



The impact of handedness on user performance in touchless input

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ARTICLE INFO

Keywords:

Touchless
Mid-air
Gesture input
Nondominant
Motor asymmetry
Fitts's law
Pointing
Dragging

ABSTRACT

People use touchless input when interacting with virtual or augmented reality. During those interactions, they may alternate between hands or use both hands simultaneously. How does handedness impact user performance in touchless input? We hypothesized that touchless inputs, owing to a lower demand for feedback control, will produce much less between-hands performance differences than traditional input devices like the mouse or stylus. In our experiments, participants performed pointing and dragging with freehand and device-based touchless inputs. Both types of touchless inputs produced significantly less degradation between hands than the mouse or stylus. Furthermore, structural equation models elucidated the relation between handedness, input type, and user performance. Our findings indicate that only input devices with relatively higher demand for feedback control produce significant between-hands performance differences.

1. Introduction

Touchless is an *input type* or interaction modality. It allows people to interact with computers using mid-air gestures—freehand (Chattopadhyay and Bolchini, 2014a), with specialized hand gloves (Sturman and Zeltzer, 1994), or with in-air devices (Nancel et al., 2011). Touchless inputs are location-independent and require neither a hard flat surface, such as a desk, nor awkward equipment (Chattopadhyay and Bolchini, 2014a). People can move freely with a head-mounted display (HMD) (Plante et al., 2006) or interact with a very large display from a distance (Nancel et al., 2011; O'Hara et al., 2014).

Touchless inputs have been widely explored in research; for playful or ephemeral engagement with public displays (Walter et al., 2013; 2014), for interacting with smart home devices (Garzotto and Valoriani, 2012), or for bimanual interactions with the dominant hand using another input device (Guimbretiére and Nguyen, 2012). More recently, researchers are examining the possibilities of touchless interactions in healthcare—for monitoring and assessments (Morrison et al., 2016), hospital use (Cronin and Doherty, 2018), or browsing medical images in sterile operating rooms (O'Hara et al., 2014). In current practice, however, touchless input is primarily used to interact with large high-resolution displays, when examining large datasets, and HMDs, for both work and play.

Regardless of the potential, individuals perform poorly with touchless inputs compared with the mouse, pen, or stylus (Habibi and Chattopadhyay, 2019; Jude et al., 2014; Nancel et al., 2011). Familiarity or

practice alone can not explain these performance differences; studies show that motor learning, induced by distributed practice, does not improve touchless performance to become as good as mouse or touch input (Jude et al., 2014). Most theories attribute the inferiority of touchless performance to a lack of passive haptic feedback and gorilla-arm fatigue (Boring et al., 2009; Nancel et al., 2015). We expected, that due to this lack of haptic feedback, *handedness* will impact touchless inputs differently than other traditional inputs. Note that by passive haptic feedback we mean stimulating a sense of touch to provide a manner of guidance in movement control (Nancel et al., 2011; Oakley et al., 2000), neither force feedback nor tactile feedback (Oakley et al., 2000).

Handedness in lateralized individuals signifies a specialization of motor function (Goble et al., 2006; Todor and Doane, 1978). Right-handed people prefer the use of their right hand, which is considered their dominant or preferred hand. Cognitive science and neuroscience studies indicate that performance differences between dominant and nondominant hands in lateralized individuals are due to cerebral hemispheric specialization (Durnford and Kimura, 1971; Shenton et al., 2004; Sober and Sabes, 2003) (Fig. 1). In humans, brain hemispheres exhibit a specialization of function: the left hemisphere is dominant for serial or *sequential* information processing and the right for *parallel* information processing (Annett et al., 1979; Flowers, 1975; Kimura and Vanderwolf, 1970; Todor and Doane, 1978). Owing to the anatomical nature of the sensory and motor pathways to and from the hands, the right hand is typically better at sequential motor tasks—those

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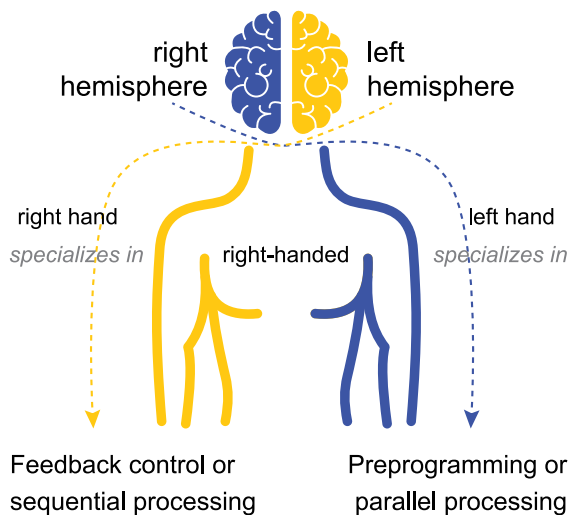


Fig. 1. The two hands of a lateralized person have complementary and specialized roles, owing to a hemispheric asymmetry. In a right-handed person, the right hand specializes in feedback control and the left in preprogramming.

requiring (sensory) feedback control, and the left hand better at parallel processing or open-loop behavior (Durnford and Kimura, 1971; Guiard et al., 1983). This notion of hemispheric asymmetry and motor complementarity in lateralized persons is largely accepted in the literature (Todor and Doane, 1978).

These motor control concepts are not foreign to human-computer interaction (HCI) research; they have been extensively used in studying rapid aimed movements and input performances (Casiez et al., 2008; Kabbash et al., 1993), e.g., ballistic and corrective movements. However, only a few studies have looked into the performance of nondominant hands across different input devices (Jude et al., 2014; Kabbash et al., 1993). Between-hands performance differences in mouse almost disappeared for larger targets and larger distances, i.e., when the relative demand for ballistic movement (little or no feedback control) was more than corrective movement (Kabbash et al., 1993). Between mouse, trackball, and stylus, trackball had the least degradation across hands in Fitts's one-dimensional (1D) pointing and dragging tasks (Kabbash et al., 1993). Any unique performance characteristic of touchless inputs due to handedness is yet to be determined.

Although the etiology of handedness remains an open issue (De Kovel and Francks, 2019; Perelle et al., 1981), it is generally accepted that hand preference initiates during prenatal phases, and is further established in early infancy (Hepper et al., 2005; Parma et al., 2017). But with prolonged daily practice, even strongly lateralized individuals can learn to perform a fine motor task with the nondominant hand as good as with the dominant hand—which is a hallmark of skilled occupations, like surgery, music, or sports (Perelle et al., 1981; Provins, 1958; 1967). For the sake of this paper, we assume that people do not require substantial motor training to use touchless input. Outside exergames, current applications are designed to call for touchless inputs occasionally—because of the associated fatigue and limited accuracy. So it is unlikely that in the future, people might be using touchless inputs as frequently, and as pervasively, as they would use the mouse, keyboard, or touch input. If that happens—and individuals attain highly developed skills in touchless input, through substantial prior training or experience, any performance differences between the dominant and nondominant hand or across input devices may disappear.

Nevertheless, touchless inputs lack haptic feedback and exclusively depend on visual and proprioceptive information (Nancel et al., 2011). So the demand for feedback control in touchless inputs should be less than other inputs like the mouse or stylus, while the demand for preprogramming (or open-loop control) should be more. If touchless

requires more preprogramming than feedback control, how would that affect the dominant hand's performance compared with the nondominant hand? Our findings can offer guidance in designing future bimanual and multimodal interaction techniques involving the touchless input. We also contribute toward understanding how handedness impacts user performance of different input devices that differ in their relative demands for feedback control.

2. Background

In our experiments, participants performed Fitts's one-dimensional (1D) and two-dimensional (2D) pointing and dragging tasks. However, the extensive literature on Fitts's law and its latest developments is only tangentially relevant here (Fitts and Peterson, 1964; Fitts and Radford, 1966; International Organization for Standardization, 2000; Kabbash et al., 1993; MacKenzie and Buxton, 1992; Soukoreff and MacKenzie, 2004). Instead, we will review the types of movement control and the relative demand for feedback control in touchless input.

2.1. Types of movement control

Broadly speaking there are two types of movement control in skilled motor performance (Flowers, 1975; Goble et al., 2006; Keele, 1968):

- **FEEDBACK CONTROL:** motor actions where feedback is processed to make corrective alterations on the way; also known as online control, closed-loop, and sequential or serial processing
- **PREPROGRAMMING:** motor actions where a set of muscle commands are structured before a movement sequence begins, allowing the entire sequence to be carried out uninfluenced by peripheral feedback; also known as programmed control, open-loop, and parallel processing

Typically, any rapid aimed movement requires some amount of feedback control (*corrective movement*) and some amount of preprogramming (*ballistic movement*) (Elliott et al., 2010; 2001; Woodworth, 1899). Right and left hands show a performance advantage in tasks that favor the processing mode of the hand's contralateral hemisphere (Fig. 1) (Goble et al., 2006; Todor and Doane, 1978). This advantage has been studied extensively in motor science and neuroscience, by systematically varying the relative demand for preprogramming and feedback control in rapid aimed movements. The between-hands performance difference is attributed to the feedforward advantages when planning a motor response (open-loop and memory-guided) and the advantages of feedback in the utilization of sensory information to correct ongoing movements (Goble et al., 2006).

So far only a few HCI studies have attempted to systematically understand how this relative demand for preprogramming vs. feedback control influences the performance of nondominant hands (Jude et al., 2014; Kabbash et al., 1993). Many more HCI studies have either drawn from or observed the two types of movement control when studying the performance of the dominant hand across different tasks (Casiez et al., 2008; Chattopadhyay and Bolchini, 2015). For example, in crossing-based tasks (Accot and Zhai, 2002), larger distances produced significantly smaller angular error in touchless input with the dominant hand, suggesting that in those task conditions, the relative demand for preprogramming was sufficiently more than feedback control to produce a medium effect ($r \sim .5$) (Chattopadhyay and Bolchini, 2015; Sullivan and Feinn, 2012).

The relative demand for feedback control depends on the amount of feedback or sensory information available during an interaction (Sigrist et al., 2013). When interacting with computers, techniques offer different types of feedback—typically some combination of visual, haptic, and proprioceptive information. Touchless input lacks a critical type of sensory feedback—*haptic*—which has been deliberated extensively since its rise to *(in)fame(y)* (Nancel et al., 2015; Norman, 2010). However, there is a significant gap in the HCI literature about how this

lack of feedback (or guidance) in touchless input impacts between-hands performance.

2.2. Feedback in touchless input

Touchless input is either *freehand*, performed with mid-air gestures (Chattopadhyay and Bolchini, 2014a), or *device-based*, performed with wearables or in-air devices (Nancel et al., 2011; Sturman and Zeltzer, 1994). In the lack of haptic feedback, that is available with a mouse or stylus, touchless interactions largely draw on proprioceptive and visual feedback.

2.2.1. Proprioceptive feedback

The input device used in mid-air offers some sort of haptic feedback in *device-based* touchless input. But *freehand* touchless input only offers proprioceptive feedback (Nancel et al., 2011). *Proprioception* is namely an individual's "sense of the relative position of neighboring limbs of the body" (Lopes et al., 2015). While proprioceptive feedback is often taken for granted in HCI techniques—it plays important roles during movement, such as controlling muscle interaction torques (Sainburg et al., 1995), timing limb segments (Cordo et al., 1994), and aiding in skilled movement acquisition (Kawato, 1999). However, when visual feedback is available, feedback utilization may be biased toward visual rather than proprioceptive information (Goble et al., 1995). Studies report that in the absence of visual guidance, right-handed individuals show a left-hand advantage in processing position-related proprioceptive information—which suggests a preference of the nondominant hand in maintaining static postures (Goble et al., 1995).

2.2.2. Visual feedback

Some interaction techniques, like imaginary interfaces, do not offer any visual feedback to touchless input (Gustafson et al., 2010). But most touchless interaction techniques offer some type of visual feedback to users (Chattopadhyay and Bolchini, 2014b; Mayer et al., 2018). In HCI, we are accustomed to thinking that the more the feedback the better (Norman, 2010); although exceptions exist to facilitate speed in experts (Kurtenbach and Buxton, 1994). But in motor control, visual feedback can deter learning (Saunders and Knill, 2004) and decrease efficiency (Mayer et al., 2018). After proprioception estimates the initial body posture and selects a motor command, hand movements are continually corrected by the visual feedback—i.e., the visual information about one's hands and the output visible on the interface (Heath, 2005; Lopes et al., 2015; Saunders and Knill, 2004; Scheidt et al., 2005). Terminal visual feedback, in terms of withdrawing vision of the target during movement execution, can facilitate learning simple tasks, such as aiming movements; but to effectively learn complex tasks, such as inter-limb coordination skills, continuous visual feedback is recommended (Sigrüst et al., 2013; Sülzenbrück, 2012).

2.2.3. Feedback control in touchless input

The design of visual feedback in touchless interactions may significantly influence the relative demand for preprogramming vs. feedback control. But we do not systematically investigate visual feedback in this paper, as our study is a first step toward understanding the effects of handedness on touchless performance. In our experiments, visual feedback is kept the same across all conditions, so as not to confound other effects. But it is important to note that just the availability of visual feedback adds to the demand for feedback control.

It would be incorrect to assume that because touchless input lacks haptic feedback, it demands much more motor preprogramming than feedback control, and hence, will most definitely produce a nondominant-hand advantage in goal-directed aiming movements. Even without the haptic feedback, touchless interactions offer visual and proprioceptive sensory information that needs processing. While the nondominant hand is more adept at processing proprioceptive information, humans are biased toward the utilization of visual feedback

(Goble et al., 1995). We cannot, thus, simply deduce the impact of handedness on touchless performance based on prior studies on motor behavior or other computer inputs. Our work addresses this knowledge gap in the HCI literature.

In this paper, we demonstrate *how* and *why* handedness impacts different input types differently. After introducing our general method (Section 3), we examine the impact of handedness on user performance in freehand touchless input (Section 4). Freehand touchless input produced smaller performance differences between hands than a mouse in pointing and dragging tasks. Based on this result, we set out to test whether, owing to more haptic feedback, device-based touchless input would produce larger performance differences between hands than freehand touchless input, but smaller than mouse or stylus (Section 5). Results indicate handedness impacts device-based and freehand touchless inputs similarly, but mouse and stylus differently. Finally, we construct structural equation models to elucidate the role of handedness in user performance of different input devices (Section 6). A path analysis rejected the hypothesis that accuracy (or lack thereof) causes the performance differences between hands across different input types.

3. General method

3.1. Design

This study adopted a within-group design for its two experiments. In each experiment, unique participants performed pointing and dragging tasks using their dominant and nondominant hands with different input devices.

3.2. Participants

Participants were recruited via university mailing lists and word of mouth. The study was approved by the University of Illinois at Chicago (UIC) Office for the Protection of Research Subjects. A total of 40 participants were recruited. Participants were paid volunteers.

In the first experiment, 20 participants (7 females, $M_{age} = 28.8$, $SE = 1.87$) performed one-dimensional (1D) pointing and dragging tasks with freehand touchless input; in the second experiment, another 20 participants (10 females, $M_{age} = 25.5$, $SE = 1.07$) performed two-dimensional (2D) pointing and dragging with freehand and device-based touchless inputs. Participants were right-handed and regular computer users. None of them were color blind. 75% had prior experience with touchless inputs.

3.3. Apparatus






3.3.1. Input devices

Five types of input devices were used (Table 1). In experiment 1, participants used mouse, stylus, and freehand touchless input with passive infra-red markers (*TouchlessWmarker*, Fig. 2); in experiment 2, participants used mouse, stylus, markerless freehand touchless input (*TouchlessWomarker*), and device-based touchless input (*TouchlessWdevice*). Table 1 lists the apparatus details and input device resolutions. VICON is a sub-millimeter accurate motion tracking system that is more reliable than off-the-shelf markerless motion tracking apparatus like Kinect or Leap Motion. Our system consisted of 14 Bonita 10 cameras in a circular arrangement (3.7 m diameter). Each camera tracked motion at 250 FPS and 1 MP resolution. We chose a marker-based method to increase the internal validity of our experiments—while trading off some ecological validity.

3.3.2. Setting

During the experiments, participants were seated in a chair about 2 meters away from a high-resolution, tiled large display. The display constituted of 12 tiles and each tile's resolution was 1366×768 pixels (Fig. 2). Participants could rest their elbows on a table in front of them,

Table 1
Detail specifications of the five input devices used in this study.

Input device	Details	Resolution	Exp (s)
 Mouse	wireless; Logitech M185	25.4 μm (1000 PPI)	1 & 2
 Stylus	Wacom tablet; Intuos Pro Medium, PTH-651	2.5 μm (10160 PPI)	1 & 2
 TouchlessWmarker	in-air pinch gesture; gesture recognition algorithm was developed in-house, and implemented using marker-based motion tracking with passive infra-red markers and a VICON motion capture system	200 μm	1
 TouchlessWdevice	a PlayStation (PS) 3 Move Motion Controller was fitted with passive infra-red markers and tracked by the VICON motion capture system	200 μm	2
 TouchlessWomarker	Microsoft HoloLens 1	2.5k radiants	2

but were not constrained to do so at all times. In *TouchlessWdevice*, target selection was accomplished by pressing the ‘X’ button of the PS3 controller. In *TouchlessWomarker*, target selection was accomplished by using HoloLens’s *Air Tap* gesture. When using HoloLens, dragging requires a delay between target selection and post-selection movement. This exact delay is currently unavailable in hardware specifications. Thus, an estimate of 1.2 s, which was empirically determined, was subtracted from the logged task completion times.

3.3.3. Pointer acceleration and control-display (CD) gain

Pointer acceleration was set to zero for all five inputs. How pointer acceleration impacts handedness in touchless input is left for future work.

Mouse and stylus inputs were directly mapped to the display (Saunders, 2015) while accounting for the hand’s resolution (0.35 degrees; Cavallari et al., 2016). Table 2 lists the CD_{\min} and CD_{\max} of touchless inputs; they were computed following prior work in this area (Casiez et al., 2008; Cavallari et al., 2016; Nancel et al., 2015). Across all conditions, CD_{\min} was less than CD_{\max} . Within this range, the constant CD gains for touchless inputs were heuristically determined in a pilot study. The following heuristics were used: (1) avoid cross-lateral inhibition (Chattopadhyay and Bolchini, 2015; Schofield, 1976) and contralateral performance differences (Carson et al., 1992; Elliott and Chua, 1996) by deterring participants from crossing the body midline during aiming movements, (2) allow precise goal-directed manual aiming without producing clutching issues (Nancel et al., 2015), and (3) ensure that all trials can be comfortably performed while resting the elbow on a flat surface should participants so desire (Jude et al., 2014).

Our five input types vary widely in terms of capabilities, operating range, and manual dexterity (Table 1). Owing to that, it was not feasible to have the same CD gain across all input types. Neither would the results then have any external validity, because in any practical application, the CD of an input device is set to realize the best achievable user performance.

3.4. Tasks and procedure

Both experiments used a within-subject design with two primary

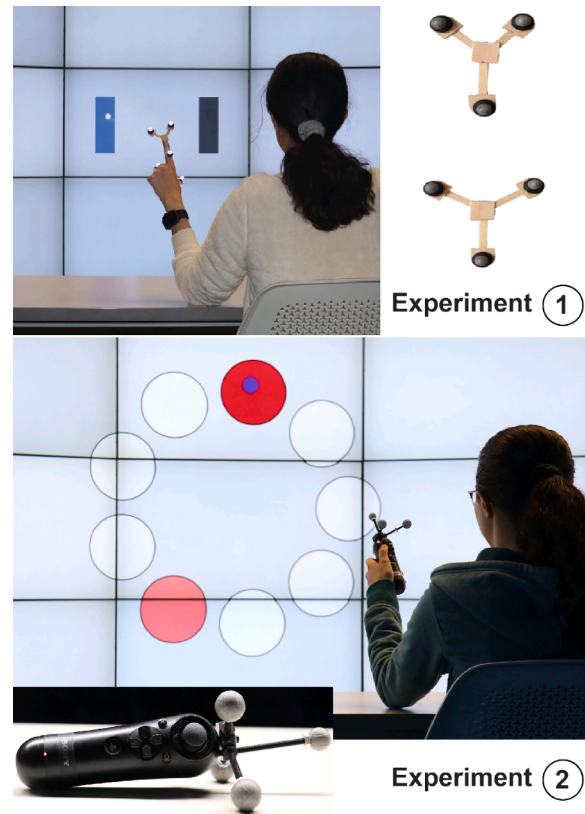


Fig. 2. The apparatus used in Experiments 1 and 2.

factors: HAND and INPUT. The potential effects of target width and movement amplitude were controlled by introducing AMPLITUDE-WIDTH combinations as a secondary within-subjects factor. We systematically varied these factors in the context of (1) *pointing* and (2) *dragging* tasks. Participants performed Fitts’s one-dimensional (1D) reciprocal pointing and dragging tasks in Experiment 1 and two-dimensional (2D) pointing and dragging tasks in Experiment 2 (Fig. 2).

Experiments were conducted on two days, at least one day apart, with each participant using one hand a day. Upon consent, participants provided demographics and practiced for about 10 min. Data were logged by an in-house software and sessions were video recorded. A block constituted of nine or ten trials; after each block, participants were required to take at least a 10-second break, but they could rest for as long as they wanted. In case of an error, a trial was restarted. Participants had to successfully complete all trials to move on to the next block. Each of the two separate experimental sessions lasted for about 30 to 40 min.

3.5. Independent variables

The independent variables for this study were $HAND \in \{Right, Left\}$ and INPUT. Both experiments used 16 AMPLITUDE-WIDTH (A-W) combinations in the two tasks. The order of INPUT, HAND, and A-W combinations were randomized; pointing and dragging tasks were counterbalanced using a Latin Square. Table 3 lists the levels of the independent variables

Table 2

CD gains for the touchless inputs. Their operating range (OR) was assumed to be 60 deg (Nancel et al., 2015) and hand resolution 0.35 deg (Cavallari et al., 2016).

Input device	CD_{\min}	CD_{\max}	CD
TouchlessWmarker	1	3.65	3.5
TouchlessWdevice	1	11.89	4
TouchlessWomarker	1	4	4

Table 3
The independent variables and research design for this study.

	Experiment 1	Experiment 2
Design	2 × 3	2 × 4
Tasks	1-dimensional (1D) pointing and dragging	2-dimensional (2D) pointing and dragging
Input	<i>TouchlessWmarker, Mouse, Stylus</i>	<i>TouchlessWdevice, TouchlessWmarker, Mouse, Stylus</i>
Amplitude	14.34, 28.69, 43.03, 57.37 cm	32, 34, 36, 38 cm for <i>TouchlessWmarker</i> 60, 70, 80, 90 cm for all other inputs
Width	3.59, 7.17, 10.76, 14.34 cm	4, 6, 8, 10 cm for <i>TouchlessWmarker</i> 12, 15, 17, 20 cm for all other inputs
Total trials	20 participants × 10 repetitions × 16 A-W combinations × 3 inputs × 2 hands × 2 tasks = 38,400	20 participants × 9 repetitions × 16 A-W combinations × 4 inputs × 2 hands × 2 tasks = 46,080

used in Experiments 1 and 2. The A-W combinations for the *TouchlessWmarker* condition had to be set differently because the HoloLens has a limited field of view.

Across both experiments, the index of difficulty (ID) ranged from 1 to 4. The range is smaller compared with studies that examine traditional input devices, such as the mouse, pen, or stylus. However, a smaller range of ID values is typical in studies exploring freehand touchless input (Brown et al., 2014; Guinness et al., 2015)—because smaller target widths could often be missed out by participants and not allow for a good measurement of the achievable performance.

3.6. Dependent variables

We measured user performance. The primary dependent variable was efficiency or movement time (MT). The secondary measures were accuracy or error rate (ER), variable error (VE), constant error (CE), throughput (TP), effective target width (W_e), Fitts’s regression coefficients a and b , and hand-paths. TP was computed as $TP = ID_e / MT$, where $ID_e = \log_2(A / W_e + 1)$. For 1D pointing and dragging, W_e was computed as $W_e = 4.133 \times SD_x$; for 2D tasks, following (Wobbrock et al., 2011), W_e was computed as $4.133 \times SD_{x,y}$, where:

$$SD_{x,y} = \sqrt{\frac{\sum_{i=1}^N \left(\sqrt{(x_i - \bar{x})^2 + (y_i - \bar{y})^2} \right)^2}{N - 1}} \quad (1)$$

Error rate captured the percentage of misses in the total number of trials. Variable error measured the standard deviation of movement endpoints along the horizontal axis for 1D tasks and horizontal and vertical axes for 2D tasks (Wobbrock et al., 2011). Constant error, the systematic bias to overshoot or undershoot targets, was measured as the mean deviation from the target center.

4. Handedness impacts mouse and stylus, but not freehand touchless input

4.1. Hypotheses

As discussed earlier, performance differences between hands stem from their specialized roles. In a right-handed person, the right hand specializes in feedback control and the left in preprogramming. Thus, when tasks require more feedback control than preprogramming, the left hand performs poorly than the right hand (Guiard et al., 1983; Todor and Doane, 1978).

Freehand touchless input lacks passive haptic feedback, but still uses visual and proprioceptive information (Chattopadhyay and Bolchini, 2014a; 2015; Nancel et al., 2011). Nevertheless, compared with other

traditional inputs like the mouse, pen, or stylus, touchless offers less feedback, and in turn, less demand for feedback control and more use of preprogrammed motor plans. As a result, we expected that the dominant hand will have much less advantage over the nondominant hand in touchless than a mouse or stylus—i.e., between-hands performance differences in freehand touchless input will be smaller than inputs offering haptic feedback. In prior work, between-hands differences in movement time were more obvious than the differences in accuracy, and accuracy occasionally improved with practice (Annett et al., 1979; Flowers, 1975; Peters and Durling, 1979; Todor and Doane, 1978). Therefore, we chose the more reliable metric movement time (MT) as our primary dependent variable.

The most fundamental, low-level operations in direct manipulation interfaces are the actions of pointing (target selection) and dragging (target manipulation). Dragging is a variation of pointing and the user performance for both these tasks can be modeled similarly (MacKenzie et al., 1991). But different input types impact pointing and dragging performances differently (Cockburn et al., 2012; Kabbash et al., 1993; MacKenzie et al., 1991). In Experiment 1, we tested the following hypotheses:

H1. Freehand touchless input will produce smaller between-hands performance differences than (a) mouse and (b) stylus in pointing.

H2. Freehand touchless input will produce smaller between-hands performance differences than (a) mouse and (b) stylus in dragging.

4.2. Data analysis preliminaries

Prior to data analysis, individual performance differences across participants were checked; for all participants, movement time (MT) and error rate (ER) were correlated with the overall performance measures. MT was positively skewed and log-transformed; thus, replications of unique experimental conditions were represented by their median. A GLMM with standard repeated measures REML technique was used that handled participants as a random factor. For GLMM, the R `lme4` package was used (Bates et al., 2014). We report F -statistic using type III ANOVA with *Satterthwaite approximation*, and pairwise comparisons (using pooled variance) with *Bonferroni* correction. Initial level of significance (α) was set to .05.

We found a significant learning effect across blocks. *Holm-Sidak* tests on the block averages at each INPUT × HAND revealed that the first block differed significantly from the rest of the nine blocks, but the rest did not differ among themselves. Data from the first block were discarded. We then conducted a multivariate outlier analysis; trials were eliminated if the values were more than four times the Cook’s distance from the mean (Cook, 1979). Following similar studies (Rabbitt, 1966), trials immediately following the deviate trials were also eliminated. Overall, 3% of the data were eliminated from the analysis.

Similar to prior studies, participants would occasionally make a selection gesture considerably outside the general area where targets were displayed (Zhai et al., 2004). These were not motor errors, but occurred due to cognitive lapses (e.g., forgetting the target destination amidst a trial and repeatedly moving in the opposite direction) or instrument error (e.g., a movement endpoint was recorded, but the distance between the endpoint and the target center was eight times the target size). Such errors were not counted when computing error rates, following prior work (Zhai et al., 2004).

4.3. Results

In Experiment 1, the independent variables were HAND ∈ {Right, Left} and INPUT ∈ {TouchlessWmarker, Mouse, Stylus}. We report here the primary dependent variable movement time (MT). The secondary dependent variables, error rates (ER), throughput (TP), and Fitts’s regression coefficients, a and b , can be found in the Supplementary Section S1.

4.3.1. Pointing

A linear mixed effect model (LMM) found a significant main effect of INPUT, $F(2, 95) = 63.38, p < 0.0001$, and HAND, $F(1, 95) = 48.53, p < 0.0001$ on MT. Significant interaction effects were also found for INPUT x HAND, $F(2, 95) = 21.98, p < 0.0001$. The overall effect size of the fitted model was large, $\Omega_0^2 = 0.78$. Pairwise comparisons found that *freehand touchless* input produced significantly smaller between-hands performance differences than both *mouse* and *stylus* (Table 4). H1(a) and H1(b) were supported.

4.3.2. Dragging

Similar to pointing, an LMM found a significant main effect of INPUT, $F(2, 95) = 154.28, p < 0.0001$, and HAND, $F(1, 95) = 6.30, p = 0.0138$ on MT. Significant interaction effects were found for INPUT x HAND, $F(2, 95) = 5.15, p = 0.0075$. The overall effect size of the fitted model was large, $\Omega_0^2 = 0.79$. Pairwise comparisons found that *freehand touchless* input produced significantly smaller between-hands differences than *mouse*—but not *stylus* (Table 4). H2(a) was supported, but not H2(b).

Mean MTs are reported in Table 5. For both pointing and dragging, LMMs found only a significant main effect of INPUT on ER; participants made significantly more errors with touchless input than mouse or stylus. But within an input type (except stylus-dragging), participants performed at comparable error rates; there were no significant differences between HANDS. Mean ER by hands for mouse, stylus, and freehand touchless input can be found in the Supplementary Section S1.1.

4.4. Summary

Overall, freehand touchless input produced significantly smaller between-hands performance differences than mouse and stylus. However, *stylus-dragging* did not produce a greater degradation between hands than freehand touchless input (Table 4); neither did the dominant right hand show a marked advantage over the left (Fig. 3).

Following these results, two primary questions arose. Are these findings specific to 1D tasks? Are they specific to a particular type of touchless input? Would handedness impact user performance of device-based touchless input differently? We examined these research questions in the following section.

5. Handedness neither impacts freehand, nor device-based touchless input

5.1. Hypotheses

Touchless inputs can be freehand, based on motion tracking (Wang et al., 2018), such as HoloLens, or device-based, where users hold an input device in mid-air (Nancel et al., 2011), such as the HTC Vive controllers. Device-based touchless inputs provide some sort of passive haptic feedback, thereby offering more guidance than freehand touchless inputs (Nancel et al., 2011). Nevertheless, the feedback offered is much less than most other inputs, like the mouse or stylus.

Thus, we expected that the dominant hand will have much more advantage over the nondominant hand in device-based than freehand touchless input—i.e., freehand touchless input will produce smaller

Table 4
Pairwise comparisons of between-hands differences in MT.

Pairwise comparisons	t	p	d
POINTING			
TouchlessWmarker, Mouse	9.90	< 0.0001*	2.21
TouchlessWmarker, Stylus	6.30	< 0.0001*	1.41
DRAGGING			
TouchlessWmarker, Mouse	3.47	0.003*	0.78
TouchlessWmarker, Stylus	1.61	0.12	0.36

*Significant.

Table 5

MT (ms) for mouse, stylus, and freehand touchless input.

Input device	Right hand	Left hand
POINTING		
Mouse	M = 836, SD = 177	M = 1230, SD = 271
Stylus	M = 904, SD = 209	M = 1202, SD = 311
TouchlessWmarker	M = 1490, SD = 305	M = 1406, SD = 307
DRAGGING		
Mouse	M = 1131, SD = 257	M = 1452, SD = 343
Stylus	M = 997, SD = 187	M = 1102, SD = 235
TouchlessWmarker	M = 2464, SD = 795	M = 2334, SD = 706

between-hands performance differences than device-based touchless input. Furthermore, similar to freehand touchless input, device-based touchless input will produce smaller differences between hands than a mouse or stylus. In Experiment 2, we tested the following hypotheses.

H3. Freehand touchless input will produce smaller between-hands performance differences than device-based touchless input in pointing.

H4. Freehand touchless input will produce smaller between-hands performance differences than device-based touchless input in dragging.

H5. Device-based touchless input will produce smaller between-hands performance differences than (a) mouse and (b) stylus in pointing.

H6. Device-based touchless input will produce smaller between-hands performance differences than (a) mouse and (b) stylus in dragging.

5.2. Data analysis preliminaries

Data pre-processing was similar to Section 4.2. Individual performance differences across participants were correlated with the overall performance measures. *Holm-Sidak* tests on the block averages at each INPUT x HAND revealed that the first two blocks differed significantly from the rest of the seven blocks, but the rest did not differ among themselves. Data from the first two blocks were discarded. Following outlier analysis, 4% of the data were eliminated.

5.3. Results

In Experiment 2, the independent variables were HAND \in {Right, Left} and INPUT \in {TouchlessWdevice, TouchlessWmarker, Mouse, Stylus}. We report here the primary dependent variable movement time (MT) and the following secondary dependent variables: error rates (ER), variable error (VE), constant error (CE), and hand-paths. Throughput (TP) and Fitts's regression coefficients can be found in the Supplementary Section S2.

5.3.1. Testing H3

An LMM found a significant main effect of INPUT, $F(3, 133) = 10.86, p < 0.0001$, and HAND, $F(1, 1333) = 52.26, p < 0.0001$ on MT. Significant interaction effects were also found for INPUT x HAND, $F(1, 133) = 8.26, p < 0.0001$. The overall effect size of the fitted model was large, $\Omega_0^2 = 0.65$. Pairwise comparisons revealed non-significant differences between the between-hands performance differences (MT) of freehand touchless input (TouchlessWmarker) and device-based touchless input (TouchlessWdevice, Table 6; Fig. 4). H3 was not supported.

5.3.2. Testing H4

Similar to pointing, an LMM found a significant main effect of INPUT, $F(3, 133) = 64.30, p < 0.0001$, and HAND, $F(1, 133) = 23.29, p < 0.0001$ on MT. Significant interaction effects were also found for INPUT x HAND, $F(1, 133) = 6.32, p < 0.0005$. The overall effect size of the fitted model was large, $\Omega_0^2 = 0.71$. Pairwise comparisons revealed non-significant differences between the between-hands performance differences (MT) of freehand touchless input (TouchlessWmarker) and device-based touchless input (TouchlessWdevice, Table 6). H4 was not supported.

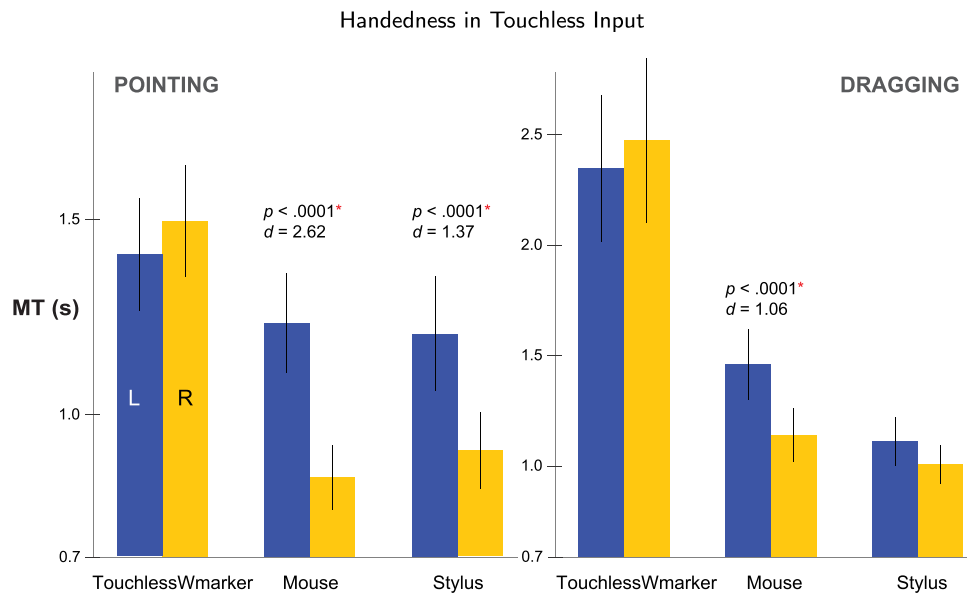


Fig. 3. Between-hands performance differences for mouse, stylus, and freehand touchless input. Error bars = 95% CI.

Table 6

Pairwise comparisons of between-hands differences in MT.

Pairwise comparisons	t	p	d
POINTING			
TouchlessWmarker, TouchlessWdevice	0.88	0.39	0.20
TouchlessWdevice, Mouse	7.43	< 0.0001*	1.66
TouchlessWdevice, Stylus	5.14	< 0.0001*	1.15
TouchlessWmarker, Mouse	4.50	0.0002*	1.01
TouchlessWmarker, Stylus	2.70	0.01*	0.60
DRAGGING			
TouchlessWmarker, TouchlessWdevice	0.30	0.77	0.07
TouchlessWdevice, Mouse	4.54	0.0002*	1.01
TouchlessWdevice, Stylus	3.33	0.004*	0.74
TouchlessWmarker, Mouse	3.38	0.003*	0.75
TouchlessWmarker, Stylus	2.68	0.01*	0.60

*Significant.

5.3.3. Testing H5 and H6

Pairwise comparisons found that device-based touchless input produced significantly smaller between-hands differences than both the mouse and stylus in pointing and dragging (Table 6). H5 and H6 were supported. Mean MTs are reported in Table 7.

5.3.4. MT vs. ID

Fig. 5 shows how MT for pointing varies with ID and AMPLITUDE-WIDTH combinations. Note that the right-hand advantage in mouse disappears for device-based and freehand touchless input. Results were similar for stylus-pointing and dragging tasks.

5.3.5. Error rates

For pointing, we found a significant main effect of INPUT on ER, $F(3, 133) = 10.45, p < 0.0001, \Omega_0^2 = 0.44$, but not HAND or INPUT x HAND. For dragging, there was only a significant interaction effect of INPUT x HAND, $F(3, 133) = 4.16, p = 0.008, \Omega_0^2 = 0.24$. Table 8 lists the mean error rates for all input types and hands.

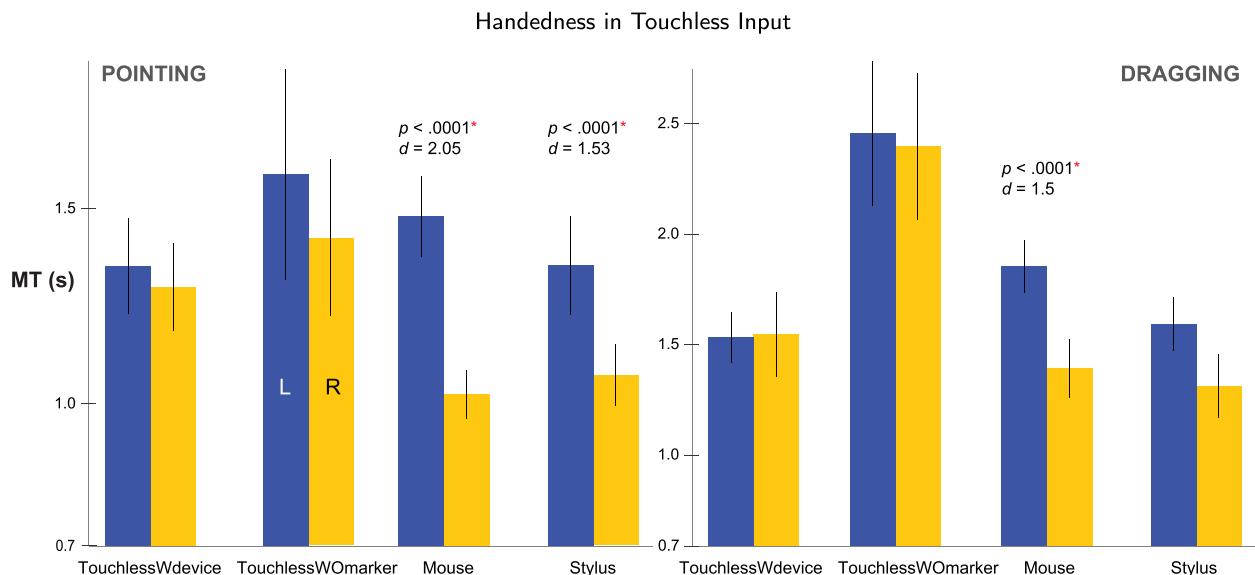


Fig. 4. Between-hands performance differences for mouse, stylus, and touchless inputs. Error bars = 95% CI.

Table 7
MT (ms) for mouse, stylus, and touchless inputs.

Input device	Right hand	Left hand
POINTING		
Mouse	$M = 1022, SD = 133$	$M = 1477, SD = 220$
Stylus	$M = 1070, SD = 168$	$M = 1352, SD = 269$
TouchlessWOMarker	$M = 1420, SD = 427$	$M = 1585, SD = 579$
TouchlessWdevice	$M = 1297, SD = 240$	$M = 1351, SD = 262$
DRAGGING		
Mouse	$M = 1384, SD = 281$	$M = 1845, SD = 254$
Stylus	$M = 1032, SD = 307$	$M = 1584, SD = 258$
TouchlessWOMarker	$M = 2386, SD = 707$	$M = 2446, SD = 699$
TouchlessWdevice	$M = 1536, SD = 407$	$M = 1523, SD = 246$

5.3.6. Constant and variable error

For both pointing and dragging, INPUT type had a significant effect on CE, but HAND did not. When pointing, between-hands differences in CE were significantly less for TouchlessWOMarker compared with Mouse, $t(19) = 3.16, p = 0.005, d = 0.71$. Results were similar for TouchlessWdevice, $t(19) = 3.28, p = 0.004, d = 0.73$. Both hands exhibited a tendency to undershoot the target center for touchless inputs, except TouchlessWOMarker-Pointing (Table 9).

VE was measured as W_e . We found a significant effect of HAND on W_e for mouse and stylus in pointing and dragging, but not for any types of touchless input (Table 10).

5.3.7. Hand-paths

Although not directly pertinent to any of our hypotheses, we provide three (randomly chosen) examples of hand-paths for touchless and non-touchless inputs (Fig. 6 and Supplementary S2.3). A visual assessment of these paths indicates that for the left hand, the trajectories for touchless inputs are smoother than the mouse or stylus. This smoothness of trajectories may be explained by the fact that non-touchless inputs utilize more feedback (i.e., sensory information to correct ongoing movements) than touchless inputs. More experiments are needed to further investigate this relation.

Table 8
Mean error rates (%) for input types.

	POINTING		DRAGGING	
	Right	Left	Right	Left
Mouse	4.29	4.44	1.83	4.68
Stylus	11.11	14.46	1.35	5.16
TouchlessWOMarker	6.59	7.58	2.93	2.84
TouchlessWdevice	11.07	9.15	1.71	2.42

Table 9
Constant errors (in cm).

	POINTING		DRAGGING	
	Right	Left	Right	Left
Mouse	0.65	0.02	0.34	0.23
Stylus	- 1.03	- 1.4	0.11	- 0.09
TouchlessWOMarker	0.02	- 0.01	- 0.1	- 0.03
TouchlessWdevice	- 2.22	- 2.13	- 0.88	- 0.46

Table 10
Mean effective target width (W_e) in cm.

	POINTING		DRAGGING	
	Right	Left	Right	Left
TouchlessWOMarker				
W = 4	9.15	9.21	5.71	6.43
W = 6	9.81	9.76	6.43	7.31
W = 8	10.87	10.79	7.13	8.2
W = 10	10.97	11.31	8.1	8.59
∇ W	10.21	10.25	6.84	7.64
TouchlessWdevice				
W = 12	13.56	14.42	10.32	10.89
W = 15	16.26	15.36	11.57	12.67
W = 17	17.44	17.74	12.55	13.75
W = 20	19.8	20	13.96	14.52
∇ W	16.77	16.78	12.12	12.95

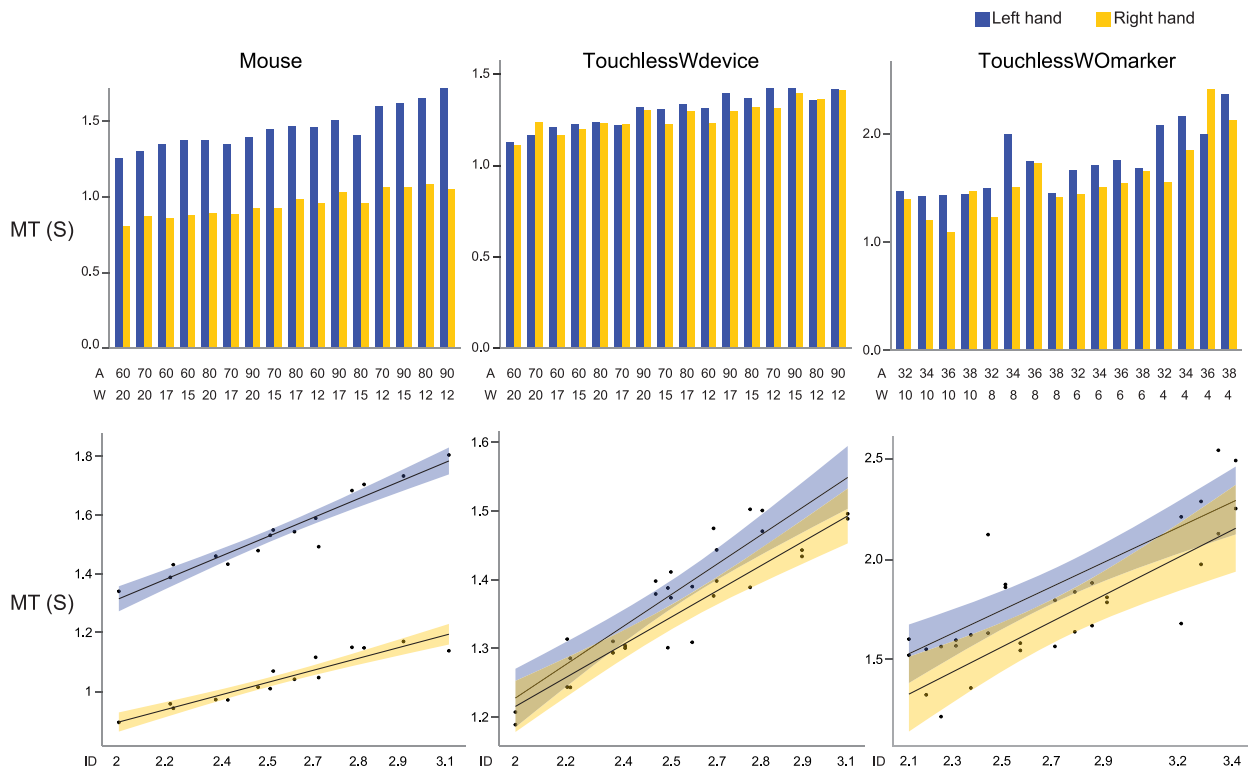


Fig. 5. When pointing, the right-hand advantage in mouse disappears for device-based and freehand touchless input.

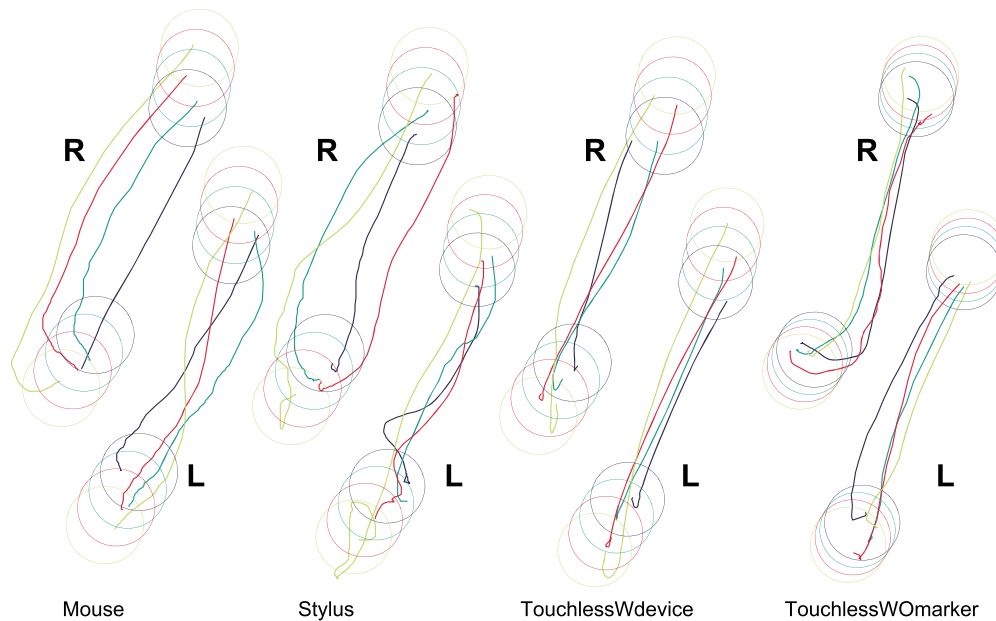


Fig. 6. Hand-paths of a pointing trial for four different amplitudes. Note that the left-hand-paths are more straight for touchless inputs.

5.4. Summary

We expected that owing to more haptic feedback, device-based touchless input will produce larger between-hands performance differences than freehand touchless input. But it did not. In terms of *time*, handedness neither impacted freehand, nor device-based touchless input.

However, like freehand touchless input, the between-hands differences in device-based touchless input was much smaller than the mouse or stylus. These results support our premise—that the lack of feedback, and in turn, relatively less demand for feedback control in touchless inputs lessens the (dominant) right hand's performance advantage in visually guided goal-directed aiming movements.

Our data, however, can be interpreted from two other perspectives. First, it could be that both hands are equally inefficient in using touchless inputs, and with practice the between-hands performance differences would become larger, and similar to mouse or stylus. Although, it should be noted that manual asymmetries are not due to practice differences between hands (Helsen et al., 1998). Second, it could be that the difference in error rates between input devices (Table 8) caused the time differences between hands across different input devices. Next, we test out this claim. How practice influences the impact of handedness on touchless performance is left for future work.

6. Why handedness impacts different inputs differently

Based on the theory of hemispheric asymmetry and functional motor complementarity in lateralized persons (see Sections 1 and 2), we proposed that between-hands performance differences will be much less in inputs that offer little feedback, like touchless, than mouse or stylus. But the results of our empirical studies could be interpreted differently—that the accuracy differences between input devices cause the between-hands differences in efficiency (movement time). We test this causal hypothesis using structural equation modeling or path analysis, which can disprove a model that postulates causal relations among variables (Kline, 2015). Our objective was to either retain or reject this model based on its correspondence to the data (Gunzler et al., 2013).

Input type had a significant main effect on accuracy in pointing, but not dragging (see Section 5.3.5). Thus, we used pointing data ($n = 1280$). Accuracy was measured as median error rates (ER) and efficiency

as movement time (MT). INPUT was a multicategorical independent variable (4 levels; hence, 3 contrasts) in the mediation analysis (Hayes and Preacher, 2014).

Fig. 7 presents M1, reporting the (significant) standardized path coefficients of a mediation analysis. The model depicts a causal relation from input types to differences in movement times between hands, mediated by accuracy. We tested the significance of these relative indirect effects using bootstrapping procedures. The R mediation package was used (Tingley et al., 2014). The bootstrapped unstandardized relative indirect effects were not statistically significant ($ps \geq 0.8$). M1 was rejected. Treating INPUT as a continuous variable, ordered by the demand for feedback control (mouse > stylus > device-based touchless > freehand touchless input), produced the same result.

As the structural equation model shows (Fig. 7), the effect of INPUT on time differences between hands could not be accounted for by error rates. Thus, we can eliminate this alternative explanation of our findings.

7. Discussion

As virtual reality (VR) and augmented reality (AR) technologies mature and high-resolution, large displays become affordable, the use of touchless input in interaction techniques, whether via a device in mid-air, like a smartphone, or device-less, is expected to rise. So now is a crucial time to better understand the fundamental mechanics of touchless performance. One such aspect is the impact of handedness on user performance in touchless input.

Our results indicate that the dominant hand shows no performance advantage in touchless inputs whether an input device is involved (Table 4; Fig. 3) or not (Table 6; Fig. 4). Touchless inputs are different from non-touchless inputs, like the mouse or stylus, in many ways. Nevertheless, we show that a possible explanation for why handedness impacts these inputs differently is how they vary in their relative demands for feedback control. Both device-based and freehand touchless inputs produced significantly less time differences between hands than inputs offering more feedback, like the mouse or stylus—regardless of the touchless apparatus (marker-based vs. markerless in Experiments 1 and 2, respectively; Table 1). The dominant and nondominant hands performed similarly with touchless inputs, whereas with the mouse and stylus the dominant right hand showed a marked advantage over the left

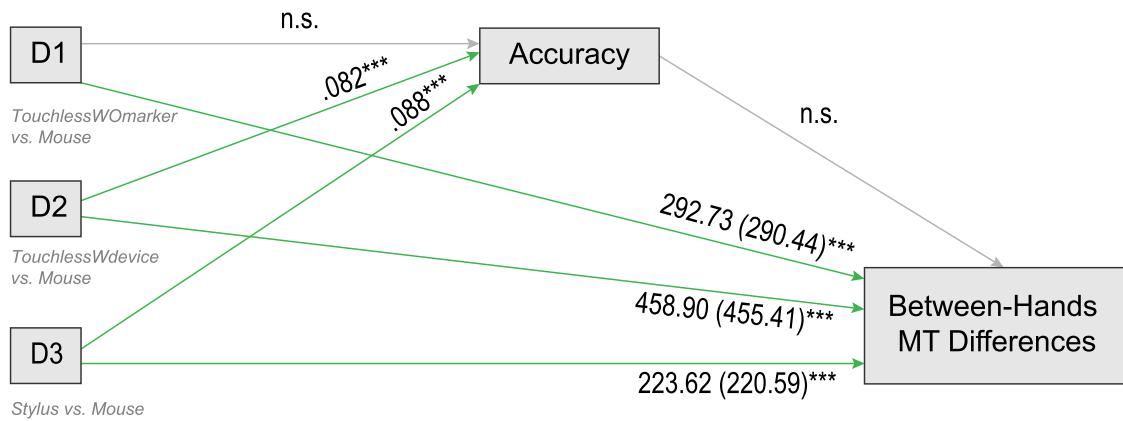


Fig. 7. The effect of input type on time differences between hands was not mediated via error rates. *** $p < 0.0001$.

(Figs. 3 and 4).

However, a noticeable exception was *stylus-dragging*; like touchless inputs, there was no significant right-hand advantage (Tables 5 and 7), which indicates two things. First, the task mechanics and input device together formulate the relative demand for feedback control. Second, the right hand probably lost its advantage over the left hand because stylus-dragging was only constrained by endpoints, not the path, like steering. Then, strictly speaking, stylus-dragging should demand more feedback control than touchless-dragging, because the stylus needs to touch the tablet surface at all times during dragging, while in touchless the hand can move freely in mid air. Indeed, the between-hands performance difference in stylus-dragging was significantly more than touchless-dragging (Table 6). However, that was not the case for dragging in 1D (Table 4)—which reaffirms our earlier conclusion that in strongly lateralized individuals, the impact of handedness on user performance depends on the HCI task and input device.

Thus, what we found about the impact of handedness on touchless performance is limited to the type of tasks we explored—pointing and dragging. The dominant hand may exhibit a marked advantage in some other tasks, like steering (Accot and Zhai, 1997), or not show any advantage in others, like panning-and-zooming (Nancel et al., 2011), pose-triggered selection (Bailly et al., 2011), and crossing-based selection (Accot and Zhai, 2002; Luo and Vogel, 2014).

Nevertheless, across different tasks, touchless input is more fatiguing than other inputs, such as the mouse, pen, or touch. To combat those fatigue effects, each block of trials was followed by a mandatory, open-ended break, and participants were encouraged to rest their elbow on a flat surface—following prior work (Guimbretière and Nguyen, 2012; Jude et al., 2014). Study videos revealed that when using touchless input, participants alternated between resting their elbow on the table and keeping it suspended in mid-air. But this was unlikely to confound our results as prior work reports no effect of elbow placement type on touchless performance (Brown et al., 2014).

In realistic scenarios, however, touchless input is rarely used while resting arms on a table, but mostly while moving around freely. Thus, our study settings somewhat threatened the *ecological validity* of our findings. We acknowledge this limitation. But note that in realistic scenarios, people would not continuously interact with touchless input and carry on thousands of trials—which was needed in our study to draw statistical inferences. A touchless interaction in realistic scenarios would be sporadic and momentary, thereby less fatiguing. By allowing participants to rest their elbows on a table at any time, we made a trade-off between *internal* and *ecological validity*.

Another trade-off between *internal* and *external validity* was to use VICON, a sophisticated motion tracking system, instead of an off-the-shelf system, like the Leap Motion. Because touchless input hardware is rapidly improving, and we cautiously anticipated a small effect of handedness on touchless performance, all study design choices were

made to ensure a high internal validity.

However, our effect sizes were medium-to-large (Tables 4 and 6). Still, more studies are needed to understand how handedness impacts touchless performance in noisy environments and more constrained, realistic tasks. As we discussed earlier in the paper, some additional variables that could influence touchless performance in more realistic scenarios are the amount of prior practice with touchless input, the type of visual feedback available, and pointer acceleration.

Finally, time (MT) was our primary performance metric (Tables 4–7), because of its universal use in the handedness literature (Annett et al., 1979; Flowers, 1975; Peters and Durding, 1979; Todor and Doane, 1978). The impact of handedness on touchless throughput (TP) was similar to time (see Supplementary). Although aware of the different formulations for computing throughput (Zhai, 2004), we opted for the one most commonly reported in the HCI literature ($TP = ID_e/MT$)—to aid in future comparisons. For the same reason, we refrained from using other esoteric performance metrics (e.g., Jude et al., 2014). Nevertheless, we report all descriptive statistics for any such computations.

Since movement time was our primary metric, it is imperative to consider any possible impacts of a speed-accuracy trade-off (Peternel et al., 2017; Plamondon and Alimi, 1997; Zhai et al., 2004). A well-established trade-off in goal-directed aiming movements is that, the faster a movement, the less accurate it is, and thus the higher the probability to miss the goal (Peternel et al., 2017; Woodworth, 1899). Could it be that the between-hands time differences between input devices (Tables 4 and 6) were simply an artifact of the different error rates (Table 8)?

We tested this alternate explanation of our data and rejected it (see Sections 5.3.5 and 6). First, there was no significant main effect of INPUT on accuracy in dragging (Table 8). Second, there was a significant main effect of INPUT on accuracy in pointing, but that did not mediate the between-hands time differences across input devices (Fig. 7). Third, there was always a significant INPUT \times HAND interaction effect on time (see Sections 4.3.1, 4.3.2, 5.3.1, and 5.3.2). Thus, the impact of handedness on touchless performance cannot be explained by just a speed-accuracy trade-off; rather, our results support the theory of hemispheric asymmetry and functional motor complementarity.

8. Conclusion

The last decade has seen an exponential growth of touchless technologies, and consequently, interaction techniques. The use of touchless input is only expected to soar with the maturation of virtual reality (VR) and augmented reality (AR) technologies. But in spite of its potential, touchless input is limited by the lack of haptic feedback and gorilla-arm fatigue. In this paper, we examined whether this lack of feedback plays a role in how touchless performance differs between the two hands. Controlled experiments, grounded in the theories of motor behavior and

prior empirical studies of computer inputs, found that touchless performance barely degrades between hands, compared with either mouse or stylus. Furthermore, the between-hands performance differences in freehand and device-based touchless inputs were equally slim. These findings can inform future bimanual and multimodal interaction techniques involving the touchless input.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Acknowledgments

We thank the UIC Electronic Visualization Laboratory (EVL) for the apparatus used in the experiments, and our study participants for their time.

Supplementary material

Supplementary material associated with this article can be found, in the online version, at [10.1016/j.ijhcs.2021.102600](https://doi.org/10.1016/j.ijhcs.2021.102600)

References

- Accot, J., Zhai, S., 1997. Beyond Fitts' law: models for trajectory-based HCI tasks. *Proceedings of the ACM SIGCHI Conference on Human Factors in Computing Systems*, pp. 295–302.
- Accot, J., Zhai, S., 2002. More than dotting the i's—foundations for crossing-based interfaces. *Proceedings of the SIGCHI Conference on Human Factors in Computing Systems*, pp. 73–80.
- Annett, J., Annett, M., Hudson, P., Turner, A., 1979. The control of movement in the preferred and non-preferred hands. *Q. J. Exp. Psychol.* 31 (4), 641–652.
- Bailly, G., Walter, R., Müller, J., Ning, T., Lecolinet, E., 2011. Comparing free hand menu techniques for distant displays using linear, marking and finger-count menus. *IFIP Conference on Human-Computer Interaction*. Springer, pp. 248–262.
- Bates, D., Mächler, M., Bolker, B., Walker, S., 2014. Fitting linear mixed-effects models using lme4. *arXiv preprint arXiv:1406.5823*.
- Boring, S., Jurmu, M., Butz, A., 2009. Scroll, tilt or move it: using mobile phones to continuously control pointers on large public displays. *Proceedings of the 21st Annual Conference of the Australian Computer-Human Interaction Special Interest Group: Design: Open 24/7*. ACM, pp. 161–168.
- Brown, M.A., Stuerzlinger, W., Filho, E.M., 2014. The performance of un-instrumented in-air pointing. *Proceedings of Graphics Interface 2014*. Citeseer, pp. 59–66.
- Carson, R.G., Goodman, D., Elliott, D., 1992. Asymmetries in the discrete and pseudocontinuous regulation of visually guided reaching. *Brain Cogn.* 18 (2), 169–191.
- Casiez, G., Vogel, D., Balakrishnan, R., Cockburn, A., 2008. The impact of control-display gain on user performance in pointing tasks. *Hum. Comput. Interact.* 23 (3), 215–250.
- Cavallari, P., Bolzoni, F., Bruttini, C., Esposti, R., 2016. The organization and control of intra-limb anticipatory postural adjustments and their role in movement performance. *Front. Hum. Neurosci.* 10, 525.
- Chattopadhyay, D., Bolchini, D., 2014. Touchless circular menus: toward an intuitive UI for touchless interactions with large displays. *Proceedings of the 2014 International Working Conference on Advanced Visual Interfaces*. ACM, pp. 33–40.
- Chattopadhyay, D., Bolchini, D., 2014b. Understanding visual feedback in large-display touchless interactions: an exploratory study.
- Chattopadhyay, D., Bolchini, D., 2015. Motor-intuitive interactions based on image schemas: aligning touchless interaction primitives with human sensorimotor abilities. *Interact. Comput.* 27 (3), 327–343.
- Cockburn, A., Ahlström, D., Gutwin, C., 2012. Understanding performance in touch selections: tap, drag and radial pointing drag with finger, stylus and mouse. *Int. J. Hum. Comput. Stud.* 70 (3), 218–233.
- Cook, R.D., 1979. Influential observations in linear regression. *J. Am. Stat. Assoc.* 74 (365), 169–174.
- Cordo, P., Carlton, L., Bevan, L., Carlton, M., Kerr, G., 1994. Proprioceptive coordination of movement sequences: role of velocity and position information. *J. Neurophysiol.* 71 (5), 1848–1861.
- Cronin, S., Doherty, G., 2018. Touchless computer interfaces in hospitals: A review. *Health Inform. J.* 25 (4), 1325–1342.
- De Kovel, C.G., Francks, C., 2019. The molecular genetics of hand preference revisited. *Sci. Rep.* 9 (1), 1–9.
- Durnford, M., Kimura, D., 1971. Right hemisphere specialization for depth perception reflected in visual field differences. *Nature* 231 (5302), 394.
- Elliott, D., Chua, R., 1996. Manual asymmetries in goal-directed movement. Elliott, D., Roy, E.A. (Eds.), *In: Manual asymmetries in motor performance*. CRC, Boca Raton, FL, pp. 143–158.
- Elliott, D., Hansen, S., Grierson, L.E., Lyons, J., Bennett, S.J., Hayes, S.J., 2010. Goal-directed aiming: two components but multiple processes. *Psychol. Bull.* 136 (6), 1023.
- Elliott, D., Helsen, W.F., Chua, R., 2001. A century later: Woodworth's (1899) two-component model of goal-directed aiming. *Psychol. Bull.* 127 (3), 342.
- Fitts, P.M., Peterson, J.R., 1964. Information capacity of discrete motor responses. *J. Exp. Psychol.* 67 (2), 103.
- Fitts, P.M., Radford, B.K., 1966. Information capacity of discrete motor responses under different cognitive sets. *J. Exp. Psychol.* 71 (4), 475.
- Flowers, K., 1975. Handedness and controlled movement. *Br. J. Psychol.* 66 (1), 39–52.
- Garzotto, F., Valoriani, M., 2012. Don't touch the oven: motion-based touchless interaction with household appliances. *Proceedings of the International Working Conference on Advanced Visual Interfaces*. ACM, pp. 721–724.
- Goble, D.J., Lewis, C.A., Brown, S.H., 2006. Upper limb asymmetries in the utilization of proprioceptive feedback. *Exp. Brain Res.* 168 (1-2), 307–311.
- Goble, J.C., Hinckley, K., Pausch, R., Snell, J.W., Kassell, N.F., 1995. Two-handed spatial interface tools for neurosurgical planning. *Computer* 28 (7), 20–26.
- Guiard, Y., Diaz, G., Beaubaton, D., 1983. Left-hand advantage in right-handers for spatial constant error: preliminary evidence in a unimanual ballistic aimed movement. *Neuropsychologia* 21 (1), 111–115.
- Guimbretière, F., Nguyen, C., 2012. Bimanual marking menu for near surface interactions. *Proceedings of the SIGCHI Conference on Human Factors in Computing Systems*. ACM, pp. 825–828.
- Guinness, D., Jude, A., Poor, G.M., Dover, A., 2015. Models for rested touchless gestural interaction. *Proceedings of the 3rd ACM Symposium on Spatial User Interaction*, pp. 34–43.
- Gunzler, D., Chen, T., Wu, P., Zhang, H., 2013. Introduction to mediation analysis with structural equation modeling. *Shanghai Arch. Psychiatr.* 25 (6), 390.
- Gustafson, S., Bierwirth, D., Baudisch, P., 2010. Imaginary interfaces: spatial interaction with empty hands and without visual feedback. *Proceedings of the 23rd Annual ACM Symposium on User Interface Software and Technology*. ACM, pp. 3–12.
- Habibi, P., Chattopadhyay, D., 2019. A left-hand advantage: motor asymmetry in touchless input. *Extended Abstracts of the 2019 CHI Conference on Human Factors in Computing Systems*. ACM, p. LBW2114.
- Hayes, A.F., Preacher, K.J., 2014. Statistical mediation analysis with a multicategorical independent variable. *Br. J. Math. Stat. Psychol.* 67 (3), 451–470.
- Heath, M., 2005. Role of limb and target vision in the online control of memory-guided reaches. *Motor Control* 9 (3), 281–309.
- Helsen, W.F., Starkes, J.L., Elliott, D., Buekers, M.J., 1998. Manual asymmetries and saccadic eye movements in right-handers during single and reciprocal aiming movements. *Cortex* 34 (4), 513–530.
- Hepper, P.G., Wells, D.L., Lynch, C., 2005. Prenatal thumb sucking is related to postnatal handedness. *Neuropsychologia* 43 (3), 313–315.
- International Organization for Standardization, 2000. *Ergonomic Requirements for Office Work with Visual Display Terminals (VDTs): Requirements for Non-Keyboard Input Devices*. ISO.
- Jude, A., Poor, G.M., Guinness, D., 2014. An evaluation of touchless hand gestural interaction for pointing tasks with preferred and non-preferred hands. *Proceedings of the 8th Nordic Conference on Human-Computer Interaction: Fun, Fast, Foundational*. ACM, pp. 668–676.
- Kabbash, P., MacKenzie, I.S., Buxton, W., 1993. Human performance using computer input devices in the preferred and non-preferred hands. *Proceedings of the INTERACT'93 and CHI'93 Conference on Human Factors in Computing Systems*. ACM, pp. 474–481.
- Kawato, M., 1999. Internal models for motor control and trajectory planning. *Curr. Opin. Neurobiol.* 9 (6), 718–727.
- Keele, S.W., 1968. Movement control in skilled motor performance. *Psychol. Bull.* 70 (6p1), 387.
- Kimura, D., Vanderwolf, C., 1970. The relation between hand preference and the performance of individual finger movements by left and right hands. *Brain* 93 (4), 769–774.
- Kline, R.B., 2015. *Principles and Practice of Structural Equation Modeling*. Guilford Publications.
- Kurtenbach, G., Buxton, W., 1994. User learning and performance with marking menus. *Proceedings of the SIGCHI Conference on Human Factors in Computing systems*, pp. 258–264.
- Lopes, P., Ion, A., Mueller, W., Hoffmann, D., Jonell, P., Baudisch, P., 2015. Proprioceptive interaction. *Proceedings of the 33rd Annual ACM Conference on Human Factors in Computing Systems*. ACM, pp. 939–948.
- Luo, Y., Vogel, D., 2014. Crossing-based selection with direct touch input. *Proceedings of the SIGCHI Conference on Human Factors in Computing Systems*, pp. 2627–2636.
- MacKenzie, I.S., Buxton, W., 1992. Extending Fitts' law to two-dimensional tasks. *Proceedings of the SIGCHI Conference on Human Factors in Computing Systems*. ACM, pp. 219–226.
- MacKenzie, I.S., Sellen, A., Buxton, W.A., 1991. A comparison of input devices in element pointing and dragging tasks. *Proceedings of the SIGCHI Conference on Human Factors in Computing Systems*, pp. 161–166.
- Mayer, S., Schwind, V., Schweigert, R., Henze, N., 2018. The effect of offset correction and cursor on mid-air pointing in real and virtual environments. *Proceedings of the 2018 CHI Conference on Human Factors in Computing Systems*. ACM, p. 653.
- Morrison, C., Huckvale, K., Corish, B., Dorn, J., Kontschieder, P., OHara, K., Team, A.M., Criminisi, A., Sellen, A., 2016. Assessing multiple sclerosis with kinect: designing computer vision systems for real-world use. *Hum. Comput. Interact.* 31 (3-4), 191–226.
- Nancel, M., Pietriga, E., Chapuis, O., Beaudouin-Lafon, M., 2015. Mid-air pointing on ultra-walls. *ACM Trans. Comput. Hum. Interact. (TOCHI)* 22 (5), 1–62.

- Nancel, M., Wagner, J., Pietriga, E., Chapuis, O., Mackay, W., 2011. Mid-air pan-and-zoom on wall-sized displays. *Proceedings of the SIGCHI Conference on Human Factors in Computing Systems*. ACM, pp. 177–186.
- Norman, D.A., 2010. Natural user interfaces are not natural. *Interactions* 17 (3), 6–10.
- Oakley, I., McGee, M.R., Brewster, S., Gray, P., 2000. Putting the feel in 'look and feel'. *Proceedings of the SIGCHI Conference on Human Factors in Computing Systems*, pp. 415–422.
- O'Hara, K., Gonzalez, G., Sellen, A., Penney, G.P., Varnavas, A., Mentis, H.M., Crimini, A., Corish, R., Rouncefield, M., Dastur, N., et al., 2014. Touchless interaction in surgery. *Commun. ACM* 57 (1), 70–77.
- Parma, V., Brasselet, R., Zoia, S., Bulgheroni, M., Castiello, U., 2017. The origin of human handedness and its role in pre-birth motor control. *Sci. Rep.* 7 (1), 1–9.
- Perelle, I.B., Ehrman, L., Manowitz, J., 1981. Human handedness: the influence of learning. *Percept. Motor Skills* 53 (3), 967–977.
- Peternel, L., Sigaud, O., Babič, J., 2017. Unifying speed-accuracy trade-off and cost-benefit trade-off in human reaching movements. *Front. Hum. Neurosci.* 11, 615.
- Peters, M., Durdin, B., 1979. Left-handers and right-handers compared on a motor task. *J. Motor Behav.* 11 (2), 103–111.
- Plamondon, R., Alimi, A.M., 1997. Speed/accuracy trade-offs in target-directed movements. *Behav. Brain Sci.* 20 (2), 279–303.
- Plante, T.G., Cage, C., Clements, S., Stover, A., 2006. Psychological benefits of exercise paired with virtual reality: outdoor exercise energizes whereas indoor virtual exercise relaxes. *Int. J. Stress Manag.* 13 (1), 108.
- Provins, K., 1958. The effect of training and handedness on the performance of two simple motor tasks. *Q. J. Exp. Psychol.* 10 (1), 29–39.
- Provins, K.A., 1967. Motor skills, handedness and behaviour. *Aust. J. Psychol.* 19 (2), 137–150.
- Rabbitt, P., 1966. Errors and error correction in choice-response tasks. *J. Exp. Psychol.* 71 (2), 264.
- Sainburg, R.L., Ghilardi, M.F., Poizner, H., Ghez, C., 1995. Control of limb dynamics in normal subjects and patients without proprioception. *J. Neurophysiol.* 73 (2), 820–835.
- Saunders, J.A., Knill, D.C., 2004. Visual feedback control of hand movements. *J. Neurosci.* 24 (13), 3223–3234.
- Saunders, W., 2015. *Designing a Foot Input System for Productive Work at a Standing Desk*. University of Waterloo. Master's thesis.
- Scheidt, R.A., Conditt, M.A., Secco, E.L., Mussa-Ivaldi, F.A., 2005. Interaction of visual and proprioceptive feedback during adaptation of human reaching movements. *J. Neurophysiol.* 93 (6), 3200–3213.
- Schofield, W., 1976. Hand movements which cross the body midline: findings relating age differences to handedness. *Percept. Motor Skills* 42 (2), 643–646.
- Shenton, J.T., Schwoebel, J., Coslett, H.B., 2004. Mental motor imagery and the body schema: evidence for proprioceptive dominance. *Neurosci. Lett.* 370 (1), 19–24.
- Sigrist, R., Rauter, G., Riener, R., Wolf, P., 2013. Augmented visual, auditory, haptic, and multimodal feedback in motor learning: a review. *Psychon. Bull. Rev.* 20 (1), 21–53.
- Sober, S.J., Sabes, P.N., 2003. Multisensory integration during motor planning. *J. Neurosci.* 23 (18), 6982–6992.
- Soukoreff, R.W., MacKenzie, I.S., 2004. Towards a standard for pointing device evaluation, perspectives on 27 years of Fitts' law research in HCI. *Int. J. Hum. Comput. Stud.* 61 (6), 751–789.
- Sturman, D.J., Zeltzer, D., 1994. A survey of glove-based input. *IEEE Comput. Graph. Appl.* 14 (1), 30–39.
- Sullivan, G.M., Feinn, R., 2012. Using effect size or why the *p* value is not enough. *J. Grad. Med. Educ.* 4 (3), 279–282.
- Tingley, D., Yamamoto, T., Hirose, K., Keele, L., Imai, K., 2014. *Mediation: R package for causal mediation analysis*.
- Sülzenbrück, S., 2012. The impact of visual feedback type on the mastery of visuo-motor transformations. *Z. Psychol.* 220 (1), 3–9.
- Todor, J.I., Doane, T., 1978. Handedness and hemispheric asymmetry in the control of movements. *J. Motor Behav.* 10 (4), 295–300.
- Walter, R., Bailly, G., Müller, J., 2013. Strikeapose: revealing mid-air gestures on public displays. *Proceedings of the SIGCHI Conference on Human Factors in Computing Systems*. ACM, pp. 841–850.
- Walter, R., Bailly, G., Valkanova, N., Müller, J., 2014. Cuenesics: using mid-air gestures to select items on interactive public displays. *Proceedings of the 16th International Conference on Human-Computer Interaction with Mobile Devices & Services*. ACM, pp. 299–308.
- Wang, W., Wu, X., Chen, G., Chen, Z., 2018. Holo3dgis: leveraging microsoft hololens in 3Dgeographic information. *ISPRS Int. J. Geo-Inf.* 7 (2), 60.
- Wobbrock, J.O., Shinohara, K., Jansen, A., 2011. The effects of task dimensionality, endpoint deviation, throughput calculation, and experiment design on pointing measures and models. *Proceedings of the SIGCHI Conference on Human Factors in Computing Systems*. ACM, pp. 1639–1648.
- Woodworth, R.S., 1899. Accuracy of voluntary movement. *Psychol. Rev.* 3 (3), i.
- Zhai, S., 2004. Characterizing computer input with Fitts' law parameters - the information and non-information aspects of pointing. *Int. J. Hum. Comput. Stud.* 61 (6), 791–809.
- Zhai, S., Kong, J., Ren, X., 2004. Speed-accuracy tradeoff in Fitts' law tasks on the equivalency of actual and nominal pointing precision. *Int. J. Hum. Comput. Stud.* 61 (6), 823–856.