increasing $\boldsymbol{K_\Delta}$ We did not find a main effect of K_Δ. However, there was an interaction effect between K_Δ & λ ($\beta = -11.49$, 95% CrI [-22.47, -1.00]) indicating a *decrease in accuracy for increasing* K_Δ *and* λ. This is depicted by the decreasing values of the blue data across all three columns in Figure 3. This result fails to support our hypothesis and is contrary to what we expected.

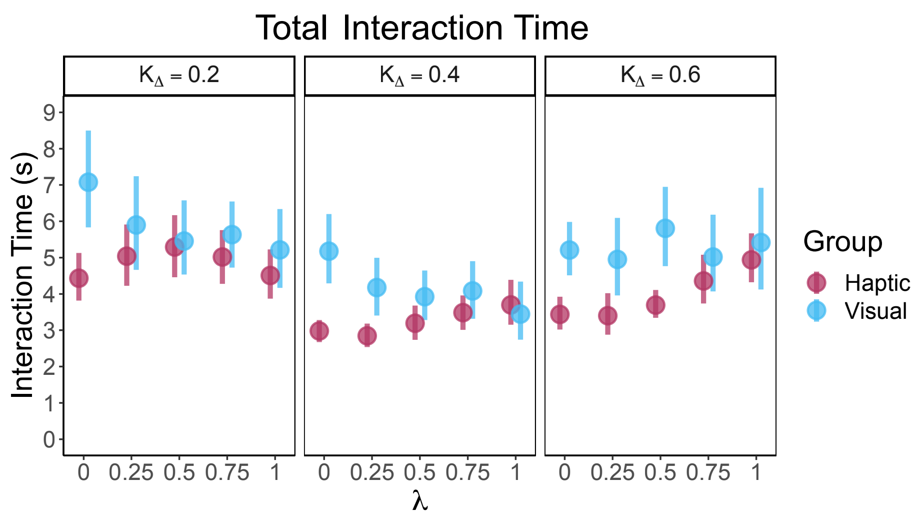

Fig. 4. Total Interaction Time: collated into three columns by increasing K_Δ. The x-axis shows λ increasing from 0 to 1. The y-axis shows the average interaction time across participants and trials. The *group* is denoted by color: Haptic (pink) and Visual (blue). Circles mark the mean, and lines show the 95% CI.

Temporal Analysis In addition to perceptual responses, we recorded hand data during each trial. From this, we computed the total time spent interacting with either spring within each trial and built a model of the same form as M1 and M2, but now predicting interaction time rather than accuracy.

M2 is a better predictor of interaction time than M1. Within this model, there were several main effects. First, as K_Δ increases, interaction time decreases ($\beta = -3.91$, 95% CrI [-7.71, -0.19]) – depicted by the decline of values between the columns of data (Figure 4). Both interaction effects had notable results. First, λ & K_{Δ} demonstrated that interaction time increased for larger values of λ and K_{Δ}. Finally, the interaction effect between λ & *group* highlighted that interaction time decreased as λ increased for the *visual group* while the opposite was true for the *haptic group* – compare pink and blue trends in Figure 4.

7 Discussion

We ran a user study to learn how non-congruent visual and referred haptic information affects our perception of stiffness. Our study found that accuracy decreased as visual discrepancy (λ) increased (H1). This result, at least with the *visual group*, aligns with related work [15, 2] – which found distinct visual dominance when $\lambda = 1$. We did not find support for (H2: Participants will be more accurate in discriminating object stiffness as stiffness (K_{Δ}) increases.) but rather determined that accuracy decreased with increasing stiffness. For $K_{\Delta} = 0.4$ & $K_{\Delta} = 0.6$, this aligns with the original study. We see a more sudden drop in accuracy between $\lambda = 0$ & $\lambda = 0.25$ (Figure 3), but this is likely due to the increased scaling of visual change we introduced (Equation 3). We used smaller values of K_{Δ} – and the relative λ values resulted in less total deformation under these cues. Thus, even with stronger haptic cues, some people are still drawn to the visual information. Furthermore, we find that this effect persists even when haptic information is referred from the fingertips to the wrist.

We do see differences when $K_{\Delta} = 0.2$ in the *visual group* – λ has a weaker effect when the two springs are most similar in stiffness. Contrarily, the *haptic group* was able to distinguish the stiffer spring very accurately, which suggests it was not too confusing of a task. One possible explanation is that the *visual group* was using proprioception to make their choice – as the hand moves more for the reference spring when $\lambda > 0$. In the original study, the authors claim people "ignored all kinesthetic hand position information regarding spring deformation" [15]. However, participants in the study may be using their proprioception, as they need to move their arm increasingly further down to compress the reference spring as λ increases. Additionally, prior work has found that people overestimate the thumb's displacement [10], indicating that our proprioceptive sense is quite strong and could have large effects on perception. Future work could explore the effects of proprioception by adjusting displacement directly, rather than the indirect approach through λ that we use here. Related work has considered proprioception in relation to reaching redirection in virtual reality, where the difference in proxy hand and world hand is a bias input into their sensorimotor model [6]. This could also be adapted to consider multisensory inputs from interactions with redirection and haptic feedback.

One difference in our results, compared to prior work, is the observation of two different response strategies: haptic-focused and visual-focused. We were careful to not introduce any bias or instructions that would lead participants to favor one type of information more than another. It seems that people in the *haptic group* used timing, band tightening, and smoothness information. P2 said

"When it tightened faster, I perceived it ultimately as tighter." Alternatively, in the *visual group*, the tightening often took a backseat to the rate of change of tightening and the perception of hand motion. P5 said "When the wrist band was tightened smoothly the spring felt the more stiff". P13 said "The most important factor to the stiffness felt like the perception of my hand's position vs the visual on screen. In particular, some springs felt like they were pulling rather than pushing, and these I rated as softer than springs which gave the visual of pushing." These statements indicate that for some, the integration involved more than just the visuals and the forces felt in the trial. However, both groups used similar strategies when $\lambda = 0$ as these values result in similar accuracy between groups (Figure 3). As P13 said "When the visuals were similar or the same, the tightness of the band was what I decided by: the tighter the band, the stiffer I perceived the spring." Perception is highly driven by our priors about sensory information and important to take into consideration when designing naturalistic interactions in virtual reality environments.

Finally, we considered interaction time as a measure of uncertainty. Both visual and haptic-focused groups interact more with the comparison spring that is most similar to the reference, suggesting greater confusion and uncertainty about these two cues that feel similar. For the *haptic group*, in the two stiffest comparisons ($K_{\Delta} = 0.4$ or 0.6), interaction time increases as λ increases (Figure 4). Many commented that their strategy was to fully compress both springs (e.g., P6 "I just relied on the haptics and the tighter the wristband felt when the spring was completely compressed, the stiffer I interpreted the spring to be."), thus, when λ is large, it takes longer to push the reference spring down. For the smallest stiffness difference (K_{Δ}), there was a more uniform distribution – possibly because it was a more confusing set of signals to distinguish and that changes in λ result in less visual change for smaller values of K_c. For the *visual group*, interaction time decreases with increasing λ for $K_{\Delta} = 0.2$ and 0.4. This aligns with comments that people used visual information (when present) to make their decisions – so larger values of λ would be easy to discriminate. The trend does not continue for $K_{\Delta} = 0.6$ and requires more experiments to understand fully.

8 Conclusion and Future Work

We demonstrate that visual manipulations when integrated with referred haptic feedback, influence stiffness perception (a finding that resonates with previous research). This study advances our understanding of referred haptic feedback, especially in scenarios involving multisensory signal perception. To determine the extent and range of the technology, we need to study further information that is both congruent and mismatched – as well as how people respond to this mismatch. Individual perception is shaped by personal sensory priors, rather than visual dominance or optimal integration.

Future research should explore how individuals' sensory priors influence their interaction with multisensory environments. Exploring these subjective experiences can help us build multisensory haptic systems that cater to individual differences. Our approach promises advancements in virtual reality technologies and offers insights into optimizing sensory experiences by considering individual perceptual biases. – e.g., using visual manipulations for those that have a larger prior on visual information to limit the power and output required of haptic devices.

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