Improving Input Accuracy on Smartphones for Persons who are Affected by Tremor using Motion Sensors

KATRIN PLAUMANN*, MILOS BABIC, TOBIAS DREY, WITALI HEPTING, DANIEL STOOSS, and ENRICO RUKZIO, Ulm University, Germany

Having a hand tremor often complicates interactions with touchscreens on mobile devices. Due to the uncontrollable oscillations of both hands, hitting targets can be hard, and interaction can be slow. Correcting input needs additional time and mental effort. We propose a method for automatically correcting such inputs based on motion data, gathered both with the devices' sensors and a small wearable sensor on the finger used for tapping. The development was informed by interviews with persons with tremor. Two empirical studies showed that our method, involving both smartphone and finger motion sensors without changing the user interface, allows users with tremor to select objects with up to 40 % fewer misses.

CCS Concepts: • **Human-centered computing** → *Touch screens*; *Ubiquitous and mobile computing systems and tools*; *Smartphones*; *Mobile phones*; *Mobile devices*; *Accessibility technologies*; *Accessibility systems and tools*; *Accessibility design and evaluation methods*;

Additional Key Words and Phrases: Tremor, Smartphone, Accessibility, Touchscreen, Evaluation, Tapping

ACM Reference Format:
Katrin Plaumann, Milos Babic, Tobias Drey, Witali Hepting, Daniel Stooß, and Enrico Rukzio. 2017. Improving Input Accuracy on Smartphones for Persons who are Affected by Tremor using Motion Sensors. *Proc. ACM Interact. Mob. Wearable Ubiquitous Technol.* 1, 4, Article 156 (December 2017), 30 pages. https://doi.org/10.1145/3161169

1 INTRODUCTION

In recent years, the prevalence of touchscreens has increased to the point where our daily lives are unimaginable without them. Smartphones, e.g., are used for text and voice messages, email, social applications, and calendar management amongst others [30]. Inherent to interacting with touchscreens is direct manipulation of objects, like touching or tapping. Examples for such manipulations are typing text, selecting elements from lists and menus, selecting buttons and checkboxes, and activating radio buttons. Successful selection might be influenced by both external and internal factors. External factors may be target size, light conditions, noise, smudge impeding touch detection and unsteady environments (e.g. public transport).

Internal factors like limited focus on the task, walking, occlusion, and certain user characteristics can also negatively influence successful target selections. One such characteristic is hand tremor. Through the oscillation of one or both hands, hand tremor makes it very hard to hold devices in a stable position. Furthermore,

*This is the corresponding author, katrin.plaumann@uni-ulm.de

This work was partially conducted within the Emmy Noether research group Mobile Interaction with Pervasive User Interfaces funded by DFG and the SenseEmotion project funded by BMBF.
Authors' address: Katrin Plaumann; Milos Babic; Tobias Drey; Witali Hepting; Daniel Stooß; Enrico Rukzio, Ulm University, James Franck Ring, Ulm, 89081, Germany, <firstname>.<lastname>@uni-ulm.de.

2474-9567/2017/12-ART156 $15.00
https://doi.org/10.1145/3161169

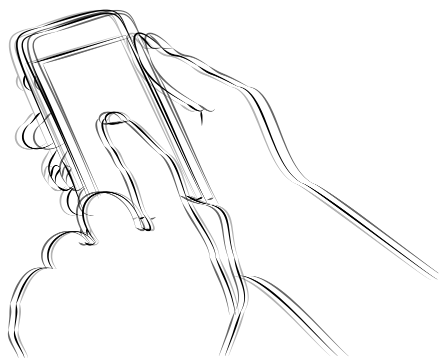

Fig. 1. Tremor in ones hands makes both holding a smartphone and tapping on the touchscreen cumbersome. Through to the uncontrollability of the movements, targets are missed and interaction times are longer. We propose using the motion sensors in the smartphone and a motion sensor placed on ones finger to detect tremor related movements and correct resulting misses.

the selecting finger's movements cannot be controlled as precisely as needed for successful interactions with touchscreens.

The reasons for tremor vary, including neurological diseases like Parkinson's and essential tremor, but tremor can also occur as a side effect of medication or as enhanced physiological tremor in stressful situations [28, 34]. Essential tremor, the most common movement disorder [16, 28] affects approximately 0.4 % of the population of all ages, although its prevalence increases dramatically with age, with 6.3% of people aged 60-65 and 21.7% of older than 95 years affected [14]. It is estimated that about 7 million in the U.S. are affected by essential tremor [15]. Considering the estimated 2 billion smartphone users worldwide [8], likely 8 million people with tremor own a smartphone.

Since smartphones are today foremost used by younger people (30% of 65 or older in the US own a smartphone [1]), tremor might be seen as a marginal problem. Yet, it should not be neglected that tremor does affect young people. Additionally, the number of senior users adopting smartphones has increased [25]. Furthermore, and even more important, today's heavy smartphone users are ageing. And it seems unlikely that we will stop using a technology that became ubiquitous to us. Driven by the demographic change, the portion of the population affected by this problem is likely to increase in the future. Besides age, tremor intensity depends on various factors, including medication, caffeine intake, sleep, strong emotions, and exhaustion [23]. Tremor is not only more intense in stressful situations, but can exacerbate stress by provoking frustration.

We explored the resulting problems in mobile scenarios by interviewing persons with hand tremor. The results indicate that tremor often causes missed targets and longer interaction times, forces users to concentrate hard and can lead to frustration. Prior research has shown that tremor also correlates with text entry performance on smartphones [24]. So far, correcting input for persons affected by tremor on mobile touchscreens using motion data is rarely researched. Rather, alternative interaction styles were introduced [36, 43]. While those techniques are helpful and improve interaction, they also require to learn a new interaction style and possibly changes to the user interface. Motion sensors of smartphones have been proven to reliably detect and classify types of tremor [5, 6, 13, 39], although this data has to the best of our knowledge not yet been used to correct misses caused by tremor. To research the feasibility of using motion sensors to correct misses caused by tremor, we developed a method based on NoShake [29], accounting for tremor in both hands. We show in two user studies that with this approach, successful selections can be increased.

In this paper, we make three main contributions: (1) An assessment of difficulties persons with tremor face when using mobile touchscreens derived from interviews with persons affected by tremor (n=4). (2) A correction method for tremor-induced misses, accounting for both hands' oscillations. The method uses data of smartphones' motion sensors and an off-the-shelf motion sensor fixed to ones finger. (3) Two empirical evaluations of different versions of said correction. In the first evaluation, we tested different versions of our algorithm with healthy participants by inducing tremor with electrical muscle stimulation (EMS) (n=28), and compared the performance of the motion sensors to more accurate data from a motion capturing system. Our results show that off-the-shelf motion sensors are sufficiently accurate to allow tremor correction. In the second study, our method was tested with participants having a hand tremor (n=6). We show that with the best configuration, involving both smartphone and finger motion sensors without changing the user interface, misses can be reduced up to 40%.

In the remainder of this paper, we will reflect upon related work and describe the conducted interviews. Subsequently, we will present our correction approach and both of its evaluations, as well as its limitations.

2 RELATED WORK

2.1 Motor Impairments and Touchscreen Interaction

Touchscreen accessibility for persons with motor impairments has been explored in previous work. Examples include analysis of tapping behaviour and proposing of correction models [21], surveys and field studies of general smartphone usage [22], video analysis [2], and interviews regarding touchscreen accessibility [35]. Results show that smartphones empower persons with motor impairments [2, 22] and are generally liked and used [35]. However, smartphone use can be hindered by having difficulties accessing them and concerns regarding the use of speech input when touchscreen use is not feasible [22]. Users might customize the devices or use them in unintended ways [2]. Using touchscreens may require a higher level of dexterity than users have, and even accessibility features could be hard to use [35]. Additionally, tapping behaviour varies not only between persons with different impairments, but also between usage sessions from the same person. This should be considered when developing correction models [21].

Our method does not apply a general offset correction, but adjusts to users' current situation and tremor intensity. Further, we focus on users affected by hand tremor.

2.2 Input Techniques for Persons with Tremor

Nicolau and Jorge [24] analysed text entry performance and tremor intensity in older adults. They found that with an increased tremor intensity, the number of missed targets also increases. They propose several guidelines that should be considered to ensure accessible keyboards for people with tremor.

Swabbing [19, 36] is an input technique especially designed for older adults with intention tremor. Elements are selected with swipe gestures, allowing users to leave their finger on the screen. This provides more stability and leads to more accurate selections.

Zhong et al. proposed enhanced area touch [43], where ambiguous touches were resolved by asking users to confirm their selection, either on a magnified version of parts of the user interface or in a list with corresponding user interface elements. An evaluation showed that using lists decreased error rate while both versions increased task completion time. Additional feedback from study participants revealed that steep learning curves should be avoided in such an assistive system.

With Barrier Pointing [10], users get additional support by resting a stylus on the screen and guiding it along the edges of said screen. This could provide people with tremor with more stability, and thus improve interaction.

Goal Crossing [38] is an alternative to area pointing, where targets are selected when crossed. This allows users to leave their finger on the screen, which gives them more stability.

The aforementioned solutions involve changes to the interaction technique or the interface, while our correction approach can be incorporated into existing interfaces and does not require users to change current input techniques.

2.3 Tremor Detection with Motion Sensors

Carignan et al. [5, 6] developed a tremor recognition software using smartphones' motion sensors. They compared their application with tremor detection based on accelerometers used in laboratories and tremor classification by medics. Carignan et al. found that tremor can reliably be detected with smartphones. Kostikis et al. [13] developed a diagnosis tool for Parkinson's Disease, which also includes tremor detection. They found their tool being feasible for diagnosis. Since different tremor types have different frequency bands, Woods et al. proposed a method to distinguish between tremor occurring as a symptom of Parkinson's Disease and essential tremor [39].

While all of these applications showed that tremor can be detected using modern smartphones, we go a step further and use the smartphone's motion sensors to correct misses.

2.4 Improving Accuracy on Touchscreens

Improving touch-based interaction in general is a widely researched field in human computer interaction. Examples include the work of Xia et al. [41], where touch locations were predicted by tracking the path the finger followed while tapping. In a Fitts'-Law-based test, Bi and Zhai [3] found that using Bayesian statistics is more effective when predicting the most likeliest hit target than the visual boundary criterion. Weir et al. [37] proposed using a user specific model for machine learning. Their approach needed 200 training touches. Another machine-learning-based approach by Buschek et al. [4] only needs 60 touches to learn user behaviour, and can be transferred between devices. Goel et al. [11] increased writing performance especially while walking based on displacement and acceleration features as well as finger movement on the screen.

While we also aim at optimizing touch based interaction, and also use similar data to reach that goal, we focus on improving the accessibility for people affected by hand tremor. Thus, we need to make different considerations. E.g., tremor intensity changes over time, and is not coherent within one person in all situations.

2.5 Using Finger Mounted Devices for Input

In recent years, mounting devices on users' fingers has become common in HCI research, as a recent survey article by Shilkrot et al. shows [31]. Devices vary in form, size, used sensors, actions provided and usage domain. Yet, those devices are intended to be worn on ones finger to increase interaction space or solve interaction problems. Examples for such devices include the work of Yang et al. [42], who developed a device worn at the tip of one's finger used to allow always-available finger input. Kienzle and Hinckley proposed LightRing, a ring equipped with motion sensors used to detect finger gestures [12]. Xia et al. [40] proposed a finger-mounted stylus to assist interactions with ultra-small touchscreens.

We also use a finger-mounted device, or rather a finger-mounted motion sensor, to gather motion data of both tremor oscillations and tapping movements.

3 ASSESSING TREMOR AFFECTED PERSONS' DIFFICULTIES WITH SMARTPHONES

To gain a better understanding of how people with tremor use mobile touchscreens, we conducted semi-structured interviews with four participants affected by essential tremor.

3.1 Procedure

All interviews were held in person at our institute. Interviews were both audio and video recorded. Participants' interactions with devices were recorded on video. At the beginning of each interview, its purpose was explained.

Device	**Type**	**Display Size**
Galaxy Nexus	Smartphone	4.65 in
Samsung Galaxy S3 Mini	Smartphone	4.00 in
Nexus 7	Tablet	7.00 in
Samsung Galaxy Tab 10.1	Tablet	10.10 in
Sony Ericsson Experia Mini	Mobile Phone w/ QUERTY Keyboard	3.00 in
Samsung SGH-A800	Clamshell Phone w/ 12 Key Keyboard	-
LG Watch Urbane	Smartwatch	1.30 in

Table 1. List of devices used as probes in the interviews.

Participants then gave their consent and filled in a questionnaire regarding their demographic data and background information about their tremor. Participants were further asked to draw spirals [27] to assess their tremor severity. During the following interview, participants were asked about their typical mobile touchscreen usage behaviour, configurations and customizations they made, and compensation strategies regarding every day scenarios like writing, reading, and editing contact information. Participants were invited to demonstrate certain behaviours with their own devices. Besides, diverse other mobile devices (Table 1) were used as probes to demonstrate and compare usage behaviours. Each interview lasted between one and one and a half hours. Participants received € 15 compensation. The interviews were approved by our Institutional Review Board (IRB).

3.2 Participants

Four participants (one female) were recruited through flyers and newspaper ads. Participants' age ranged between 25 and 63 years (mean: 36.75 (15.27 SD)). All participants had essential tremor for between 10 and 60 years. All participants were right handed and owned a smartphone, three reporting using it often. Table 2 shows the demographic data, tremor intensity according to the spiral drawing, and prior experience with mobile touchscreens for each participant.

3.3 Findings

All audio recordings were transcribed to text, while the link to the accompanying video recordings of participants handling devices was kept through annotations. The interviews were coded by three researchers using open and sub-sequential axial coding. During an iterative process, codes were discussed, compared and refined in order to achieve a consistent interpretation of the interviews, leading to categories and general themes. Conflicts were resolved through discussion and revisiting of transcripts and recordings.

3.3.1 Need for stabilisation. Due to the uncontrollable oscillations of both hands, participants found it hard to hold devices in stable positions. Thus, they all developed strategies to stabilize the device and the hand interacting with the device. Those strategies included approaches to reduce the oscillations and placing the device on still surfaces, when available. Oscillations of the hands were reduced by additionally stabilizing hands and arms. This was achieved by pressing the upper arms to the torso, as can be seen in Figure 2. This position is likely to be adopted in mobile scenarios and where no surface is available. If still surfaces were available, they were either used to place the device on, or to lean on the forearms and hands (Figure 2). None of the participants used their phone with only one hand, all used both hands. Either one hand was holding the device while the other was

Fig. 2. Typical device holding strategies.

used for touch interaction, or the device was held in both hands and thumbs were used for interaction. Figure 2 illustrates typical device holding positions. The additional need for stabilisation further complicates interaction while walking, leading to either stopping or avoiding using smartphones while walking.

3.3.2 Customisations to account for tremor. Participants made very little to no customizations to their devices; two of them were aware of how to change settings. One participant increased the font size. Except P3, all participants used a QWERTY keyboard (P3's phone had a 12-key physical keyboard). One person used Swipe for text input, as leaving the finger on the screen gives them more stability and control. One participant mentioned

	P1	**P2**	**P3**	**P4**
Sex	F	M	M	M
Age	25	29	63	30
Ocupation	Intern	Student	Retiree	Unemployed
Tremor Severity *	Slight	Slight	Moderate	Marked
Years w/ Tremor	10	15	60	30
Smartphne Use per Day	10 h	6h	0.1h	2h
Used Applications **	Communication Social Media Games	Communication Tools Social Media Games Entertainment Other	-	Communication Social Media Games

* *Tremor Severity is given based on spiral drawings according to the following scale: slight (< 0.5 cm), moderate (0.5–1 cm), marked (1–2 cm), and severe (> 2 cm)*
** *Used Applications are categories given ordered accordung how frequent participants used them, with the first named category being the most often used one.*

Table 2. Background data of interview participants.

an add-on hardware keyboard being desirable. Not adapting the settings to one's needs goes in accordance with findings from Zhong et al. [43], where participants were not aware of available accessibility features.

3.3.3 Device acquisitions. Participants tended to avoid changing devices. Once they got accustomed with a certain device type and found how to best use it, they did not want to invest in learning how to use other device types. So one strategy was to always buy phones of a certain product line from a certain vendor. This is similar to users with motor impairments avoiding steep learning curves as Zhong et al. showed [43]. There is also a trade off between device price, functionality, and robustness. Since devices are more likely to fall down and break, they should not be too expensive and rather robust (see Figure 2 for an example of a broken touchscreen), but still provide a certain level of functionality. For this reason two participants used smartphones instead of mobile or feature phones, although phones with physical keyboards would be easier to interact with. Regarding the screen size, prior research as well as our participants pointed out that larger displays allowed for larger interaction elements and were thus easier to use. However, larger devices tend to be harder to hold; in particular two-handed strategies (Figure 2) are not as comfortable on large devices as they are on smaller devices.

3.3.4 Interacting with mobile user interfaces. All participants always found ways to interact with their devices as they needed, yet not without facing certain obstacles. As already mentioned, larger interaction elements are preferred, but also the distance between elements should be as large as possible to avoid ambiguous input. The mental effort for hitting small targets is very high, tasks like correcting text or selecting checkboxes involve much concentration. Since correcting text involves hitting a very small target in close proximity to other possible targets, this task is very cumbersome. One participant mentioned that sometimes "... correcting a message takes longer than to compose it." Therefore, typos are only corrected when the text's meaning is otherwise changed or obscured. Using dictionaries and auto correction has both advantages and disadvantages: on the one hand, typing accuracy and speed can be increased because typos are automatically corrected and words are not needed to be spelled out, but if words are not included or included but falsely spelled, it is all the harder to correct them. There is a tendency towards physical keys and haptic feedback, though one participant actively deactivated vibrotactile feedback for their softkey keyboard.

Regarding the usability of applications, the general approach could be described as trial and error. Rather than pondering its usability beforehand, participants tried applications and decided then if they could and would use them again. Direct input was preferred over indirect input with e.g. a stylus. Speech input was not seen as feasible, mostly due to its inherent characteristics and problems (e.g. usage of dialects, privacy concerns). One participant, though, used audio recordings as a form of note taking during the day.

Another topic for all participants was the volatility of their tremor. The tremor intensity varied from day to day. Things perfectly doable on one day were very hard to achieve on other days. Some of those variations could be predicted (e.g., after drinking coffee or when being ill), yet sometimes there seems to be no reason for those fluctuations, or even short bursts. The observations of Montague et al. [21] are quite similar. Tremor seems to be not only different from person to person, but also differs for one person at different points of time.

3.4 Implications for Improving Input

Our findings indicate several implications for an assistive system improving input performance for persons with tremor. First, compensation strategies include stabilisation of both hands. Second, the oscillations of the finger interacting with the device can also impede interactions. Therefore, both hands have to be regarded. It seems not sufficient to only compensate for movements of the hand holding the device. Additionally, the correction approach should adapt to the current situation and changes in tremor intensity. That way, day to day variations of the tremor can be accounted for. Additionally, the correction should not require users to switch to a new interaction technique, since they avoid learning curves and stick with their familiar ways of interacting with

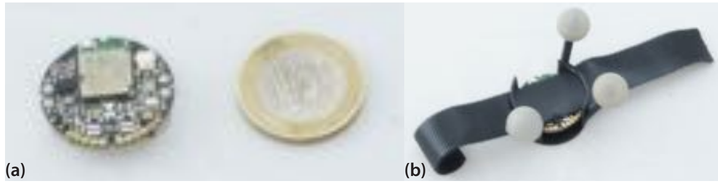

Fig. 3. The Meta Wear RPRO sensor alone (a) and in its 3D printed case with Velcro straps (b).

devices. Also, since users would rather not change settings or adapt their phone to their needs, no changes in settings menus should be required. Hence, we implemented an input correction approach accounting for tremor in both hands. Further, our approach can run in the background of any application, and does not require users to change their way of interacting with their device.

4 IMPROVING INPUT WITH MOTION SENSORS

4.1 Approach

Our general approach in correcting input was to use the built-in motion sensors of modern smartphones as a means of detecting the tremor related motions. With this knowledge, target misses caused by the unintended tremor motions should be corrected. This way, people with tremor could use their phones and applications as intended, and would neither have to learn a new interaction technique nor would such a new technique have to be incorporated into existing applications. Yet, since both hands oscillate involuntarily, the motions of both hands would have to be measured. Additionally to the built-in smartphone motion sensors, we therefore used a small motion sensor to wear on ones finger. This sensor, a Meta Wear RPRO [18], can be seen in Figure 3. It has a diameter of 2.4 cm and a weight of 2 g. Power is supplied by a coin cell. The sensor was placed in a 3D printed case and fixed to one's finger with a Velcro strap (Figure 3). The sensor was connected to the phone via Bluetooth Low Energy. Using finger worn devices to increase the interaction space or improve input is a current trend in HCI [31]. Yet, since our approach is modular, it can also be used only with the correction based on the phone's motion sensors.

Figure 4 shows the raw signals from both the finger's motion sensor (Figure 4 a), the phone's motion sensors (Figure 4 b), and both sensors' signals in the same chart (Figure 4 c) over the time period of one second. The data was collected from a person with tremor in both hands. The person was sitting, holding a phone in one hand while having the finger sensor attached to the other hand. This position was also used in our studies. As can be seen, the intensities of the signals measured with the phone are lower than the intensities measured with the finger sensor. One explanation is that the tremor intensity for both hands might vary. Yet furthermore, the weight of the phone introduces additional mass to the shaking hand, thus causing a decrease in intensity while the frequency stays the same (roughly 10 Hz for both hands). The graphs also show that while the frequency is rather consistent, the intensity and shape of each signal changes over time, even in such a short timespan as one second. This supports the findings of Montague et al. [21].

Since none of the authors have a tremor, and tremor as such is hard to simulate, we used gloves inducing tremor with electrical muscle stimulation (EMS) [20] throughout the implementation for iterative testing. To not interfere with the capacitive display of the used smartphone, we cut off the tip of the finger used for tapping as depicted in Figure 5. The tremor could be induced with different frequencies and amplitudes, simulating different conditions and severities [26]. The simulator consisted of a standard EMS device connected to two gloves. Each glove was attached to one pin (positive charge on one side, negative on the other) via a conducting button (Figure 5). The fabric of the gloves was interwoven with metallic threads, so that the impulse was lead

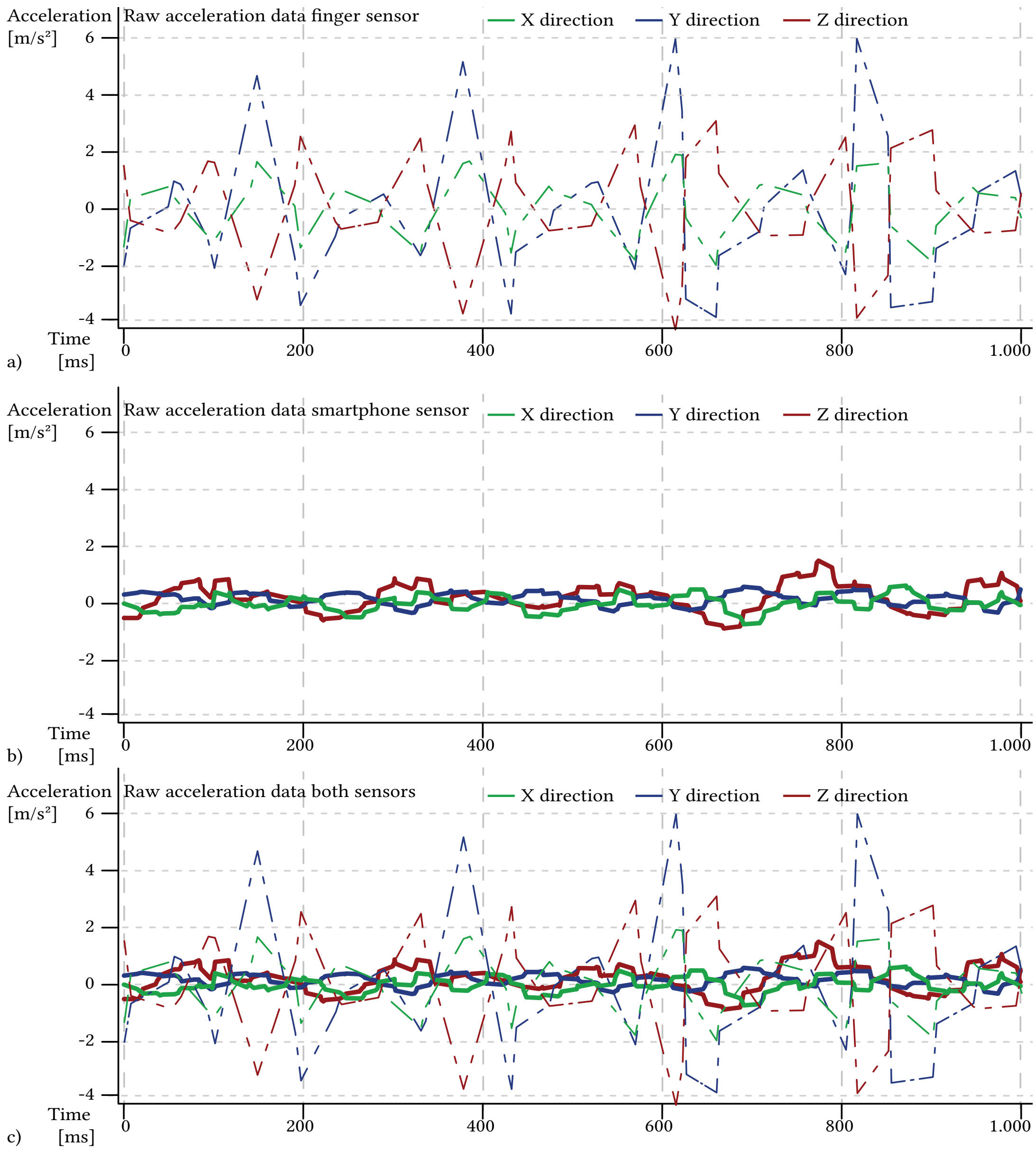

Fig. 4. The raw signals for from the finger sensor (a) and the phone sensor (b) as well as both sensors' data in one graph (c) over the time period of one second. The finger sensor data is depicted with dotted lines, while the phone sensor data is shown as thick solid lines. Acceleration in x direction us coloured green, in y direction blue and red in z direction. Both signals were derived from the same participant while holing the phone in one hand and having the finger sensor attached to the other hand. Note that the accelerations measured with the phone's sensor is remarkably smaller compared to the accelerations measured with the finger's sensor. This is due to the weight of the phone introducing additional mass and thus decreasing the tremor intensity. This effect is accounted for by different parameter values in our correction.

Parameter	Smartphone	Finger sensor
Circular buffer	0.4s	0.02s
Shake window	0.1s	0.1s
Shake threshold	0.3	0.05
Spring damper k	0.000,001	0.000,001
Scale a	10	20

Table 3. The adjusted parameters of NoShake used for our tremor correction. The implementations running for the smartphone and the finger sensor have different parameters due to holding the phone affecting the tremor motions in ones hand.

to the hand muscles via the gloves. All hand muscles were actuated. Since positive charge was applied to one hand and negative charge to the other, the current flew in one direction and no cross currents occurred. Only healthy persons without contraindications towards EMS were allowed to use the tremor simulating gloves. Our IRB approved simulating tremor as described.

4.2 Using NoShake as Basis

The basis for the output correction was the NoShake algorithm presented by Rahmati et al. [29]. NoShake employs a physics model where the screen content is seen as a mass, fastened with springs and dampers to the screen's edges. In the model, motions are absorbed by those springs and dampers, so that the screen content is stabilized in a certain position. In the original implementation, the screen content moves in the opposite direction of the movement based on the phones' accelerations. NoShake was originally not intended to compensate for tremor, but for stabilizing content for improving reading in every day mobile scenarios like walking.

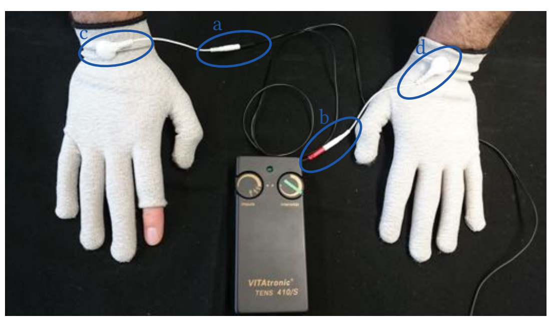

Fig. 5. Gloves simulating tremor with electrical muscle stimulation (EMS). To not interfere with the smartphones' display, the tip of the tapping finger was cut off. The use of EMS was approved by our IRB. The two pins (negative charge coloured red (marked b in the picture), positive charge coloured black (marked a in the picture)) are each connected to one glove with metallic buttons (c and d in the picture). The fabric of the gloves is interwoven with metallic threads, which lead the current to the hands. That way, all muscles in both hands were actuated. Since each one pin with a different charge was connected to one glove, the current only flows in one direction and no cross currents across the chest occur. To further prevent any complications, only healthy persons with no contraindications were allowed to use the tremor simulator. The use of tremor simulating gloves as described was approved by our IRB.

Yet, it accounts for oscillations, and furthermore adjusts to the current situation and tremor frequency, which is what our interviews and previous work [21] has shown to be mandatory for tremor correction. However, the motions involved in these scenarios have other characteristics than tremor related motions. For instance, tremor has a higher frequency and is more rhythmical. Thus, we needed to adjust several parameters. All parameters are listed in Table 3. Some parameters were set based on tremor characteristics, e.g. the *shake window*, others were derived with iterative testing during the development. Therefore, authors as well as members of our research group tested the tremor correction with target selection tasks with different parameter values. In the following, we describe how each parameter was derived based on which assumptions. First, we set the initial *shake window* to 0.1 seconds for both smartphone and finger sensor. This corresponds to a tremor frequency of 10 Hz. Essential tremor, the most common movement disorder, occurs with frequencies between 4 and 11 Hz, while enhanced physiological tremor (the tremor healthy persons might experience under stress) covers the frequencies between 7 and 12 Hz [7, 39]. Thus, a value of 0.1 seconds seemed appropriate. As noted in the original NoShake paper [29], the parameters k representing the spring damper, a representing the scale, and the *shake threshold* have to be set depending on the application scenario. Therefore, we iteratively tested several values for those parameters during the development of our tremor correction. The parameter k, representing the spring mass damper, was finally set to $0.000,001$ both for smartphone and finger sensor implementation. Thus, the "springs" in our model are rather flexible, accounting for the small rapid movements of tremor rather then the slow bumps accounted for in the original implementation of NoShake. The parameter for scale, a, was set to 10 for the smartphone and to 20 for the finger implementation. Thus, the finger's positions were more strongly shifted than the phones. This, as well as different values for the circular buffer and the shake threshold, are due to the smartphones weight influencing the shaking of the holding hand. As illustrated in Figure 4, the weight of the phone decreases the amplitude of the tremor. The *shake threshold* was set to 0.3 for the smartphone implementation and to 0.5 for the finger sensor implementation. We found a *circular buffer* of 0.4 seconds for the smartphone implementation and 0.02 seconds for the finger sensor implementation feasible, since these values allowed a fast calculation (long circular buffers increase the computation cost [29]) and still provide reasonable time to consider the tremor related finger and hand movements.

In the following, we will explain the correction using the smartphones sensors (henceforth called output correction), and the correction using the finger sensor (henceforth called input correction), as well as how they were combined and how we distinguished between actual taps and tremor related motions [26].

4.3 Output Correction

For the output correction, that is the correction based on the acceleration data of the smartphone, we identified two different possible forms. First, as described in the original publication of NoShake [29], the screen content could be changed according to the results of the correction. We will call this visible output correction. However, we found that the permanent readjustment of positions of user interface elements could also confuse users and lead to searching for elements and the feeling of having to chase and catch a certain element. Prior research also shows that changing the user interface can confuse users [43]. Thus, we implemented a version where the visible representations of user interface elements do not change, however the interactive areas oscillate around their visible representations according to the algorithm results. This concept is illustrated in Figure 6, where the actual visual representation of a target is depicted as dark grey circle. Upon detecting an oscillation and calculating the corrected position of said target, the area in which users have to tap to activate that target is moved. The corrected target area is depicted as light grey circle. Taps in that light grey area a regarded as taps falling within the dark grey area (the actual target). All the while, the user interface coordinates of the visual representation of the target have not changed [26]. Following the approach of the original implementation [29],

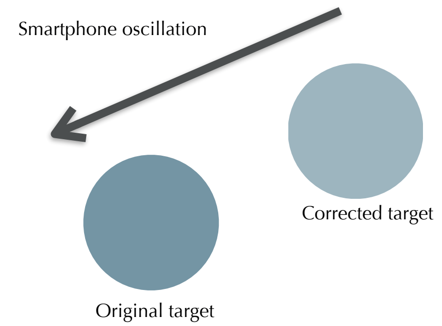

Fig. 6. The principle of the output correction, that is the correction based on the phone's motion sensors. Based on the oscillations of the smartphone, the coordinates of the target are recalculated into the corrected ones. This approach can be used in two ways: first, the visual representation of the user interface elements can change according to the corrections, e.g. the darker target appearing at the lighter coloured target's position. Second, only the interactive area of a user interface element could change. In that case, the darker coloured target would always keep its user interface coordinates, however only touches in the area of its correction (e.g. the lighter coloured area) would be regarded as taps.

both the visually corrected and the not visually corrected targets are always completely present on the screen, meaning that neither of them is cut off when reaching the screen's edge.

4.4 Input Correction

The input correction uses the acceleration data of the finger sensor as basis for its implementation of NoShake [29]. Figure 7 shows the basic principle: The original touchpoint is corrected according to current finger motions, and if the corrected touchpoint falls in the corrected target area, the corresponding user interface element is selected. To achieve this, the results of the NoShake algorithm are buffered in a queue for 0.2 seconds. The distance used to correct the tap detected with the smartphone is calculated as the average over the entries in that queue. For the direction of this distance, we referred from using the direction provided by the finger sensor. Using the direction based on the finger sensor's data would require transforming the sensor plane onto the smartphone plane using

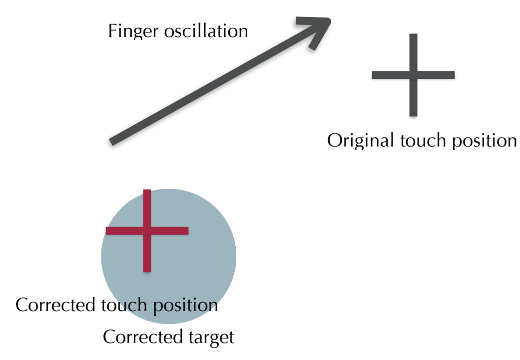

Fig. 7. The input correction uses a combination of the motion data provided by the finger sensor and the movement of the finger on the touchscreen. Based on that data, the original touchpoint is corrected and at best hits the corrected target, either visible or not visible.

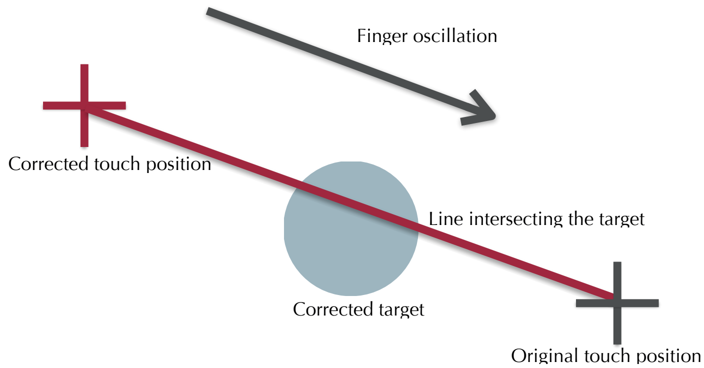

Fig. 8. In cases where the corrected touchpoint did not hit the corrected target, it proved feasible to draw a line between the corrected and the original touchpoint. The target intersected by that line is then regarded as selected.

gyroscope data, which we found had insufficient accuracy. Instead, we used the direction the finger travelled on the screen while touching it, e.g. between the *finger down* and the *finger up* event. For smartphones where the touchscreen resolution does not provide sufficient accuracy for this approach, we implemented a fallback solution. In such a case, we incorporate the motion sensors of the smartphone. The direction of the oscillation of the smartphone during the touch event is measured and used. In cases where the calculated corrected touchpoint did not hit the corrected target area, we found that the correct target could still be selected by drawing a line between the original and corrected touchpoint. The corrected target area intersected by that line was than selected. This approach is depicted in Figure 8 [26].

4.5 Tap Detection

Tremor does not only lead to selecting not intended targets, but also to completely involuntary selections. In some cases, through the tremor motions, the touchscreen is accidentally touched and elements might be selected. Also, including accelerations resulting from tapping movements should not be included in the NoShake algorithm, since they might distort the correction. Thus, we further implemented a tap detection based on the finger's accelerations using a dynamic threshold approach. We compared the current accelerations of the finger in all three directions with the average accelerations over the last 0.4 seconds. If a current acceleration in at least one direction was more than three times higher than said average, the motion was regarded as a tap. The dynamic adjustment of this acceleration comparison guarantees that the detection works with different tremor amplitudes [26].

5 USER STUDY WITH INDUCED TREMOR

To test the above described approach, we conducted two user studies employing a two dimensional tapping task based on the ISO 9241-9 tapping test. Therefore, our correction method was incorporated into the FittsTouch mobile application provided by MacKenzie [17]. In the first study, we induced tremor to healthy participants using electrical muscle stimulation (EMS). According to Woods et al. [39], tremor is "... characterised by synchronous bursts of antagonistic muscles", and can thus be simulated with EMS. We simulated tremor with the frequency of about 8 Hz. Essential tremor, the most common movement disorder, occurs with frequencies between 4 and 11 Hz, while enhanced physiological tremor (the tremor healthy persons might experience under stress) covers the frequencies between 7 and 12 Hz [7, 39]. Thus 8 Hz covers both tremors.

This approach was taken for two reasons. First, we expected that with this approach we would achieve a larger sample size in shorter time. Second, this allowed us to recruit participants who all had previous experience with smartphones and touchscreens. The study received full approval by our institution's IRB. In a follow up study described later in this paper we conducted a similar user study with participants with tremor.

5.1 Participants

Participants were recruited at our institution via flyers and mailing lists. Potential participants were screened regarding the use of EMS to induce tremor. At the beginning of that screening, potential participants had to sign a form expressing they had no electrical or metallic implants, cardiovascular conditions, seizures, were not pregnant, had no skin changes, neuritis, thrombosis, or wounds at the hands. After giving consent, potential participants tried the tremor inducing gloves (Figure 5). They were told to immediately express any discomfort they experienced. Participants were told to hold their arms outstretched in front of them. The frequency of the tremor was set to 8 Hz. The intensity was very slowly increased, until either participants felt uncomfortable or until participants' hands shook with an amplitude of between 0.5 and 1 cm, corresponding to a moderate tremor on the Fahn-Tolosa-Marin Tremor Rating Scale [33]. If participants felt uncomfortable, they were not included in the user study. The tremor amplitude was measured using motion capturing. Participants wore the finger sensor later needed for the correction. Three markers were attached to its case, so that it could be tracked with motion capturing. The screening procedure took about 10 minutes, participants were rewarded with a bar of chocolate. After the screening, three participants decided to not participate in the actual study. The remaining 28 participants (10 women) were between 18 - 36 years old (mean: 25.39 (5.19 SD)). All were either students or researchers at our institution. Three participants were left handed. All had previous experience with and owned smartphones.

5.2 Study Design

The study used a within subject design, with every participant being exposed to all conditions. To compensate for carry-over effects, conditions were counterbalanced. Independent variables were the size of the targets, the distance between the targets, and the correction approach. Target sizes were 5 mm, 7 mm, and 9 mm, based on previous studies and recommendations of the Android styleguide. For the same reasons, the distances 30 mm and 40 mm were chosen. We further employed six versions of our correction approach, plus no correction as a baseline. The six versions of correction are explained in the following. First, we were interested which version of our output correction (visible or non visible) works best. Thus, three correction versions were tested with visible changes to the user interfaces, the remaining three versions without visible changes to the user interface. Of each of those groups of three, one correction employed only the data measured with the smartphone, since we wanted to know if a feasible input correction was possible without having to wear a device on ones finger. Additionally, the full correction (data from smartphone and finger sensor used) was tested, as well as a version of the full correction using motion capturing data as ground truth. We deliberately omitted from testing input correction without output correction since in mobile usage scenarios, output correction would always be possible since modern smartphones included the needed motion sensors. Further, the hand holding the phone is always shaking due to the tremor, needing to have some form of correction. The input correction, however, introduces the need for a new piece of hardware, namely the motion sensor attached to ones finger. This could be problematic for users, and thus it seemed feasible to test only output correction and output correction plus input correction. Dependent measures were the movement time needed to successfully select a target and the number of misses occurring while selecting a target. The movement times were calculated based only on successful attempts, e.g. when a participant needed several attempts for selecting a target only the last (successful) attempt was regarded. The movement time for one participant and one condition was calculated as the mean of all successfully selected

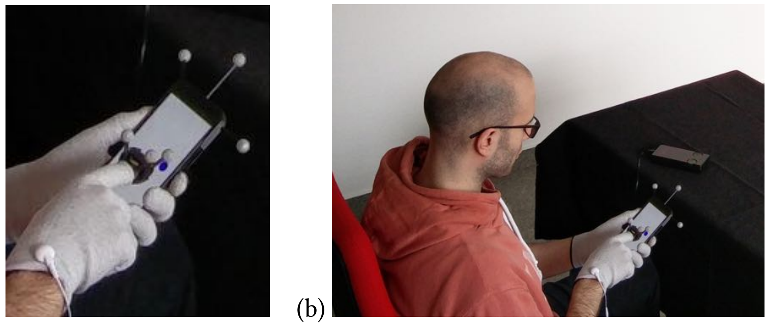

Fig. 9. The study situation. Participants held the phone with one hand while taping with the other (a), while being seated at a table (b).

16 targets. The number of misses was calculated as number of misses occurring while trying to select a target. This corresponds to the analysis approach suggested by Soukoreff and MacKenzie [32].

5.3 Apparatus

The study was performed in a room at our institution. For motion capturing, we used an OptiTrack system, calibrated to submillimetre accuracy. Each three markers were attached to the smartphone (Nexus 5x) and the finger sensor (MetaWear CPRO), as depicted in Figure 9.

Our aim was to provide a feasible tremor correction based on already built-in and commodity motion sensors. However, to show how feasible our approach is, we also implemented a version of our correction using data from a motion capturing system. Motion capturing systems provide far more accurate data, and can thus be used to provide a ground truth for our system. We used an OptiTrack system to track both smartphone and finger sensor. We calibrated the system so that it provided us with position data in submillimetre accuracy. Three retroreflecting markers were attached to the finger sensor as well as to the smartphone (Figure 9). Since the motion capturing system only provides us with position data (e.g., Euler Coordinates and Quaternions), and not acceleration data, we had to calculate our corrections based on position data.

5.4 Procedure

After giving informed consent, participants were seated in front of a table. They put the tremor simulating gloves and the finger sensor on and held their arms stretched out in front of them to set the tremor intensity. As during the screening, the frequency was set to 8 Hz and the intensity was adjusted in such a way that the tremor amplitude lay between 0.5 and 1 cm. Participants were instructed to hold the smartphone in their nondominant hand and tap with the dominant one. Participants then completed each condition in counterbalanced order. They were instructed to select the targets as fast as possible, to simulate quick mobile interactions. All targets had to be selected eventually. Participants were omitted from propping their arms on the table or use other means of stabilisation. Participants were unaware of the correction approaches and the current condition. They always wore the finger sensor and could pause after each condition. After all conditions, participants filled in a questionnaire regarding their demographic data. All participants were compensated with € 10.

5.5 Results

5.5.1 Movement time. The movement times are depicted in Figure 10 and shown in Table 5. As can be seen, there are only small divergences in movement times between corrections. Only for the largest targets and

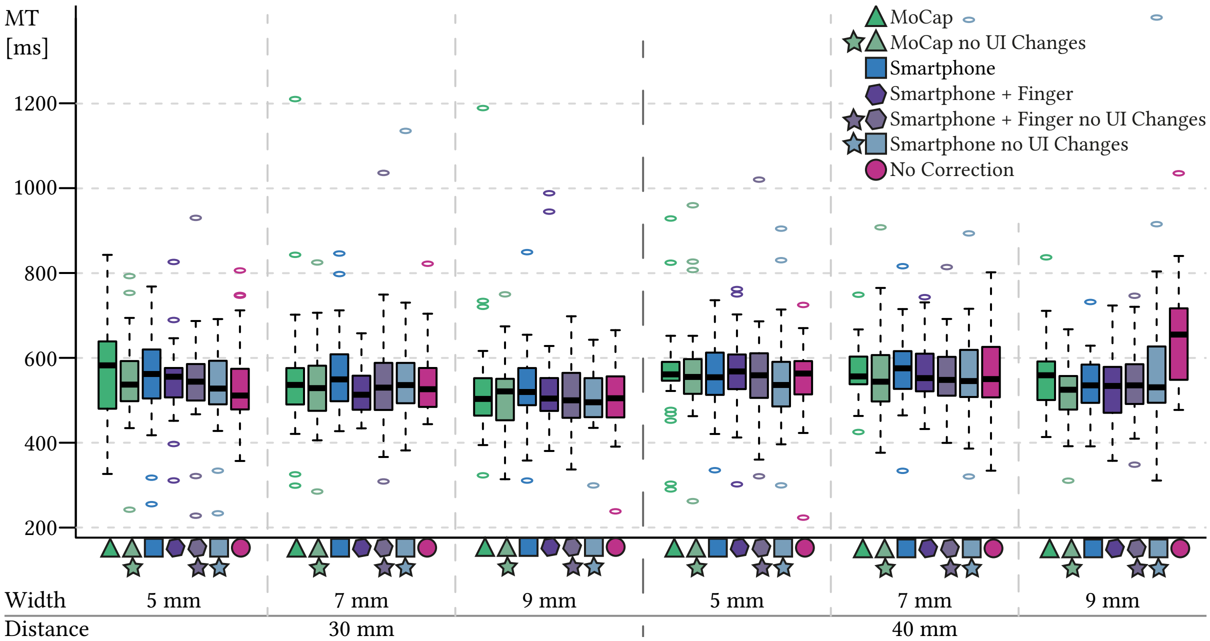

Fig. 10. The mean movement times for each correction. As can be seen, the movement times are all rather close, except for the movement time for the largest targets with the longest distance: here, all corrections are visibly faster than no correction.

longest distance between targets does the movement time for no correction look longer. A 3 *x* 2 *x* 7 repeated measures ANOVA on aligned rank transformed data with correction, target width and distance between target as independent and movement time as dependent factor revealed small significant main effects for target width ($F_{2,1107} = 10.7623$, $p < 0.001$, $\eta_p^2 = 0.02$) and distance between targets ($F_{1,1107} = 54.9753$, $p < 0.001$, $\eta_p^2 = 0.05$) as well as for correction ($F_{6,1107} = 2.7608$, $p < 0.05$, $\eta_p^2 = 0.01$). As expected, large targets were selected faster (540.75 ms (113.67 SD)) than medium (558.74 ms (113.27 SD)) and small ones (554.20 ms (107.48 SD)). Also, targets with short distances were acquired faster than targets with long distances (538.37 ms (109.88 SD) and 564.10 ms (112.07 SD), respectively). All applied correction methods led to faster movement times than

Target Size	**5 mm**		**7 mm**		**9 mm**	
Target Distance	**30 mm**	**40 mm**	**30 mm**	**40 mm**	**30 mm**	**40 mm**
Correction: MoCap	566.7 (110.1)	565.4 (121.2)	561.0 (168.4)	566.6 (64.2)	535.4 (155.0)	557.5 (85.6)
MoCap no UI Changes	549.8 (103.8)	571.9 (127.5)	533.1 (103.2)	562.8 (102.5)	510.4 (85.0)	517.9 (74.9)
Smartphone	549.6 (104.7)	566.6 (95.3)	568.7 (100.6)	578.5 (88.5)	531.2 (97.3)	536.7 (71.4)
Smartphone + Finger	548.5 (92.5)	568.0 (91.6)	520.8 (62.4)	566.4 (76.3)	539.0 (134.9)	528.4 (75.4)
Smartphone + Finger no UI Changes	542.9 (116.5)	562.7 (121.3)	549.4 (138.4)	560.9 (87.7)	511.0 (75.1)	543.0 (91.8)
Smartphone no UI Changes	529.2 (95.7)	553.0 (122.4)	555.2 (138.2)	585.9 (191.4)	510.4 (78.0)	589.4 (200.4)
No Correction	540.0 (116.5)	544.4 (90.8)	547.8 (82.7)	565.3 (105.9)	505.6 (88.1)	654.8 (123.4)

Table 4. The resulting mean movement times per correction, target width and distance between targets (standard deviation in brackets).

	Target Size	5 mm		7 mm		9 mm	
	Target Distance	**30 mm**	**40 mm**	**30 mm**	**40 mm**	**30 mm**	**40 mm**
Correction	MoCap	0.77 (0.58)	0.84 (0.73)	0.36 (0.50)	0.33 (0.33)	0.19 (0.31)	0.12 (0.18)
	MoCap no UI Changes	0.78 (0.55)	1.14 (0.88)	0.42 (0.55)	0.32 (0.41)	0.17 (0.28)	0.15 (0.25)
	Smartphone	1.26 (0.94)	1.24 (0.68)	0.37 (0.39)	0.53 (0.48)	0.23 (0.41)	0.22 (0.30)
	Smartphone + Finger	0.78 (0.58)	0.85 (0.75)	0.30 (0.32)	0.38 (0.44)	0.15 (0.24)	0.20 (0.27)
	Smartphone + Finger no UI Changes	0.80 (0.67)	0.71 (0.64)	0.35 (0.37)	0.27 (0.23)	0.19 (0.34)	0.16 (0.25)
	Smartphone no UI Changes	1.09 (0.75)	1.42 (0.91)	0.45 (0.41)	0.53 (0.53)	0.24 (0.33)	0.26 (0.30)
	No Correction	1.32 (1.12)	1.27 (0.73)	0.30 (0.20)	0.52 (0.60)	0.24 (0.43)	0.27 (0.36)

Table 5. The resulting mean misses per target (standard deviation in brackets) for each correction, target width and distance between targets.

no correction (559.64 ms (110.9 SD). The fastest correction method was using motion capturing data of both the phone and the finger, and did not change the user interface (540.98 ms (101.85 SD)). The second fastest correction used the motion sensor data of both smartphone and finger sensor, and also did not change the user interface (545.00 ms (107.15 SD)), followed by the correction using the same motion sensor data but changed the user interface (545.15 ms (92.14 SD)), using only the smartphone's motion sensors and not changing the user interface (553.87 ms (145.56 SD)), using the smartphone's motion sensors and changing the user interface (555.23 ms (93.81 SD)), and the correction using motion capturing data and changing the user interface(558.75 ms(121.56 SD)). Pairwise comparisons with Tukey HSD could not show significant differences between corrections and target widths.

Significant interactions were found for target width and distance between targets ($F_{2,1107} = 5.5744$, $p < 0.01$, $\eta_p^2 = 0.01$), with the increase in movement time for medium and especially larger targets being more pronounced for the long distance between targets. Further, the interactions between correction method and target size ($F_{12,1107} = 2.9789$, $p < 0.001$, $\eta_p^2 = 0.03$) as well as with distance between targets ($F_{6,1107} = 3.0089$, $p < 0.01$, $\eta_p^2 = 0.02$) were significant, showing that the effect of all correction methods in contrast to using no correction was more pronounced for larger and more distant targets.

5.5.2 Misses. The mean misses per target are depicted in Figure 11. As can be seen, when used with both sensors (smartphone and finger), our correction approach reduces misses. The numeric results are also shown in Table 5. A 3 *x* 2 *x* 7 repeated measures ANOVA performed on aligned rank transformed data revealed significant main effects for correction ($F_{6,1107} = 35.1158$, $p < 0.001$, $\eta_p^2 = 0.16$), target width ($F_{2,1107} = 801.0160$, $p < 0.001$, $\eta_p^2 = 0.59$), and distance between targets ($F_{1,1107} = 18.7396$, $p < 0.001$, $\eta_p^2 = 0.02$). Smaller targets were selected with more misses than medium sized and large ones (1.20 (0.79 SD), 0.39 (0.43 SD), and 0.20 (0.3 SD), respectively). Tukey HSD posthoc tests confirmed these differences being significant ($p < 0.01$). Regarding the correction methods, the correction involving only smartphone sensors and not changing the user interface lead to more misses than no correction (0.66 (0.73 SD) and 0.66 (0.79 SD)). The correction involving only smartphone sensors and not changing the user interface only lead to slightly fewer misses (0.64 (0.72 SD)). The fewest misses were possible with our correction approach including data from both smartphone and finger and not changing the user interface (0.41 (0.51 SD)) followed by the MoCap version of said correction and changes to the user interface (0.44 (0.54 SD)), which was only sightly better than the smartphone version using both smartphone and finger sensors and changes to the user interface (0.44 (0.54 SD)). The Mocap version with no changes to the user interface achieved 0.49 (0.63 SD) misses at average. The results of the posthoc Tukey HSD tests for correction methods are shown in Table 6. As can be seen, all correction approaches including acceleration data from the

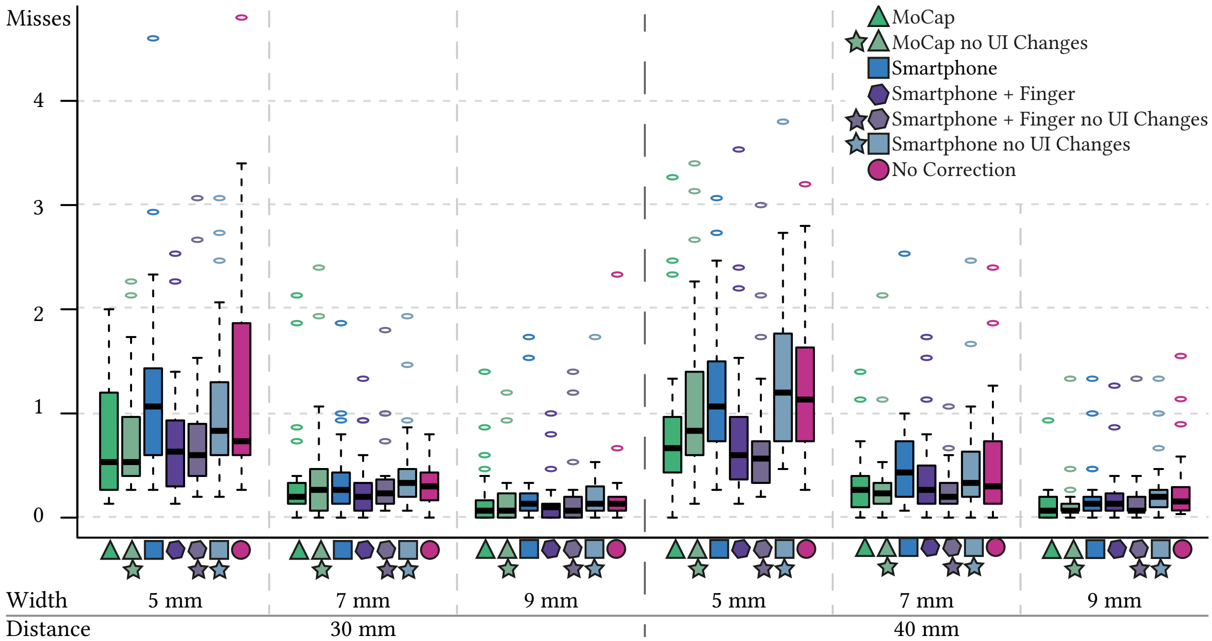

Fig. 11. The mean misses per target for each correction, target width and distance between targets. As can be seen, all correction methods involving both hand's tremor lead to fewer misses than no correction. Additionally, the effect of our correction is especially visible for small targets.

smartphone as well as from the finger sensor significantly outperformed using no correction, whereas the two correction approaches only relying on smartphone acceleration data did not significantly outperform using no correction. Also, all correction approaches including both smartphone and finger acceleration data significantly outperformed the correction approaches using only the smartphone's acceleration data. The only remaining significant difference occurred between the correction using MoCap data and not changing the user interface and the corresponding correction using smartphone and finger motion data and not changing the user interface.

Additionally, the interactions between correction and target width ($F_{12,1107} = 10.7236$, $p < 0.001$, $\eta_p^2 = 0.10$) as well as between correction and distance between targets ($F_{6,1107} = 2.7236$, $p < 0.05$, $\eta_p^2 = 0.01$) were significant. Using no correction for medium sized targets lead to fewer misses than the corrections relying only on smartphone's motion data. Targets with the longer distance between them were selected with fewer misses using both correction approaches relying on motion data from finger and smartphone and not changing the user interface. Additionally, the interaction between target width and distance between targets ($F_{2,1107} = 3.4323$, $p < 0.05$, $\eta_p^2 = 0.01$) was significant, with distance increasing misses more pronounced for small targets than for medium and large ones. This means that our correction methods seem to work better on the more difficult, that is smaller targets. When comparing the number of misses of our overall best correction approach, using smartphone and finger sensors without changing the user interface, we still achieved improvements for even large targets. While for the small targets (5 mm), the improvements were 39.39% and 44.10% for 30 mm and 40 mm distance respectively, we could achieve an improvement of 48.10 % for 7 mm sizes targets with a distance of 40 mm. For 9 mm sized targets, the improvement amounted to 20.83% for 30 mm distance and 40.74% for 40 mm distance.

Corrections		p - Value
MoCap	MoCap no UI Changes	0.3536
	Smartphone	<.0001 ***
	Smartphone + Finger	0.9998
	Smartphone + Finger no UI Changes	0.9550
	Smartphone no UI Changes	<.0001 ***
	No Correction	<.0001 ***
MoCap no UI Changes	Smartphone	<.0001 ***
	Smartphone + Finger	0.5960
	Smartphone + Finger no UI Changes	0.0330 *
	Smartphone no UI Changes	<.0001 ***
	No Correction	<.0001 ***
Smartphone	Smartphone + Finger	<.0001 ***
	Smartphone + Finger no UI Changes	<.0001 ***
	Smartphone no UI Changes	1.0000
	No Correction	0.9985
Smartphone + Finger	Smartphone + Finger no UI Changes	0.8202
	Smartphone no UI Changes	<.0001 ***
	No Correction	<.0001 ***
Smartphone + Finger no UI Changes	Smartphone no UI Changes	<.0001 ***
	No Correction	<.0001 ***
Smartphone no UI Changes	No Correction	0.9851

Table 6. The resulting p-values for the pairwise comparisons between the corrections (Tukey HSD). As can be seen, the correction approaches incorporating smartphone and finger motion data significantly outperformed no correction and the correction approaches only relying on the smartphone's motion data. Also, the correction using MoCap data and not changing the user interface significantly outperformed the corresponding correction using smartphone and finger motion data and not changing the user interface.

5.6 Discussion

Our results show that correcting tremor related misses based on motion data has the potential to reduce movement time and, more importantly, the number of misses for selecting a target. The differences between our correction approach using motion sensors and our approach using motion capturing data are marginal, leading us to the assumption that the accuracy of the used motion sensors is sufficient. As we suspected based on the results of our interviews, we found that incorporating both motion sensors (phone and finger sensor) leads to a stronger reduction of misses, while using only the phones motion sensors does not reduce misses. This indicates that it could be more important to correct the input. However, since we did not test conditions where only the input was corrected we cannot be fully certain and have to leave this to future evaluations. Also the corrections had an increased effect for smaller and more distant targets. Since these targets are more difficult to select, an increased effect of the correction is desirable.

6 USER STUDY WITH PERSONS WHO ARE AFFECTED BY TREMOR

To confirm the positive results from the previous study, and to test our correction approaches with the actual target user group, we conducted a second user study with persons with tremor. The study was approved by our institution's Institutional Review Board. We referred from including corrections using motion capturing data as ground truth, because the previous study showed that using motion sensors is sufficient. Yet more important, this allowed us to include participants who could not come to our lab by visiting them.

Target Size	5 mm		7 mm		9 mm	
Target Distance	30 mm	40 mm	30 mm	40 mm	30 mm	40 mm
Correction						
Smartphone	658.8 (101.2)	693.2 (94.4)	632.9 (154.4)	667.2 (129.0)	612.2 (171.2)	635.8 (157.0)
Smartphone + Finger	701.9 (207.6)	712.7 (148.7)	599.2 (145.3)	693.1 (219.3)	642.8 (183.7)	626.3 (200.0)
Smartphone + Finger no UI Changes	694.6 (142.1)	693.0 (136.6)	652.5 (179.4)	650.3 (152.1)	622.9 (169.5)	613.3 (169.4)
Smartphone no UI Changes	673.2 (123.7)	678.1 (119.7)	621.9 (161.3)	675.4 (158.7)	588.3 (182.3)	649.1 (187.5)
No Correction	704.3 (208.9)	703.6 (144.3)	653.3 (138.3)	708.5 (177.1)	589.0 (187.1)	702.8 (299.7)

Table 7. The resulting mean movement times in milliseconds (standard deviation in brackets) for each correction, target width and distance between targets.

6.1 Participants

Participants were recruited through newspaper adverts, Google ads, flyers in leisure facilities for senior citizens and through support groups. Six persons (one female) participated in our study, one with juvenile and five with essential tremor. The age ranged between 22 and 69 years (mean 33.17 (23.47 SD)). All participants were right handed and had previous experience with smartphones. Tremor intensity was tested with the spiral test as was done with the interview participants. Two participants had a slight, three a moderate, and one a severe tremor.

6.2 Study Design

The study design was basically the same as in the previous study. The only difference was that we did not include correction methods based on motion capturing data as ground truth, reducing the number of corrections to five.

6.3 Apparatus

The apparatus was the same as in the previous study, without the motion capturing system.

6.4 Procedure

The procedure was the same as in the previous study, yet since the participants of this study had a tremor, no tremor was induced. Every participant was exposed to 30 conditions (two distances between targets, two target widths, five corrections). In each condition, participants eventually selected 15 targets, resulting in 450 successful selections per participant and 2700 successful selections in total.

6.5 Results

6.5.1 Movement Time. The mean movement times for each correction approach are depicted in Figure 12. The results are also displayed in Table 7. A $3\,x\,2\,x\,5$ repeated measures ANOVA on aligned ranked transformed data revealed significant main effects for target width ($F_{2,145} = 7.69, p < 0.001, \eta_p^2 = 0.10$) and distance between targets ($F_{1,145} = 10.27, p < 0.01, \eta_p^2 = 0.07$). Close targets were faster selected than more distant ones (643.19 ms (157.22 SD) and 680.09 ms (160.46 SD), respectively), and smaller targets were slower selected than medium and large ones (691.33 (136.63 SD), 657.38 (152.13 SD), and 636.22 (183.80 SD), respectively). Tukey HSD posthoc tests could not reveal further significant differences. The individual results for each participant are depicted in Figure 13. Each graph resembles on participant, their tremor intensity is noted above the graph. Following the results of the analysis of all data, the individual data show little effect of correction method on movement time, while especially for participants 5 and 6 target size and distance between targets seem to have an effect on movement time. Participants 4 and 5, both with slight tremor, as well as participant 6 with moderate tremor seem to have faster movement times than the other three participants.

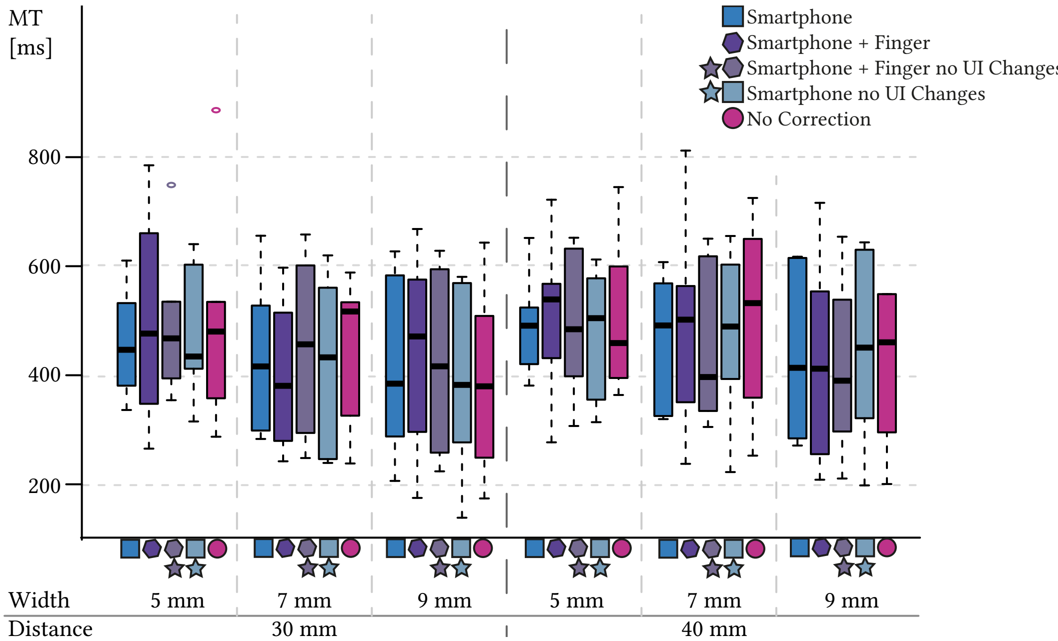

Fig. 12. The results for movement time for each correction, target width and distance between targets. As can be seen, the differences are rather small.

6.5.2 Misses. Figure 14 depicts the mean misses for each selection task,the mean misses are shown in Table 8. A 3 *x* 2 *x* 5 repeated measures ANOVA on aligned rank transformed data revealed significant main effects for correction type ($F_{4,145} = 9.98$, $p < 0.001$, $\eta_p^2 = 0.22$), distance between targets ($F_{1,145} = 23.62$, $p < 0.001$, $\eta_p^2 = 0.14$) and target width ($F_{2,145} = 87.71$, $p < 0.001$, $\eta_p^2 = 0.55$). Close targets were less often missed than distant ones (0.42 (0.64 SD) and 0.61 (1.54 SD), respectively). Small targets were more often missed than medium and large ones (1.17 (1.87 SD), 0.27 (0.24 SD), and 0.09 (0.10 SD), respectively). Tukey HSD posthoc tests revealed the differences between small and medium as well as large targets both being significant ($p < 0.001$). Regarding correction approaches, using no correction (0.61 (1.20 SD)) lead to more misses than using the corrections involving both smartphone and finger motion data (0.39 (0.66 SD)), relying only on the smartphone's motion data and not changing the user interface (0.39 (0.46 SD)), as well as smartphone and finger motion data without changing

	Target Size	**5 mm**		**7 mm**		**9 mm**	
	Target Distance	**30 mm**	**40 mm**	**30 mm**	**40 mm**	**30 mm**	**40 mm**
Correction	Smartphone	1.04 (1.12)	2.93 (4.89)	0.26 (0.23)	0.36 (0.32)	0.14 (0.13)	0.10 (0.12)
	Smartphone + Finger	0.76 (1.00)	0.99 (1.01)	0.17 (0.20)	0.24 (0.24)	0.01 (0.03)	0.10 (0.11)
	Smartphone + Finger no UI Changes	0.93 (0.87)	0.46 (0.55)	0.30 (0.28)	0.33 (0.40)	0.09 (0.10)	0.08 (0.07)
	Smartphone no UI Changes	0.82 (0.49)	0.86 (0.64)	0.18 (0.14)	0.24 (0.08)	0.04 (0.05)	0.18 (0.16)
	No Correction	1.13 (1.09)	1.80 (2.42)	0.32 (0.30)	0.27 (0.18)	0.04 (0.07)	0.06 (0.10)

Table 8. The resulting mean misses per target (standard deviation in brackets) for each correction, target width and distance between targets.

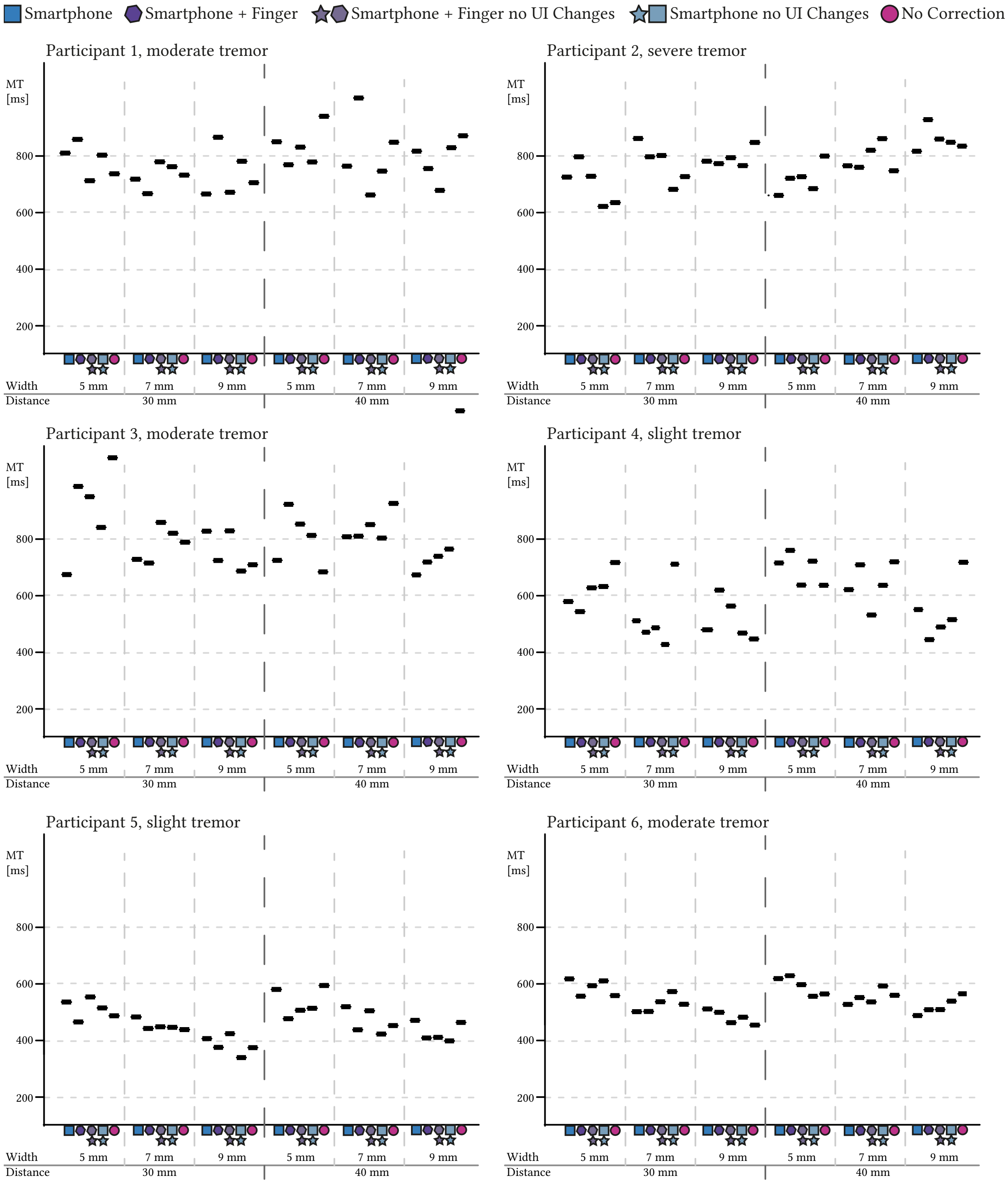

Fig. 13. The results for movement time for each participant, correction, target width and distance between targets.

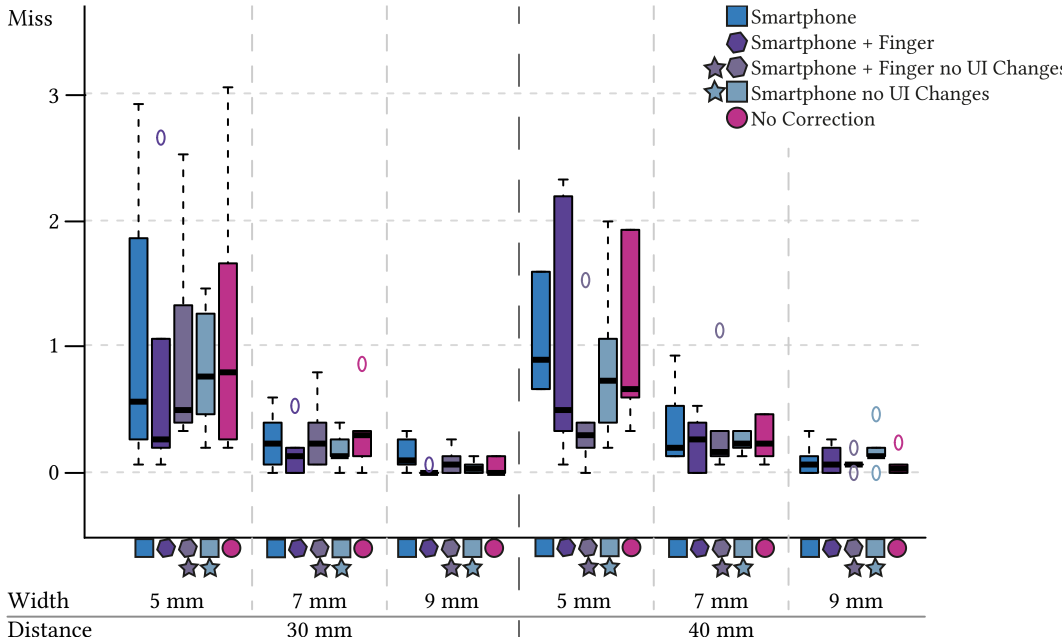

Fig. 14. The mean misses per target for each correction, target width and distance between targets. As can be seen, the correction method involving both hand's tremor motions allows more accurate selection, resulting in fewer misses especially for small targets.

the user interface (0.36 (0.52 SD)), with the latter resulting in the fewest misses, that is 40% less than no correction. Only the correction relying on the smartphone's motion data and changing the user interface lead to more misses than no correction (0.81 (2.15 SD)). The results of posthoc pairwise comparisons with Tukey HSD for the correction methods are shown in Table 9. As can be seen, the correction approaches incorporating smartphone

Corrections		p - Value
Smartphone	Smartphone + Finger	***0.0003*** ***
	Smartphone + Finger no UI Changes	***<.0001*** ***
	Smartphone no UI Changes	***0.0004*** ***
	No Correction	0.6742
Smartphone + Finger	Smartphone + Finger no UI Changes	0.8900
	Smartphone no UI Changes	0.9999
	No Correction	***0.0267*** *
Smartphone + Finger no UI Changes	Smartphone no UI Changes	0.8366
	No Correction	***0.0013*** **
Smartphone no UI Changes	No Correction	***0.0376*** *

Table 9. The resulting p-values for the pairwise comparisons between the corrections (Tukey HSD). As can be seen, the correction approaches incorporating smartphone and finger motion data or only the smartphone's motion data without changing the user interface significantly outperformed no correction and the correction approaches only relying on the smartphone's motion data and changing the user interface.

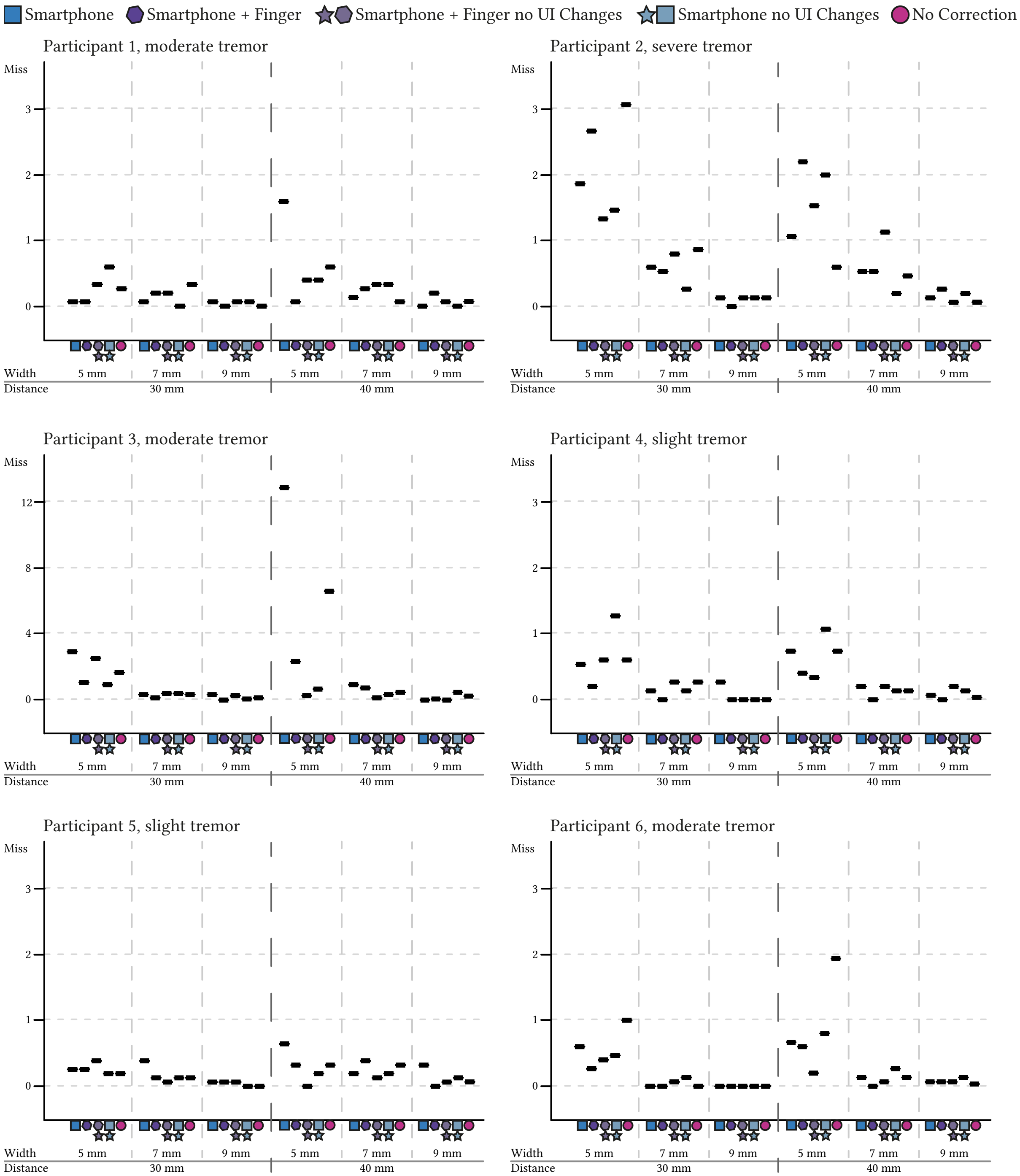

Fig. 15. The mean misses per target for each participant, correction, target width and distance between targets. Note the different scaling of the y axis for participant 3.

and finger motion data or only the smartphone's motion data without changing the user interface significantly outperformed no correction and the correction approaches only relying on the smartphone's motion data and changing the user interface.

Significant interactions were found for correction method and target width ($F_{8,145} = 3.73, p < 0.001, \eta_p^2 = 0.17$) as well as target distance ($F_{4,145} = 8.00$, $p < 0.001$, $\eta_p^2 = 0.18$). Using the correction involving both smartphone and finger motion data and not changing the user interface decreased the misses more for more distant targets than for closer targets, while this was inverted for all other correction approaches. The decrease in misses of said correction was also more pronounced for small targets than for the other corrections. The interaction between target width and distance between targets was also significant ($F_{2,145} = 4.72$, $p < 0.05$, $\eta_p^2 = 0.06$), with long distances between targets more severely increasing selection difficulty especially for small targets. When comparing the improvements achieved for each condition, we see that for 5 mm targets with 30 mm distance, using both smartphone and finger sensors for correction achieved 17.70% fewer misses without UI changes and 32.74% fewer misses with changing UI. For 5 mm targets with a distance of 40 mm, the improvement achieved by the correction involving both smartphone and finger sensors and not changing the UI amounted to 74.44% fewer misses. For the 7 mm sizes targets, we could achieve 6.25% fewer misses when using both smartphone and finger sensors and not changing the UI and 46.88% fewer misses with the same sensor configuration but visibly changing the UI (both for 30 mm distances). For 7 mm targets with 40 mm distance, using either both smartphone and finger sensor or only the smartphone sensor without changing the user interface lead to 11.11% fewer misses. For 9 mm sized targets with a distance of 30 mm, the correction employing smartphone and finger sensors and visibly changing the user's interface even amounted to a reduction of misses of 75%.

The individual results for each participant are depicted in Figure 15. Each graph resembles one participant, their tremor intensity is noted above the graph. The individual graphs show that the less difficult the study condition was, the fewer was any correction needed. In such cases, corrections could even introduce more misses. However, the more severe the tremor is, the more correction is needed for targets with moderate difficulty (see the error rates for the targets with 7 mm width for participant 2, severe tremor). When looking at each participant, we find that for participant 4, who has a slight tremor, the correction approach employing both smartphone and finger sensors and changing the user interface according to the correction result seems to lead to better results than the other correction approaches, even for easier selection tasks. For the two easiest targets, 9 mm with both distances, no correction was needed. Participant 5, also with a slight tremor, achieved relatively low error rates without corrections. For 5 mm targets with 40 mm distances, corrections even introduced more errors. Yet, for the other conditions, the corrections improved the low error rates even further, especially the correction approach involving both smartphone and finger sensors and not changing the user interface. Participant 6, having a moderate tremor, also achieved rather few misses for large and moderate targets without any correction. As with other participants, correcting when not needed might have introduced slightly more misses for one condition (target size 7 mm and target distance 30 mm). When target distance was increased to 40 mm for 7 mm sized targets, both corrections employing smartphone and finger sensors reduced misses. In both conditions involving 5 mm sized targets, all corrections dramatically reduced misses, with the correction approaches using both smartphone and finger sensors leading to the fewest misses. Participant 3, also having a moderate tremor, had the most difficulties with selecting the 5 mm targets with 40 mm distance. Please note that therefore the scale for this participant's graph in Figure 15 differs from all other graphs. Yet in this extreme case, our correction using both smartphone and finger sensors without changing the user interface as well as using only smartphone sensors without changing the user interface drastically reduced misses, the first bringing the number of misses close to zero. Remarkably, for targets with 5 mm width and 30 mm distance using both smartphone and finger sensors without changing the user interface did not lead to a comparable result. For this condition, using only the smartphone's sensors without changing the user interface led to the best result. Considering the results for the remaining (easier) conditions, where fewer corrections were necessary, it seems that for this participant the correction approach involving only smartphone sensors and not changing the user interface overall led to better results, although the same correction approach led to more misses in the small target conditions for participant 4 (slight tremor). Participant 1 was the third participant with a moderate tremor. As with participant 3, the correction approach involving only the smartphone's motion sensors and changing the user interface increased misses for targets with 5 mm width and 40 mm distance. Using only the phones motion sensors without changing the user interface also led to an increase in misses for three conditions. As with the other participants, corrections applied when not needed could increase misses. Yet when needed, both corrections involving smartphone and finger sensors reduced misses, with visually correcting targets leading to higher reduction. Participant 2 was the only participant with a severe tremor. The graph shows that for this participant, the correction success seems to depend on the distance between targets. When the distance was 40 mm, the tested corrections (except using only smartphone sensors and not changing the user interface for medium sized targets and using both sensors and not changing the user interface for large targets) seemed to increase misses. For conditions with 30 mm distance between targets, however, all correction approaches reduced misses or at least did not increase them. The correction approach employing both smartphone and finger sensors without changing the user interface more than halved the misses for small targets. Using only smartphone data without changing the user interface reducing misses for medium sized targets even more dramatically.

6.6 Discussion

The results of this study, conducted with participants with tremor, confirmed the results of the previous study that correcting input based on motion sensors strongly decreases error rate, with the best correction approach (using both smartphone and finger motion data and not changing the user interface) overall leading to 40 % fewer misses. Again, accounting for both hands leads to more successful selection than only using the phone sensors data. Interestingly, the correction based solely on phone's sensors and visually correcting the targets leads to more misses even than using no correction. A closer look at the data and study sessions revealed, that this effect can be attributed to one participant, who had considerable trouble with the moving targets. The constant changing of the user interface seemed too confusing. Further, through the input being not corrected, the participant more or less guessed where they should touch. Since in this study only six persons participated, we can only speculate if this behaviour is an isolated case or occurs in larger parts of the population. However, since the correction approaches with no visual changes to the user interface both with and without inclusion of the input correction perform far better than when no correction is applied, we argue that our approach does increase selection accuracy and should best be used without visual changes to the user interface. As in the first study, the statistical analysis suggests that our correction approaches seem to have a larger effect on smaller targets. Yet these are the targets which are more difficult to select, having a more than three times higher error rate compared to medium sized targets and up to 30 times higher error rate than large targets. Thus corrections for smaller targets are way more often needed, making the higher effect corrections have on these targets desirable. Broken down to each condition, however, we could still observe that even for large targets (see Table 9, 9 mm width and 30 mm distance, the easiest condition) high improvements are achievable. The individual analysis of misses showed that we could dramatically reduce misses, especially for small targets. The analysis also showed that especially in cases where no correction was needed, applying any correction could lead to more misses. One reason for this could be the used shake window of 0.1 s. We think that by dynamically adjusting this time window to the actual current tremor frequency, we could further improve the correction. In this way, we would only regard data frames from the current shake, and thus reduce influences of previous shakes or not having all data frames of the current shake. Since tremor frequencies differ from person to person, are not steady within one person, and tremor related motions might change during controlled movements, this approach could lead to more robust corrections. Another possible solution is to use different values for the parameters k and a for different target sizes, yet the feasibility of this approach is subject to future work. For the only participant with severe tremor, targets with a distance of 40 mm between them were harder to select with corrections. We contribute this to the large correction distances needed for this tremor causing targets reaching the edge of the screen too soon causing misses. Yet, our correction achieved considerable less misses for targets with only 30 mm distances for the same participant. The individual analysis also showed that there are participants for whom changing the user interface according to the correction seems more appropriate than not changing the user interface. Since the sample size is small, and HCI literature rather pointing in the direction that changing user interfaces confuse users [9, 43], it stands to question whether this is a personal preference or a characteristic of persons with tremor. Yet, the overall results and most of the individual ones show that it is certainly feasible to use motion sensors to correct tremor related misses as we described in this paper. Even with the configuration used in our study, misses could be drastically reduced.

On the implications of testing our corrections with users with induced and users with actual tremor. The main reason we conducted the first user study with induced tremor was not to avoid testing our correction with users with real tremor, but to initially test our correction with a large and easy to recruit sample to ensure a certain level of functionality before inviting users with actual tremor. In case our correction approach would not have worked out in the first study, we would have made alternations before conducting further studies with users with real tremor, a target group considerably harder to recruit. Also, simulating tremor helped us a lot during the development of our correction, since non of the authors nor anybody in the research group has a tremor. Thus we find our approach feasible, and large parts of both studies are coherent. Yet there should be no doubt that the first study was never indented to our could replace the second study, where the actual target users were involved. The second study is the main study of our paper. Testing input techniques with users with induced tremor can only give a hint of how those techniques work. Persons who actually have tremor cope with it every day, for many years. Throughout their daily life they develop compensation strategies. Those strategies can be developed consciously, and therefore communicated when asked in interviews, but also unconsciously, and therefore hard to communicate but nevertheless leading to different behaviour from persons without tremor. User who are induced with a tremor are highly unlikely to having developed such strategies, nor do they have any experience with tremor. Having a tremor and interacting with anything is completely new to them, so they behave differently. When using induced tremor during the development, one has to be cautious to not over-fit the correction to one certain tremor frequency and intensity combination, but to many. Also, actual tremor might be more volatile and vary more during one usage session than the induced one. Albeit initial tests are feasible with induced tremor as stated above, this does not absolve one from understanding who persons with tremor interact with devices (as we did in our interviews), nor from testing with persons who are affected by real tremor (as we did in our second user study).

7 LIMITATIONS

One limitation of the interviews and the second study is the relatively small sample size. It stands to question whether our results would be different if more persons would have participated. Yet, the results of our interviews are coherent and understandable, and furthermore confirm results from previous work. Regarding the evaluation of our correction approach, we deliberately conducted a user study with induced tremor. This way, we could find results based on a larger sample size, and large portions of the results are coherent with the results from the second user study.

One could question the applicability of our correction approach to real world applications, since the selection tasks were rather abstract. However, our study design is based on the ISO 9241-9 norm, which is widely used in human computer interaction to test input techniques. Furthermore, this paper only covers the initial development of our correction approach, in future work we will focus on its applicability in real life scenarios.

Mounting an additional device on ones finger might not be preferable by some users. Yet, our results show that detecting and accounting for the tremor in the input finger increases the accuracy even more (using both smartphone and finger sensor data and not visually changing the user interface outdoes the corresponding condition without considering the finger sensors data by 7.7 %), and might thus be necessary. In future work, we will investigate how tremor can reliably be detected with only the smartphone's means, and if a device more worn like a ring at the base of ones finger is feasible.

The corrected targets being always completely present on the screen imposes certain limitations regarding the interface design. E.g., there has to be a sensible area around the edges of the screen where no content is displayed, so that this space can be used for corrected targets. In times of ever increasing screen sizes, this seems bearable. Yet it seems also feasible that when using our correction approach without visually corrected targets (which also seems to achieve the better results), to cut off corrected targets at the screen's edge. The visual integrity of the user interface would not be distorted, since the corrected target is not visible. This would allow to use the full screen space. Whether the correction would achieve similar or even better results is subject of our future research in this area.

8 CONCLUSION

Hand tremor complicates interactions with touchscreen based smartphones, leading to slow interactions and more misses when selecting targets. Using interviews, we assessed difficulties persons with tremor face when interacting with modern smartphones.

Further, we proposed a method to increase selection accuracy using off-the-shelf motion sensors. We showed that using our method increases input accuracy in two consecutive user studies, both with induced tremor and real tremor. Our results show that misses can be reduced up to 40 % when using both smartphone and finger motion data and not changing the user interface. Our method is not only valuable in mobile touchscreen scenarios, but since the input correction seems to be more important than the sole output correction, we argue that our method could also be applied to stationary touchscreens used in kiosk systems, ticket machines and wall sized displays and plan to investigate this further in future works.

Future plans regarding our method include increasing robustness for selection tasks in more cluttered user interfaces (e.g., keyboards) as well as evaluating how the selecting fingers oscillation can be detected without fixing motion sensors on it, e.g. by using changes in touchscreens' capacity while hovering.

REFERENCES

[1] Anderson, M. Technology device ownership: 2015. Pew Research Center (2015). http://www.pewinternet.org/files/2015/10/PI_2015-10-29_device-ownership_FINAL.pdf.

[2] Anthony, L., Kim, Y., and Findlater, L. Analyzing user-generated youtube videos to understand touchscreen use by people with motor impairments. In *Proceedings of the SIGCHI Conference on Human Factors in Computing Systems*, CHI '13, ACM (New York, NY, USA, 2013), 1223–1232.

[3] Bi, X., and Zhai, S. Bayesian touch: A statistical criterion of target selection with finger touch. In *Proceedings of the 26th Annual ACM Symposium on User Interface Software and Technology*, UIST '13, ACM (New York, NY, USA, 2013), 51–60.

[4] Buschek, D., Rogers, S., and Murray-Smith, R. User-specific touch models in a cross-device context. In *Proceedings of the 15th International Conference on Human-computer Interaction with Mobile Devices and Services*, MobileHCI '13, ACM (New York, NY, USA, 2013), 382–391.

[5] Carignan, B., Daneault, J.-F., and Duval, C. *Measuring Tremor with a Smartphone*. Springer New York, New York, NY, 2015, 359–374.

[6] Daneault, J.-F., Carignan, B., Codère, C. ., Sadikot, A., and Duval, C. Using a smart phone as a standalone platform for detection and monitoring of pathological tremors. *Frontiers in Human Neuroscience 6* (2013), 357.

[7] Deuschl, G., Bain, P., and Brin, M. Consensus statement of the movement disorder society on tremor. *Movement Disorders 13*, S3 (1998), 2–23.

[8] eMarketer Inc. 2 billion consumers worldwide to get smart(phones) by 2016. eMarketer Inc. (2014). http://www.emarketer.com/Article/2-Billion-Consumers-Worldwide-Smartphones-by-2016/1011694.

[9] Findlater, L., and Wobbrock, J. Personalized input: improving ten-finger touchscreen typing through automatic adaptation. In *Proceedings of the SIGCHI Conference on Human Factors in Computing Systems*, ACM (2012), 815–824.

[10] Froehlich, J., Wobbrock, J. O., and Kane, S. K. Barrier pointing: Using physical edges to assist target acquisition on mobile device touch screens. In *Proceedings of the 9th International ACM SIGACCESS Conference on Computers and Accessibility*, Assets '07, ACM (New York, NY, USA, 2007), 19–26.

[11] Goel, M., Findlater, L., and Wobbrock, J. Walktype: Using accelerometer data to accomodate situational impairments in mobile touch screen text entry. In *Proceedings of the SIGCHI Conference on Human Factors in Computing Systems*, CHI '12, ACM (New York, NY, USA, 2012), 2687–2696.

[12] Kienzle, W., and Hinckley, K. Lightring: Always-available 2d input on any surface. In *Proceedings of the 27th Annual ACM Symposium on User Interface Software and Technology*, UIST '14, ACM (New York, NY, USA, 2014), 157–160.

[13] Kostikis, N., Hristu-Varsakelis, D., Arnaoutoglou, M., Kotsavasiloglou, C., and Baloyiannis, S. Towards remote evaluation of movement disorders via smartphones. In *2011 Annual International Conference of the IEEE Engineering in Medicine and Biology Society* (Aug 2011), 5240–5243.

[14] Louis, E. D., and Ferreira, J. J. How common is the most common adult movement disorder? update on the worldwide prevalence of essential tremor. *Movement Disorders 25*, 5 (2010), 534–541.

[15] Louis, E. D., and Ferreira, J. J. How common is the most common adult movement disorder? update on the worldwide prevalence of essential tremor. *Movement Disorders 25*, 5 (2010), 534–541.

[16] Louis, E. D., Ottman, R., and Allen Hauser, W. How common is the most common adult movement disorder? estimates of the prevalence of essential tremor throughout the world. *Movement disorders 13*, 1 (1998), 5–10.

[17] MacKenzie, S. Fitts' law software download. Last accessed: September 20, 2016.

[18] MbientLab. Metawear RG/RPro, 2016. Website visited: 04.01.2016.

[19] Mertens, A., Koch-Körfges, D., Jochems, N., and Schlick, C. M. Touchscreen-based input technique for people with intention tremor. In *3rd International Conference on Human System Interaction* (May 2010), 236–240.

[20] Moll, P. W. Alterssimulationsanzug gert, Mar. 2016.

[21] Montague, K., Nicolau, H., and Hanson, V. L. Motor-impaired touchscreen interactions in the wild. In *Proceedings of the 16th International ACM SIGACCESS Conference on Computers & Accessibility*, ASSETS '14, ACM (New York, NY, USA, 2014), 123–130.

[22] Naftali, M., and Findlater, L. Accessibility in context: Understanding the truly mobile experience of smartphone users with motor impairments. In *Proceedings of the 16th International ACM SIGACCESS Conference on Computers & Accessibility*, ASSETS '14, ACM (New York, NY, USA, 2014), 209–216.

[23] National Institute of Neurological Disorders and Stroke. Tremor fact sheet. http://www.ninds.nih.gov/disorders/tremor/detail_tremor.htm, 2016. Last accessed: August 16, 2016.

[24] Nicolau, H., and Jorge, J. Elderly text-entry performance on touchscreens. In *Proceedings of the 14th International ACM SIGACCESS Conference on Computers and Accessibility*, ASSETS '12, ACM (New York, NY, USA, 2012), 127–134.

[25] Pew Research Center. The smartphone difference (2015). http://www.pewinternet.org/2015/04/01/us-smartphone-use-in-2015/.

[26] Plaumann, K., Babic, M., Drey, T., Hepting, W., Stooß, D., and Rukzio, E. Towards improving touchscreen input speed and accuracy on smartphones for tremor affected persons (demo). In *Proceedings of the 2016 ACM International Joint Conference on Pervasive and Ubiquitous Computing: Adjunct (Demo)*, UbiComp '16, ACM (New York, NY, USA, 2016), 357–360.

[27] Pullman, S. L. Spiral analysis: A new technique for measuring tremor with a digitizing tablet. *Movement Disorders 13*, S3 (1998), 85–89.

[28] Puschmann, A., and Wszolek, Z. K. Diagnosis and treatment of common forms of tremor. In *Seminars in neurology*, vol. 31, © Thieme Medical Publishers (2011), 065–077.

[29] Rahmati, A., Shepard, C., and Zhong, L. Noshake: Content stabilization for shaking screens of mobile devices. In *Pervasive Computing and Communications, 2009. PerCom 2009. IEEE International Conference on* (March 2009), 1–6.

[30] Sahami Shirazi, A., Henze, N., Dingler, T., Pielot, M., Weber, D., and Schmidt, A. Large-scale assessment of mobile notifications. In *Proceedings of the SIGCHI Conference on Human Factors in Computing Systems*, CHI '14, ACM (New York, NY, USA, 2014), 3055–3064.

[31] Shilkrot, R., Huber, J., Steimle, J., Nanayakkara, S., and Maes, P. Digital digits: A comprehensive survey of finger augmentation devices. *ACM Comput. Surv. 48*, 2 (Nov. 2015), 30:1–30:29.

[32] Soukoreff, R. W., and MacKenzie, I. S. Towards a standard for pointing device evaluation, perspectives on 27 years of fitts law research in hci. *International journal of human-computer studies 61*, 6 (2004), 751–789.

[33] Stacy, M. A., Elble, R. J., Ondo, W. G., Wu, S.-C., and Hulihan, J. Assessment of interrater and intrarater reliability of the fahntolosamarin tremor rating scale in essential tremor. *Movement Disorders 22*, 6 (2007), 833–838.

[34] Sullivan, K. L., Hauser, R. A., and Zesiewicz, T. A. Essential tremor: epidemiology, diagnosis, and treatment. *The neurologist 10*, 5 (2004), 250–258.

[35] Trewin, S., Swart, C., and Pettick, D. Physical accessibility of touchscreen smartphones. In *Proceedings of the 15th International ACM SIGACCESS Conference on Computers and Accessibility*, ASSETS '13, ACM (New York, NY, USA, 2013), 19:1–19:8.

[36] Wacharamanotham, C., Hurtmanns, J., Mertens, A., Kronenbuerger, M., Schlick, C., and Borchers, J. Evaluating swabbing: A touchscreen input method for elderly users with tremor. In *Proceedings of the SIGCHI Conference on Human Factors in Computing Systems*, CHI '11, ACM (New York, NY, USA, 2011), 623–626.

[37] Weir, D., Rogers, S., Murray-Smith, R., and Löchtefeld, M. A user-specific machine learning approach for improving touch accuracy on mobile devices. In *Proceedings of the 25th Annual ACM Symposium on User Interface Software and Technology*, UIST '12, ACM (New York, NY, USA, 2012), 465–476.

[38] Wobbrock, J. O., and Gajos, K. Z. A comparison of area pointing and goal crossing for people with and without motor impairments. In *Proceedings of the 9th International ACM SIGACCESS Conference on Computers and Accessibility*, Assets '07, ACM (New York, NY, USA, 2007), 3–10.

[39] Woods, A. M., Nowostawski, M., Franz, E. A., and Purvis, M. Parkinsons disease and essential tremor classification on mobile device. *Pervasive and Mobile Computing 13* (2014), 1 – 12.

[40] Xia, H., Grossman, T., and Fitzmaurice, G. Nanostylus: Enhancing input on ultra-small displays with a finger-mounted stylus. In *Proceedings of the 28th Annual ACM Symposium on User Interface Software & Technology*, UIST '15, ACM (New York, NY, USA, 2015), 447–456.

[41] Xia, H., Jota, R., McCanny, B., Yu, Z., Forlines, C., Singh, K., and Wigdor, D. Zero-latency tapping: Using hover information to predict touch locations and eliminate touchdown latency. In *Proceedings of the 27th Annual ACM Symposium on User Interface Software and Technology*, UIST '14, ACM (New York, NY, USA, 2014), 205–214.

[42] Yang, X.-D., Grossman, T., Wigdor, D., and Fitzmaurice, G. Magic finger: Always-available input through finger instrumentation. In *Proceedings of the 25th Annual ACM Symposium on User Interface Software and Technology*, UIST '12, ACM (New York, NY, USA, 2012), 147–156.

[43] Zhong, Y., Weber, A., Burkhardt, C., Weaver, P., and Bigham, J. P. Enhancing android accessibility for users with hand tremor by reducing fine pointing and steady tapping. In *Proceedings of the 12th Web for All Conference*, W4A '15, ACM (New York, NY, USA, 2015), 29:1–29:10.

Received February 2017; revised July 2017; accepted October 2017