# Quantifying Touch: New Metrics for Characterizing What Happens *During* a Touch


Junhan Kong
junhank@uw.edu
The Information School,
DUB Group, University of Washington
Seattle, WA, USA

Mingyuan Zhong
James Fogarty
myzhong@cs.washington.edu
jfogarty@cs.washington.edu
Paul G. Allen School of Computer Science & Engineering, DUB Group,
University of Washington
Seattle, WA, USA

Jacob O. Wobbrock
wobbrock@uw.edu
The Information School,
DUB Group, University of Washington
Seattle, WA, USA



## ABSTRACT

Measures of human performance for touch-based systems have focused mainly on overall metrics like touch accuracy and target acquisition speed. But touches are not atomic—they unfold over time and space, especially for users with limited fine motor function, for whom it can be difficult to perform quick, accurate touches. To gain insight into what happens *during* a touch, we offer 15 target-agnostic touch metrics, most of which have not been mathematically formalized in the literature. They are touch direction, variability, drift, duration, extent, absolute/signed area change, area variability, area deviation, area extent, absolute/signed angle change, angle variability, angle deviation, and angle extent. These metrics regard a touch as a time series of ovals instead of a mere $(x, y)$ coordinate. We provide mathematical definitions and visual depictions of our metrics, and consider policies for calculating our metrics when multiple fingers perform coincident touches. To exercise our metrics, we collected touch data from 27 participants, 15 of whom reported having limited fine motor function. Our results show that our metrics effectively characterize touch behaviors including fine-motor challenges. Our metrics can be useful for both understanding users and for evaluating touch-based systems to inform their design.



## CCS CONCEPTS

• **Human-centered computing → Touch screens**.

## KEYWORDS

Touch input, touch screens, touch metrics, human performance, limited fine motor function.

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## 1 INTRODUCTION

With the proliferation of modern touch-enabled devices such as smartphones, tablets, watches, and other surfaces, touch input has become perhaps the most prevalent form of input to computer systems. As with mouse pointing and text entry [37, 48, 49, 59, 60], understanding human performance with touch-based systems can reveal opportunities for improved device and interface design. To date, most measures of human performance with touch-based systems have mainly focused on overall performance like accuracy and target acquisition speed (e.g., [3, 4, 19, 23, 24, 44]). However, a touch is not an atomic event; it unfolds over space and time [43]. Therefore, examining what happens *during* a touch might yield insights into users' touch behaviors and any underlying causes of touch inaccuracy. It might also afford designers the chance to improve device or interface designs, or enable software to usefully adapt to users' touch behaviors at runtime. Particularly for accessibility, measuring what happens *during* a touch could help designers make touch interactions more accessible. For example, if a system measures how much a user "drifts" on the screen while their finger is down before lifting, the system can enlarge their widgets at runtime to accommodate.

A similar idea motivated prior work by MacKenzie et al. [37], who formulated measures for what happens *during* a mouse pointing movement, rather than just relying on overall speed and accuracy to understand pointing performance (Figure 1). MacKenzie et al. formulated seven new accuracy measures that captured properties of the cursor's *path* of movement. Building on this work, Keates et al. [33] used MacKenzie et al.'s metrics with people with motor impairments, introducing six new path measures along the way. Hwang et al. [26] built upon this work yet further, conducting submovement analyses of motion-impaired users with 12 additional metrics. In each case, examining the *path* of movement by formalizing new quantitative metrics revealed *why* overall speed and accuracy differences emerged.

Inspired by this prior work, we aim to understand *why* human performance with touch screens emerges the way it does. Certainly, some of our touch metrics have been previously used in individual studies or in *ad hoc* ways, as was the case for some of the aforementioned cursor measures. But few of our metrics have been formalized mathematically so as to be operationalized in a reusable, generalizable way. Furthermore, our metrics have not, to the best of our knowledge, been applied to the study of touch behaviors by people with and without limited fine motor function.

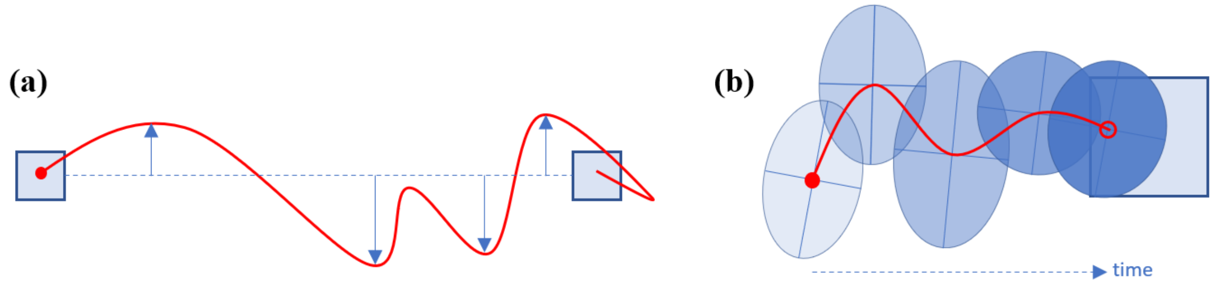


**Figure 1: (a) MacKenzie et al. [37] defined metrics for quantifying what happens during a mouse pointing movement, revealing underlying causes of speed and accuracy outcomes. For example, the variability ("wiggliness") of a movement can be quantified. (b) In an analogous fashion, we formulate 15 metrics for quantifying what happens during a touch, which is not atomic but unfolds over time and space, even if only briefly. For example, a user might land outside a target, then slide into the target and lift, creating touch ovals with various areas, orientations, and dimensions along the way.**

To these ends, we formalized 15 target-agnostic touch metrics, many of which are analogues inspired by MacKenzie et al. [37]. They are: touch direction, variability, drift, duration, extent, absolute/signed area change, area variability, area deviation, area extent, absolute/signed angle change, angle variability, angle deviation, and angle extent. Instead of treating a touch as an atomic event or single $(x, y)$ coordinate, our metrics regard a touch as a time series of ovals approximating a finger's contact area from finger-down to finger-up. Thus, a "touch process" [43] can contain movement of the touch oval centroid and change of the touch oval size, orientation, and shape. For each of our 15 metrics, we provide a mathematical formula and intuitive description. We also include visual depictions of some of our metrics to convey their purposes.

In addition, ambiguity arises when multiple fingers touch concurrently. Although our metrics are defined on a per-finger basis, we address the issue of how to handle multiple concurrent touches. Specifically, we discuss three policies for defining the touch process in multi-finger situations. The three policies are *first-down*, *longest-lived*, and *sum-of-all*. These three policies converge to the same definition in the case of a single-finger touch. Our study results also show that all three policies are viable and result in similar conclusions, even if their specific values change.

To put our metrics through their paces, we conducted a user study to collect touch data on a Microsoft Perceptive Pixel (PPI) interactive tabletop display. Our study collected complete touch oval information from 27 participants, 15 of whom reported having limited fine motor function with different specific fine motor challenges. We then computed all 15 of our touch metrics on our data and ran both descriptive and inferential statistics. Our results show that our metrics effectively characterize users' touch behaviors. Specifically, we found that our metrics uncover differences among people with no, moderate, and severe fine motor challenges. We also found that each metric correlates with a different subset of specific fine motor challenges. Additionally, we found that for multi-finger touches, the *longest-lived* policy and the *sum-of-all* policy yielded the same conclusions in characterizing users' touch processes, while the *sum-of-all* policy magnifies the differences between user groups.

Importantly, none of our 15 metrics are "target-aware" [2, 11]; rather, our metrics are "target-agnostic" [56], calculable using only the touch data itself without knowledge of target locations or dimensions. Being target-agnostic is an immensely useful property because, in practice, it is generally infeasible for software to know what a target is and whether a user was intending to touch [11, 12] (This challenge becomes trivial in an artificial testbed, but not at runtime with software "in the wild.") Despite being target-agnostic, our touch metrics can nonetheless explain why overall touch accuracy is low or high. Thus, our metrics can help understand users' touch abilities and inform better designs of touch-based systems that can adapt to these abilities.

The major contributions of this work are:

- Formalizing 15 target-agnostic touch metrics to characterize what happens during a touch;
- Proposing and investigating three policies for handling inadvertent multi-finger situations during a touch;
- Exercising our metrics in a formal study of 15 participants with and 12 participants without limited fine motor function.

## 2 RELATED WORK

Our work attempts to "pry the cover" off a touch to characterize what happens "inside" it. As noted above, prior work by MacKenzie et al. [37] pried the cover off mouse pointing to understand more than just speed and accuracy, but *how* pointing unfolds over time and space. To this end, MacKenzie et al. devised accuracy measures that include movement variability, offset, error, axis crossings, and more for evaluating mouse pointing, revealing differences among input devices. Keates et al. [33] extended MacKenzie et al.'s measures to better understand pointing by people with limited fine motor function. Through a study of mouse movements by users with motor impairments, Keates et al. characterized movement distributions and submovement characteristics, finding significant differences between people with and without upper-body motor impairments. Hwang et al. [26] further analyzed submovements by people with motor impairments. These papers inspired the current work[1] and point to the value of characterizing input *processes*, not just *outcomes*. That said, none of the metrics from MacKenzie et al. [37], Keates et al. [33], or Hwang et al. [26] can be applied directly to touch. For example, most of their metrics require a known target and a task axis between the mouse position and

[1]The current work also builds upon an ACM ASSETS 2021 poster [34]. This offered only a subset of metrics and exercised only four of them on a previously collected data set [14] that lacked complete touch-oval information (e.g., no oval major or minor axes, no areas or orientations). The current work formulates more metrics, collects an original data set, and exercises all metrics on complete touch-oval information.

target center; moreover, a mouse cursor only occupies a single $(x, y)$ position at one time, whereas a touch occupies an area, abstracted as an oval. Therefore, we developed custom metrics pertaining to touch; furthermore, our metrics are target-agnostic, making them practical to deploy in actual systems [2, 11, 12, 56].

Holz and Baudisch [23, 24] sought to understand factors affecting touch performance by modeling how users perceive their own touch input, specifically their intended versus actual point of contact. They did not formulate a set of metrics for quantifying touch, as we do here, but they devised the *generalized perceived input point model* [23] and the *projected center model* [24] to help characterize perceptual aspects of the touch process. Their work examined users' mental models through user studies, interviews, and analyses based on a series of pointing studies, identifying sources of inaccuracy in touch devices as a result of the parallax between the top and bottom of the finger. Bi and Zhai [6], using a different approach, conceptualized touch input in target selection as an uncertain process, and proposed a *Bayesian touch criterion* to statistically model the probabilistic distribution of touch selections. In other work, Bi et al. [5] proposed *FFitts law* to model finger-touch based inputs on touch screens, which reflects relative precision due to the speed-accuracy tradeoff and captures the absolute precision of finger touch.

Beyond understanding, characterizing, and modeling touch input, researchers have sought to improve touch performance through the invention and evaluation of new touch input techniques. In early work, Potter et al. [45] evaluated three strategies for target selection on touch screens, finding lift-off with an offset cursor to be most accurate. Sears and Shneiderman [47] evaluated a stabilization technique for improving touch accuracy. More recently, Vogel and Baudisch presented *Shift* [50], which uses an offset lens to magnify touch targets when multiple targets are beneath the finger. Cao et al. proposed *ShapeTouch* [7] to utilize touch regions and motion to infer virtual contact forces, enabling pseudo-force-based interaction techniques. Benko et al. [3] designed high-precision touch selection techniques by utilizing two fingers that together dynamically adjust the control-display (C-D) gain. Harrison et al. [21] used machine learning classification to distinguish the sounds made by finger tips, pads, nails, and knuckles, extending the "interaction vocabulary" of touch-based systems. Holz and Baudisch [25] went even further with *Fiberio* to detect fingerprints on a touch table with a custom fiber optic plate. On the output side, Wigdor et al. [54] created *Ripples*, which are visualizations accompanying users' touches to provide vital feedback and reduce touch errors. These are just some of the many interaction techniques developed to improve human performance with touch-based systems. By contrast, our metrics contribute to *understanding* human performance at a fine-grained level. Indeed, they could be used to explain why and how some of these touch-improvement techniques succeed.

Some work has also attempted to improve touch accuracy, not through novel interaction techniques, but through advanced machine learning. For example, Weir et al. [52, 53] used Gaussian process regression to improve touch accuracy. Kumar et al. [35] collected capacitive touch images and trained convolutional neural networks (CNNs) to improve touch accuracy. Mayer et al. [39] used CNNs to infer finger orientation from capacitive touch images.

The accessibility of touch-based systems for people with disabilities has also been a focus of prior work, particularly because touch-based systems are often inaccessible [8]. For example, Findlater et al. [13] studied users' target acquisition performance on touch screens, finding that touch accuracy and usability issues still persist for people with limited fine motor function. To improve systems' accessibility, Kane et al. [28] used accessible touch and gesture interactions in *SlideRule* to create the first finger-driven screen reader. Kane et al. [30] also developed *Access Overlays* for interactive tabletops—software-based "layers" that impose various interaction techniques on displayed content to make it more accessible to blind users. This approach was extended to physical documents using computer vision in *Access Lens* [29]. Similarly, Guo et al. [20] used computer vision and crowdsourcing in *StateLens* to model dynamic touch screen interfaces, and provide guidance for blind users while using existing inaccessible touch screens. Using hardware, Kane et al. [31] created *Touchplates* to provide physical-tactile landmarks when interacting with tabletop displays. In a related fashion, Zhang et al. [61] created *Interactiles* to provide physical-tactile interactions on smartphones. Wacharamanotham et al. [51] presented *Swabbing* for improving target selection accuracy for users with tremor. A similar technique proposed by Mertens et al. [40] called *TRABING* enables users to continuously move over desired targets, improving accuracy for people with tremor. Guerreiro et al. [19] studied characteristics of mobile touch screen interfaces to provide tools for better interface design for motor-impaired users. Montague et al. [41, 42] investigated shared user models and user interface adaptivity for making touch applications more accessible, and examined motor-impaired touchscreen interactions in the wild. Sarcar et al. [46] proposed the *Touch-WLM* model for making predictions of how users with given abilities enter text, then optimized touch screen layouts for users with tremor and dyslexia. Mott et al. created both *Smart Touch* [43] and *Cluster Touch* [44] to resolve intended touch locations by people with motor impairments through template matching of segmented "frames" of the touch process and clustering, respectively. Cluster Touch was also directed towards people incurring situational impairments [55] due to walking; similarly, Goel et al. created *WalkType* [17] and *ContextType* [18] for improving touch accuracy on smartphone keyboards while walking. Although some of our metrics (e.g., touch drift) were used in an ad hoc fashion in prior work, they were not formalized mathematically, leaving them open to variations of implementation and interpretation.

Relatedly, researchers have analyzed touch behaviors to detect specific diseases that relate to impaired motor function. Mastoras et al. [38] extracted statistical features from keystroke sequences to detect depressive disorder. Giancardo et al. [16] and Arroyo-Gallego et al. [1] used hold time (e.g., the interval between key press and release) and flight time (e.g., the interval between one key's release and the next key's press) to distinguish early-stage Parkinson's disease (PD). Iakovakis et al. [27] used normalized flight time and normalized pressure to detect declines in fine motor function in early PD patients. Kay et al. [32] created *PVT-Touch* to implement the *Psychomotor Vigilance Task* [10] as a robust clinical tool for assessing issues related to sleep loss. These projects demonstrate the ability to use touch behaviors for disease- or condition-specific diagnoses and tracking. In contrast, our touch metrics are general, capable of illuminating touch behaviors that could be useful in a variety of applications (e.g., we provide examples in Section 7).

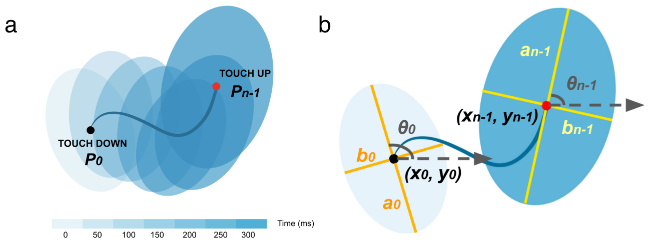


**Figure 2: (a) A sequence of $n$ touch ovals $P_0, ..., P_{n-1}$ from finger-down to finger-up along a time axis. (b) The first touch oval in the sequence has centroid $(x_0, y_0)$, angle $\theta_0$, major axis $a_0$, and minor axis $b_0$. The last touch oval has centroid $(x_{n-1}, y_{n-1})$, angle $\theta_{n-1}$, major axis $a_{n-1}$, and minor axis $b_{n-1}$.**

## 3 OUR TOUCH METRICS

In this section, we formalize 15 touch metrics for characterizing what happens *during* a touch. Although some of our metrics are admittedly not new (e.g., touch duration), most have never been previously conceptualized or given to mathematical formalism. As a general principle, our metrics result in values closer to zero when touches are closer to "perfect" (i.e., when a single finger lands and lifts instantaneously from the same place). Similarly, our metrics generally increase in magnitude as touches are further from "perfect" (i.e., as a finger moves, rotates, changes area, or persists on the screen). We begin by conceptualizing the "anatomy of a touch" as a time series of ovals.

### 3.1 Anatomy of a Touch

Our touch metrics are designed to capture what happens during a touch process, which, in the very least, consists of a finger-down oval and a finger-up oval (Figure 2). Additional ovals might be created if the finger moves during the touch or if the touch software samples the finger position at regular intervals. Our metrics are defined assuming only one finger is in contact with the screen, an assumption we revisit in Section 3.5.

Let $n$ be the total number of touch input events captured from finger-down to finger-up, inclusive. A touch process can be defined as a sequence of touch ovals $P_0, ..., P_{n-1}$, where finger-down is $P_0$ and finger-up is $P_{n-1}$. Then, for the $i^{th}$ oval:

- $(x_i, y_i)$ is the location of its centroid;
- $a_i, b_i$ are the lengths of its major and minor axes, respectively;
- $\theta_i$ is the angle, in radians, of the major axis relative to the $+x$ axis (i.e., straight right on the screen);
- $S_i$ is the oval's size, calculated as $\pi a_i b_i / 4$;
- $T_i$ is the oval's timestamp.

### 3.2 Metrics Based on Touch Location and Time

In our first of three categories, we formalize five touch metrics based on location and time. These metrics are touch direction, variability, drift, duration, and extent.

*3.2.1 Touch Direction.* Touch direction is the angle formed between the centroids of the finger-down and finger-up ovals. Intuitively, this metric indicates the overall direction that a touch moved. Conceptually, we define straight right $(+x)$ from the finger-down centroid as 0°, straight left $(-x)$ as 180°, straight up $(-y)$ as 90°, and straight down $(+y)$ as 270°, although our mathematical definition uses radians.

$$\text{Direction} = \left\{ \begin{array}{l} \tan^{-1}[(y_{n-1} - y_0)/(x_{n-1} - x_0)], \text{ if } x_0 \neq x_{n-1} \\ \pi/2, \text{ if } x_0 = x_{n-1}, y_0 > y_{n-1} \text{ (straight up)} \\ 3\pi/2, \text{ if } x_0 = x_{n-1}, y_0 < y_{n-1} \text{ (straight down)} \\ \text{undefined, if } x_0 = x_{n-1}, y_0 = y_{n-1} \text{ (no movement)} \end{array} \right\} \in [0, 2\pi)$$

*3.2.2 Touch Variability.* Touch variability is the total distance covered by successive touch inputs from finger-down to finger-up. Intuitively, this metric indicates how much distance was covered during a touch (e.g., its "jitter").

$$\text{Variability} = \sum_{i=1}^{n-1} \sqrt{(x_i - x_{i-1})^2 + (y_i - y_{i-1})^2} \in [0, \infty)$$

*3.2.3 Touch Drift.* Touch drift is the Euclidean distance from finger-down to finger-up. Intuitively, this metric indicates how far away a touch finished from where it started.

$$\text{Drift} = \sqrt{(x_{n-1} - x_0)^2 + (y_{n-1} - y_0)^2} \in [0, \infty)$$

*3.2.4 Touch Duration.* Touch duration is the time elapsed from finger-down to finger-up. Intuitively, this metric indicates how long a touch persisted.

$$\text{Duration} = (T_{n-1} - T_0) \in [0, \infty)$$

*3.2.5 Touch Extent.* Touch extent is the Euclidean distance between the most distant two oval centroids. Intuitively, this metric indicates the spatial range of the touch process.

$$\text{Extent} = \max_{i,j \in 0,\ldots,n-1} \sqrt{(x_j - x_i)^2 + (y_j - y_i)^2} \in [0, \infty)$$

| |  |  |  |  |  |
|---|---|---|---|---|---|
| Variability | Low | High | High | High | Very High |
| Drift | Medium | Low | High | Low | High |
| Extent | Medium | Medium | High | High | High |

**Table 1: Example traces of touch oval centroids and their touch variability, drift, and extent. This table was inspired by Figure 5 from MacKenzie et al. [37].**

### 3.3 Metrics Based on Touch Area

In our second of three categories, we formalize five touch metrics based on touch area. The metrics are absolute area change, (signed) area change, area variability, area deviation, and area extent.

*3.3.1 Touch Absolute Area Change.* The absolute area change of a touch is the change in area between finger-up and finger-down ovals. Intuitively, this metric indicates the difference in area between the start and end of a touch.

$$\text{Absolute Area Change} = |S_{n-1} - S_0| \in [0, \infty)$$

*3.3.2 Touch Area Change.* The (signed) area change of a touch is the same as above, but positive if finger-up is larger than finger-down; negative or zero otherwise. Intuitively, this metric indicates whether a touch grew (+) or shrank (-), and by how much.

$$\text{Area Change} = (S_{n-1} - S_0) \in (-\infty, \infty)$$

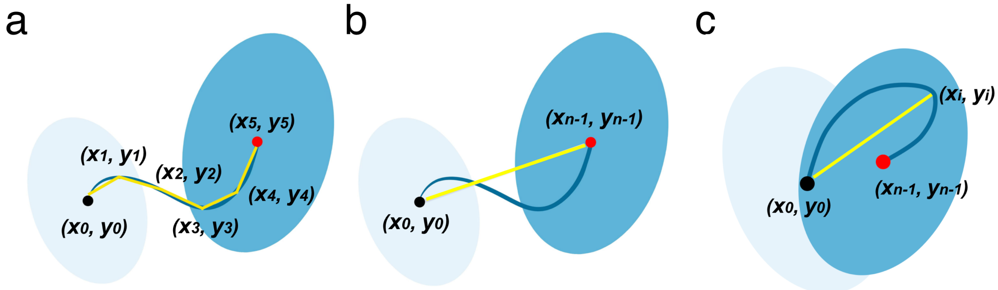


**Figure 3: Depictions of (a) touch variability, (b) touch drift, and (c) touch extent. The blue ovals centered at the black and red dots represent the first and the last touch ovals of the sequence, respectively. The dark-blue line represents the centroid trace, and the yellow line represents the respective metric.**

*3.3.3 Touch Area Variability.* The variability in touch area is the cumulative change in area over all touch ovals from finger-down to finger-up. Intuitively, this metric indicates how "stable" the size of a touch was during its lifetime.

$$\text{Area Variability} = \sum_{i=1}^{n-1} |S_i - S_{i-1}| \in [0, \infty)$$

*3.3.4 Touch Area Deviation.* The deviation in touch area is the standard deviation of touch oval area over the duration of the touch. Intuitively, this metric indicates how much the area changed from one oval to the next during the touch process.

$$\text{Area Deviation} = \sqrt{\frac{\sum_{i=0}^{n-1}(S_i - \bar{S})^2}{n-1}} \in [0, \infty), \text{ where } \bar{S} = \sum_{i=0}^{n-1} S_i/n$$

*3.3.5 Touch Area Extent.* The extent of a touch's area is the difference between the largest and smallest touch areas from finger-down to finger-up. Intuitively, this metric indicates the range of touch areas that occurred during the touch process.

$$\text{Area Extent} = \left[\left(\max_{i \in 0,\ldots,n-1} S_i\right) - \left(\min_{j \in 0,\ldots,n-1} S_j\right)\right] \in [0, \infty)$$

## 3.4 Metrics Based on Touch Angle

In our third of three categories, we formalize five touch metrics based on oval angles, that is, the angle of the major axis relative to the $+x$-axis (straight right), which is defined as $0°$. These metrics are absolute angle change, (signed) angle change, angle variability, angle deviation, and angle extent.

Note that two touch angles with greatly different values can, in fact, be quite close to each other (e.g., 359° and 1° are only 2° apart). Therefore, to make our metrics accurately reflect the amount of angle change during a touch, we define the angle change from $\theta_1$ to $\theta_2$ as

$$\theta_2 - \theta_1 = \Delta\theta_{1,2}$$

where $\Delta\theta_{1,2}$ is the angle between $\theta_1$ and $\theta_2$ in $(-\pi, \pi]$. Also, counter-clockwise is considered positive and clockwise is considered negative.

*3.4.1 Touch Absolute Angle Change.* The absolute angle change of a touch is the change in the major axis angle from finger-down to finger-up. Intuitively, this metric indicates how much the finger orientation changed between the start and end of a touch.

$$\text{Absolute Angle Change} = |\theta_{n-1} - \theta_0| \in [0, \pi]$$

*3.4.2 Touch Angle Change.* The (signed) angle change of a touch is the same as above, but positive when counterclockwise and negative when clockwise. Intuitively, this metric indicates whether the finger rotated counterclockwise or clockwise, and by how much.

$$\text{Angle Change} = (\theta_{n-1} - \theta_0) \in (-\pi, \pi]$$

*3.4.3 Touch Angle Variability.* The variability in touch angle is the cumulative change of the major axis angle over the duration of the touch. Intuitively, this metric indicates how "jittery" the orientation of the finger was during a touch.

$$\text{Angle Variability} = \sum_{i=1}^{n-1} |\theta_i - \theta_{i-1}| \in [0, \infty)$$

*3.4.4 Touch Angle Deviation.* The deviation in touch angle is the standard deviation of the major axis angle over the duration of the touch. Intuitively, this metric indicates how much the finger orientation changed from one oval to the next during a touch.

$$\text{Angle Deviation} = \sqrt{\frac{\sum_{i=0}^{n-1}(\theta_i - \bar{\theta})^2}{n-1}} \in [0, \infty), \text{ where } \bar{\theta} = \sum_{i=0}^{n-1} \theta_i/n$$

*3.4.5 Touch Angle Extent.* The extent of a touch's angle is the angle between the two major axes that are farthest apart in orientation. Intuitively, this metric indicates the range of angles that the major axis covered throughout the touch.

$$\text{Angle Extent} = \left(\max_{i,j \in 0,\ldots,n-1} |\theta_j - \theta_i|\right) \in [0, \pi]$$

For a theoretical "perfect touch," where the finger-down oval exactly coincides with the finger-up oval and the touch is instantaneous, 14 metrics will equal zero and *touch direction* will be undefined. In practice, of course, there should be some elapsed time between finger-down and finger-up, with distinct ovals for each captured event. Of course, the number of ovals and their properties one receives depend upon the software and hardware comprising the sensing platform one is using. For example, some Android smartphones and tablets do not reliably report major and minor axis information. In our study, described below, we used a Microsoft Perceptive Pixel (PPI) display with custom software that we wrote to ensure all necessary oval information was reported for calculation of our 15 touch metrics.

Table 1 offers a few example touch centroid traces to illustrate the intuitive differences among three of our touch metrics. Recall that touch variability is the total distance covered by successive touch ovals; touch drift is the distance from finger-down to finger-up; and

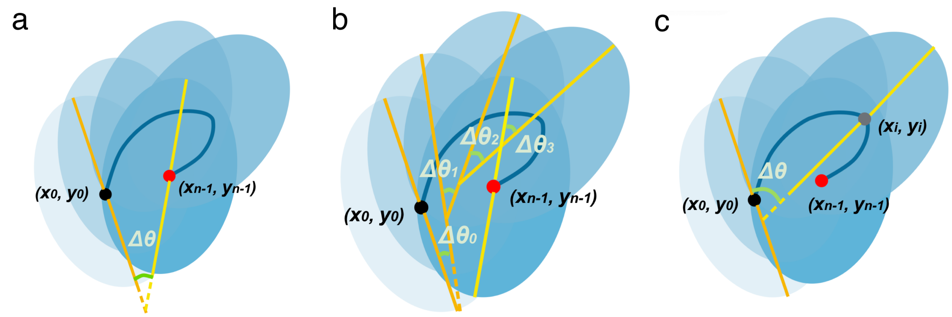


**Figure 4: Depictions of (a) touch angle change, (b) touch angle variability, (c) touch angle extent. The blue ovals represent the touch oval sequence, the orange & yellow lines represent the major axes of ovals, and the green arcs represent measured angles.**

touch extent is the distance between the two most distant touch ovals that occurred during the touch process.

## 3.5 Handling Multiple Concurrent Fingers

Our 15 metrics assume that a single finger is performing a touch. Indeed, future research could explore additional metrics specifically meant to characterize multi-touch behaviors. But our metrics can nonetheless be used in multi-touch situations, and inadvertent multi-touch events can and do occur, especially for people with limited fine motor function or for people in impairing situations. Therefore, we address the question of which "policy" to adopt for our metrics when multiple concurrent touches occur. To this end, we explore three policies: *first-down*, *longest-lived*, and *sum-of-all*.

In discussing these three policies, we regard a *touch trace* as the successive touch ovals associated with a single finger, and a *touch process* as the collection of touch ovals from the first finger-down to the last finger-up, even if they are different fingers. Under this view, a single touch process can contain multiple touch traces if multiple fingers touch the screen.

*3.5.1 First-Down Policy.* As a baseline, we examined the *first-down* policy, which defines a touch process by whichever finger is first to land on the touch-sensitive display. If other fingers land on the display while the first finger is still present, they are simply ignored. This policy is obviously naïve and sometimes incorrect, but serves as a useful point of comparison.

*3.5.2 Longest-Lived Policy.* With the *longest-lived* policy, a touch process is defined by whichever finger persists on the touch-sensitive display the longest. Thus, all fingers are tracked during the touch process, and once the process has ended, the finger with the greatest duration is used to calculate our 15 touch metrics. This policy has the benefit that short-lived fingers are often the result of unintentional contact with the display surface.

*3.5.3 Sum-Of-All Policy.* With the *sum-of-all* policy, we avoid trying to discern which finger is most "indicative" of the user's intended touch process, and instead include *all* touch traces in the calculation of our metrics. As unintentional finger-touches are often short-lived and produce relatively few touch events, they naturally contribute little to the sum of touch oval data than the finger indicative of the user's actual intentions. For people with limited fine motor function, multiple fingers contacting the screen can even be an indicator of their fine motor abilities and can be reflective of their challenges using a device. Thus, for this policy, we first calculate our 15 metrics for the touch traces of all fingers that appear, and then simply sum these over the entire touch process.

The above three policies provide a pragmatic approach to handling cases where multiple fingers appear in a touch process that only requires a single finger. As we show below, all three policies resulted in similar empirical conclusions in our user study, which only required single-finger touches and no swipe or pinch gestures to be performed. As for metrics to specifically characterize multi-touch behaviors, we leave their formulation to future work.

# 4 STUDY METHOD

In this section, we describe a formal user study to put our 15 metrics through their paces. We conducted this study using custom software we built for the Microsoft Perceptive Pixel (PPI) display, which is capable of giving complete oval information for touch down, move, and up events. The goal of our study was to understand whether and how our metrics might characterize users' touch behaviors, particularly any differences between users with and without limited fine motor function.

## 4.1 Participants

We recruited 27 participants, 15 of whom reported having limited fine motor function (LFMF), using email solicitations, phone calls, convenience sampling, and snowball sampling (Table 2). On average, participants with LFMF were 63.8 years old ($SD$ = 18.8), with 8 women and 7 men. Reported health conditions included essential tremor (5), arthritis (4), Charcot-Marie-Tooth disease (1), enhanced physiological tremor (1), idiopathic tremor (1), referral nerve pain (1), spinal cord injury (1), tendinitis (1), and traumatic brain injury (1). Reported specific fine motor challenges included tremor (53.3%), spasm (40.0%), numbness (6.7%), stiffness (53.3%), pain (46.7%), rapid fatigue (26.7%), poor coordination (13.3%), low strength (33.3%), slow movements (20.0%), difficulty gripping (33.3%), difficulty lifting (20.0%), difficulty holding (20.0%), difficulty holding still (26.7%), difficulty forming hand postures (26.7%), and difficulty controlling movement direction (13.3%) and distance (13.3%). Participants without LFMF were, on average, 34.8 years old ($SD$ = 22.0), with 8 women and 4 men.

## 4.2 Apparatus

To collect touch data, we developed a custom testbed program for use on a Microsoft Perceptive Pixel (PPI) 55-inch tabletop display connected to a PC running Windows 10. The testbed ran a Universal Windows Platform (UWP) application we wrote in C#. The purpose of the testbed was to present participants with a series of crosshairs

| Participants w/ Limited Fine Motor Function (LFMF) | | | | | Participants w/o LFMF | | |
|---|---|---|---|---|---|---|---|
| *ID* | *Gender* | *Age* | *Diagnosis* | *Fine Motor Challenges* | *ID* | *Gender* | *Age* |
| **A1** | woman | 22 | Tendinitis in wrist | Stiffness, rapid fatigue | **B1** | woman | 21 |
| **A2** | man | 68 | N/A | Low strength | **B2** | woman | 23 |
| **A3** | man | 77 | Arthritis | Stiffness, pain, slow movements,<br>difficulty gripping, difficulty holding,<br>difficulty holding still,<br>difficulty forming hand postures | **B3** | man | 23 |
| **A4** | man | 59 | Mild referral<br>nerve pain | Pain, poor coordination,<br>difficulty forming hand postures,<br>difficulty controlling movement distance | **B4** | woman | 25 |
| **A5** | woman | 75 | Arthritis,<br>Charcot-Marie-Tooth<br>disease | Tremor, spasm, stiffness, pain, rapid fatigue,<br>poor coordination, low strength,<br>slow movements, difficulty gripping,<br>difficulty lifting, difficulty holding still,<br>difficulty forming hand postures | **B5** | woman | 26 |
| **A6** | man | 71 | Essential tremor | Tremor, slow movements | **B6** | woman | 29 |
| **A7** | woman | 67 | Essential tremor | Tremor, spasm, pain | **B7** | man | 23 |
| **A8** | woman | 68 | Essential tremor | Tremor, spasm, stiffness, low strength,<br>difficulty gripping, difficulty holding | **B8** | woman | 37 |
| **A9** | woman | 81 | Arthritis | Tremor, stiffness, pain,<br>difficulty gripping, difficulty lifting | **B9** | woman | 80 |
| **A10** | woman | 71 | Essential tremor | Tremor, stiffness, pain, rapid fatigue,<br>low strength, difficulty holding still,<br>difficulty controlling movement direction,<br>difficulty controlling movement distance | **B10** | woman | 24 |
| **A11** | man | 78 | Essential tremor | Tremor | **B11** | man | 24 |
| **A12** | man | 34 | Enhanced physiological tremor | Spasm, pain, rapid fatigue | **B12** | man | 82 |
| **A13** | woman | 78 | Arthritis, Samilial<br>idiopathic tremor | Tremor, spasm, stiffness, low strength,<br>difficulty lifting, difficulty holding still,<br>difficulty controlling movement direction | | | |
| **A14** | man | 32 | Spinal cord injury | Spasm, difficulty gripping, difficulty holding,<br>difficulty forming hand postures | | | |
| **A15** | woman | 76 | Traumatic brain injury | Numbness, stiffness | | | |

**Table 2: Demographics of participants with and without limited fine motor function (LFMF).**

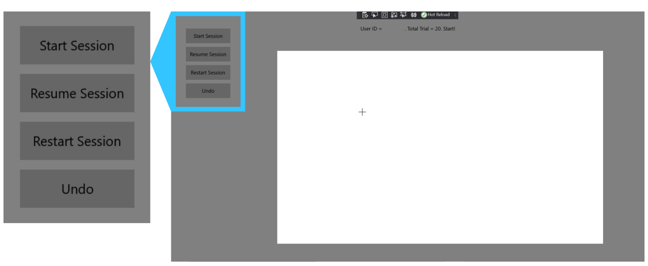


**Figure 5: Our custom tabletop testbed. Four buttons in the top-left enabled the experimenter to control the study: start session, resume session, restart session, and undo. The participant ID and trial number were displayed at the top. The large white rectangular region was defined by the participant to indicate their comfortable reach area. Crosshairs were randomly generated within this region.**

that they touched as accurately as they could. All touch events (finger down, move, and up) were logged as touch ovals. Each oval was reported with its centroid location, orientation, major and minor axis lengths, and a timestamp.

To ensure participants could reach the crosshairs presented to them, before the trials began, participants were asked to indicate the area of the tabletop that they could comfortably reach by touching the four corners of a rectangle of their choosing (Figure 5). During

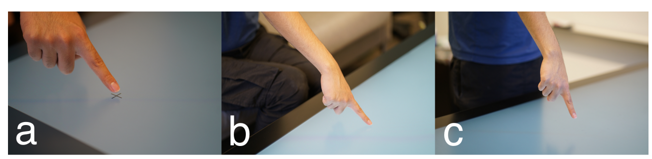


**Figure 6: (a) A participant using a finger to tap on a crosshairs target. (b) The sitting posture for participants who preferred it. (c) The standing posture for participants who preferred it.**

trials, crosshairs were generated at random $(x, y)$ locations only within this rectangle. The crosshairs themselves had a line thickness of 1 pixel and a radius of 10 pixels, and participants were told to touch the crosshairs' centers as accurately as they could. The PPI display was placed on a desk for participants who preferred to stand, or on a coffee table for participants who preferred to sit (Figure 6).

## 4.3 Procedure

Study sessions were conducted in-person following all COVID-19 health and safety protocols, with approval from our university's Institutional Review Board (IRB). After a brief introduction to the study and the collection of demographic information via a questionnaire (see Table 2), participants were asked to draw a rectangular area on the screen indicating the region in which they were comfortable reaching. Each participant then completed 10 practice trials to familiarize themselves with the study. A single trial consisted of touching a crosshairs that was drawn at a random $(x, y)$ location within the comfortable reach area. After the practice trials, each participant completed 10 blocks of 20 trials for a total of 200 trials. (With 27 participants, our data set consisted of $200 \times 27 = 5400$ touch trials in all.) Short breaks were offered between each block of trials. Upon completing all pointing trials, participants were asked to rate how challenging they thought the trials were on a Likert-type scale ranging from "1=very easy" to "7=very difficult." They were also asked about anything they found challenging during the trials, and any difficulties they have using touch screen devices in their daily lives. The study session took ~45 minutes for participants with limited fine motor function (LFMF), and <30 minutes for participants without LFMF. Participants with LFMF were compensated $40 USD and participants without LFMF were compensated $15 USD.

## 4.4 Design and Analysis

The purpose of our study was to exercise our touch metrics and see how they differ for participants with and without limited fine motor function (LFMF). In formal experiment terms, our study involved a single between-subjects factor indicating whether someone reported having LFMF or not. That said, during our study sessions, we observed that the touch abilities of participants with LFMF varied a great deal, as some participants experienced significant difficulty touching crosshairs while others had almost no difficulty. To ensure that our analysis took into account such differences, we further grouped our participants into three levels having different degrees of fine motor challenge: *None*, *Moderate*, and *Severe*.

The *None* group included participants who did not report having LFMF and who did not show any observable signs of having limited fine motor function during the study. The *Moderate* group included participants who (1) reported having LFMF, but reported that they were having a "good day" on the day of their study session, or (2) reported having LFMF, but reported that they found ways of accommodating their fine motor challenges such that their touch screen use was not affected, or (3) did not report having LFMF, but showed some observable signs of having limited fine motor function during the study. Finally, the *Severe* group included the participants who both reported having LFMF and showed observable signs of having fine motor challenges. These participants also described having difficulty operating touch screen devices in their everyday lives. In total, we had 11 participants in the *None* group, 10 participants in the *Moderate* group, and 6 participants in the *Severe* group.

For inferential statistics, because most of our metrics were conditionally non-normal, we used the rank transform procedure of Conover and Iman [9] to apply midranks to our 15 touch metrics before conducting our analyses of variance using linear mixed models [15, 36], resulting in nonparametric analyses. Our single factor was *Impairment* with three levels: *None*, *Moderate*, and *Severe*, as described above. In addition, we ran separate analyses with each specific fine motor challenge (e.g., "tremor") as a dichotomous fixed effect. As is customary, all models included *Participant* as a random factor to account for repeated measures [36]. Any *post hoc* pairwise comparisons following significant or marginal omnibus tests were corrected with Holm's sequential Bonferroni procedure [22].

# 5 RESULTS

In this section, we present the results of our study. These results include an examination of the effects of *Impairment* and of each specific fine motor challenge on our 15 touch metrics. The boxplots in Appendix A show each of our 15 touch metrics by the three levels of *Impairment*. We also show associations between specific self-reported fine motor challenges and the 15 touch metrics (see Table 3). But first, we discuss our choice of touch policy for resolving inadvertent multiple touches (see Section 3.5).

## 5.1 Choosing a Touch Policy

Overall, 1.2% of trials had more than one finger touch the surface. By level of *Impairment*, multiple fingers occurred in 0.1% (*None*), 0.5% (*Moderate*), and 4.4% (*Severe*) of trials.

We calculated our 15 touch metrics using the policies discussed in Section 3.5. In conducting our analyses, we found that the results from all three touch policies generally agreed. Specifically, our analyses revealed that in 77.2% of touch processes that had multiple fingers, the finger to land first on the table was also the longest-lived finger, explaining the convergence of results for the *first-down* and *longest-lived* policies. The *sum-of-all* policy also resulted in the same conclusions, but with the differences magnified, owing to the inclusion of all fingers that touched the surface during a touch process. Given the convergence of the three policies, we proceed using the *sum-of-all* policy for the remainder of our analyses.

## 5.2 How Our Metrics Reveal Touch Behaviors

Appendix A shows means and standard deviations for all 15 metrics by level of *Impairment*. Visually, it is apparent that the *Severe* group tended to have somewhat higher values for many of our touch metrics. Non-parametric analysis indicates a significant main effect of *Impairment* on touch variability ($\chi^2_{2,N=5400} = 15.55, p < .001$), drift ($\chi^2_{2,N=5400} = 11.58, p < .01$), duration ($\chi^2_{2,N=5400} = 10.85, p < .01$), extent ($\chi^2_{2,N=5400} = 12.86, p < .01$), and area change ($\chi^2_{2,N=5400} = 6.46, p < .05$). Furthermore, *Impairment* had a marginal effect on absolute area change ($\chi^2_{2,N=5400} = 4.78, p = .092$).

*Post hoc* pairwise comparisons among levels of *Impairment* revealed that the *Severe* group had significantly higher touch variability ($t_{24} = -3.76$, $p < .01$), drift ($t_{24} = -3.27$, $p < .01$), duration ($t_{24} = -3.28$, $p < .01$), and extent ($t_{24} = -3.43$, $p < .01$) than the *None* group, and marginally higher area change ($t_{24} = -2.51$, $p = .057$) than the *None* group. The *Severe* group also had significantly higher touch variability ($t_{24} = -3.31$, $p < .01$), drift ($t_{24} = -2.80$, $p < .05$), and extent ($t_{24} = -2.98$, $p < .05$) than the *Moderate* group. Thus, it seems that some of our metrics are indeed capable of revealing differences in touch behaviors among our three groups.

Along with examining the effects of *Impairment* on our 15 touch metrics, we also examined correlations between specific fine motor challenges and our metrics. Recall that at the start of our study, participants indicated whether or not they experienced various fine motor challenges (see Section 4.1), namely tremor, spasm, numbness, stiffness, pain, rapid fatigue, poor coordination, low strength, slow movements, difficulty gripping, difficulty lifting, difficulty holding, difficulty holding still, difficulty forming hand

| | Tremor | Spasm | Stiffness | Pain | Poor Coordination | Difficulty Lifting | Difficulty Holding Still | Difficulty Forming Hand Postures | Difficulty Controlling Movement Distance |
|---|---|---|---|---|---|---|---|---|---|
| Direction | – | – | 3.08 · | – | – | 5.66 ∗ | 3.91 ∗ | – | – |
| Variability | 8.07 ∗∗ | – | 3.38 · | 4.95 ∗ | – | 3.89 ∗ | – | – | – |
| Drift | 6.39 ∗ | – | 2.74 · | 4.45 ∗ | – | 3.46 · | – | – | – |
| Duration | 8.27 ∗∗ | 3.57 · | – | – | – | – | – | – | 3.11 · |
| Extent | 7.04 ∗∗ | – | 3.02 · | 4.64 ∗ | – | 3.52 · | – | – | – |
| Absolute Area Change | 3.94 ∗ | – | – | – | – | – | – | – | – |
| Area Change | 3.90 ∗ | – | – | – | – | – | – | – | – |
| Area Variability | 2.73 · | – | – | – | – | – | – | – | – |
| Area Deviation | 2.71 · | – | – | – | – | – | – | – | – |
| Area Extent | 3.04 · | – | – | – | – | – | – | – | – |
| Absolute Angle Change | – | – | – | 3.72 · | – | – | – | 4.01 ∗ | – |
| Angle Change | 2.86 · | – | – | – | 6.00 ∗ | – | – | – | 2.77 · |
| Angle Variability | – | – | – | 3.51 · | – | – | – | 3.08 · | – |
| Angle Deviation | – | – | – | – | – | – | – | 3.50 · | – |
| Angle Extent | – | – | – | 3.30 · | – | – | – | 3.23 · | – |

**Table 3: Chi-square ($\chi^2$) statistics for all significant ($p < .05$) and marginal ($p < .10$) effects of each fine motor challenge on the touch metrics for people with *vs.* people without the given challenge. All $\chi^2$-statistics are for $\chi^2_{2,N=5400}$. Significance indicators: $\cdot p < .10$, $*p < .05$, $**\ p < .01$.**

postures, difficulty controlling movement direction, and difficulty controlling movement distance. These challenges were indicated in a dichotomous fashion ("yes" or "no") at participants' discretion.

All significant ($p < .05$) and marginal ($p < .10$) correlations between these specific fine motor challenges and our touch metrics are presented in Table 3.[2] This table reveals, for each specific fine motor challenge, the touch metrics with which it significantly (or marginally) correlates compared to people without that challenge. For example, people who self-reported experiencing tremor showed a significant correlation with touch variability, drift, duration, extent, and absolute area change; and marginal correlations with area variability, area deviation, area extent, and angle change compared to people who did not report experiencing tremor. Taken as a whole, then, we can use these results to understand how people experiencing different fine motor challenges tended to exhibit certain corresponding touch behaviors, as revealed by our touch metrics.

## 6 DISCUSSION

Overall, touch variability, drift, duration, extent, and (signed) area change distinguished well among our three *Impairment* groups, especially between the *None* and *Severe* groups. To a lesser extent, the same can be said of absolute area change. Our results match our expectations that people with limited fine motor function might experience more challenges while using touch screens, and therefore would have higher values for some metrics. Our findings also comport with those of Findlater et al. [13], which showed increased pointing errors on touch screens and a high frequency of spurious touches for people with limited fine motor function. Moreover, our results also align with what we observed during our study sessions, namely that participants in the *Severe* group experienced greater difficulty touching accurately than those in either the *None* or *Moderate* groups. Furthermore, the touch behaviors of participants in the *None* and *Moderate* groups were often difficult to distinguish during study sessions, and so we are not surprised to find few statistically detectable differences between them.

Many or all of touch variability, drift, duration, and extent were associated with tremor, stiffness, pain, and difficulty lifting. Touch duration was also associated with spasm and difficulty controlling movement distance. Touch direction was associated with stiffness, difficulty lifting, and difficulty holding still. Touch extent was associated with tremor, stiffness, pain, and difficulty lifting. Touch angle change was associated with tremor, poor coordination, and difficulty controlling movement distance. These associations, once revealed by our analyses, generally are quite intuitive.

Although most of the area and angle metrics did not show significant differences between *Impairment* groups, they were nonetheless useful in characterizing different specific fine motor challenges. The touch area metrics were positively correlated with tremor (absolute area change, signed area change, area variability, area deviation, and area extent). Certain touch angle metrics were also positively correlated with tremor (signed angle change), pain (absolute angle change, angle variability, angle extent), poor coordination (signed angle change), difficulty forming hand postures (absolute angle change, angle variability, angle deviation, and angle extent), and difficulty controlling movement distance (signed angle change).

Among all specific fine motor challenges, tremor had an impact on the most individual touch metrics. This finding is intuitive, as tremor directly affects people's finger movements and use of touch screen devices. Also, stiffness was correlated with touch direction, variability, drift, and extent, which also comports with our expectations, as stiffness might result in reduced finger movement. Although challenges like pain, difficulty lifting, and difficulty forming hand postures also had associations with a few of our metrics, their expected effects on our touch metrics are less directly

[2]Fine motor challenges mentioned in Section 4.1 but not shown in Table 3 exhibited no detectable correlations with our touch metrics; they are omitted for clarity of presentation.

predictable. Regardless, our findings on the whole show that our metrics are useful in characterizing a number of different fine motor challenges, and can be helpful for understanding users' different behaviors and challenges while using touch screens.

Our findings also match findings in the earlier ACM ASSETS work which analyzed a subset of the metrics [34], that people who self-reported as having limited fine motor function tended to have significantly larger touch variability, drift, duration and extent than people who did not self-report thusly. We believe that our metrics can benefit future accessibility research, by providing additional information for understanding motor-impaired touch behaviors in empirical studies, as well as enabling inventions of accessible systems with our metrics – for example, ability-aware systems that dynamically adapt to users' touch abilities (Section 7).

## 6.1 Limitations

As with any study, ours had limitations. To acquire full touch-oval information, our study was run on a Microsoft Perceptive Pixel (PPI) tabletop display, which required us to be co-located with our participants in a lab setting. A more ecologically valid touch data set could be obtained from people's everyday smartphone use, although based on our testing, many Android smartphones fail to report complete touch-oval data, making this approach challenging. Future smartphone models might remedy this limitation.

Although we were able to recruit 15 participants who reported having limited fine motor function, and 12 participants otherwise, our sample of 27 participants was still relatively small considering the large variety and severity of fine motor challenges. With more participants, we would probably be able to identify stronger and more correlations between fine motor challenges and our 15 touch metrics, likely resolving many of our marginal results into statistically significant ones. Furthermore, many of our participant volunteers were quite tech-savvy, and might have found ways to adapt their touch behaviors to accommodate their fine motor challenges. Our distinguishing of participants with moderate and severe fine motor challenges enabled us to detect performance differences between them, but having more participants in each group would enable some statistical trends to further emerge.

Finally, our goal was to isolate participant touches using a testbed showing crosshairs as, effectively, single-pixel targets. It remains to be seen whether participants' touch behaviors would be the same on "real" user interfaces with, for example, buttons, hyperlinks, scroll bars, and menus, to name a few. A future version of our study could not only include crosshairs as targets, but also genuine user interfaces whose targets are typical of touch-based applications.

# 7 FUTURE WORK

In addition to addressing the limitations above, strategic directions for future work are numerous. This work provided an initial scientific exploration into 15 touch metrics and their association with limited fine motor function. Going forward, systems could be implemented that observe a user's touch behaviors and offer possible adaptations for improving the usability or accessibility of their user interfaces, even at runtime. For example, if a system detects high touch variability, drift, extent, area change, area variability, and angle change, it might be reasonable for it to hypothesize that its user experiences tremor and could benefit from larger target sizes, an idea consistent with ability-based design [57, 58]. Note that such a hypothesis could be drawn *without* knowing anything about the specific targets in the user interface or the particular user's intention, as all 15 of our touch metrics are *target-agnostic* [56]. This property of our metrics makes them easy to implement in a way that avoids the vast complications of having to identify targets in a user interface [2, 11, 12, 56]. Besides adaptive or personalized user interfaces, our metrics might also be used by software designed to diagnose or track human motor functioning. For example, a personal health application of our metrics might allow a user to self-track their touch performance with our 15 metrics to see whether they are affected by medication, time of day, fatigue, therapy, or progressive symptoms. Yet another future application of this work is in studies comparing touch screens, user groups, or user situations. We anticipate that numerous future research and development projects might benefit from measuring more than just touch accuracy and speed, using our metrics to understand *why* overall touch performance is what it is.

# 8 CONCLUSION

Current human performance measures for use with touch-based systems have focused mainly on overall performance like touch accuracy and target acquisition speed. But to understand what happens *during* a touch, we formalized 15 target-agnostic touch metrics: touch direction, variability, drift, duration, extent, absolute / signed area change, area variability, area deviation, area extent, absolute / signed angle change, angle variability, angle deviation, and angle extent. Instead of treating a touch as an atomic event, our metrics regard a touch as a time series of touch ovals approximating a finger's contact area from finger-down to finger-up. For each of our 15 metrics, we provided the mathematical formula and intuitive description of what the metric means. We also included visual depictions of some of our metrics to aid understanding. We also described three policies to handle cases where multiple fingers inadvertently contact the screen during a touch.

To exercise our 15 metrics, we built a custom testbed for an interactive tabletop and collected complete touch-oval data from 27 participants, 15 of whom reported having limited fine motor function. Our analysis showed that our metrics could effectively distinguish unimpaired from impaired touch behaviors. Our metrics were also significantly associated with different self-reported fine motor challenges. Thus, our metrics can shed light on the underlying causes of touch inaccuracy, and can further help understand users' touch abilities. Conceivably, our metrics might inform the design of touch-based systems. Touch devices and touch accuracy will remain important for many years to come; our metrics can contribute to a better understanding of both.

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# REFERENCES


[1] Teresa Arroyo-Gallego, María Jesus Ledesma-Carbayo, Alvaro Sánchez-Ferro, Ian Butterworth, Carlos S Mendoza, Michele Matarazzo, Paloma Montero, Roberto López-Blanco, Veronica Puertas-Martin, Rocio Trincado, et al. 2017. Detection of motor impairment in Parkinson's disease via mobile touchscreen typing. *IEEE Transactions on Biomedical Engineering* 64, 9 (2017), 1994–2002.

[2] Ravin Balakrishnan. 2004. "Beating" Fitts' law: virtual enhancements for pointing facilitation. *International Journal of Human-Computer Studies* 61, 6 (2004), 857–874.

[3] Hrvoje Benko, Andrew D Wilson, and Patrick Baudisch. 2006. Precise selection techniques for multi-touch screens. In *Proceedings of the ACM SIGCHI Conference on Human Factors in Computing Systems*. 1263–1272.

[4] Joanna Bergstrom-Lehtovirta, Antti Oulasvirta, and Stephen Brewster. 2011. The effects of walking speed on target acquisition on a touchscreen interface. In *Proceedings of the 13th International Conference on Human Computer Interaction with Mobile Devices and Services*. 143–146.

[5] Xiaojun Bi, Yang Li, and Shumin Zhai. 2013. FFitts law: modeling finger touch with fitts' law. In *Proceedings of the ACM SIGCHI Conference on Human Factors in Computing Systems*. 1363–1372.

[6] Xiaojun Bi and Shumin Zhai. 2013. 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*. 51–60.

[7] Xiang Cao, Andrew D Wilson, Ravin Balakrishnan, Ken Hinckley, and Scott E Hudson. 2008. ShapeTouch: Leveraging contact shape on interactive surfaces. In *2008 3rd IEEE International Workshop on Horizontal Interactive Human Computer Systems*. IEEE, 129–136.

[8] Sinead Carew. 2009. Touch-screen gadgets alienate blind. *Reuters, January* 8 (2009).

[9] William J Conover and Ronald L Iman. 1981. Rank transformations as a bridge between parametric and nonparametric statistics. *The American Statistician* 35, 3 (1981), 124–129.

[10] David F Dinges and John W Powell. 1985. Microcomputer analyses of performance on a portable, simple visual RT task during sustained operations. *Behavior research methods, instruments, & computers* 17, 6 (1985), 652–655.

[11] Morgan Dixon, James Fogarty, and Jacob Wobbrock. 2012. A general-purpose target-aware pointing enhancement using pixel-level analysis of graphical interfaces. In *Proceedings of the ACM SIGCHI Conference on Human Factors in Computing Systems*. 3167–3176.

[12] Abigail Evans and Jacob Wobbrock. 2012. Taming wild behavior: The input observer for obtaining text entry and mouse pointing measures from everyday computer use. In *Proceedings of the ACM SIGCHI Conference on Human Factors in Computing Systems*. 1947–1956.

[13] Leah Findlater, Karyn Moffatt, Jon E Froehlich, Meethu Malu, and Joan Zhang. 2017. Comparing touchscreen and mouse input performance by people with and without upper body motor impairments. In *Proceedings of the ACM SIGCHI Conference on Human Factors in Computing Systems*. 6056–6061.

[14] Leah Findlater and Lotus Zhang. 2020. Input Accessibility: A Large Dataset and Summary Analysis of Age, Motor Ability and Input Performance. In *Proceedings of the 22th International ACM SIGACCESS Conference on Computers and Accessibility*. 1–6.

[15] Brigitte N Frederick. 1999. Fixed-, Random-, and Mixed-Effects ANOVA Models: A User-Friendly Guide for Increasing the Generalizability of ANOVA Results. (1999).

[16] Luca Giancardo, Alvaro Sanchez-Ferro, Teresa Arroyo-Gallego, Ian Butterworth, Carlos S Mendoza, Paloma Montero, Michele Matarazzo, José A Obeso, Martha L Gray, and R San José Estépar. 2016. Computer keyboard interaction as an indicator of early Parkinson's disease. *Scientific Reports* 6, 1 (2016), 1–10.

[17] Mayank Goel, Leah Findlater, and Jacob Wobbrock. 2012. WalkType: using accelerometer data to accomodate situational impairments in mobile touch screen text entry. In *Proceedings of the ACM SIGCHI Conference on Human Factors in Computing Systems*. 2687–2696.

[18] Mayank Goel, Alex Jansen, Travis Mandel, Shwetak N Patel, and Jacob O Wobbrock. 2013. ContextType: using hand posture information to improve mobile touch screen text entry. In *Proceedings of the ACM SIGCHI Conference on Human Factors in Computing Systems*. 2795–2798.

[19] Tiago Guerreiro, Hugo Nicolau, Joaquim Jorge, and Daniel Gonçalves. 2010. Towards accessible touch interfaces. In *Proceedings of the 12th International ACM SIGACCESS Conference on Computers and Accessibility*. 19–26.

[20] Anhong Guo, Junhan Kong, Michael Rivera, Frank F Xu, and Jeffrey P Bigham. 2019. Statelens: A reverse engineering solution for making existing dynamic touchscreens accessible. In *Proceedings of the 32nd Annual ACM Symposium on User Interface Software and Technology*. 371–385.

[21] Chris Harrison, Julia Schwarz, and Scott E Hudson. 2011. TapSense: enhancing finger interaction on touch surfaces. In *Proceedings of the 24th Annual ACM Symposium on User Interface Software and Technology*. 627–636.

[22] Sture Holm. 1979. A simple sequentially rejective multiple test procedure. *Scandinavian Journal of Statistics* (1979), 65–70.

[23] Christian Holz and Patrick Baudisch. 2010. The generalized perceived input point model and how to double touch accuracy by extracting fingerprints. In *Proceedings of the ACM SIGCHI Conference on Human Factors in Computing Systems*. 581–590.

[24] Christian Holz and Patrick Baudisch. 2011. Understanding touch. In *Proceedings of the ACM SIGCHI Conference on Human Factors in Computing Systems*. 2501–2510.

[25] Christian Holz and Patrick Baudisch. 2013. Fiberio: a touchscreen that senses fingerprints. In *Proceedings of the 26th Annual ACM Symposium on User Interface Software and Technology*. 41–50.

[26] Faustina Hwang, Simeon Keates, Patrick Langdon, and John Clarkson. 2004. Mouse movements of motion-impaired users: A submovement analysis. In *Proceedings of the 5th International ACM SIGACCESS Conference on Computers and Accessibility*. 102–109.

[27] Dimitrios Iakovakis, Stelios Hadjidimitriou, Vasileios Charisis, Sevasti Bostantzopoulou, Zoe Katsarou, and Leontios J Hadjileontiadis. 2018. Touchscreen typing-pattern analysis for detecting fine motor skills decline in early-stage Parkinson's disease. *Scientific Reports* 8, 1 (2018), 1–13.

[28] Shaun K Kane, Jeffrey P Bigham, and Jacob O Wobbrock. 2008. Slide Rule: making mobile touch screens accessible to blind people using multi-touch interaction techniques. In *Proceedings of the 10th International ACM SIGACCESS Conference on Computers and Accessibility*. 73–80.

[29] Shaun K Kane, Brian Frey, and Jacob O Wobbrock. 2013. Access lens: a gesture-based screen reader for real-world documents. In *Proceedings of the ACM SIGCHI Conference on Human Factors in Computing Systems*. 347–350.

[30] Shaun K Kane, Meredith Ringel Morris, Annuska Z Perkins, Daniel Wigdor, Richard E Ladner, and Jacob O Wobbrock. 2011. Access overlays: improving non-visual access to large touch screens for blind users. In *Proceedings of the 24th Annual ACM Symposium on User Interface Software and Technology*. 273–282.

[31] Shaun K Kane, Meredith Ringel Morris, and Jacob O Wobbrock. 2013. Touchplates: low-cost tactile overlays for visually impaired touch screen users. In *Proceedings of the 15th International ACM SIGACCESS Conference on Computers and Accessibility*. 1–8.

[32] Matthew Kay, Kyle Rector, Sunny Consolvo, Ben Greenstein, Jacob O Wobbrock, Nathaniel F Watson, and Julie A Kientz. 2013. PVT-touch: adapting a reaction time test for touchscreen devices. In *2013 7th International Conference on Pervasive Computing Technologies for Healthcare and Workshops*. IEEE, 248–251.

[33] Simeon Keates, Faustina Hwang, Patrick Langdon, P John Clarkson, and Peter Robinson. 2002. Cursor measures for motion-impaired computer users. In *Proceedings of the 4th International ACM SIGACCESS Conference on Computers and Accessibility*. 135–142.

[34] Junhan Kong, Mingyuan Zhong, James Fogarty, and Jacob O Wobbrock. 2021. New Metrics for Understanding Touch by People with and without Limited Fine Motor Function. In *Proceedings of the 23th International ACM SIGACCESS Conference on Computers and Accessibility*. (To appear).

[35] Abinaya Kumar, Aishwarya Radjesh, Sven Mayer, and Huy Viet Le. 2019. Improving the input accuracy of touchscreens using deep learning. In *Extended Abstracts of the ACM SIGCHI Conference on Human Factors in Computing Systems*. 1–6.

[36] Ramon C Littell, PR Henry, and Clarence B Ammerman. 1998. Statistical analysis of repeated measures data using SAS procedures. *Journal of Animal Science* 76, 4 (1998), 1216–1231.

[37] I Scott MacKenzie, Tatu Kauppinen, and Miika Silfverberg. 2001. Accuracy measures for evaluating computer pointing devices. In *Proceedings of the ACM SIGCHI Conference on Human Factors in Computing Systems*. 9–16.

[38] Rafail-Evangelos Mastoras, Dimitrios Iakovakis, Stelios Hadjidimitriou, Vasileios Charisis, Seada Kassie, Taoufik Alsaadi, Ahsan Khandoker, and Leontios J Hadjileontiadis. 2019. Touchscreen typing pattern analysis for remote detection of the depressive tendency. *Scientific reports* 9, 1 (2019), 1–12.

[39] Sven Mayer, Huy Viet Le, and Niels Henze. 2017. Estimating the finger orientation on capacitive touchscreens using convolutional neural networks. In *Proceedings of the ACM International Conference on Interactive Surfaces and Spaces*. 220–229.

[40] Alexander Mertens, Nicole Jochems, Christopher M Schlick, Daniel Dünnebacke, and Jan Henrik Dornberg. 2010. Design pattern TRABING: touchscreen-based input technique for people affected by intention tremor. In *Proceedings of the ACM SIGCHI Symposium on Engineering Interactive Computing Systems*. 267–272.

[41] Kyle Montague, Vicki L Hanson, and Andy Cobley. 2012. Designing for individuals: usable touch-screen interaction through shared user models. In *Proceedings of the 14th International ACM SIGACCESS Conference on Computers and Accessibility*. 151–158.

[42] Kyle Montague, Hugo Nicolau, and Vicki L Hanson. 2014. Motor-impaired touchscreen interactions in the wild. In *Proceedings of the 16th international ACM SIGACCESS conference on Computers & accessibility*. 123–130.

[43] Martez E Mott, Radu-Daniel Vatavu, Shaun K Kane, and Jacob O Wobbrock. 2016. Smart touch: Improving touch accuracy for people with motor impairments with template matching. In *Proceedings of the ACM SIGCHI Conference on Human Factors in Computing Systems*. 1934–1946.

[44] Martez E Mott and Jacob O Wobbrock. 2019. Cluster Touch: Improving touch accuracy on smartphones for people with motor and situational impairments. In *Proceedings of the ACM SIGCHI Conference on Human Factors in Computing Systems*. 1–14.

[45] Richard L Potter, Linda J Weldon, and Ben Shneiderman. 1988. Improving the accuracy of touch screens: an experimental evaluation of three strategies. In *Proceedings of the ACM SIGCHI Conference on Human Factors in Computing Systems*. 27–32.

[46] Sayan Sarcar, Jussi PP Jokinen, Antti Oulasvirta, Zhenxin Wang, Chaklam Silpasuwanchai, and Xiangshi Ren. 2018. Ability-based optimization of touchscreen interactions. *IEEE Pervasive Computing* 17, 1 (2018), 15–26.

[47] Andrew Sears and Ben Shneiderman. 1991. High precision touchscreens: design strategies and comparisons with a mouse. *International Journal of Man-Machine Studies* 34, 4 (1991), 593–613.

[48] R William Soukoreff and I Scott MacKenzie. 2003. Metrics for text entry research: An evaluation of MSD and KSPC, and a new unified error metric. In *Proceedings of the ACM SIGCHI Conference on Human Factors in Computing Systems*. 113–120.

[49] R William Soukoreff and I Scott MacKenzie. 2004. 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.

[50] Daniel Vogel and Patrick Baudisch. 2007. Shift: a technique for operating pen-based interfaces using touch. In *Proceedings of the ACM SIGCHI Conference on Human Factors in Computing Systems*. 657–666.

[51] Chat Wacharamanotham, Jan Hurtmanns, Alexander Mertens, Martin Kronenbuerger, Christopher Schlick, and Jan Borchers. 2011. Evaluating swabbing: a touchscreen input method for elderly users with tremor. In *Proceedings of the ACM SIGCHI Conference on Human Factors in Computing Systems*. 623–626.

[52] Daryl Weir. 2012. Machine learning models for uncertain interaction. In *Adjunct proceedings of the 25th Annual ACM Symposium on User Interface Software and Technology*. 31–34.

[53] Daryl Weir, Simon Rogers, Roderick Murray-Smith, and Markus Löchtefeld. 2012. 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*. 465–476.

[54] Daniel Wigdor, Sarah Williams, Michael Cronin, Robert Levy, Katie White, Maxim Mazeev, and Hrvoje Benko. 2009. Ripples: utilizing per-contact visualizations to improve user interaction with touch displays. In *Proceedings of the 22nd Annual ACM Symposium on User Interface Software and Technology*. 3–12.

[55] Jacob O Wobbrock. 2019. Situationally-induced impairments and disabilities. In *Web Accessibility*. Springer, 59–92.

[56] Jacob O Wobbrock, James Fogarty, Shih-Yen Liu, Shunichi Kimuro, and Susumu Harada. 2009. The angle mouse: target-agnostic dynamic gain adjustment based on angular deviation. In *Proceedings of the ACM SIGCHI Conference on Human Factors in Computing Systems*. 1401–1410.

[57] Jacob O Wobbrock, Krzysztof Z Gajos, Shaun K Kane, and Gregg C Vanderheiden. 2018. Ability-based design. *Commun. ACM* 61, 6 (2018), 62–71.

[58] Jacob O Wobbrock, Shaun K Kane, Krzysztof Z Gajos, Susumu Harada, and Jon Froehlich. 2011. Ability-based design: Concept, principles and examples. *ACM Transactions on Accessible Computing (TACCESS)* 3, 3 (2011), 1–27.

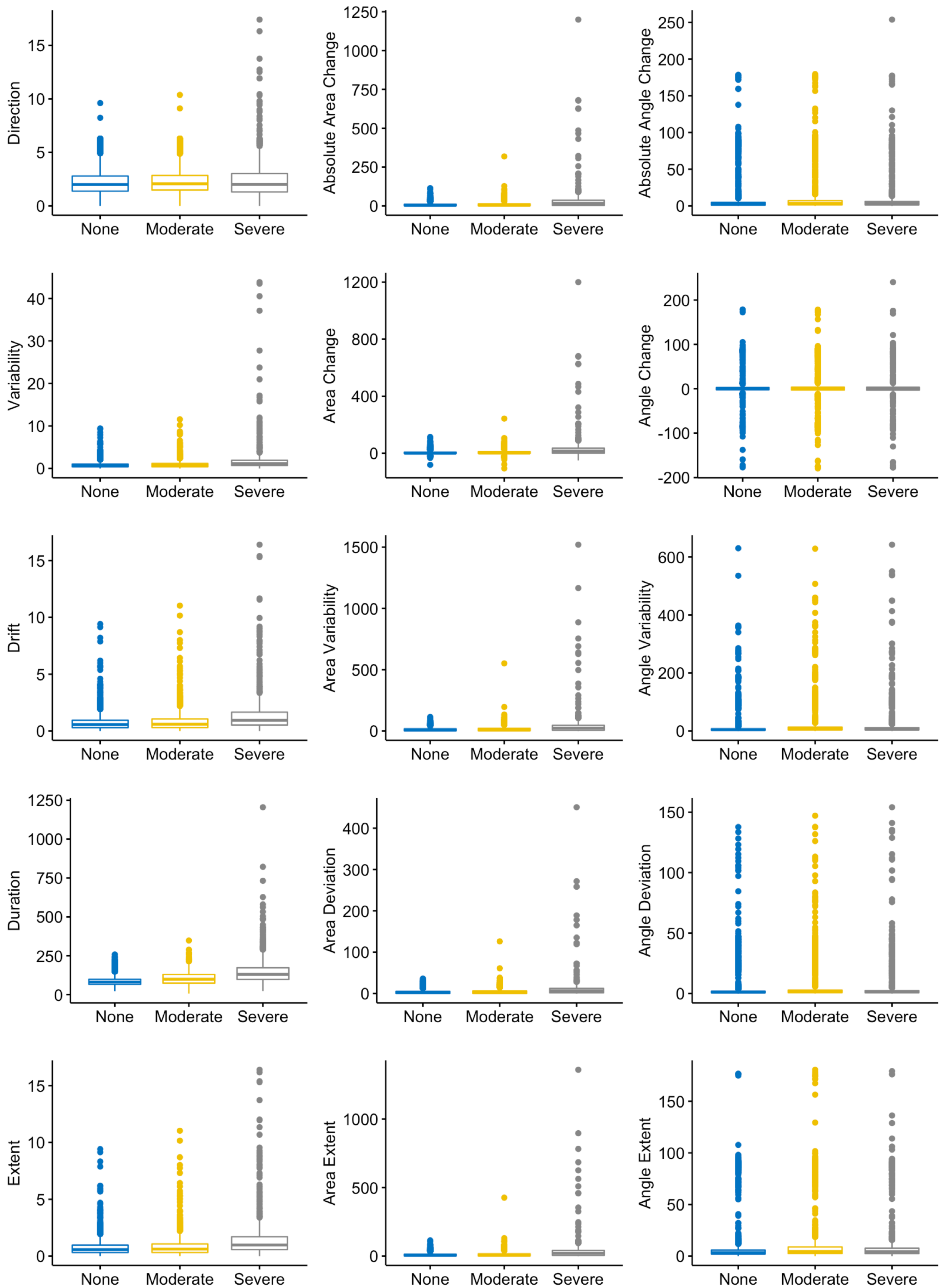
[59] Shumin Zhai. 2004. Characterizing computer input with Fitts' law parameters—the information and non-information aspects of pointing. *International Journal of Human-Computer Studies* 61, 6 (2004), 791–809.

[60] Shumin Zhai, Michael Hunter, and Barton A Smith. 2002. Performance optimization of virtual keyboards. *Human–Computer Interaction* 17, 2-3 (2002), 229–269.

[61] Xiaoyi Zhang, Tracy Tran, Yuqian Sun, Ian Culhane, Shobhit Jain, James Fogarty, and Jennifer Mankoff. 2018. Interactiles: 3D printed tactile interfaces to enhance mobile touchscreen accessibility. In *Proceedings of the 20th International ACM SIGACCESS Conference on Computers and Accessibility*. 131–142.


# A DISTRIBUTION OF VALUES OF TOUCH METRICS BY LEVEL OF *IMPAIRMENT*

The 15 boxplots below show distribution of values of all 15 touch metrics by level of *Impairment*. The plots are vertically organized such that the first column shows metrics based on touch location and time (Section 3.2), the second column shows metrics based on touch area (Section 3.3), and the third column shows metrics based on touch angle (Section 3.4).


Direction
Absolute Area Change
Absolute Angle Change
Variability
Area Change
Angle Change
Drift
Area Variability
Angle Variability
Duration
Area Deviation
Angle Deviation
Extent
Area Extent
Angle Extent
None
Moderate
Severe