Squish This: Force Input on Soft Surfaces for Visual Targeting Tasks

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ABSTRACT

Today's typical input device is flat, rigid and made of glass. However, advances in sensing technology and interaction design suggest thinking about input on other surface, including soft materials. While touching rigid and soft materials might feel similar, they clearly feel different when pressure is applied to them. Yet, to date, studies only investigated force input on rigid surfaces. We present a first systematic evaluation of the effects of compliance on force input. Results of a visual targeting task for three levels of softness indicate that high force levels appear more demanding for soft surfaces, but that performance is otherwise similar. Performance remained very high (~5% for 20 force levels) regardless of the compliance, suggesting force input was underestimated so far. We infer implications for the design of force input on soft surfaces and conclude that interaction models used on rigid surfaces might be used on soft surfaces.

CCS CONCEPTS

• **Human-centered computing → User studies**.

KEYWORDS

Soft Surfaces, Force Input, Pressure Input, User Study

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1 INTRODUCTION

With computing devices becoming increasingly ubiquitous, input devices are also becoming increasingly diverse. Work in HCI [18, 54] and material science [32] are proposing solutions to enable interactions on arbitrary surfaces, steering designers to appropriate everyday objects for input [1, 4, 34]. Consequently, we witness the development of interaction techniques on surfaces which are not rigid like glass, but soft, such as clothing [21, 33, 35], furniture [54], or even human skin [51, 52].

If merely touched, rigid and soft surfaces feel similar. However, soft surfaces deform under the pressure of the user's finger (see Figure 1), which provides additional sensory cues by stimulating tactile and kinesthetic receptors [17, 20, 43]. Several studies showed that we perceive the compliance[1] of a surface mostly through deformations because the surface wraps around the fingertip and induces more tactile innervation [28, 47]. It is therefore reasonable to assume that these additional sensory cues provided by soft materials have an effect on the user performance while interacting with force input.

Force input is a common focus of studies in HCI, mostly because it is a compelling alternative or complement to conventional touch interactions, as it merely requires one finger and fingertip-sized interactive surfaces. Its benefits have been demonstrated on rigid surfaces for one-handed control of a slider's value [11], access out-of-reach areas on a mobile device [9], or quickly select commands in linear menus [5, 8, 29, 30, 36, 57] using visual feedback. However, to the best of our knowledge, only few studies investigated force input performance on soft surfaces [6, 45], and none investigated systematically the effect of the surface compliance on the user performance. Thus, it is unclear whether interaction techniques developed on rigid surfaces can be used on soft surfaces.

To address this gap in knowledge, we present an experiment evaluating user performance of force input on soft surfaces for visual targeting tasks. Building on best practices from previous work [5, 8, 29, 36, 57], we designed a task that consists in matching a force level using a slider controlled by the force applied on three soft surfaces (Figure 1). Our results indicate that targeting high force levels is more demanding on compliant surfaces (i.e., higher selection times and number of crossings). Nevertheless, the error rate remained low (~5%) for a dense scale of 20 levels, regardless of the compliance level. As previous work reported best results using 10±2 levels [5, 8, 29, 30, 36, 57], we conclude force input was underestimated so far. Based on these findings, we propose use cases leveraging force input and infer implications for the design

[1] compliance is the inverse of stiffness, i.e., "the amount an object deforms in response to an applied force" [28]

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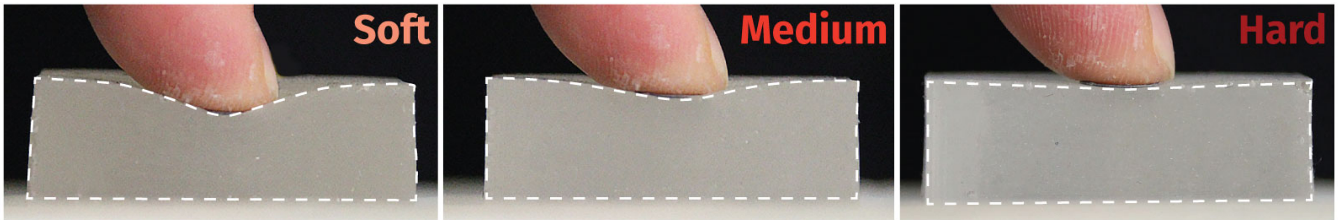

Figure 1: The three surfaces (silicone samples) used in our study. A pressure sensor is located between the fingertip and the surface. In this example, the user applies a force of 10N on each surface, inducing different material deformations.

of force input on soft surfaces. We finally conclude that interaction techniques used on rigid surfaces might be used on soft surfaces.

2 RELATED WORK

To date, most studies investigated force input in the context of rigid surfaces [5, 36, 41, 44, 57], but studies on soft surfaces are more scarce [6, 45, 53]. Those studies which do investigate force input on soft materials either do not systematically vary compliance [45, 53] or use too few participants to be conclusive [6]. It is therefore not clear if changing the surface compliance affects force input performance.

2.1 Force Input Performance

Most studies focusing on force input investigated users' ability to accurately select absolute force levels [5, 8, 29, 30, 36, 57]. A typical task consists of moving a cursor to a visual target – the cursor is controlled by applying a normal force and the visual target indicates the desired force level. In this case, the size of the target level can vary to increase of decrease the difficulty of the task. Such a task corresponds to conventional linear menu selections using a pointing cursor.

These studies investigated multiple force scales with varying number of levels to cover various difficulty levels (e.g., 8, 10, or 12) with a reported maximum of 16 [41]. The inferred consensus of these studies is that users can accurately control force for scales below 10±2 levels [5, 8, 29, 30, 36, 57], and their performance greatly decreases with denser scales. Yet, it is important to note these studies were performed in different contexts (e.g., pen input [36] or back-of-device interactions [8]) and focused on specific force ranges. In comparison, we explore force input using a single finger on a compliant surface, and we let users define comfortable force ranges in our study.

2.2 Visual Mapping

The output of a pressure sensor depends both on the sensor design and the compliance of the materials it is connected to. In contrast, human perception rarely differs from Weber's law [16] which follows a logarithmic trend. Consequently, the visual mapping of the sensor's output plays an important role in the user performance as it provides a good trade-off between the mechanical and perceptual scales.

Previous work presented different visual mappings to explore their impact on the user performance. Cechanowicz et al. showed the advantages of a quadratic mapping [5], and Shi et al. the advantages of using a dynamic mapping based on a magnifying lens metaphor [41] over a linear mapping. Nevertheless, these works did not discuss the output of the pressure sensors, hence it is unclear what is the effective end-to-end mapping. Stewart et al. proposed to use a transimpedance amplifier to produce a linear output from an original logarithmic output and showed high accuracy rates ($\geqslant$98%) for 9 levels [44]. We implement the same solution in our experiments since studies using linear mappings demonstrated good accuracies [8, 29, 30, 44].

2.3 Selection Mechanism

Several strategies exist to select a force level (see [36] for a comparison): the users can *dwell*, *quickly release* the finger from the sensor, or produce a specific *pattern* in the force profile [11, 36]. Several studies demonstrated that *dwelling* leads to better performances mainly by reducing the number of crossings (i.e., the cursor enters and leaves the target level) [5, 36, 57]. For dense scales, however, the user accuracy is more vulnerable to small jitter creating many crossings, hence *quick release* is more adequate. It is unclear how this mechanism was implemented in previous studies so far, despite the great impact it can have. To address this issue, Corsten et al. demonstrated an efficient way to recognizing such mechanisms based on the human model processor or CMN model [10]. We implemented this strategy for our experiments.

3 EXPERIMENTAL SETUP

In this section we present the experimental setup used in our experiment. We first present the fabrication process of the three soft surfaces (Figure 1). We then introduce the pressure sensor and explain the calibration protocol. We sought to better understand the sensor response curve to provide a 1-to-1 mapping for users, thus enabling a visual linear mapping. Doing so, we minimize the bias introduced by the inherent features of the sensor and allow better generalizability of the empirical results.

3.1 Fabricating the Soft Surfaces

Silicone is widely used as a material for creating soft interfaces [4, 31, 46, 51]. Its crosslinking ratio, i.e., mass ratio between the elastomer and curing agent, can be controlled to produce various Young's moduli [50]. This powerful advantage allows experimenters to create specific deformable surfaces and facilitates replicability of experiments [49]. We created three samples of $3.6{\times}3.6{\times}1.5cm^3$ using Sylgard 184 silicone [7]. We tested the perceived softness of

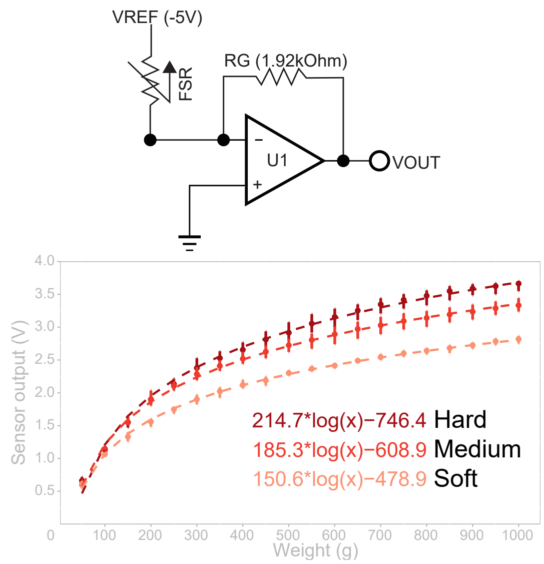

Figure 2: Schematics of the circuit (top). Sensor output in relation to the force applied on each surface (bottom). The dots represent each measure and the error bars 95% CIs of six rep-etitions. The dashed lines represent models fitted using non-linear least square regressions.

six samples with mass ratios ranging from 30:1 to 12:1 and picked three of them that we judged equidistant in terms of softness with respective ratios of 30:1, 24:1, and 12:1 to represent a *soft*, *medium*, and *hard* surface (Figure 1). Based on the model proposed by Wang et al. [50], their approximate Young's moduli are 0.67MPa, 0.83MPa, and 1.67MPa, respectively. These moduli translate roughly to Shore hardness A of 50, 20, and 10. We experience their softness similar to a hard pencil eraser, an elastic rubber band, and a foamy ball.

3.2 Sensing and Calibrating Pressure

3.2.1 Sensor and Setup Configuration. We use the Interlink longtail FSR400 [23], a commercial pressure sensor smaller than the fingertip (∅5.08mm, see Figure 1), for two main reasons: previous studies used the same or a similar device [5, 41, 55–57], and it facilitates the replicability of the study [49] compared to a custom-made sensor. During the experiment, the users applied normal forces using their index finger directly on the sensor. The index finger was the only finger in contact with the surface and the hand was resting on the table. We placed the sensor on top of the three samples for all tasks to sense the pressure applied between the fingertip and the surface beneath (c.f. Figure 1). The flexibility and size of the sensor does not hinder deformations of the surface. The contact mechanics of such a system can be approximated by Hertz' model for a sphere (the fingertip) indenting a flat elastic sample as follows:

$$p_{max} = \frac{1}{\pi}\left(\frac{6E^{*^2}F}{R^2}\right)^{2/3} \tag{1}$$

With p_{max} being the maximum pressure at a force F for a sphere radius of R and an effective combined elastic modulus of sample and skin E^*.

We implemented the transimpedance circuit from [29, 44, 57]. Its schematic is depicted in Figure 2-left We used an Agilent E3634A power supply, a LM358N opamp, and an Arduino UNO to read the sensor output. The experiment logic ran on a Dell XPS15 9570 with a Intel Core I7 (2.20GHz) processor. We connected the Arduino through USB and displayed all the visual stimuli on the laptop's screen (15 inches) using the Unity3D software. Based on the ADC conversion rate and transfer of 4 integers at 9600 baud, we calculate a delay of approximately 0.204ms with an additional average delay of 8ms added by the Unity frame rate.

3.2.2 Calibrating the sensor. Based on Equation 1, we expect the output of the FSR to be sub-linear. To verify this, we recorded the sensor's output in relation with the force applied using a scale. We placed the samples on a scale and pressed with the fingertip to reach a target weight. We recorded the output six times for each weight (see Figure 2). As predicted, the sensor output increases sub-linearly with force and are lower for more compliant samples at equal force. We modeled the calibration curves with smooth non-linear functions and thus translated the FSR output for each sample into an applied force in Newton. Doing so, we carefully map the sensor's output to a linear response.

4 EFFECTS OF COMPLIANCE ON FORCE INPUT PERFORMANCE

We study in this experiment how the compliance of a soft surface affects force input performance. We use a within-subject design with three independent variables: the compliance of the surface (SURFACE), the number of levels composing the force scale (SCALE), and the target force level (TARGET). In the following, we present in more details our experimental design and the results of this experiment.

Task. Users control a linear cursor by varying the amount of force they exert on a soft, medium, or hard surface. They must reach a target force level on a discrete level scale. Once the users reach the required amount of force, they must quickly release their finger [10]. This task is similar to a command selection task in a linear menu.

Participants. We recruited 24 right-handed participants in our local university (15m, 9f, 0d), aged from 21 to 37 (mean=28, SD=4). They were compensated with 10€ each.

Independent Variables. We consider three independent variables: the compliance of the surface (SURFACE), the number of levels composing the scale (SCALE), and the actual levels to select (TARGET).

For SURFACE, we used three compliance levels, representing a *Soft*, *Medium*, and *Hard* surface, as presented in the previous section.

For SCALE, we first conducted pilots with scales ranging from 8 to 12 levels as proposed in the literature, but noticed that users would easily reach high accuracy and could cope with higher densities. We therefore tested increasingly higher number of levels, settling at 20. We eventually used three SCALES composed of 12 (*S12*), 16 (*S16*), and 20 levels (*S20*).

For TARGET, we followed a conventional procedure [5, 36] for selecting target levels independently of the scale used (cf. Figure 3). We considered an interval from 0 to 1000 and chose equidistant values in this interval: 180 (*Very Low*), 360 (*Low*), 540 (*Medium*), 720 (*High*), and 900 (*Very High*). We then extend the scale on the

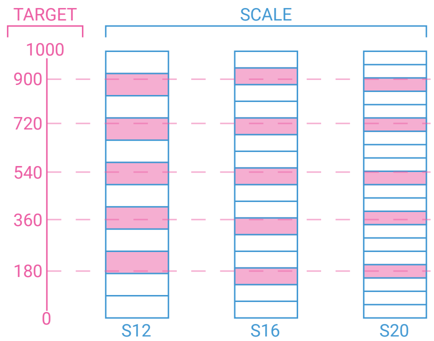

Figure 3: Representation of the interaction between the TARGET and SCALE independent variables. We follow a similar approach as Ramos et al. [36].

same interval to make each value correspond to a unique level. The corresponding levels span from low to high force to provide a good understanding of the user performance.

Dependent Variables. We evaluate the user performance with three metrics: the percentage of correctly completed trials (*success rate*), for how long did the participant apply force (*selection time*), and how many times the participant entered and left the targeted level (*crossings*).

We supplement these quantitative measures with the subjective preference of surface type (ranked, allowing ties) and 7-levels Likert-scale items reporting on perceived *comfort* (7-Very Comfortable), *accuracy* (7-Very Accurate), and *physical demand* (7-Not Demanding) for each SURFACE.

Procedure. Participants initially provided the maximum force level they could comfortably perform. We then set this maximum value as the maximum of the force scales. This ensured that each participant could comfortably complete the experiment. They chose ranges from 0N to 6.60N [5.08, 9.78][2] (*Soft*), 5.04N [4.11, 6.32] (*Medium*), and 4.88N [4.06, 5.91] (*Hard*), which correspond to similar force ranges studied in previous studies (cf. Table 1 in Discussion section). We do not observe systematic differences between participants.

We asked the participants to reach the required level using a label indicating the level to select, briefly stabilize to ensure their selection, and then quickly release their finger. To start a trial, participants had to press quickly on the sensor similar to a mouse click. To detect the level selected we implemented the algorithm suggested by Corsten et al. [10]: we average the values of the sensor output in a time window of 50ms, ending 240ms before the end of the movement.

We counterbalanced the order of SURFACE and SCALE individually; we counterbalanced SURFACE, then for each of its levels, we counterbalanced SCALE. Before starting the experiment, the participants trained by targeting all TARGETS in *S16* with the sensor laying on the table (i.e., not a compliant surface). They then performed the task on each SURFACE consecutively, and for each SCALE they had to select all the TARGETS two times in a randomized order. This procedure was repeated twice. Overall, we capture the data of 24×3×3×5×4=4320 trials (#Participants × #SURFACE × #SCALE × #TARGET × #Repetitions). Each experiment lasted around one hour. On completing the experiment, we asked the participants to rank the SURFACES and complete the Likert-item questions.

Analysis. We report results using estimation techniques (i.e., emphasizing on effect sizes and confidence intervals rather than p-values[3]) as recommended by the APA [15]. We, therefore, assess the differences between two populations by depicting the differences of their means. All error bars depicted in the figures represent bootstrapped 95% CIs.

4.1 Results

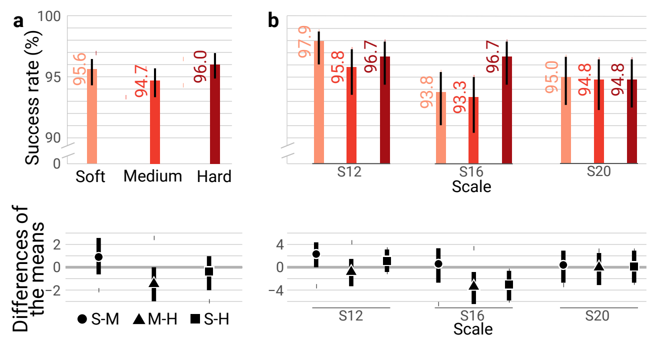

Figure 4: Success rate of each surface (a-top) and the means differences (a-bottom). Success rate in function of the scale (b).

Success rate. Overall, the participants were very accurate on every SURFACE, with an average success rate of 95.42% (Figure 4). As we can see at the bottom of Figure 4a, the CIs of the differences of the means are large and near or even crossing zero, thus showing no evidence of a difference. If we narrow the focus to the accuracy reached for each SCALE (Figure 4b), we observe little evidence of the participants performing better on the *Hard* surfaces using 16 levels (*S16*). This first observation indicates the surface compliance does not have an effect on the success rate. Moreover, it is surprising to see that the participants reached high accuracy for all SCALES, which hints they might still be very accurate with denser scales.

Selection time. We depict the selection times for each SURFACE on Figure 5. We can observe clear differences between the SURFACES: selections with the *Soft* are slower (despite rather small ∼0.2s). The differences between the means depicted on Figure 5 display rather strong evidence of this difference. This result indicates that using the *Soft* surface, participants needed more time to reach the levels or to stabilize on an individual level before releasing their finger. If this interpretation is correct, we should observe differences in the *crossings* produced by the participants.

Crossings. We depict the crossings produced for each SURFACE and TARGET on Figure 6. We can observe an interesting pattern: the *Soft* surface leads to more crossings only in high force levels

[2] [LL, UL] represents lower and upper limits of 95% bootstrapped CIs

[3] Analyzing results with null hypothesis significance testing (NHST) is increasingly being criticized by statisticians [2, 12, 19] and HCI researchers [3, 13, 14, 24]. The term effect size here simply refers to the measured difference of means. While we make use of estimation techniques, a p-value approach reading of our results can be done by comparing our CIs spacing with common p-value spacing as shown by Krzywinski and Altman [27] and we provide the empirical data here https://osf.io/v5dtk/.

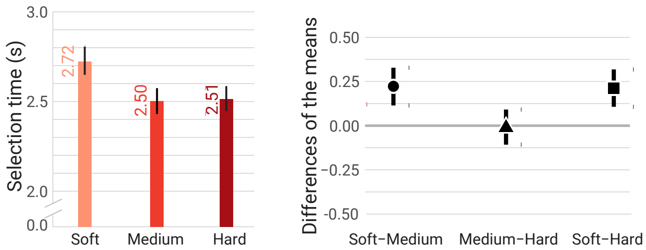

Figure 5: Selection time for each SURFACE (left), and the differences of the means (right).

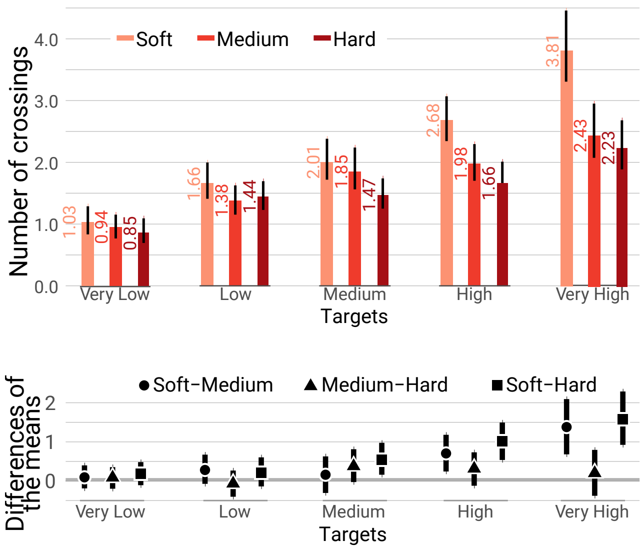

Figure 6: Number of crossings relative to all SURFACEs and TARGET (top), and the means differences (bottom).

(i.e., *High* and *Very High*, Figure 6-bottom). We also observe little evidence of a difference between the *Soft* and *Hard* surfaces for *Medium* values.

User preference. When asked to rank the surfaces following their personal preference, the *Hard* surface was most frequently ranked first (*Hard*-12, *Medium*-7, *Soft*-5). The *Soft* surface was most frequently ranked second (*S*-14, *M*-10, *H*-7) while the third place was more even (*M*-7, *S*-5, *H*-5). However, we do not find evidence of a pattern in the ranking, implying the order of the ranking varied across participants (differences of the means: *Soft* vs. *Medium* 0.0 [-0.46, 0.38], *Medium* vs. *Hard* -0.29 [-0.71, 0.16], *Soft* vs. *Hard* -0.29 [-0.67, 0.13]).

Apparently, different participants appreciated the *Soft* and *Hard* surfaces for the same reasons; they provided a good control (*Soft* "felt more in control" P24, "more control using the soft surface" P19; *Hard* "I can achieve better accuracy" P22, "Stiff surface feels like giving more control over the pressure" P7). Some participants remarked that the *Soft* surface was accurate in low values ("soft one is preferred for low values" P9, "the soft one is good for the smaller values" P1) but inaccurate in high values ("on the high values its kind of uncomfortable" P1, "too inaccurate to select high values" P13,

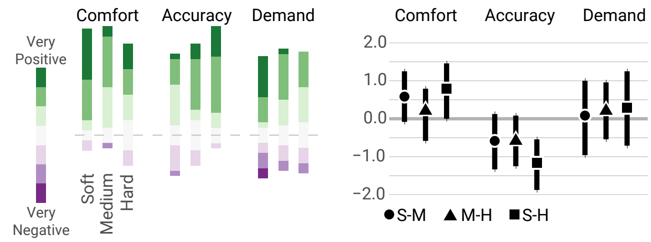

Figure 7: Answers of the questionnaire's Likert-scales that the participants had to fill at the end of the experiment (left). Differences of the means (right).

"especially difficult to achieve accuracy around the maximum pressure" P22).

This variability in the preferences is also noticeable in the results of the Likert-scales (Figure 7). Our results show a trend that the participants found the *Soft* surface to be more *comfortable* (Figure 7b), but they perceived it as less accurate than the *Hard*, probably as result of the difficulties in targeting high force levels. The three surfaces were comparably *demanding*.

5 DISCUSSION

We discuss in this section the results of the experiment by focusing on the two primary outcomes: we only observed a small effect of the surface compliance on the user performance, and observed higher force input capacity than previously reported in the literature. We offer an explanation derived from contact mechanics of the fingertip for the differences observed.

5.1 Small Effect of Compliance

We did not find evidence of a difference in the user accuracy across surfaces. This primary outcome suggests that interaction models used on rigid surfaces transfer to compliant surfaces. However, we observed that targeting high force levels on compliant surfaces was more challenging (i.e., higher selection times and more crossings). While we observed differences between the soft surface and the others, one can wonder why we do not observe such differences between the medium surface and the others. Despite the three surfaces *feel* equidistant, the relationship between a change in physical parameters and the corresponding perceived magnitude is typically non-linear [48]. The medium and hard surfaces are closer in the physical space than the medium and soft surfaces, as their Young's moduli indicate.

It is important to note that cutaneous cues were reported to dominate kinesthetic cues in tactile perception of sample softness [47]. Assuming that the cutaneous mechanoreceptors sense pressure, we need to discuss how the sensed contact pressure increases with increasing applied force. The derivative of pressure with respect to force (Equation 1) decreases with increasing force and with decreasing elastic modulus. The higher the force and the more compliant the samples, the less pressure increase is sensed when the force is increased. These arguments are directly reflected in the calibration curves of the pressure sensor (Figure 2-bottom). Hence, the tactile

Table 1: Comparison of results from the literature to ours. We focus on the results obtained with the 20-levels scale. By contextualizing our results, we highlight the higher force input capacity observed in our study.

Study	**Our study**	Cechanowicz et al. [5]	BackXPress [8]	Mizobuchi et al. [30]	McLachlan et al. [29]	Pressure Widgets [36]	PressureFish [41]	Wilson et al. [57]
Technique	**Quick Release**	QR	Tap	Dwell	Tap	QR	Dwell	QR
Force Range (Newton)	**0-5.51 [4.80, 6.57]**	NR	0-4	0-4	0-10	NR	NR	0-3.5
Level Number	**20**	12	7	10	10	12	16	10
Success Rate (%)	**94.7 [93.5, 95.8]**	58.0	69.4	~89.0	89.3	~89.0	~72.0	~64.0
Selection Time (s)	**2.86 [2.78, 2.95]**	~3.30	3.50	~4.80	2.89	~0.80	~1.65	~2.45
Crossings	**2.58 [2.41, 2.78]**	~2.6	NR	NR	NR	~0.95	~0.45	4.7

input characteristic for the feedback requested from the user becomes flat for high force levels and compliant samples, making the task more difficult.

This highlights a crucial interplay between the *sensor's output*, the *compliance* of the surface, and the *visual mapping*. Although we mapped the sensor's output to a linear response, this output remains prone to jitters in high force levels, even more as the surface compliance increases. To counter this effect, it is important to carefully design the visual mapping accordingly. Previous work proposed various alternatives [5, 36], but did not contextualize their results with a discussion of the sensor's output. As this output changes on soft surfaces, this discussion becomes even more relevant. We only evaluated a linear visual mapping in our study, thus we are missing data to assess the impact of other mappings. We conjecture, however, an exponential discretization of the force scale would improve the accuracy on more compliant surfaces by cancelling out jitter. Further research is needed in this direction.

Studies that investigated the compliance of material reported that users prefer interacting with soft materials [25, 26], although they do not perform better using them. We do not observe clear evidence of a preference for soft surfaces but a trend that participants perceived the soft surface as more comfortable. However, the participants felt less accurate when using a soft surface in general.

5.2 High Input Capacity

Surprisingly, we observed very high accuracy even using dense force scales of 20 levels; on average, the participants completed 95.2% of the selections correctly throughout the experiment. It is important to note we reached saturation in this experiment, i.e., we observed high accuracy with the densest scale, which indicates the force input capacity might be even higher. This observation contrasts with results from the literature. Previous work reported user performance greatly decreases for scales denser than 10±2 levels. To give a clearer understanding of this difference, we compare most relevant previous work to ours in Table 1.

We note two main factors that might explain this difference: the *force range* and the *selection technique*. While many studies did not report the force range and others used a fixed force range (see Table 1), we adapted it to each participant to make the task more comfortable for them. This resulted in wider average force spans. Also, we implemented a *quick release* selection mechanism following precise guidelines from Corsten et al. [10]. In contrast, other studies do not specify the implementation of this selection mechanism [5, 36]. In addition, *quickly releasing* the finger is less prone to jitters and crossings than *dwelling*, hence our participants likely benefited from this mechanism in denser scales. We also explain the shorter selection times we observed with 20-levels scales by this optimized selection technique. Based on these juxtapositions, we conclude force input has been underestimated so far; its input capacity is higher than previously expected provided an appropriate calibration scheme is used. These results highlight the potential of using force input on various surfaces.

6 IMPLICATIONS

When designing interfaces on arbitrary surfaces, the input method is typically spatial. Systems which use force input are comparatively rare. This is unfortunate as force input is a compelling means to provide subtle input requiring minimal movements in a wide variety of contexts. For instance, one could interact on the cheek [40] or sleeve [35] to control AR goggles and input text using force [59], interact on the armchair of an augmented sofa [54, 58] to control a TV, or leverage force input in the context of thumb-to-finger interactions [42] (Figure 8). One explanation of why this is seldom done is because the throughput is relatively low. Our study suggests that this general consensus might be wrong, and that carefully implemented force input devices provide a much higher input fidelity than is generally assumed in the HCI community.

This conclusion should come as no surprise to musicians who regularly demonstrate high level of force control when they use force to modulate musical expression. In fact, the music industry has embraced force input with pressure sensitive input devices such as the Joué Keyboard [22], Roli's Seaboard [38], or Sensel's Morph [39]. Although such instruments typically rely on continuous input in contrast to the discrete tasks we studied, our study results highlight the high expressivity that force input enables. Interestingly Sensel's Morph and the Joué Keyboard provide users with a relatively rigid interaction surface, while Roli's high-end Seabord is soft. In fact *soft* is one of the selling points of the Seabord, often used as the first word to describe the device. But is soft truly better?

Our analysis showed no evidence that soft is better for force input, but neither is it worse than rigid. This suggests that when designers choose the rigidity of the input device they can focus fully on the application context or user preferences, without worrying that choice of material will have a significant impact on user performance. Similarly, the results also indicate that interaction methods can be transferred between devices of varying compliance, again providing the designer with a freedom of choice.

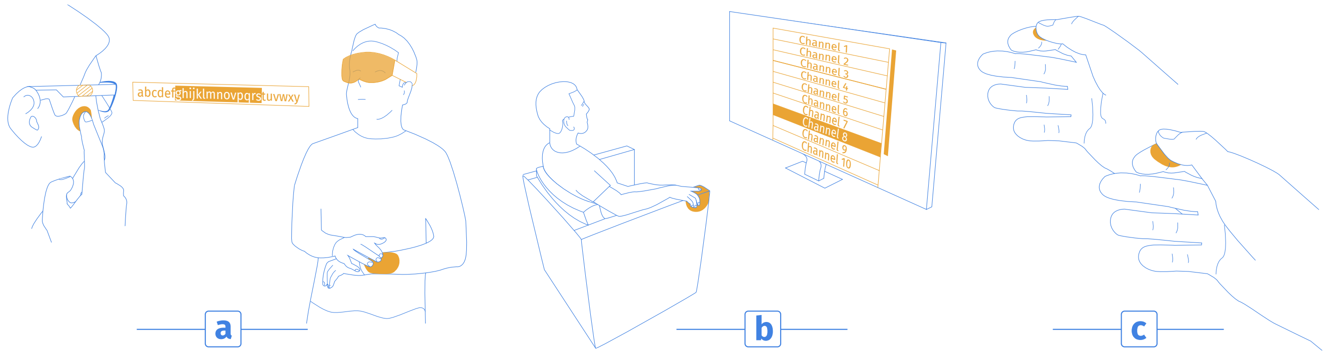

Figure 8: Use cases of force input on soft surfaces. a) Using the cheek [40] or an augmented jacket [35], the user can interact with AR goggles to input text [59]. b) With an augmented sofa [54], the user can control a remote TV with minimal movements. c) Leveraging force input for thumb-to-finger interactions [42] minimizes finger movements to maximize the input capacity over space.

However, to fully leverage this freedom of design, mapping and calibration should be given special attention in sensor implementations:

- *Mapping.* There are several mapping steps which occur. The first is mapping from the sensor output to the perceptual experience of force, i.e. the visual mapping. Previous work has shown that optimizing this mapping improves input performance [5, 36, 41], but did not discuss how it should adapt to the sensor's output. This knowledge is important because on compliant surfaces, the force-displacement curve of the material affects the sensing device, which also depends on the sensor used. Which brings use to the second mapping step, mapping the compliance of the surface to the sensor's output. Designers must carefully consider this mapping step to design comfortable force interactions on various surfaces.
- *Calibration.* To enable comfortable force interactions, designers need to consider calibrating their devices to the users' capabilities. In our study, we observed that users are comfortable with different force ranges and that there might be a trend these force ranges change depending on the surface properties. Furthermore, as high force levels lead to more demanding efforts on compliant surfaces, designers should privilege lower force levels in this context by adapting the force scales (e.g., non-linear distributions).

Our final recommendation is to *use the force.* A powerful advantage of force over other input methods is that it only requires fingertip-sized interactive areas and leverage subtle interactions. Besides, our results indicate its high input capacity makes it an interesting supplement or even alternative to touch in various ubiquitous contexts. Indeed, while augmenting tiny parts of furniture or clothes would constrain touch interactions, it could attenuate false activation issues while leveraging minimal finger movements using force input. We strongly encourage designers to think beyond touch interactions and leverage force input on various surfaces.

7 LIMITATIONS AND FUTURE WORK

Applying Normal Forces with the Index Finger. Our study focused on normal forces applied vertically using the index finger. Hence, it is unclear how our results transfer to multi-finger interactions like squeezing or pinching a material [4, 33, 37], or using one finger to press on other fingers (e.g., pressing two fingertips together).

Silicone Surfaces. Soft interfaces consist of various types of materials [4]. We focused on silicon surfaces as it allowed us to control the Young's modulus of these surfaces while facilitating the replicability of our results. However, many soft interfaces have integrated sensors, use other materials, or simulate compliance following specific patterns that provide non-linear compliant feedback [4]. As the compliance seems to only have a small effect on the user performance, non-linear compliant behaviors should not differ. Still, further investigations are required.

Visual Mappings. We linearized the sensor's output to minimize biases linked to its inherent characteristics, and used a linear visual mapping accordingly. Our results indicate that selections in high force ranges suffer from such a mapping and would likely benefit from an exponential mapping. Future work should address both mappings in more details to compensate for high forces on soft surfaces and likely enhance the input capacity.

Comparison to other Input techniques. We highlighted the high input capacity of force input and showed its potentials as an independent interaction means. However, it remains unclear how force input compares to other interaction means, and whether it provides some benefits over them. While we believe force input is a great complement or alternative to touch, further studies should investigate this claim in more detail.

8 CONCLUSION

We presented a user experiment investigating the effects of surface compliance on force input for visual targeting performance. The results show evidence of higher input capacity than reported previously in the literature, and that selecting high force levels on soft surfaces is more demanding. We infer from these results that previous findings on rigid surfaces transfer to soft surfaces. Our results show the potential of force input as a complement or alternative to touch in interfaces for ubiquitous computing, and point out the interplay between the pressure sensor's output, the surface compliance, and visual mapping that designers must consider when designing force interactions on soft surfaces. Based on these results, we presented use cases as examples to encourage designers to think beyond conventional touch input and leverage the power of force input on soft surfaces.

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