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The contributions of skin stretch and kinesthetic information to static weight perception

Femke E. van Beek, *Member, IEEE*, Raymond J. King, Casey Brown, and Massimiliano Di Luca, *Member, IEEE*

Abstract—In this study, we examined the contributions of kinesthetic and skin stretch cues, in isolation and together, to the static perception of weight. In two psychophysical experiments, we asked participants either to detect on which hand a weight was presented or to compare between two weight cues. Two closed-loop controlled haptic devices were used to present weights with a precision of 0.05g to an end-effector held in a pinch grasp. Our results show that combining skin stretch and kinesthetic information leads to better weight detection thresholds than presenting uni-sensory cues does. For supra-threshold stimuli, Weber fractions ranged from 22-44%. Kinesthetic information was less reliable for lighter weights, while both sources of information were equally reliable for weights up to 300g. Our data for lighter weights complied with an Optimal Integration model, while for heavier weights, measurements were closer to predictions from a Sensory Capture model. The difference might be accounted for by the presence of correlated noise across the two cues with heavier weights, which would affect model predictions such that all our data could be explained through an Optimal Integration model. Our experiments provide device-independent measures that can be used to inform, for instance, skin stretch device design.

I. INTRODUCTION

Weight perception has been a topic of scientific enquiry since the origin of the field of psychophysics. Numerous researchers have measured the precision and accuracy of weight perception in various tasks, as can be seen in a review by Jones [1]. Various attempts have been made to disentangle the contributions of the two primary sources of information in haptic weight perception: kinesthetic and tactile [2]. Kinesthetic mechanoreceptors encode information on the state of muscles, tendons, and joints, while the four tactile mechanoreceptors respond to deformations of the skin. It has proven difficult, however, to analyze the contributions of the two sources of information in isolation. One of the limitations has been the absence of a device that allows for independent control of kinesthetic and tactile cues. In this experiment, we used a closed-loop controlled haptic device to render weight with a precision of 0.05g. The device simulated the static weight of a virtual object held in a stationary pinch grasp by exerting force on the end-effector held between the fingers. This approach allowed us to separate kinesthetic weight cues from tactile ones. For tactile information specifically, the major cue in such

an interaction is most likely tangential deformation (i.e., shearing) of the skin on the fingertips [3]. Throughout this paper, we will refer to this type of information as *skin stretch*.

We are interested in skin stretch because of numerous recent attempts to simulate virtual object weight using this cue (e.g., [3]). Only a few studies assessed the contribution of both skin stretch and kinesthetic information to providing the sensation of weight [4]–[6]. One of the limitations of these types of studies is that the magnitude of skin stretch stimulation is often either not reported in units of mass, or it is not continuously monitored. Therefore, the results obtained in these papers cannot be generalized and can only be replicated using the specific devices described in the papers. Giachritsis et al. mitigated this problem by using real weights to assess the precision of both types of information [6]. To separate the cues, they used thimbles to eliminate tactile information and a hand rest to reduce kinesthetic contributions. Their results suggest that skin stretch and kinesthetic cues are integrated when assessing the weight of a real object. Although their method has merit, the use of real weights introduces confounding factors, such as the influence of different lifting styles on the magnitude of inertial forces and the limits in stimulus range imposed by having to manufacture each stimulus. Therefore, we used an approach similar to Giachritsis et al. [6], but we used carefully-controlled virtual weights with a slow onset and offset, and asked participants to not move their hands during weight presentation. This allowed us to study (static) perception of weight without inertia.

In Experiment 1, we investigated the detection performance for the single and combined cues, whereas in Experiment 2, we studied the supra-threshold precision of weight discrimination for the single and combined cues. We compared our observed data to two candidate models, since finding an underlying model would allow us to make predictions about stimuli that were not tested in this experiment. We tested an Optimal Integration model [7], which shows how the means and variances of cues can be pooled, and a Sensory Capture model, in which the most reliable modality is the only one that is represented in the multi-sensory percept [8]. Together, these results provide device-independent guidelines for rendering weight of virtual objects through one or both types of information.

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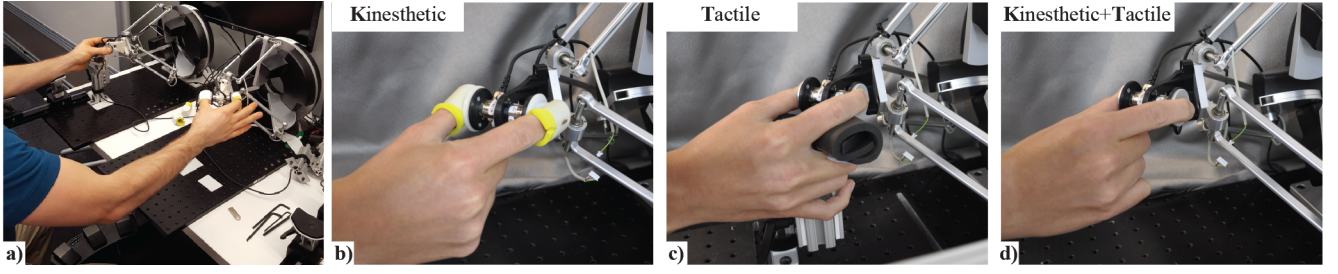


Fig. 1. Overview of the setup and the three experimental conditions. a) Overview of the entire setup, showing the arm supports, hand rests, thimbles, and haptic devices. The participant is experiencing condition K with his right hand and condition T with his left hand. b) Close-up of the kinesthetic condition (K), in which the participant's elbow is supported while he actively holds up his forearm and hand. The custom-fitted thimbles attenuate tactile information. c) Close-up of the tactile condition (T), in which the participant's elbow and forearm are supported, and his thumb and index finger are resting on a padded finger rest, while holding the end-effector with his bare fingers. In this condition, kinesthetic information is attenuated. d) Close-up of the combined cue condition (KT), in which the participant holds the end-effector with his bare fingers and only his elbow is supported.

MATERIAL AND METHODS

Participants

In Exp.1, 10 participants performed the study, 8 males and 2 females. Three additional participants completed the experiment, but due to technical issues their data sets were not recorded correctly and could not be used. The participants were 34 ± 5 years old (mean \pm standard deviation), and all were right handed. In Exp.2, 19 participants performed the study, 6 males and 13 females. Two additional participants completed the experiment, but their data was not analyzed as their performance never exceeded chance level. The participants were 35 ± 10 years old, and 17 were right handed. All participants gave written informed consent prior to taking part, were naive to the purpose of the experiment, and were compensated for their time. None of them had any history of neurological disorders. All experiments were approved by WIRB, and were carried out in accordance with the relevant guidelines and regulations.

Experimental setup

For both experiments, we used a setup comprised of two 3-DoF haptic devices (Omega 3.0, ForceDimension, customized in a similar way as discussed in [9]), each equipped with two 6-axis force-torque sensors at the end-effector (Nano17, ATI) to allow closed-loop control of the rendered stimuli. The precision of force rendering was 0.05g once the system had reached target force level. Participants held the custom end-effectors of the Omega in a pinch grasp between their thumbs and index fingers. The force-torque sensors were placed directly underneath the aluminum finger plates. The movement and force data from both force feedback devices were recorded throughout the experiment. Three conditions were used, see Fig. 1 for an overview of the setup and conditions. The first was kinesthetic only (K): a uni-sensory condition in which participants wore the custom thimbles to ensure that the majority of the tactile weight information was removed. A variety of 3D printed thimbles with different thumb angles were used to ensure that each participant could comfortably hold the end effector. The thimbles were padded with participant-adjustable foam to ensure a tight fit on all finger sizes. In this way, the thimbles

provided pressure around the fingers, which prevented the skin from stretching and thus removed most of the task-relevant tactile information. Participants rested their elbows on a support, while holding up their forearms and hands. The second was tactile only (T): a uni-sensory condition in which participants rested their elbows and forearms on a support, while resting their thumbs and index fingers on a padded finger rest, such that most of the kinesthetic information was removed. The third was kinesthetic-tactile (KT): a multi-sensory condition in which participants held the device with bare fingers, while their arm posture was the same as in condition K. Throughout the experiment, participants wore headphones playing white noise to cancel any possible auditory cues. They were asked to provide their responses using foot pedals. In Exp.1, they wore custom glasses that prevented them from seeing their hands. In Exp.2, participants wore a head-mounted display (Rift, Oculus VR) for this purpose. Visual information, presented on a screen (Exp.1) or the HMD (Exp.2), was used to guide participants to the center of the workspace. As soon as participants reached the starting position, which was always the same, visual feedback was removed and the trial started.

Protocol

The participants' task was to hold the instrumented end-effectors of the two haptic devices as stationary as possible and to compare the sensation of weight between their two hands. A 2-alternative forced choice (2AFC) task was used,

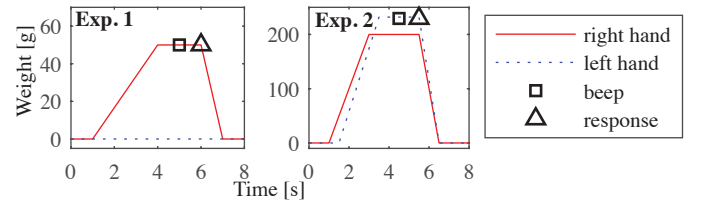


Fig. 2. Typical example of force profiles to illustrate the protocol. One second after both the forces had reached their maximum force level, a beep indicated that participants could provide their answer. Upon answering, the force was ramped down in 1s. a) Exp.1, in which a 3s force ramp was used and only 1 hand was presented with a force. b) Exp.2, in which both hands received a force cue, which was ramped up in 2s in a staggered fashion.

so participants had to choose which side was perceived to be heavier and indicate this using foot pedals. The stimuli comprised only downward forces, and no inertial effects were rendered in response to participants' movements. For an illustration of the protocol, see Fig. 2. Each cue was initiated with a linear increase (3s in Exp.1, 2s in Exp.2). Once the first stimulus reached the stationary force level, the second stimulus was ramped up 0.5 ± 0.05 s (mean \pm standard deviation) after. One second after the second force stimulus had reached its constant level, participants were prompted for a response by a sound. They were instructed to keep their hands as steady as possible and to base their perception on the stationary force level. Both forces remained constant until participants provided a response, after which they were ramped down (1s). By staggering the ramp-up force while keeping the ramp time constant, participants could neither use the ramp time nor directly compare the ramp slope as an indication of the final force magnitude. In Exp.1, a slower ramp was used to eliminate any additional cues about the presence of a stimulus.

In Exp.1, we measured force detection thresholds for the 3 different cue types. The experiment consisted of 3 blocks and took about 1 hour in total. Each block consisted of measuring the threshold of a single cue, by presenting a force cue on one hand only, and asking participants to indicate which hand received a cue. The stimuli were weights of 10, 20, 30, 40, 50, 60, 80, or 100g. The side at which the force was applied was pseudo-randomized. Each stimulus pair was repeated 12 times, resulting in 96 trials per condition.

In Exp.2, we measured supra-threshold precision (JND) of weight perception for the 3 different cue types. The experiment consisted of 9 blocks and took about 3 hours, divided over 3 one-hour sessions. Each block consisted of measuring the perceptual precision of a single cue type. The same type of cue was presented to each hand, and participants were asked to indicate which hand received the heavier cue, at 3 reference weights: 100, 200, and 300g. The comparison stimuli deviated from the reference weight by $\pm 8, 16, 24$, or 32% . The side at which the reference weight was applied was pseudo-randomized. Each stimulus pair was repeated 12 times, resulting in 96 trials per reference weight.

In both experiments, the order of the force cues was randomized and the order of reference and comparison stimulus was counterbalanced. The order of the blocked conditions was counterbalanced between participants. At the start of all experiments, 12 familiarization trials were performed.

Statistical analyses

For all experiments, we calculated the proportion with which the comparison stimulus was chosen as being the heavier stimulus, as a function of the weight of the comparison stimulus. A psychometric function (see Fig. 3 for a typical example) was fitted to the proportion of responses of each participant and condition by using the maximum likelihood procedure provided in the Palamedes toolbox [10]. In Exp.1, the PSE was fitted, while in Exp.2 it was constrained to be at the reference weight. In both experiments, the slope

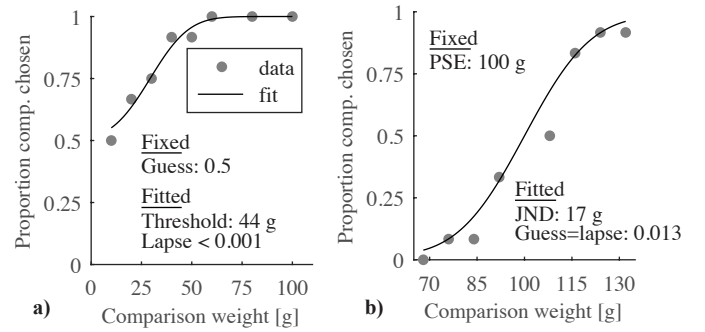


Fig. 3. Example data and fits. a) The detection threshold (Exp.1) is the weight at which the proportion of responses was 0.84 in the fit. b) The JND (Exp.2) is the difference between the weight at which the proportion of responses was 0.84 in the fit and the reference weight.

was fitted as a free parameter, and the lapse rate was fitted in the range $[0, 0.05]$. The guess rate was set to 0.5 in Exp.1, while it was constrained to be the same as the lapse rate in Exp.2. In Exp.1, we calculated the detection threshold by determining the weight at which the proportion of responses was 0.84. In Exp.2, we used the difference between the weight at which the proportion of responses was 0.84 and the reference weight for assessing the JND. To determine the goodness-of-fit of the psychometric curves, the model used to fit the data was compared to a “saturated” model in 1000 simulations. For a more detailed description of this procedure, see Kingdom and Prins [11]. A goodness-of-fit of less than 0.05 was considered to be an outlier, and was removed from the analysis.

For predicting multi-sensory performance using the Optimal Integration and Sensory Capture models, measured uni-sensory data were used. For the Optimal Integration model, predictions of detection thresholds were made using the Pythagorean Theorem [12]:

$$d'_{KT} = \sqrt{d'^2_K + d'^2_T} \quad (1)$$

for which d' -values were calculated from the response proportions using the Palamedes toolbox. For predicting multi-sensory JNDs, the following equation was used [7] (which is equivalent to the optimal Weighted Summation model [8]):

$$\text{JND}_{KT} = \sqrt{\frac{\text{JND}_K^2 \text{JND}_T^2}{\text{JND}_K^2 + \text{JND}_T^2}} \quad (2)$$

Thus, using the Optimal Integration model, the multi-sensory condition is always predicted to have less noise than any of the uni-sensory conditions. For predicting detection thresholds and JNDs using the Sensory Capture model, the best performing uni-sensory conditions were used for each participant and reference weight [8].

Parameteric and Bayesian repeated measures ANOVAs were performed on the DTs and JNDs, to test the effect of condition and reference weight. If the sphericity criterion was not met, Greenhouse-Geisser correction was used. When appropriate, Bonferroni-corrected post-hoc tests, t -tests and

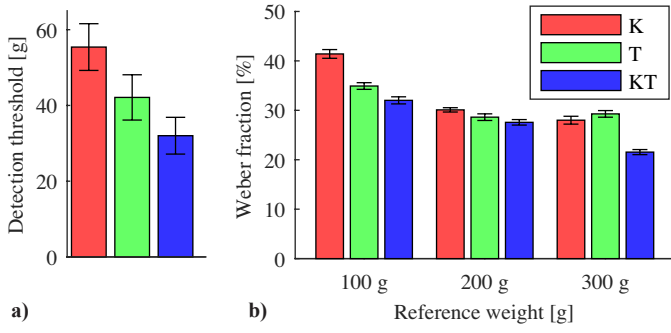


Fig. 4. Detection thresholds and JNDs for conditions K, T, and KT in colored bars, with error bars representing standard error of the mean. a) Detection thresholds for Exp.1. b) Weber fractions for Exp.2. Note that the kinesthetic condition does not perform very well for light weights.

Wilcoxon signed-rank tests were performed. All t -test results employed two-tailed probabilities. For ANOVAs and t -tests, an α level of 0.05 was used. For Bayesian statistics, BF_{01} were used, which represents the degree to which the data supports a hypothesis (i.e., the presence of a main effect) [13]. A $BF_{01} < 0.067$ ($BF_{01} > 3$) is considered strong evidence that the main effect is present (absent).

Movement data were analyzed by calculating the difference between the lowest and highest vertical position of the end effector on each trial. Force data were analyzed by calculating the average sum of the inward force exerted on the index and thumb force sensor, thus representing the average squeeze force exerted during the trials. To assess the effect of weight on movement and force data, linear regressions with intercept and slope were calculated for each participant, condition, and experiment.

II. RESULTS

In Exp.1, we measured weight detection thresholds for conditions K (kinesthetic cues only), T (tactile cues only), and KT (both kinesthetic and tactile cues present), as shown in Fig. 4a. Two of the 30 psychometric curves were discarded for not meeting the goodness-of-fit criterion. The resulting thresholds were 55 ± 6 g for K, 42 ± 6 g for T, and 32 ± 5 g for KT (mean \pm standard error). A one-way repeated measures ANOVA on the measured thresholds showed a significant effect of condition, with $F_{2,14} = 13$, $p < 0.001$, $\eta_p^2 = 0.65$, $BF_{01} = 0.021$. Bonferroni-corrected posthoc tests show that the KT condition differed significantly from the K condition ($t_8 = 4.7$, $p = 0.007$), whereas the other conditions did not differ significantly from each other (KT and T: $t_7 = 2.7$, $p = 0.083$; K and T: $t_8 = 2.5$, $p = 0.11$). The threshold for KT predicted from modeling was 31 ± 5 g for Optimal Integration and 43 ± 5 g for K for Sensory Capture, as shown in 5. Two paired samples t -tests, with Bonferroni-corrected α s of 0.025, showed that KT measurements did not differ from predictions of the Optimal Integration model ($t_7 = -0.37$, $p = 0.72$, $BF_{01} = 2.8$), while they did differ from the Sensory Capture ones ($t_8 = 3.1$, $p = 0.015$, $BF_{01} = 0.21$).

In Exp.2, we measured discrimination thresholds for supra-threshold stimuli in conditions K, T, and KT, by asking

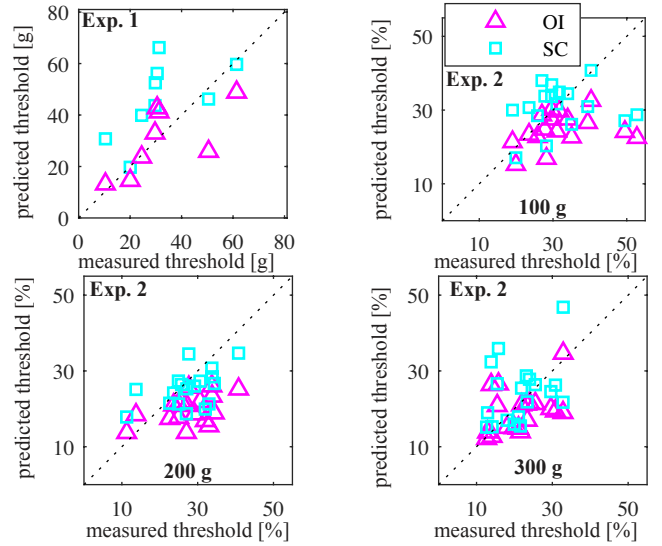


Fig. 5. Correlations between measured multi-sensory thresholds and predictions from the Optimal Integration model (magenta triangles) and Sensory Capture model (cyan squares). For Exp.1, The Optimal Integration model seems to capture measured data well, while participants performed better than predictions of the Sensory Capture model. For Exp.2, the measured thresholds are worse (i.e., higher) than the ones predicted from Optimal Integration for 100 and 200g, while the Sensory Capture model performs better at modeling data for these weights.

participants which hand received the heavier cue. Both hands received the same type of cue, and a range of test stimuli were compared to reference stimuli of 100, 200, and 300g. The JNDs for the three reference weights and the three conditions are shown in Fig. 4b, with five of the 171 fits being discarded because of not meeting the goodness-of-fit criterion. A two-way repeated measures ANOVA on the measured JNDs with the within-subjects factors ‘condition’ and ‘reference weight’ showed a significant effect of both weight ($F_{2,26} = 13$, $p < 0.001$, $\eta_p^2 = 0.51$, $BF_{01} < 0.0067$) and condition ($F_{2,26} = 4.5$, $p = 0.021$, $\eta_p^2 = 0.26$, $BF_{01} = 0.048$). The interaction effect was significant too ($F_{4,52} = 2.7$, $p = 0.040$, $\eta_p^2 = 0.17$, $BF_{12} = 1.2$). Bonferroni-corrected posthoc testing of the ‘weight’ and ‘condition’ factors showed that 100g differs from 200g and 300g (100 to 200: $t = 3.4$, $p = 0.005$; 100 to 300: $t = 4.8$, $p < 0.001$), while 200g and 300g do not differ significantly from each other ($t = 2.0$, $p = 0.15$). Conditions K and KT differ significantly ($t = 3.2$, $p = 0.008$), while the others do not (K and T: $t = 0.94$, $p > 0.99$; KT and T: $t = 2.2$, $p = 0.099$). To test the Optimal Integration and Sensory Capture models (see Fig. 5), two separate repeated measures ANOVAs were performed, in which the measured and predicted KT thresholds were compared, while using weight as the second ‘within-subject’ factor. Bonferroni-correction was used to adjust α to 0.025. The measured thresholds differed significantly from the ones predicted from Optimal Integration ($F_{1,13} = 27$, $p < 0.001$, $\eta_p^2 = 0.67$, $BF_{01} < 0.0067$), while they did not differ significantly from predictions from the Sensory Capture model ($F_{1,15} = 0.028$, $p = 0.87$, $\eta_p^2 = 0.002$, $BF_{01} = 4.6$).

Both the grip force data (Fig. 6a) and the movement data

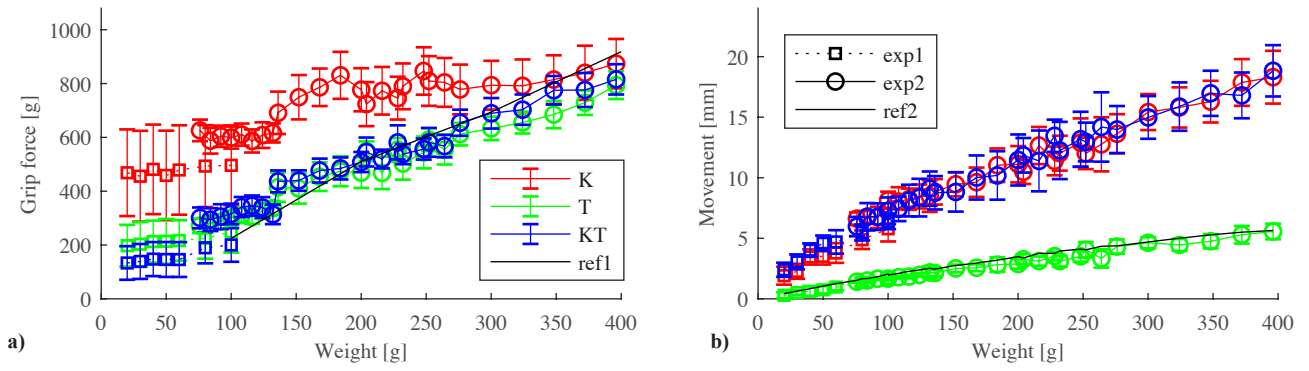


Fig. 6. Median force and position data across all experiments (different line styles and markers) and conditions (different colors), with error bars indicating ± 1 standard error. a) Grip force data, representing the mean squeeze force between thumb and index finger per trial. For smaller weights, participants exerted the largest grip forces in condition K, which was probably caused by wearing the thimbles. Data from literature (ref1 in solid black [14]) indicate that the grip force modulation in conditions T and KT resembles that observed for real objects with comparable material properties. b) Movement data, representing the downward movement per trial. For condition T, expected vertical movements based on finger impedance measurements from literature (ref2 in solid black [15]) match the measured movements closely. Thus, very little movement beyond that caused by skin stretch was present in that condition.

(Fig. 6b) show a gradual increase with presented weight, which is confirmed by their slopes being significantly greater than 0 in a Wilcoxon signed-rank test ($W_{83} = 3570, p < 0.001$, $BF_{01} < 0.067$ for force, $W_{83} = 3570, p < 0.001$, $BF_{01} < 0.067$ for movement). To provide a reference for the amount of hand movement present, we selected data from literature from users statically holding a silk-padded object [14] (required grip force for holding a hard object depends on its material properties, and our end effectors had a smooth aluminum surface). The comparison data, plotted in Fig. 6a, suggest that grip forces for conditions without thimbles are in the range expected from literature, while they are higher for the lighter weights in condition K. To compare movements measured in condition T to skin stretch data from literature, we used finger pad impedance data from Pataky et al. [15]. The authors show that finger pad stiffness depends on grip force, so we calculated expected stiffnesses and resulting predicted movements from measured grip forces, which align well with measured movements in condition T (Fig. 6b).

DISCUSSION

We investigated the contribution of skin stretch and kinesthetic cues to the perception of static weight up to 300g. Our experiments provide device-independent measures of detection thresholds and Just Noticeable Differences for both types of information alone, and for their combination. Combining cues led to better weight detection thresholds than presenting uni-sensory cues did. Weber fractions ranged from 22 to 44% for supra-threshold stimuli. Kinesthetic information was generally less reliable for lighter weights, whereas for heavier weights up to 300g the two cues were roughly equally reliable. These results can be used as guidelines for designing skin-stretch devices for presenting weight to users.

To assess the validity of our experimental setup, we investigate the degree to which our setup was able to present tactile and kinesthetic weight cues, separately and in conjunction. We used a force onset ramp that was much slower than lifting an object in a natural setting. Moreover, participants were required to maintain a static posture, while

one of the most salient cues for weight perception is inertia, which is why the Exploratory Procedure for judging weight is moving an object up and down [16]. We restricted our experiment to static weight with a slow force increase for two reasons. Firstly, we wanted to be able to distinguish between the perception of static weight and of inertia, since they likely both influence the final percept of weight. Secondly, limiting kinesthetic stimulation is even harder in a dynamic task, since that would require a grounded finger rest that would move along with the participant's movements. The slow force increase was helpful to ensure participants kept their hands as static as possible in the kinesthetic condition.

The question now remains to which degree the static weight presentation might be unnatural, which could have affected the experience and thus the external validity of the results. Although we cannot be certain of the participants' subjective experience, we can look at signatures that imply 'normal' behaviour. Such a signature is the tight coupling between lifting force and grip force, which is present in normal lifting of objects, and also in static holding of weights [14], [17]. Our grip force data (Fig. 6a) highlights an increase with presented weight, and are comparable to grip force data from literature [14]. Grip forces were higher in the K condition, probably due to the thimbles, but we still see the modulation of grip force with presented weight, which all points to participants showing natural behaviour.

Furthermore, we can assess how well we separated kinesthetic from tactile cues. For the K condition, the custom thimbles with participant-specific padding were tight-fitting, so the skin was unable to move and pressure was exerted around the finger constantly, which was unrelated to the presented force. For the T condition, we can compare our movement data to literature. Fig. 6b shows a good agreement between measured movements in our T condition and predictions from literature [15]. These data from literature represent impedance measurements when constraining the finger up to the Proximal Interphalangeal joint, so very little movement beyond skin stretch was present when stretching the fingertip

tangentially. This suggests that the most important cue in our T condition was indeed skin stretch.

The thresholds in our study are worse than those reported in literature. In Exp.1, the DT in our KT condition (which is closest to ‘natural’ weight presentation) was 32g, while literature reports thresholds as low as 10g [18], [19]. In Exp.2, our Weber fractions for the KT condition were 20-30%, while literature reports a range between ~9-13% for unconstrained lifting of real objects, which is ~1.5 times worse for static perception of real objects placed in the hands [1]. Giachritsis et al. [6] reports JNDs of 15-25% for active lifting of real objects. These differences are probably due to the absence of inertial cues in our experiment, which resembles a very slow placement of a real object on a stationary hand. Thus, our result show that even in a static situation, the force ramp caused by placing a weight on a user’s hand is an important cue for weight perception.

Research in experimental settings similar to ours [4] suggests that tactile information is more precise than kinesthetic for smaller weights, while for weights of 300g and heavier, tactile sensitivity is greatly reduced and kinesthetic information becomes the more reliable source. We observe similar trends in our data, but we do not see the massive deterioration of tactile sensitivity at higher weights. The authors attribute the deterioration to saturation of the tactile stimulus, meaning they believed they approached the limit of skin stretch sensation for the finger pad. However, their skin stretch device did not deliver force-controlled stimuli, so we cannot tell if their tactile 300g cue reflected a physical 300g weight cue. Additionally, the finger pad is unlikely to approach its stretch limit at 300g, as work on the shear properties of the finger pad shows increasing displacements with increasing force up to 5mm at 5N (510g) [15], which agrees with the movements in our T condition being ~4mm for 400g. Thus, the tactile sensation of the finger pad not being fully saturated at 300g is in agreement with the material properties of the finger pad, and the results in Minamizawa et al. could be due to device limitations. This slight discrepancy between literature and our results actually indicates the importance of obtaining device-independent measures of perceptual performance.

Our measured detection thresholds match predictions from the Optimal Integration model, whereas results of JNDs are more in line with predictions from the Sensory Capture model. It seems unlikely that participants change the way they integrate information when the weight range changes. Our results cannot conclusively resolve this paradox, but an alternative hypothesis is that our sensory inputs were corrupted by correlated noise, which is known to reduce the benefits of Optimal Integration [20]. Given that both types of information were provided by the same device, rendering noise would be present in both cues. Increasing the rendered force leads to more instability in haptic systems [21], and thus correlated noise is likely to only have a noticeable influence for weights well above detection threshold. Thus, we propose that Optimal Integration of skin stretch and kinesthetic information was present in both experiments, but the benefit of integration was reduced for heavier supra-

threshold stimuli.

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