Squeezy-Feely: Investigating Lateral Thumb-Index Pinching as an Input Modality

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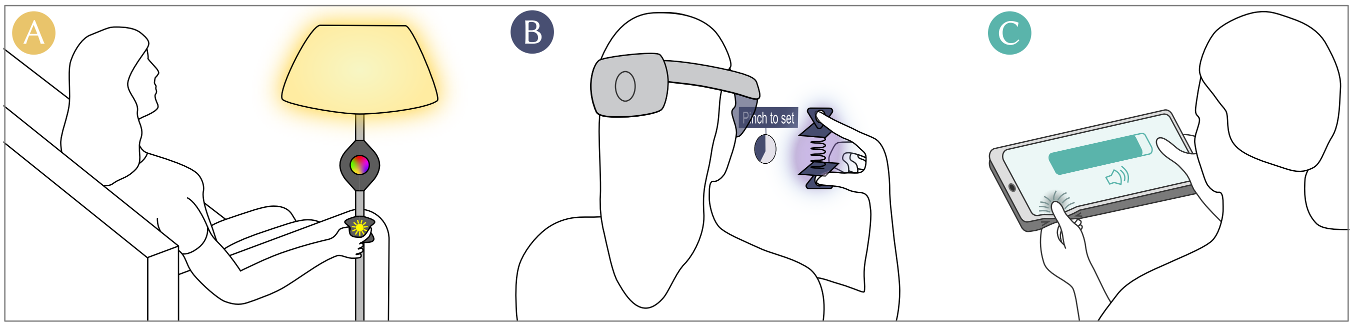

Figure 1: With Squeezy-Feely, we investigate the potential of lateral thumb-index pinching as an input modality, applicable in many scenarios ranging from ubiquitous appliances (A) and mid-air Mixed Reality (B) to deformable surfaces (C).

ABSTRACT

From zooming on smartphones and mid-air gestures to deformable user interfaces, thumb-index pinching grips are used in many interaction techniques. However, there is still a lack of systematic understanding of how the accuracy and efficiency of such grips are affected by various factors such as counterforce, grip span, and grip direction. Therefore, in this paper, we contribute an evaluation (N = 18) of thumb-index pinching performance in a visual targeting task using scales up to 75 items. As part of our findings, we conclude that the pinching interaction between the thumb and index finger is a promising modality also for one-dimensional input on higher scales. Furthermore, we discuss and outline implications for future user interfaces that benefit from pinching as an additional and complementary interaction modality.

CCS CONCEPTS

• **Human-centered computing** → **Human computer interaction (HCI)**; **User studies**.

KEYWORDS

Input; Pinching; Deformation; Mixed Reality; Thumb-to-finger; User Studies

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1 INTRODUCTION

From squeezing pliers to holding a key: the human hand has evolved a considerable dexterity for powerful and precise grips. These range from power grips, most suitable for achieving a firm bond between hand and object, to precision grips, evolved to allow for fine-grained and complex manipulations and deformations of objects [17]. Such sophistication offers vast potential for use in interactive systems (see Figure 1), in particular as it combines the complexity of motion with proprioceptive and in many cases also tactile feedback.

Research has started to explore grips, ranging from thumb-to-finger [28, 59] or mid-air [6, 71] interactions to the deformation of objects [52, 58, 69] or interactive surfaces [51, 61]. In particular, the *pinching* grip between the thumb and index finger has become particularly widespread, ranging from the pinch-to-zoom gestures on touch-enabled devices [35, 74] to the pinch-to-tap mid-air gesture employed in Mixed Reality [47, 70]. While pinching is a promising modality, research still lacks a fundamental understanding of the key factors for human performance for varying spans and directions of grip, and objects with different rigidity, exerting a counterforce.

Therefore, this paper contributes an investigation of the human capabilities for lateral pinching between the thumb and side of the pulp of the index finger, one of the most commonly used precision grips [16]. The contributions of this paper are two-fold: First, we contribute the results of a controlled experiment with 18 participants, which examines human capabilities to control the distance between the thumb and index finger for varying counterforces, initial grip spans, and direction of grip on different scales in a visual target acquisition and selection task. Second, based on the results of the experiment, we provide implications for designing future pinchable user interfaces that utilize lateral pinching as a complementary interaction modality.

2 RELATED WORK

This paper is situated in the areas of hand-grip performance, deformation interaction, and thumb-to-finger pinching interaction.

2.1 Hand-Grip Performance

The hand can perform various grips that have been classified by research in different taxonomies [17, 41]. According to Feix et al. [17], grips can be grouped into power, intermediate, and precision grips and differ whether the thumb is abducted or adducted. Belonging to one of the most commonly used grips [16], we focus on the *lateral pinch*, a grip performed with the thumb and the lateral side of the index finger (e.g. holding a key). In Feix' taxonomy, this grip is categorized as intermediate in terms of force [17] and is most suited for lightweight objects (median mass 150 g [16]) with the most suited rigidity between rigid (withstands full grip force) and floppy (deforms heavily).

Moreover, research in physiology has investigated the biomechanical properties of hand grips, such as the maximum voluntary force [60] and the maximal grip span [56] in detail:

First, the *maximal voluntary force* is an important measure not only in the context of this paper but also in physiotherapy and medicine, often consulted to evaluate the rehabilitation of subjects. It depends on the specific grip [15] and is also influenced by the surface texture, significantly decreasing for low-friction paper compared to high-friction rubber, as shown by Na Jin Seo [55]. Interestingly, Stegink Jansen et al. have investigated whether the maximum voluntary strength performed for the lateral pinch is influenced by the posture of the forearm [60]. While they did not conclude on a definitive effect, they recommend varying the forearm position. In consequence, we vary the direction in which the pinch is performed to study whether it is an influencing factor for pinching accuracy, efficiency, or user experience.

Second, the *maximal grip span* is an important measure and is defined as the maximum distance between the distal phalanxes of the thumb and index finger. Obviously, this measure depends on the individual hand size, but its mean for adults, according to de La Fuente and Bix [12], is 104.17 mm ($\sigma = 13.90$ mm).

Third, grasping performance has been studied, for instance, by Martin-Brevet et al. [36]. They investigate grasping and unloading forces exerted on the faces of a parallelepiped object to confirm that an uninstrumented object is suited for complex motion behavior.

While previous works consider the force and grip span, they do not cover how precise humans can adjust their span on-demand for varying counterforce and span, and direction of the grip.

2.2 Deformation Interaction

Research has started to explore deformations as an engaging and powerful input modality: One stream investigates deformation input as a supplement to touch input on interactive surfaces and objects. This ranges from applying pressure at specific points [18, 29, 34, 38, 50, 51] to various other deformations, such as stretching [22, 62, 81], squeezing [25, 69, 72], pinching [65], or variation of the entire shape of an object [30, 80]. More complex deformations of interactive surfaces utilize optical tracking systems [31, 32, 49] or depth cameras [61, 64] in the environment to sense deformations such as folding [31, 49, 64], rolling [32], or bending [33, 61].

Moreover, flexible textiles [45, 46] or interactive objects can be deformed for input by embedding sensors [38, 44, 63, 67, 69, 72] or using optical sensing [19, 26, 48, 61, 62, 73]. Different approaches also employ capacitive [42], resistive [3, 20, 58], or piezoelectric [50, 51] sensing. Sensing of complex deformations is often achieved using tape [5, 77], plastic [9], silicone [57, 58, 82], printed materials [52, 68], or foils [50, 51].

This paper, in contrast, specifically focuses on pinching and aims to provide implications that can guide the exploration of pinching as an additional deformation interaction.

2.3 Thumb-to-Finger & Pinching Interaction

Research has started to investigate pinch gestures several decades ago, for instance, to scale objects [35], to support panning [74], and to move objects [75, 76]. Especially on interactive surfaces, they have gained a lot of attention due to the popularity of the iPhone, one of the firsts smartphones utilizing the pinch-to-zoom concept. Since then, research has investigated pinching of synthetic skin interfaces [65], for navigation [24], with two hands [40], on two-sided surfaces [79], and of textiles [23]. Further, Avery et al. [2] propose techniques to improve pinch-to-zoom to reduce clutching and panning. In the context of interactive surfaces, research has also started to study the performance of pinch gestures on multi-touch surfaces [27, 66]. While Tran et al. [66] compare varying types of gestures, Hoggan et al. [27] further investigate between-finger distances, as well as different angles and positions on the 2D surface.

Another important domain of pinching interactions are mid-air gestures. In this context, pinching has been explored, for instance, for freehand interfaces [6, 71], using a handheld device [54], as a selection method [47, 70], and to avoid the Midas touch problem [8].

In addition, research has further explored the human palm for body-centric interaction [13, 37] and thumb-to-finger micro gestures [28, 59] that utilize the dexterity of finger motions. While Choi et al. [10] contribute a wearable haptic interface that simulates weight and grasping that can actively generate a counterforce between thumb and index finger, they do not investigate the human capabilities for linear input while performing a lateral pinch.

In contrast to previous works that focus on a specific domain, this paper aims at a more generalized investigation on pinching performance that provides insights that apply to a wide variety of contexts, such as touch surfaces and mid-air gestures.

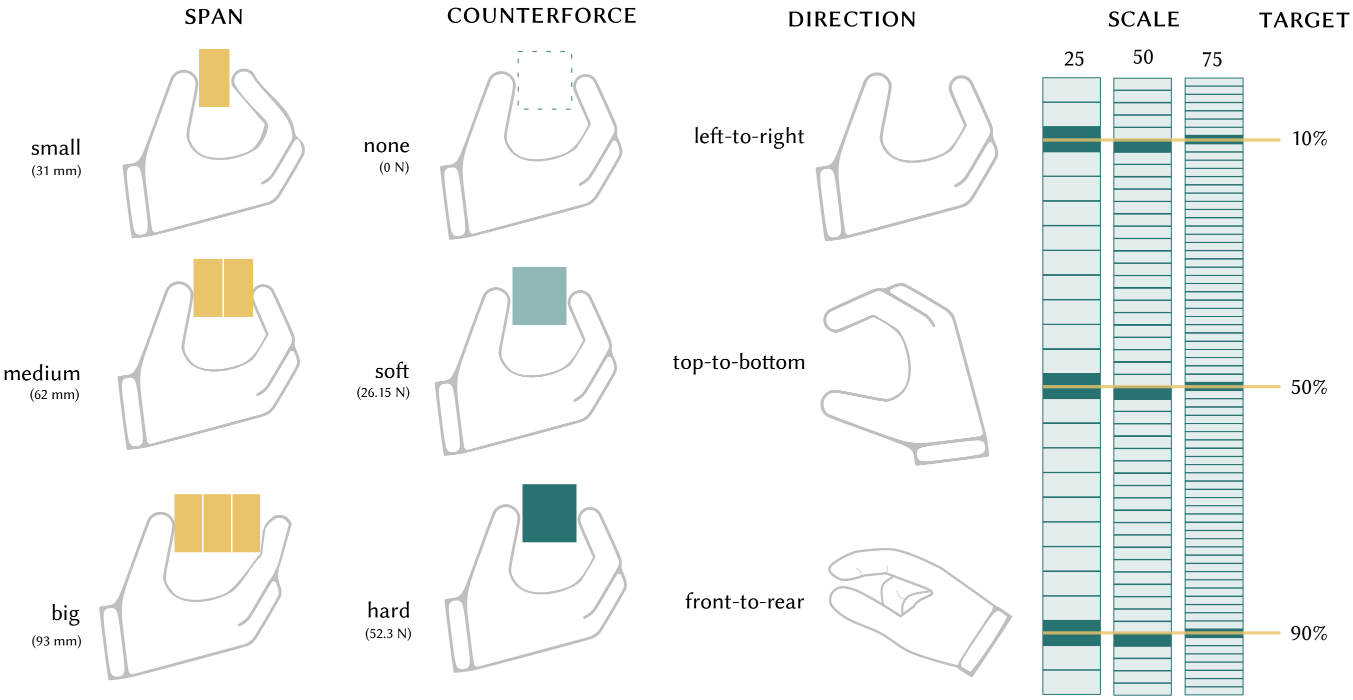

Figure 2: The five independent variables varied in the controlled experiment: the initial SPAN of the object between the thumb and index finger, its COUNTERFORCE, the user's DIRECTION, the granularity of the SCALE and the relative TARGET position on the respective scale.

3 METHODOLOGY

We performed a controlled experiment based on the mechanics of finger movement that investigates the accuracy, efficiency, and user experience of lateral pinching as an input modality for pinchable user interfaces. We defined the following research questions:

RQ1 How does the *span* and *counterforce* of the object in hand and the *direction* of the holding hand affect the accuracy, efficiency, and user experience of visual targeting?

RQ2 How does the granularity of the presented *scale* and the location of the *target* influence the accuracy, efficiency, and user experience?

RQ3 How does the *span*, *counterforce*, *direction*, and *scale* influence the human ability to steadily hold a certain level of pinching?

3.1 Task

Analogous to Fruchard et al. [18], we employ a visual target acquisition and selection task as follows: Participants interacted with the system by pinching an object between their thumb and index finger. That is, they reduce the distance between their thumb and the index finger (and thus increase the force applied) to increase the input value. We visualized this distance on a nearby display as a highlighted cell on a linear scale of cells (see Figure 2).

In more detail, participants start with a pre-set maximal distance of their fingers, implied by the size of the object in hand. Their first task was to vary their finger's distance to move the highlighted cell to a target cell, displayed by the system. They confirm the beginning and the end of each trial with a clicker in their non-dominant hand. After confirming completion, their second task was to steadily hold the final posture for three seconds without additional visual feedback.

3.2 Design

3.2.1 Independent Variables. To gain a comprehensive understanding of the potential factors that influence the accuracy, efficiency, and user experience of pinchable user interfaces, we varied the following five independent variables, as illustrated in Figure 2:

SPAN The initial grip span influences the physical distance on which a pinching interaction is performed. It is, thus, a promising factor to investigate. We grounded our levels in the mechanics of the human hand: As the mean grip span between the thumb and the index finger's distal phalanx of adults is 104.17 mm (σ = 13.90 mm) [12], we vary our levels of SPAN as equidistant percentages of the mean grip span: BIG (90% or 93 mm), MEDIUM (60% or 62 mm), and SMALL (30% or 31 mm). We opted for 90% instead of 100% of the maximal grip span to also accommodate participants with smaller grip spans and avoid hyperextension. Based on pretests, we decided on a minimum of 30% (i.e. only 31 mm) to provide a workable pinch distance and chose 60% to obtain an equidistant third level.

COUNTERFORCE We assume that the counterforce, i.e. the repelling force exerted by an object or other means, is a relevant factor for lateral pinching. Therefore, we vary the counterforce

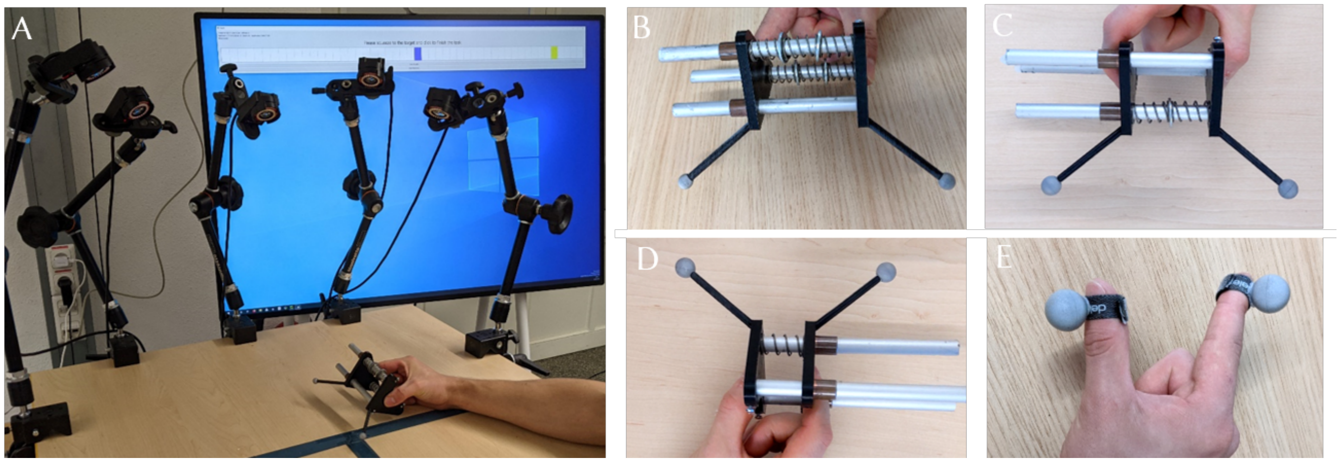

Figure 3: Using an optical tracking system (A), we track the variation in distance as a measure for the applied force with a spring-based mechanism: We vary the counterforce and span by adding multiple springs only in series, only in parallel or both (B, C, D). In case of no counterforce, the distance is measured at the fingertips (E).

required to pinch in our experiment. We derive our levels based on the mean maximum voluntary force for lateral pinching of 87.16 N (mean of men and women, right hand, $\sigma = 19.3\,\mathrm{N}$), as reported by Stegink Jansen et al. [60]. We vary the counterforce as equidistant percentages of this force: hard (60% or 52.3 N), soft (30% or 26.15 N), and none (0% or 0 N). As the maximum voluntary force is the absolute limit and is not intended for sustained repetitions, we conducted a pre-test where we asked to maximize force to a still comfortable limit. In consequence, we chose a maximum value of 60% of the maximum voluntary force to avoid exhausting participants during the study We consider this to yield more feasible results than using maximum force values. In addition, we added a 0% level, i.e. pinching in air, as it promises to give insights into the performance of commonly used mid-air pinch gestures, one of the most widely used types of pinching input.

direction Stegink Jansen et al. [60] conclude that the forearm position should be varied to measure strength for lateral pinching. As a consequence, we additionally vary the direction of the grip (relative to the user) with the following levels: left-to-right (i.e. thumb left, index finger right for right-handed participants, vice versa for left-handed), top-to-bottom (i.e. thumb bottom, index finger top), front-to-rear (i.e. thumb front, index finger back).

scale We varied the subdivision of the interaction scale between 25, 50, and 75 cells (named 25-scale, 50-scale, and 75-scale). We selected these levels based on informal pilot testing because they promised a good variance of easier and more difficult scales for participants, allowing us to investigate human performance on a broader range.

target Analogous to previous research (cf. [18]), we vary different equidistant levels of target locations (10%, 50%, and 90%) that define the corresponding cell of the respective scale the participant has to hit. In case of exactly hitting the boundary between cells of a scale, we consistently chose the cell to the right of the target location.

We varied all five independent variables in a repeated measures design, resulting in a total of $3\times3\times3\times3\times3 = 243$ conditions which equals the individual trials per participant. We counterbalanced the order of counterforce × span in a Balanced Latin Square ($3\times3 = 9$ levels, repeated twice for 18 participants) to prevent learning effects. We excluded the other factors from the Balanced Latin square to avoid constantly changing the object (as the combination of counterforce × span forms one specific object in hand) and to query one questionnaire per object. To avoid frequent changes of the grip direction that could confuse participants, we then split the randomization of direction, scale, and target as follows: For each instance of counterforce × span, we randomized the order of direction. We then randomized the order of scale × target ($3 \times 3 = 9$) for each of the three levels of direction individually to further reduce learning effects.

3.2.2 Dependent Variables. We recorded the following dependent variables for each trial:

crossings The sum of completely overshooting (from below) and undershooting (from above) the target cell.
task completion time The time between click to display the task and click to complete.
accuracy Whether the correct cell was selected when clicking.
jitter The range of variation in grip span while holding as steady as possible for three seconds after confirming completion.

To assess the user experience, the participants also answered a short post-block questionnaire after each combination of counterforce, span, and direction ($3 \times 3 \times 3 = 27$ times per participant), consisting of the following statements (on a 5-point Likert scale):

convenience Interacting with the system felt convenient.
physical demand Interacting with the system was physically demanding.

After participants finished all trials, they filled out a post-experiment questionnaire that consisted of the following statements:

counterforce rank Ranking of counterforce (best to worst).
span rank Ranking of span (best to worst).
qualitative feedback Any additional remarks.

3.3 Study Setup & Apparatus

As we aim to provide a reliable estimate for future pinchable user interfaces, we decided to track the distance between fingers with an accurate and reliable optical tracking system (OptiTrack with 200 fps) instead of force sensors. In our small measurement range, this system has errors of less than 0.1 mm [1, 43]. This is especially important as the cell width in the extreme case (highest scale combined with the smallest span) is only 0.41 mm (= $1/75 * 31\ mm$).

We mounted five cameras at a table in a narrow spherical pattern and equipped the participant and objects to pinch with retroreflective spherical markers (see Figure 3A). In the cases where the COUNTERFORCE was NONE, we tightly attached the markers to the participant's fingertips using Velcro tape (see Figure 3E). Since the span was varied in this case too, participants first held a piece of cardboard of the respective size at the beginning to define their initial grip span. In all other conditions, the markers were rigidly connected to the object through 3D-printed extensions and the object itself defined the initial grip span. We decided against attaching the markers in these conditions to the fingers because the object in hand might occlude markers at the fingers for optical tracking.

The task and instructions were displayed on a separate monitor. Participants started and confirmed each trial with a Bluetooth clicker. Before changing DIRECTION, they answered the questionnaire on a separate tablet next to the interaction area.

3.3.1 Pinch Mechanism. We ensured that the required force to fully compress the object (i.e. its COUNTERFORCE) is equal throughout varying SPAN. To that end, we developed a spring-based pinchable mechanism (see Figure 3B-D): It consists of two triangular plates (edge length 7 cm) that have a finger-shaped indentation to achieve a uniform compression point across all participants. The lower plate is firmly connected to three guide rods (Ø = 10 mm). The upper plate can move freely and smoothly along the guide rods with the help of oiled metal sleeves.

To vary the COUNTERFORCE and SPAN independently, varying numbers of the same linear spring (spring constant 1.12 N/mm, length 30 mm, compressible length 23.25 mm, inner diameter 11.3 mm, 1.39 g) are placed around one or two guide rods as follows:

(1) Using only a single spring of length 30 mm (plus 1 mm for the triangular plates), as depicted in Figure 3D, we create the combination SPAN<SMALL> (31 mm) and COUNTERFORCE<SOFT> (26.15 N) because the force required to compress a single spring over its compressible length (23.25 mm) is equal to 26.15 N (= $23.25\ mm * 1.12\ N/mm$).
(2) Using two springs in parallel, each at one guide rod, we achieve the combination SPAN<SMALL> (31 mm) and HARD (52.3 N) because two springs double the required force to 52.3 N (= $23.25\ mm * (1.12 + 1.12)\ N/mm$) as the spring constants k add up by $k + k$.
(3) Using two springs in series on a single guide rod (see Figure 3C), we increase the SPAN to the MEDIUM level. That is, the length is doubled to 60 mm (plus 1 mm for the triangular plates and 1 mm for a separation disk between springs). At the same time, the force required to fully compress both strings remains the same as the same spring constants k add up by $(1/k + 1/k)^{-1} = k/2$ but the length is doubled (i.e. $2 * 23.25\ mm * 1.12/2\ N/mm$), effectively canceling out the doubling in length with half of the spring constant. This results in the same force required to fully compress the larger object than for the smaller object, and, thus, only varies the span of the object but not its counterforce.

Following this scheme, varying levels of COUNTERFORCE and SPAN are created by combining springs in parallel (varies the force) and series (varies the span). For instance, the most complex HARD and BIG object (see Figure 3B) consists of six springs: three springs in a row (tripling length, but splitting force into thirds) at each of the two guide rods, which are parallel to each other. In total, this mechanism weights approx. 130 g (well below the median mass of 150 g, suited for lateral pinch as reported by Feix et al. [16]).

3.4 Procedure

After welcoming the participants, we introduced them to the experiment, asked them to fill out a consent form, and name their dominant hand. To avoid learning effects, we then asked the participants to freely explore the system by pinching one of the study objects with their dominant hand while watching the task visualization on the screen. Participants performed the study standing at a counter on which the elbow had to be placed. The experimenter ensured that the remaining fingers were adducted (an unconstrained posture may confound the results due to varying force [60]).

After the exploration phase, we started the system and gave the participant the first object (i.e. the first combination of COUNTERFORCE × SPAN) to pinch. Participants then started each trial by clicking and following the instructions displayed on the screen. After the click, the system highlighted the target on the screen. The participants varied their finger's distance according to the task and confirmed using the clicker in their non-dominant hand. After confirmation, the system started a countdown for three seconds and informed the participant to hold their hand as still as possible. After completing the countdown, the system told the participant to release the force to the start position before they were able to start the next trial. Once ready again, the participants started the next task using the clicker. Before switching to a different DIRECTION, participants filled out the questionnaire. After all trials, participants filled out the final and a demographics questionnaire.

We instructed the participants to focus on accuracy instead of the speed. If a target was impossible to reach, participants were instructed to try as best as they could and confirm. Participants were free to have a break between trials. Each experiment took on average 84 minutes ($\sigma = 15$ minutes). We conducted the experiment in a room of our institute's building and complied with all relevant hygiene and infection control guidelines.

3.5 Participants

We recruited 18 participants (11 male, 7 female, 0 identified as gender variant/non-conforming), aged between 21 and 33 ($\mu =$

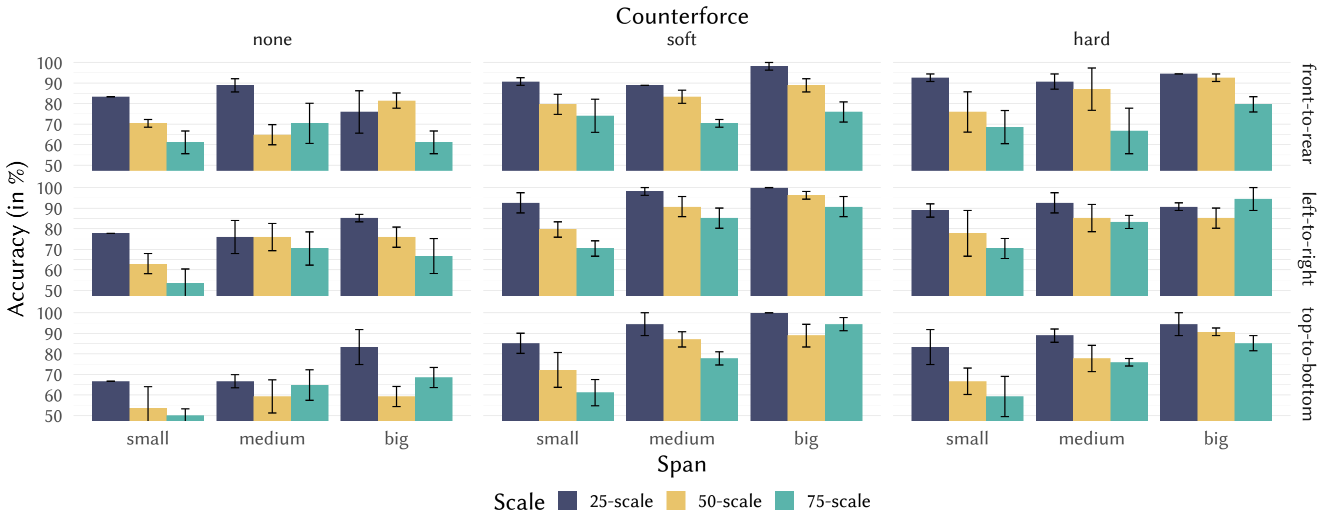

Figure 4: The accuracy per SCALE and SPAN, grouped by column-wise COUNTERFORCE and row-wise DIRECTION. Error bars show the standard error.

25.44, σ = 3.1). 16 of the participants reported being right-handed and 2 left-handed. All participants voluntarily took part in the study.

3.6 Analysis

Unless indicated otherwise, we analyzed the recorded data using five-way repeated-measures (RM) ANOVAs with the factors SPAN, COUNTERFORCE, DIRECTION, SCALE, and TARGET as the factors to uncover significant effects. We tested the data for normality using Shapiro-Wilk's test without any significant deviations. When the RM ANOVA indicated significant results, we used Bonferroni corrected pairwise t-tests for post-hoc analysis. We also report the generalized eta-squared η_G^2 as an estimate of the effect size and classify it based on Cohen's suggestions as small (> .0099), medium (> .0588), or large (> .1379) [11] as proposed by Bakeman [4]. Further, as an estimate of the mean response of the individual factors, we report the Estimated Marginal Means with 95% confidence intervals as proposed by Searle et al. [53] (denoted as μ_E in the following). For the analysis of the Likert questionnaires, we performed an Aligned Rank Transformation as proposed by Elkin et al. [14] and Wobbrock et al. [78].

4 RESULTS

In the following section, we report our results as described in the previous section.

4.1 Accuracy

As an accuracy measure, we recorded a trial as *correct* when the participant selected the target cell when confirming completion. To predict binomial *correct*, we employ a logistic mixed model (estimated with ML and BOBYQA optimizer) with the fixed effects SPAN, COUNTERFORCE, SCALE, and DIRECTION. We excluded TARGET as modeling it as a fixed factor decreased the model performance (AICX vs. AIC with target), implying a neglectable influence on the performance. The model included the participant as a random effect. The model's total explanatory power is substantial (cond. R^2 = 0.27) and the part related to the fixed effects alone (marginal R^2) is 0.17. We compute the 95% confidence intervals (CIs) and p-values using the Wald approximation. We report the semi-partial (marginal) R_{sp}^2 (with CI) for each fixed effect using the approach proposed by Nakagawa and Schielzeth [39], because it characterizes the variance that is explained by each fixed effect after adjusting for the other predictors in the model.

As shown in Figure 4, we observed accuracies ranging from 50% (σ = 5.56%) for <SMALL, NONE, TOP-TO-BOTTOM, 75-SCALE> to 100% (σ = 0%) for <BIG, SOFT, TOP-TO-BOTTOM, 25-SCALE> and also for <BIG, SOFT, LEFT-TO-RIGHT, 25-SCALE>. This indicates that certain combinations of factors have the potential for very high accuracy. In the following, we discuss the effect of factors and interactions.

DIRECTION. The analysis showed a significant ($\chi^2(2)$ = 18.72, p < .001, R_{sp}^2 = 0.002 [0.001, 0.006]) main effect of DIRECTION. Post-hoc tests confirmed a significant (p<.001) difference between LEFT-TO-RIGHT (μ_E = 86.5% [82.6%, 89.6%]) and TOP-TO-BOTTOM (μ_E = 81% [76.1%, 85.1%]).

COUNTERFORCE. The analysis showed a significant ($\chi^2(2)$ = 43.54, p < .001, R_{sp}^2 = 0.024 [0.016, 0.034]) main effect of COUNTERFORCE. Post-hoc tests confirmed significant (both p<.001) differences between NONE (μ_E = 71.7% [64.6%, 78%]) and both SOFT (μ_E = 89.9% [86.2%, 92.8%]) and HARD (μ_E = 86.3% [81.7%, 89.9%]).

SCALE. The analysis showed a significant ($\chi^2(2)$ = 119.3, p < .001, R_{sp}^2 = 0.02 [0.013, 0.029]) main effect of SCALE. Post-hoc tests confirmed significant (all p<.001) differences between all levels of SCALE: Unsurprisingly, 25-SCALE performed best (μ_E = 90.9% [87.9%, 93.1%]) compared to 50-SCALE (μ_E = 82% [77.3%, 85.9%]) and 75-SCALE (μ_E = 75.9% [70.3%, 80.8%]).

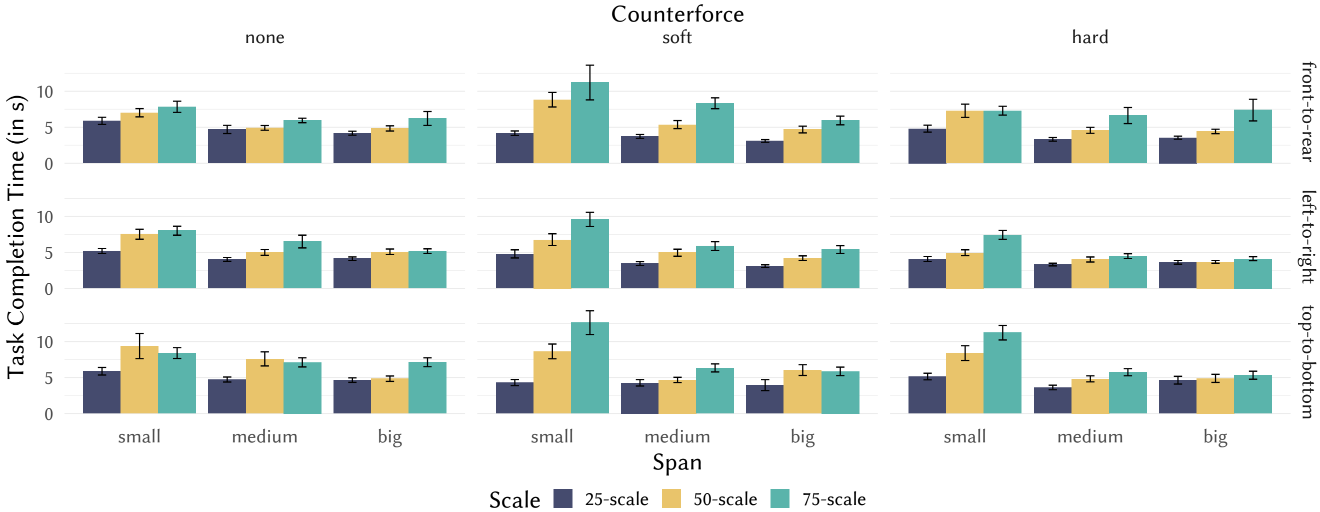

Figure 5: The task completion time per scale and span, grouped by column-wise counterforce and row-wise direction. Error bars show the standard error.

span. The analysis showed a significant ($\chi^2(2) = 70.581$, $p < .001$, $R^2_{sp} = 0.014$ [0.008, 0.022]) main effect of span. Post-hoc tests confirmed significant (all p<.001) differences between all levels of span: big performed best ($\mu_E = 89.5\%$ [86.2%, 92.1%]) compared to medium ($\mu_E = 83.9\%$ [79.5%, 87.5%]) and small ($\mu_E = 76.3\%$ [70.7%, 81.1%]).

span:direction. The analysis showed a significant ($\chi^2(4) = 13$, $p < .05$, $R^2_{sp} = 0.002$ [0.001, 0.007]) interaction effect between span and direction. Post-hoc tests confirmed a more pronounced spread of *correct* for direction<top-to-bottom>: While the accuracy was comparable between front-to-rear ($\mu_E = 80.68\%$ [74.76%, 85.49%] for small, $\mu_E = 82.7\%$ [77.12%, 87.15%] for medium, $\mu_E = 87.71\%$ [83.13%, 91.19%] for big) and left-to-right ($\mu_E = 78.15\%$ [71.82%, 83.38%] for small, $\mu_E = 87.59\%$ [83.02%, 91.07%] for medium, $\mu_E = 91.25\%$ [87.57%, 93.92%] for big), we found a more pronounced difference (all p<.01) for top-to-bottom ($\mu_E = 69.03\%$ [61.63%, 75.56%] for small, $\mu_E = 80.64\%$ [74.69%, 85.46%] for medium, $\mu_E = 80.64\%$ [74.69%, 85.46%] for big).

span:counterforce. The analysis showed a significant ($\chi^2(4) = 15.71$, $p < .01$, $R^2_{sp} = 0.002$ [0.001, 0.006]) interaction effect between span and counterforce. Post-hoc tests confirmed a more pronounced spread of *correct* for counterforce<soft>: While the accuracy was comparable between none ($\mu_E = 80.68\%$ [74.76%, 85.49%] for small, $\mu_E = 82.7\%$ [77.12%, 87.15%] for medium, $\mu_E = 87.71\%$ [83.13%, 91.19%] for big), it was significantly (p<.05, p<.001) different for soft ($\mu_E = 82.03\%$ [75.53%, 87.1%] for small, $\mu_E = 89.5\%$ [84.84%, 92.85%] for medium, $\mu_E = 94.81\%$ [91.88%, 96.73%] for big).
The analysis revealed no further interaction effects.

4.2 Task Completion Time

To measure the efficiency of participants, we recorded the task completion time (TCT) as the time between clicking to start and confirming to end a trial. As shown in Figure 5, we found values ranging from $\mu = 2.24s$, $\sigma = 0.77s$ (<big, soft, left-to-right, 25-scale, 10%>) to $\mu = 14.29s$, $\sigma = 23.72s$ (<small, soft, front-to-rear, 75-scale, 50%>).

direction. The analysis showed a significant ($F_{2,34} = 8.90$, $p < .001$, $\eta^2_G = 0.01$) main effect of direction with a small effect size. Post-hoc tests confirmed (p<.001) rising TCTs from left-to-right ($\mu_E = 5.12$s [4.37s, 5.88s]) to top-to-bottom ($\mu_E = 6.30$s [5.55s, 7.05s]).

counterforce. The analysis showed a significant ($F_{2,34} = 3.34$, $p < .05$, $\eta^2_G = 0.00$) main effect of counterforce with a small effect size. Post-hoc tests did not confirm significance between individual levels.

scale. The analysis showed a significant ($F_{2,34} = 71.39$, $p < .001$, $\eta^2_G = 0.06$) main effect of scale with a medium effect size. Post-hoc tests confirmed (all p<.001) varying TCTs for all contrasts, rising with the number of cells: 25-scale ($\mu_E = 4.23$s [3.49s, 4.96s]), 50-scale ($\mu_E = 5.82$s [5.09s, 6.56s]), and 75-scale ($\mu_E = 7.15$s [6.41s, 7.89s]).

span. The analysis showed a significant ($F_{2,34} = 19.66$, $p < .001$, $\eta^2_G = 0.05$) main effect of span with a small effect size. Post-hoc tests confirmed (both p<.001) rising TCTs from medium ($\mu_E = 5.10$s [4.27s, 5.94s]) and big ($\mu_E = 4.81$s [3.98s, 5.65s]) to small ($\mu_E = 7.28$s [6.45s, 8.12s]).

target. The analysis showed a significant ($F_{2,34} = 17.86$, $p < .001$, $\eta^2_G = 0.01$) main effect of target with a small effect size. Post-hoc tests confirmed (both p<.001) rising TCTs from 10% ($\mu_E = 5.35$s [4.62s, 6.07s]) to 90% and from 50% ($\mu_E = 5.42$s [4.70s, 6.15s]) to 90% ($\mu_E = 6.43$s [5.71s, 7.15s]).

span:scale. The analysis showed a significant ($F_{4,68} = 6.27$, $p < .001$, $\eta^2_G = 0.01$) interaction effect of span and scale with a small effect size. Post-hoc tests confirmed that the spread of TCTs

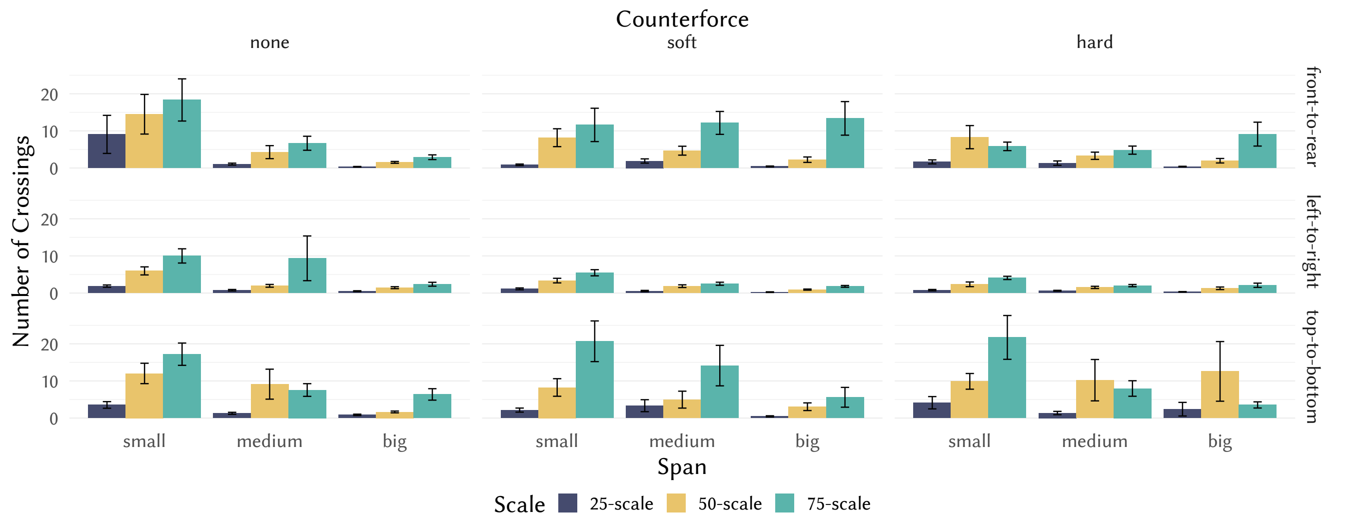

Figure 6: The number of crossings per SCALE and SPAN, grouped by column-wise COUNTERFORCE and row-wise DIRECTION. Error bars show the standard error.

across varying SCALE was more pronounced for SMALL than for both MEDIUM and BIG: While TCTs are grouped closely together for MEDIUM and BIG, the analysis for SMALL showed significant (both p<.001) differences for 25-SCALE (μ_E = 4.91s [3.97s, 5.85s]) compared to both 50-SCALE (μ_E = 7.64s [6.70s, 8.58s]) and 75-SCALE (μ_E = 9.30s [8.36s, 10.24s]).

COUNTERFORCE:SCALE. The analysis showed a significant ($F_{4,68}$ = 3.96, $p < .01$, $\eta^2_G = 0.01$) interaction effect of COUNTERFORCE and SCALE with a small effect size. Post-hoc tests confirmed that the spread of TCTs in SOFT of COUNTERFORCE was more pronounced than compared to NONE and HARD: While TCTs are grouped closely together for NONE and HARD, the analysis for SOFT showed significant (both p<.001) differences for 25-SCALE (μ_E = 3.86s [2.99s, 4.74s]) compared to both 50-SCALE (μ_E = 6.01s [5.14s, 6.88s]) and 75-SCALE (μ_E = 7.91s [7.03s, 8.78s]).

The analysis revealed no further interaction effects.

4.3 Crossings

To understanding the difficulty to hit a target in more detail, we measured the number of crossings (i.e. the number of fully under- or overshooting the target cell). As shown in Figure 6, we found values ranging from $\mu = 0.17$, $\sigma = 0.38$ (<BIG, SOFT, LEFT-TO-RIGHT, 25-SCALE, 10%>) to $\mu = 32.33$, $\sigma = 66.13$ (<SMALL, SOFT, FRONT-TO-REAR, 75-SCALE, 50%>).

DIRECTION. The analysis showed a significant ($F_{2,34}$ = 18.10, $p < .001$, $\eta^2_G = 0.01$) main effect of DIRECTION with a small effect size. Post-hoc tests confirmed (p<.01, p<.001) that there were significantly lower crossings from LEFT-TO-RIGHT (μ_E = 2.48 [0.75, 4.21]) than compared to TOP-TO-BOTTOM (μ_E = 7.26 [5.53, 8.99]) and FRONT-TO-REAR (μ_E = 5.58 [3.85, 7.31]).

COUNTERFORCE. The analysis did not show a significant main effect of COUNTERFORCE ($F_{2,34}$ = 0.41, $p > .05$).

SCALE. The analysis showed a significant ($F_{2,34}$ = 36.29, $p < .001$, $\eta^2_G = 0.03$) main effect of SCALE with a small effect size. Post-hoc tests confirmed (all p<.001) that the number of crossings significantly differs between all scales, ranging from 25-SCALE (μ_E = 1.60 [-0.13, 3.33]) and 50-SCALE (μ_E = 5.23 [3.50, 6.96]) to 75-SCALE (μ_E = 8.49 [6.76, 10.22]).

SPAN. The analysis showed a significant ($F_{2,34}$ = 15.74, $p < .001$, $\eta^2_G = 0.01$) main effect of SPAN with a small effect size. Post-hoc tests confirmed (p<.01, p<.001) that the number of crossings were significantly higher for SMALL (μ_E = 7.88 [6.10, 9.67]) than compared to both MEDIUM (μ_E = 4.49 [2.70, 6.27]) and BIG (μ_E = 2.95 [1.17, 4.74]).

TARGET. The analysis showed a significant ($F_{2,34}$ = 17.86, $p < .001$, $\eta^2_G = 0.01$) main effect of TARGET with a small effect size. Post-hoc tests confirmed (p<.05) that the number of crossings is significantly higher for 10% (μ_E = 6.35 [4.58, 8.11]) compared to 90% (μ_E = 4.18 [2.41, 5.94]).

SPAN:SCALE. The analysis showed a significant ($F_{4,68}$ = 2.68, $p < .05$, $\eta^2_G = 0.00$) interaction effect between SPAN and SCALE with a small effect size. Post-hoc tests confirmed that with rising SPAN the difference in the number of crossing across SCALE is less pronounced: While the crossings are grouped more closely together for MEDIUM and BIG, the analysis for SMALL showed significant (p<.01, p<.001) differences between 25-SCALE (μ_E = 2.80 [0.52, 5.07]) compared to both 50-SCALE (μ_E = 8.09 [5.81, 10.36]) and 75-SCALE (μ_E = 12.77 [10.49, 15.05]).

SCALE:DIRECTION. The analysis showed a significant ($F_{4,68}$ = 3.40, $p < .05$, $\eta^2_G = 0.00$) interaction effect between SCALE and DIRECTION with a small effect size.

Post-hoc tests confirmed that the number of crossings in a certain DIRECTION varies differently for SCALE. While the number of crossings is grouped closely together for 25-SCALE, increasing

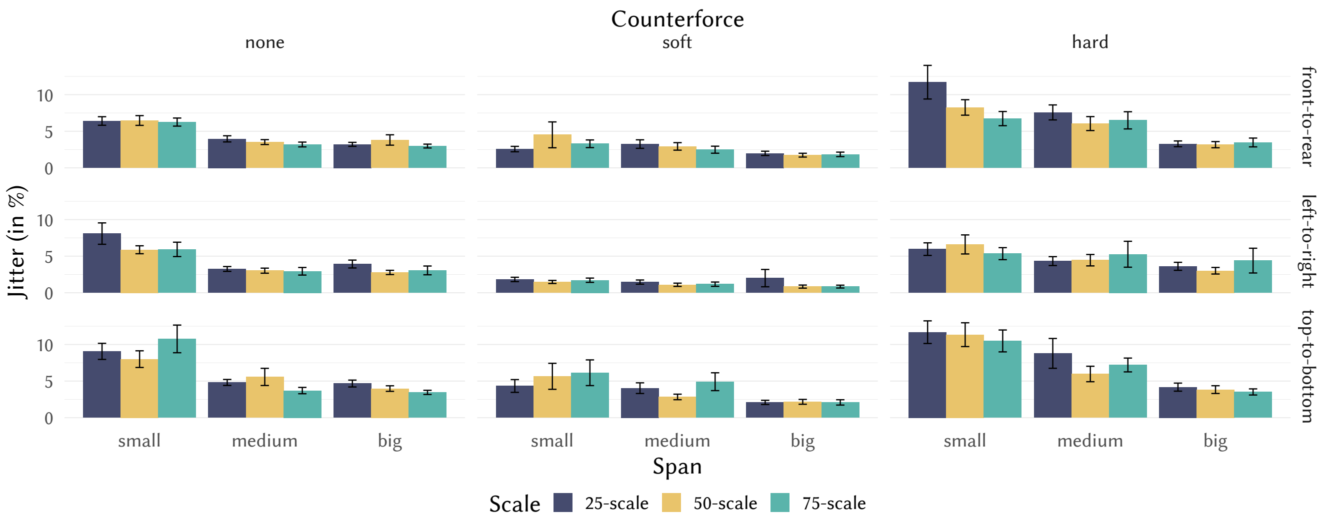

Figure 7: The jitter per SCALE and SPAN, grouped by column-wise COUNTERFORCE and row-wise DIRECTION. Error bars show the standard error.

the scale to 50-SCALE amplifies (p<.001) the differences in DIRECTION between LEFT-TO-RIGHT (μ_E = 2.29 [0.07, 4.52]) and TOP-TO-BOTTOM (μ_E = 7.97 [5.75, 10.19]). Analogously for 75-SCALE, the directions LEFT-TO-RIGHT (μ_E = 4.41 [2.18, 6.63]) and TOP-TO-BOTTOM (μ_E = 11.64 [9.42, 13.86]) also differ significantly (p<.001).

Beyond these interaction effects, the analysis revealed a three-way interaction effect between SPAN:DIRECTION:SCALE that we omit due to space limitations.

4.4 Jitter

We analyzed the jitter of participants, defined as the maximal range of deviation around the target while holding for three seconds after confirming completion. The numbers are given in percentage of the interaction range that was defined by the participant's calibration. As shown in Figure 7, we found jitter ranging from μ = 0.39%, σ = 0.27% (<BIG, SOFT, LEFT-TO-RIGHT, 75-SCALE, 50%>) to μ = 23.05%, σ = 24.44% (<SMALL, HARD, FRONT-TO-REAR, 25-SCALE, 90%>). The measurements are illustrated in Figure 7.

DIRECTION. The analysis showed a significant ($F_{2,32}$ = 16.47, $p < .001$, η^2_G = 0.02) main effect of DIRECTION with a small effect size. Post-hoc tests confirmed (p<.001, p<.01) that jitter was significantly higher for TOP-TO-BOTTOM (μ_E = 5.75% [4.93%, 6.57%]) than compared to both LEFT-TO-RIGHT (μ_E = 3.49% [2.67%, 4.31%]) and FRONT-TO-REAR (μ_E = 4.49% [3.67%, 5.30%]).

COUNTERFORCE. The analysis showed a significant ($F_{2,32}$ = 13.66, $p < .001$, η^2_G = 0.06) main effect of COUNTERFORCE with a small effect size. Post-hoc tests confirmed (p<.01, p<.001) that jitter was lower for SOFT (μ_E = 2.64% [1.60%, 3.68%]) than compared to both NONE (μ_E = 4.91% [3.88%, 5.95%]) and HARD (μ_E = 6.17% [5.14%, 7.21%]).

SCALE. The analysis showed a significant ($F_{2,32}$ = 5.48, $p < .01$, η^2_G = 0.00) main effect of SCALE with a small effect size. Post-hoc tests confirmed that jitter was significantly (both p<.05) higher for 25-SCALE (μ_E = 4.89% [4.17%, 5.61%]) than compared to both 50-SCALE (μ_E = 4.40% [3.68%, 5.12%]) and 75-SCALE (μ_E = 4.43% [3.71%, 5.15%]).

SPAN. The analysis showed a significant ($F_{2,32}$ = 38.68, $p < .001$, η^2_G = 0.06) main effect of SPAN with a small effect size. Post-hoc tests confirmed (p<.001, p<.001, p<.05) that jitter significantly differed between BIG (μ_E = 2.96% [2.13%, 3.79%]), MEDIUM (μ_E = 4.23% [3.40%, 5.06%]), and SMALL (μ_E = 6.53% [5.71%, 7.36%]).

TARGET. The analysis showed a significant ($F_{2,32}$ = 10.83, $p < .001$, η^2_G = 0.02) main effect of TARGET with a small effect size. Post-hoc tests confirmed (both p<.001) that jitter was significantly higher for 90% (μ_E = 5.79% [4.93%, 6.64%]) than for both 50% (μ_E = 4.13% [3.27%, 4.99%]) and 10% (μ_E = 3.81% [2.95%, 4.67%]).

SPAN:COUNTERFORCE. The analysis showed a significant ($F_{4,64}$ = 5.22, $p < .01$, η^2_G = 0.01) interaction effect between SPAN and COUNTERFORCE with a small effect size. Post-hoc tests confirmed that jitter in a certain COUNTERFORCE varies differently for SPAN. While the analysis showed no significant difference between variations of SPAN for COUNTERFORCE<SOFT>, we found a wider spread of jitter for the other levels of COUNTERFORCE: For COUNTERFORCE<NONE>, SPAN<SMALL> performed significantly (both p<.001) worse compared to both MEDIUM and BIG (jitter increased from μ_E = 3.77% [2.50%, 5.05%] for MEDIUM and μ_E = 3.54% [2.26%, 4.81%] for BIG to μ_E = 7.43% [6.15%, 8.70%] for SMALL). Similarly, for COUNTERFORCE<HARD>, SPAN<SMALL> performed significantly (p<.05, p<.001) worse compared to both MEDIUM and BIG (jitter increased from μ_E = 6.23% [4.96%, 7.51%] for MEDIUM and μ_E = 3.61% [2.33%, 4.88%] for BIG to μ_E = 8.68% [7.40%, 9.95%] for SMALL).

SPAN:DIRECTION. The analysis showed a significant ($F_{4,64}$ = 6.80, $p < .001$, η^2_G = 0.01) interaction effect between SPAN and DIRECTION with a small effect size. Post-hoc test confirmed that that jitter for a constant SPAN varies differently with respect to the DIRECTION: Especially for DIRECTION<TOP-TO-BOTTOM>, jitter significantly (both p<.001) differs from SMALL to both MEDIUM and BIG (an increase of jitter from μ_E = 5.31% [4.29%, 6.33%] for MEDIUM and μ_E = 3.33% [2.30%, 4.35%] for BIG to μ_E = 8.60% [7.58%, 9.63%] for SMALL).

SPAN:TARGET. The analysis showed a significant ($F_{4,64} = 12.10$, $p < .001$, $\eta^2_G = 0.01$) interaction effect between SPAN and TARGET with a small effect size. Post-hoc tests confirmed that with rising TARGET the differences in jitter across SPAN are more pronounced: While jitter is grouped more closely together for 10% and 50%, the analysis for 90% showed significant (both p<.001) differences between SMALL (μ_E = 8.71% [7.69%, 9.73%]) compared to both MEDIUM (μ_E = 4.99% [3.97%, 6.01%]) and BIG (μ_E = 3.66% [2.64%, 4.68%]).

COUNTERFORCE:TARGET. The analysis showed a significant ($F_{4,64} = 19.93$, $p < .001$, $\eta^2_G = 0.04$) interaction effect between COUNTERFORCE and TARGET with a small effect size. Post-hoc tests confirmed that with rising TARGET the spread of jitter for different levels of COUNTERFORCE increase. In the case of TARGET<90%>, jitter of HARD (μ_E = 9.80% [8.52%, 11.08%]) is significantly (both p<.001) higher compared to both NONE (μ_E = 4.29% [3.01%, 5.57%]) and SOFT (μ_E = 3.27% [1.98%, 4.55%]).

Beyond these interaction effects, the analysis revealed two three-way interaction effects between SPAN:COUNTERFORCE:SCALE and SPAN:COUNTERFORCE:TARGET that we omit due to space limitations.

4.5 Questionnaires & Subjective Feedback

In general, participants agreed that pinching as an input modality is a convenient (median = 4, mad = 1.48) way to interact (1 least, 5 most for all questions). Overall, participants agreed (median = 4, mad = 1.48) that the system was physically demanding to use. Interestingly, we were not able to find significant differences in physical demand for different levels of COUNTERFORCE.

Regarding their favorite COUNTERFORCE, participants were split between NONE (10 votes) and SOFT (8 votes). The majority ranked HARD (14 votes) the worst COUNTERFORCE and no participant ranked SOFT the worst. This is in line with qualitative feedback, e.g. P9 told us that "*without any object was much more convenient for longer use as (the fingers) became exhausting fastly. However, it also was more difficult to hit the target so I would still prefer a soft object.*" While pondering about the different levels of COUNTERFORCE, P15 remarked to "*take the one without resistance, it feels so much better pressing against air than pressing against some mechanical stuff.*"

Regarding their favorite SPAN, participants preferred MEDIUM (13 votes), followed by BIG (5 votes). No participants ranked SMALL their favorite SPAN. Participants were split about the worst SPAN between SMALL (10 votes) and BIG (8 votes). P4, among the group preferring the MEDIUM span, stated that "*larger distances between the finger allow more space to play and select the target precisely.*"

Regarding their favorite DIRECTION, participants had diverse opinions, ranging from 3 votes for TOP-TO-BOTTOM, 6 votes for FRONT-TO-REAR, and 9 votes for LEFT-TO-RIGHT. The majority, at the same time, ranked TOP-TO-BOTTOM (13 votes) the worst DIRECTION.

5 DISCUSSION & IMPLICATIONS

In the following, we discuss the findings of the experiment and derive implications for the design of pinchable user interfaces.

5.1 Size Matters: Avoid Too Small Spans

Our results strongly indicate that a SPAN in the range of medium to big is beneficial for all measures: Primarily, this is evident by significantly better accuracies for the wider spans. Also, the jitter for the smallest span was more than twice as high compared to the biggest span. This implication is further backed up by a higher number of crossings and longer TCTs for small spans. Further, not a single participant ranked the smallest span as their favorite.

13 participants ranked the medium span their favorite, but the quantitative measures paint a more diverse picture when comparing medium to big spans: Although there were no significant differences in TCTs, the jitter, the crossings, and the accuracy were significantly better for the biggest span, suggesting a benefit in overall performance.

Taken together, our analysis suggests that wider grip spans are generally more suited for an accurate and efficient pinching input with a high user experience. We hypothesize that the human ability for fine granular adjustment is constant per absolute distance delta. This favors larger grip spans, as a larger absolute range of distance is mapped to the same scale. Therefore, it is easier to reach and hold a target cell while maintaining the same fine granularity of the hand. This increases accuracy in particular, but also affects the number of crossings, since there is more time to correct an approaching over- or undershoot at a higher absolute distance.

Based on our findings, we recommend to use wider grip spans whenever possible as they offer a greater absolute distance per scale cell, particularly enhancing accuracy. In situations where small spans are more desirable, our results indicate reducing the number of options to accommodate the lower accuracy. By combining small spans with further input modalities (e.g. the translation of the fingers after pinching), a higher input capacity can still be achieved.

5.2 Don't Underestimate the Force: Use a Counterforce for Higher Accuracy

While our results indicate that accuracies of up to 100% (i.e. not a single error over all participants) are in fact possible, these were only obtained in the presence of a counterforce. Without a counterforce, participants reached accuracies of 89%, but even this result was only achieved for one condition at the lowest scale. When focusing on the highest scale, we found accuracies of up to 94% (e.g. for <BIG, HARD, LEFT-TO-RIGHT>). This is remarkable, considering that the allowed variation in the distance between thumb and index finger in this scale and span was only 1.2 mm (= $1/75 * 92\ mm$).

Reflecting the results for accuracy, in particular, the human abilities to control the distance between thumb and index finger appears to be strongly related to whether an object in the hand exerts a counterforce. This may be attributed to the fact that in addition to the proprioceptive feedback provided by the motor system, an acting counterforce also stimulates the haptic sensors, providing a more diverse basis of stimuli to control the distance between the thumb and index finger. However, our results also show rising jitter (+3.53%) for harder counterforces, most probably as it is harder to steadily control the distance towards the maximal voluntary strength.

Based on our results, we suggest the use of a soft counterforce for most situations. This is consistent with a minimum jitter (about 2.64%) measured for this level and enables users to maintain a constant target on the scale over some time (e.g. to select an element with a dwell time). When a counterforce at all is undesirable or implementable, designers of pinchable user interfaces can consider a left-to-right direction with a medium span at the lowest scale.

5.3 Avoid Top-to-Bottom

Our analysis indicates that the top-to-bottom direction is the least favorable for pinching input: While we recorded some conditions with an accuracy above 94% for this direction (e.g. in combination with <BIG, SOFT, 25-SCALE>), our results showed a significantly higher jitter, number of crossings, and TCTs. Although this suggests that the top-to-bottom direction is, at least in terms of accuracy, feasible, a majority of 13 participants ranked it their worst direction.

These results suggest that the top-to-bottom direction is less suited for linear pinching. We assume this may be related to the fact that the distance between thumb and index finger is more difficult to estimate visually in this hand position than in the left-right direction, thus negatively affecting the visual-motor loop.

Based on these results, we recommend avoiding the top-to-bottom direction if possible to increase overall efficiency and user experience. In cases when it is essential, designers should consider combining it only with lower scales or at least an intermediate span with a soft or hard counterforce.

5.4 High Scaling Allowed

We initially intended the highest scale to be an almost infeasible upper bound. Surprisingly, we found that there were several conditions with accuracies above 90% (e.g. with <BIG, HARD, LEFT-TO-RIGHT>). While, of course, lower scales offered benefits in terms of a lower number of crossings and TCTs, this illustrates the potential for lateral pinching as a very fine-grained input modality.

Interestingly, our results indicate that the jitter is significantly *higher* for the lowest scale. That is, participants held less steady when a lower scale was presented for the same counterforce, direction, and span. We hypothesize that humans may alter their cognitive model of holding as still as possible based on the latest visual stimuli. The appearance of a broader scale just before the prompt to hold still might affect the human conception of what it means to hold still.

Another interesting finding related to the effect of the target location on measurements: While the TCTs obviously increased with rising targets, the 90% location at the upper end of the scale, compared to the lower end, had the highest jitter (5.79% vs. 3.81%) but the smallest crossings (4.18 vs. 6.35) and vice versa. This is most probably related to the fact that holding still near the force limit of human motion is more challenging. At the same time, not overshooting the 10% location is harder than for the 90%.

In conclusion, our results indicate that the input capacity of lateral pinching is often up to three times higher compared to the already considerable capacity of 20 levels for applying pressure with the index finger [18]. While lower scales obviously improve accuracy and efficiency, we recommend not to fear high scales, if they are combined with at least a medium span and soft counterforce.

5.5 Implications for Mid-Air Pinching Gestures

At least since the release of the HoloLens, pinch-to-tap has become one of the standard ways to interact with Mixed Reality. It is most frequently used in top-to-bottom direction in pure mid-air. While this interaction style has proven to be versatile for binary tap interaction and subsequent translation and rotation movements, our findings suggest that this combination of direction and no counterforce is suboptimal for lateral pinching as a linear input modality. While it may be considered infeasible for users to carry an object exerting an appropriate counterforce with them, especially in highly mobile use cases, the illusion of a counterforce might be as well generated by a wearable haptic interface worn at the hand or arm (e.g. as proposed by Choi et al. [10]). Such concepts also raise the possibility of dynamically adjusting the counterforce or span based on the usage scenario and the required accuracy or efficiency.

6 LIMITATIONS & FUTURE WORK

We are convinced that this paper contributes valuable insights into the usability of pinching for interaction. However, this paper has limitations that must be considered and also raises questions for future work.

6.1 Validity & Applicability

In this paper, we aim to advance the understanding of the human capabilities of using pinching motions for linear input with computer systems. To this end, we conducted a controlled experiment, as this allows us to establish unaffected fundamental properties of pinching. Using this methodology, we can analyze the sheer effects of the independent variables presented and effectively control for any confounding factors, such as a standard camera-based tracking system or a sensor integrated into the object (e.g. constraints due to specific properties of force-sensitive resistors). However, a controlled experiment with a limited number of participants can naturally only capture a sample of real human performance. Therefore, the presented results are mainly generalizable to the user group of adults and may vary for other user groups (e.g. children or seniors). While the form factor of our apparatus focuses on an smooth and planar contact face as a baseline measure, it may be easily extended by future work to investigate the effect of varying surface textures (e.g. soft or spiky) and geometries (e.g. curved). Also, future research needs to be conducted that covers the specific technical design and associated challenges (e.g., how to reliably detect the pinching thumb and index with or without an object in hand).

We opted for a high-precision optical tracking system that captures the distance between the thumb and index finger with a high level of accuracy. Although this has provided us with a realistic and robust basis for research, it is not a practical and easily deployable solution for future pinchable user interfaces due to its enormous cost and assembly effort. Alternative solutions might be to embed force sensors into the objects to pinch or employ camera-based hand tracking systems, which are already integrated into commercially available Mixed Reality headsets. Both promise to recognize the thumb and index finger for pinching input. Hence, an implementation that considers the implications presented in this paper is already in reach. However, open research questions remain beyond mere implementation, such as how to design controls for Mixed Reality that facilitate the use of pinching for linear control (e.g. as a more space-efficient replacement of standard linear sliders) or whether there is a difference in using the dominant or non-dominant hand for pinching [21]. Future work is needed to address these challenges.

6.2 Fatigue

Fatigue could be a potential limitation to the repeated use of pinching. To further investigate whether participants were subject to fatigue during our experiment, we trained linear models for all measurements and the relative study time at which each measurement was recorded (normalized over the individual study duration). We could not find a relevant effect over the relative study time (all slopes less than -0.02). However, fatigue, in general, is a complex phenomenon that should be further examined in future work. In particular, studies should be carried out that investigate whether the hand becomes increasingly fatigued during accumulated pinch movements or whether even short rest periods, which are not uncommon in an ordinary interaction sequence, contribute to the required recovery.

6.3 Mapping Counterforces to Materials

While the elastic modulus is the standard way to characterize the reversible deformation behavior of an object, we intentionally vary our COUNTERFORCE levels as a force in newton, because this naturally transfers from research on the maximum voluntary force of pinching. However, the elastic modulus is usually expressed in pascals, which is defined as $1Pa = 1N/m^2$. Based on the average area of the first phalanx of the thumb and the first two phalanxes of the index finger of approx. $A = 970.25\ mm^2$ [7], our levels of COUNTERFORCE F can be directly transformed into the elastic modulus by $E = F/A$. This equals an elastic modulus of $E_{soft} = 26.15\ N/970.25mm^2 = 0.027$ MPa for SOFT and $E_{hard} = 52.3\ N/970.25mm^2 = 0.054$ MPa for HARD (for comparison, 0.67 MPa roughly equals a foamy ball [18]). Unfortunately, this is below the minimal values of readily available silicone. Therefore, future work should explore material compositions with a suitable elastic modulus, for instance, via 3D-printed sponge-like structures that are highly compressible due to air pockets in the material.

6.4 Selection Method

To explore the effect of the different factors independently of other influences, we decided not to implement an active selection method and chose a clicker in the non-dominant hand instead. However, to effectively use pinching as a linear input modality, an appropriate selection method is necessary. Such a method could be based on previously introduced techniques, such as quick release or dwell time. Alternatively, future selection methods may be bi-manual or leverage the information of 3D finger tracking. That is, the system may determine whether or not the thumb and index finger are in a pinch-active area. Future work is required to assess the suitability of varying selection techniques for linear pinching input.

7 CONCLUSION

We presented Squeezy-Feely, an exploration of the potential of lateral thumb-index pinching as an input method. In a controlled experiment, we evaluated the human ability to selectively control the distance between the thumb and index finger to solve a visual targeting task. For this purpose, we varied three spans of grip, three counterforces of the object, three different directions of grip, three scales (up to 75 different entries), and three different target levels. We found that, in particular, too small grip spans, a lack of counterforce, and top-to-bottom grasping have detrimental effects on accuracy, efficiency, and user experience. Also, we have shown that lateral pinching has the potential for an accurate, efficient, and usable input modality also up to the highest scale investigated. By exploring these implications, we contribute to the vision of pinching as a linear input method for future pinchable user interfaces, which can be useful for many application areas, ranging from Mixed Reality to deformable displays.

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