New Metrics for Understanding Touch by People with and without Limited Fine Motor Function

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ABSTRACT

Current performance measures with touch-based systems usually focus on overall performance, such as touch accuracy and target acquisition speed. But a touch is not an atomic event; it is a process that unfolds over time, and this process can be characterized to gain insight into users' touch behaviors. To this end, our work proposes 13 target-agnostic touch performance metrics to characterize what happens *during* a touch. These metrics are: touch direction, variability, drift, duration, extent, absolute/signed area change, area variability, area deviation, absolute/signed angle change, angle variability, and angle deviation. Unlike traditional touch performance measures that treat a touch as a single (x, y) coordinate, we regard a touch as a time series of ovals that occur from finger-down to finger-up. We provide a mathematical formula and intuitive description for each metric we propose. To evaluate our metrics, we run an analysis on a publicly available dataset containing touch inputs by people with and without limited fine motor function, finding our metrics helpful in characterizing different fine motor control challenges. Our metrics can be useful to designers and evaluators of touch-based systems, particularly when making touch screens accessible to all forms of touch.

CCS CONCEPTS

• **Human-centered computing** → **Accessibility**.

KEYWORDS

Understanding touch, limited fine motor function

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1 INTRODUCTION

Although touch screen devices like smartphones have provided convenience for and supported independence of people with disabilities [1, 9, 13], accessibility barriers still persist in the use of touch screen devices. A better understanding of "touch" itself might offer insights into ways of improving touch screen accessibility. In general, prior work has treated touch as an atomic event, essentially an (x, y) coordinate or perhaps an oval occurring at a single place in space and time. For example, prior work has examined users' target acquisition speed and accuracy on touch screens and with mice [3], and on smartphones and tablets [15], finding that touch accuracy and usability issues still persist for people with limited fine motor function. Other work has examined users' mental models while touching, identifying sources of inaccuracy in touch devices as a result of the parallax between the top and bottom of the finger [8].

But touches are not atomic—they unfold over time in a process [12]. Understanding this process can shed light on the dynamics of touch—how touches proceed from finger-down to finger-up, and what might be the underlying causes of touch inaccuracy. These insights can be important for improving touch screen accessibility, since the touch dynamics of people with limited fine motor function might illuminate ways of improving touch accuracy. To gain such insights, we need to move beyond overall metrics like touch accuracy and target acquisition time to examine what happens *during* a touch.

To approach this topic, we draw inspiration from MacKenzie et al. [10], who formulated metrics to characterize what happens during mouse pointing. Similarly, we offer 13 target-agnostic touch metrics for characterizing what happens during a touch. We regard a touch as a sequence of ovals approximating a finger's contact area from finger-down to finger-up (Figure 1a), containing the movements of oval centroids and ovals' sizes and orientations (Figure 1b). For scope, we do not explicitly formulate multi-touch metrics, but the metrics we define can be computed for multiple fingers if desired. The 13 metrics are: touch direction, variability, drift, duration, extent, absolute/signed area change, area variability, area deviation, absolute/signed angle change, angle variability, and angle deviation.

To put these metrics through their paces, we conducted a preliminary evaluation with an existing publicly available dataset published by Findlater and Zhang [4]. We calculated a subset of our

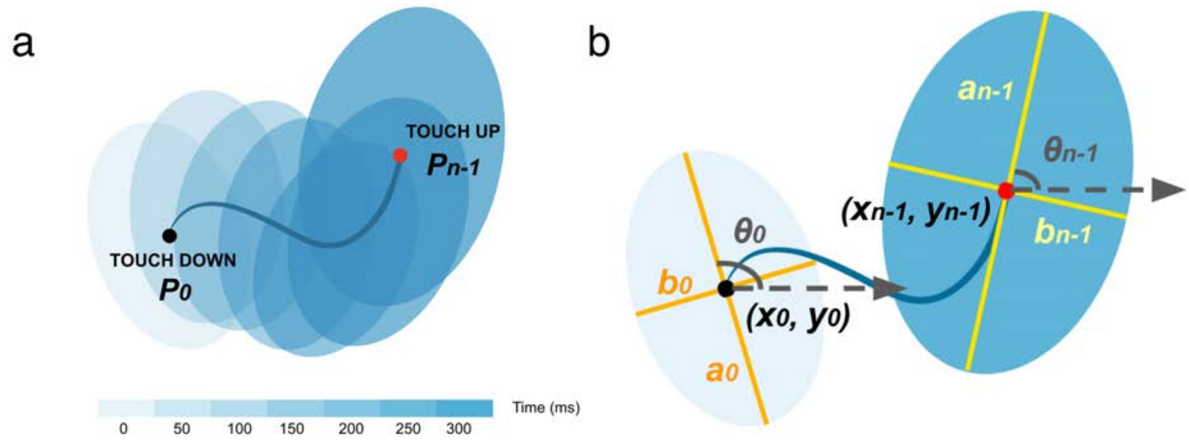

Figure 1: (a) A sequence of n touch ovals $P_0, ..., P_{n-1}$ from finger-down to finger-up along a time axis. (b) The first touch oval in the touch sequence with centroid (x_0, y_0), angle θ_0, major axis a_0, and minor axis b_0; and the last touch oval in the touch sequence, with centroid (x_{n-1}, y_{n-1}), angle θ_{n-1}, major axis a_{n-1}, and minor axis b_{n-1}.

touch metrics[1] and ran both descriptive and inferential statistics on the metrics for people with and without limited fine motor function. We found that people with limited fine motor function have higher touch variability, drift, duration, and extent than users without. Importantly, none of these metrics are synonyms with overall "target-aware" touch accuracy; rather, these are "target-agnostic" metrics calculable using only touch data, but they can explain *why* overall touch accuracy is low.

The key contributions of this work are: (1) formulating 13 target-agnostic touch metrics to characterize what happens during a touch; and (2) a preliminary analysis using these metrics to characterize the touch processes of people with and without limited fine motor function.

2 TOUCH METRICS

Our touch metrics (see Table 1) are designed to capture what happens *during* a touch. Let n be the total number of touch input events captured from finger-down to finger-up, inclusive. A touch process is 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
- θ_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 contact area, calculated as $\pi a_i b_i / 4$
- T_i is the oval's timestamp.

3 ANALYSIS OF TOUCH DATA

3.1 Data Description

We ran a preliminary evaluation using a public dataset published by Findlater and Zhang [4]. The dataset captures input behaviors on four types of tasks—pointing, dragging, crossing, and steering with a mouse and/or touch screen from 735 participants, 197 of whom self-reported having limited fine motor function, including low strength (50.0%), difficulty gripping (48.2%) and holding (34.7%), rapid fatigue (32.9%), limited range of motion (31.8%), lack of sensation (31.8%), lack of coordination (31.3%), tremor (31.2%), slow movement (25.9%), difficulty controlling movement direction (25.3%) and distance (22.4%), spasm (20.0%), and "other" (5.3%) [4].

3.2 Data Analysis

We filtered the data to extract only pointing trials on touch screen devices. We then calculated touch variability, drift, duration, and extent for each trial, and examined the distribution of each of these four metrics (see footnote 1). We found that touch variability, drift, and extent were zero-inflated, indicating that participants often did not have any finger movements between finger-down and finger-up. We also found that the non-zero data for these metrics were log-normally distributed. Therefore, as is customary with zero-inflated data [7], we separately analyzed the zero *vs.* non-zero data using mixed logistic regression [6], with self-reported limited fine motor function and all specific motor challenges as fixed effects, and with participant as a random effect. For the non-zero response data, we log-transformed it [2] prior to analysis with linear mixed effects [5] for each of our metrics.

3.3 Results and Discussion

As one might expect, having zero touch variability (i.e., the total distance of successive touch inputs from finger-down to finger-up being zero) was significantly negatively correlated with self-reported limited fine motor function (p = .005). In other words, people with limited fine motor function were less likely to have trials with zero touch variability (i.e., so-called "perfect touches"). Also, variability was significantly positively correlated with low strength (p = .029). No other correlations were statistically significant for zero *vs.* non-zero touch trials.

For the non-zero data, we found that all four touch metrics were positively correlated with participant self-reported limited

[1] We were unable to compute all 13 metrics because the data lacked complete oval information, i.e., major and minor axis lengths and orientations.

Table 1: Mathematical formulae, English descriptions, and value ranges of our touch metrics.

Touch Metric Formula	Description	Range
Direction = $\tan^{-1}((y_{n-1} - y_0)/(x_{n-1} - x_0))$ when $x_0 \neq x_{n-1}$, $\pi/2$ when vertically up, $3\pi/2$ when vertically down	The angle formed between centroids from finger-down to finger-up, using straight right ($+x$) from the finger-down centroid as 0°.	$[0, 2\pi)$
Variability = $\sum_{i=1}^{n-1} \sqrt{(x_i - x_{i-1})^2 + (y_i - y_{i-1})^2}$	The total distance of successive touch inputs from finger-down to finger-up.	$[0, \infty]$
Drift = $\sqrt{(x_{n-1} - x_0)^2 + (y_{n-1} - y_0)^2}$	The Euclidean distance from finger-down to finger-up.	$[0, \infty]$
Duration = $T_{n-1} - T_0$	The time from finger-down to finger-up.	$[0, \infty]$
Extent = $max_{i,j \in 0,\ldots,n-1} \sqrt{(x_j - x_i)^2 + (y_j - y_i)^2}$	The Euclidean distance between the most distant two oval centroids.	$[0, \infty]$
Absolute Area Change = $\lvert S_{n-1} - S_0 \rvert$	The change in area between finger-up and finger-down ovals.	$[0, \infty]$
Area Change = $S_{n-1} - S_0$	Same as above, but negative if finger-up is smaller than finger-down; non-negative otherwise.	$[-\infty, \infty]$
Area Variability = $\sum_{i=1}^{n-1} \lvert S_i - S_{i-1} \rvert$	The cumulative change in area over all touch inputs from finger-down to finger-up.	$[0, \infty]$
Area Deviation = $\sqrt{\frac{\sum_{i=0}^{n-1}(S_i - \bar{S})^2}{n}}$ where $\bar{S} = \sum_{i=0}^{n-1} S_i/n$	The standard deviation of the oval's area over the duration of the touch; intuitively, how much the area changed.	$[0, \infty]$
Absolute Angle Change = $\lvert \theta_{n-1} - \theta_0 \rvert$	The change in major axis angle from finger-down to finger-up.	$[0, \pi]$
Angle Change = $\theta_{n-1} - \theta_0$	Same as above, but counter-clockwise is positive; clockwise is negative.	$[-\pi, \pi]$
Angle Variability = $\sum_{i=1}^{n-1} \lvert \theta_i - \theta_{i-1} \rvert$	The cumulative change of the major axis angle over the duration of the touch.	$[0, \infty]$
Angle Deviation = $\sqrt{\frac{\sum_{i=0}^{n-1}(\theta_i - \bar{\theta})^2}{n}}$ where $\bar{\theta} = \sum_{i=0}^{n-1} \theta_i/n$	The standard deviation of the major axis angle over the duration of the touch; intuitively, how much the major axis angle changed.	$[0, \infty]$

fine motor function: touch variability ($p = .002$), drift ($p = .019$), duration ($p < .0001$), and extent ($p = .005$). In other words, people who self-reported as having limited fine motor function tended to have significantly larger touch variability (+26.4%), drift (+19.0%), duration (+52.2%), and extent (+22.4%) than people who did not self-report thusly. Indeed, these results seem unsurprising, confirming the ability of our metrics to capture dynamic aspects of touch performance. But although prior work has shown *that* people with limited fine motor function might move while selecting targets [11, 14], knowing the variability of their touch is 26.4% larger is a new insight as to the degree.

Taken together, our findings show that people with limited fine motor function are 75.1% less likely than people without limited fine motor function to have "perfect touches" with no movement between finger-down and finger-up. Our findings also show that people with limited fine motor function tend to have larger values in all four utilized metrics—touch variability, drift, duration, and extent—meaning that they might experience greater difficulty while interacting with touch screens. These findings match Findlater and Zhang's [4] finding of increased pointing errors on touch screens and the high frequency of spurious touches for people with limited fine motor function. Indeed, our results help to explain the reasons behind Findlater and Zhang's outcomes.

4 CONCLUSION AND FUTURE WORK

In this work, we presented 13 target-agnostic touch metrics that characterize the dynamics of touch—what happens *during* a touch from finger-down to finger-up. We conceptualized a touch process as a sequence of ovals, and formulated metrics related to touch movement, duration, and orientation. We exercised a subset of our metrics with a publicly available dataset from Findlater and Zhang [4]. We found that people with limited fine motor function are less likely to have "perfect touches" with zero movement, and overall have higher touch variability, drift, duration, and extent. For future work, we plan to conduct original studies to collect participant data with touch oval information and thoroughly evaluate our metrics to see how they characterize different types of motor control challenges. We also plan to demonstrate ways our touch metrics can inform runtime adaptations that make touch screens more accessible.

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REFERENCES

[1] Lisa Anthony, YooJin Kim, and Leah Findlater. 2013. Analyzing user-generated youtube videos to understand touchscreen use by people with motor impairments. In *Proceedings of the ACM SIGCHI Conference on Human Factors in Computing Systems*. 1223–1232.

[2] Donald A Berry. 1987. Logarithmic transformations in ANOVA. *Biometrics* (1987), 439–456.

[3] 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.

[4] 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 ACM SIGACCESS Conference on Computers and Accessibility*. 1–6.

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

[6] AR Gilmour, RD Anderson, and AL Rae. 1985. The analysis of binomial data by a generalized linear mixed model. *Biometrika* 72, 3 (1985), 593–599.

[7] Daniel B Hall. 2000. Zero-inflated Poisson and binomial regression with random effects: a case study. *Biometrics* 56, 4 (2000), 1030–1039.

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

[9] Shaun K Kane, Chandrika Jayant, Jacob O Wobbrock, and Richard E Ladner. 2009. Freedom to roam: a study of mobile device adoption and accessibility for people with visual and motor disabilities. In *Proceedings of the ACM SIGACCESS Conference on Computers and Accessibility*. 115–122.

[10] 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.

[11] Karyn Moffatt and Joanna McGrenere. 2010. Steadied-bubbles: Combining techniques to address pen-based pointing errors for younger and older adults. In *Proceedings of the ACM SIGCHI Conference on Human Factors in Computing Systems*. 1125–1134.

[12] 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.

[13] Maia Naftali and Leah Findlater. 2014. Accessibility in context: understanding the truly mobile experience of smartphone users with motor impairments. In *Proceedings of the ACM SIGACCESS Conference on Computers and Accessibility*. 209–216.

[14] Shari Trewin, Simeon Keates, and Karyn Moffatt. 2006. Developing steady clicks: a method of cursor assistance for people with motor impairments. In *Proceedings of the ACM SIGACCESS Conference on Computers and Accessibility*. 26–33.

[15] Shari Trewin, Cal Swart, and Donna Pettick. 2013. Physical accessibility of touchscreen smartphones. In *Proceedings of the ACM SIGACCESS Conference on Computers and Accessibility*. 1–8.