Title
Tap and Swipe Smartphone Gestures Indicating Hand Tremor and Finger Joint Range in Motion

Authors
Torres, Wilson O
Stuart, Hannah S

Publication Date
2023-06-04

DOI
10.1109/ecbios57802.2023.10218438

Tap and Swipe Smartphone Gestures Indicating Hand Tremor and Finger Joint Range in Motion

Wilson O. Torres
Department of Mechanical Engineering University of California, Berkeley
Berkeley, CA USA
wilson_torres@berkeley.edu

Hannah S. Stuart
Department of Mechanical Engineering, University of California, Berkeley
Berkeley, CA USA
hstuart@berkeley.edu

***Abstract*—Conditions such as multiple sclerosis or arthritis impair normative hand function by diminishing motor control and limiting finger range of motion (ROM), respectively. Day-to-day variation of these symptoms makes it difficult for physicians to track clinically relevant changes in function. This is worsened in populations that lack general access to healthcare. A smartphone holds the potential to be used as a frequent self-screening platform for changes in hand function. We use a custom smartphone application for detecting deviations in force control due to tremors and differences in finger ROM through simple tapping and swiping gestures. We conduct a 17-participant cross-sectional study, which includes two participants with known hand tremors. From the smartphone data during tap-and-hold, we see that people with hand tremors demonstrate less touchscreen force control than normative subjects. During the swiping task, we find a statistically significant moderate correlation between the path length of the swiping gesture and the maximum proximal interphalangeal joint flexion angle of the index finger. We find that different processing methods for the swiping data can reveal additional correlations with metacarpophalangeal flexion. These results are a promising start for the smartphone as an accessible screening tool for tremors and changes in finger ROM.**

Keywords—hand function, physical human-computer interaction, smartphone, human health

I. Introduction

Both finger force control and joint range of motion (ROM) are important in activities of daily living. A decrease in finger ROM can lead to a decrease in hand function and is measured when assessing recovery therapy and rehabilitation [1,2]. Simultaneously, exhibiting healthy finger force control allows the manipulation of small objects [3,4]. Various conditions can interfere with these functions. In arthritis, for example, inflammation can cause joint stiffness and prevent full ROM. Multiple sclerosis (MS), on the other hand, affects individuals' motor control and can deteriorate cutaneous sensation and finger force control, and can lead to hand tremors [3,5]. Regular screening of these symptoms is important as their severity can increase over many years [6–8].

Clinical tools to measure finger joint ROM include radiography. While this method is accurate, it is rarely done due to its high cost [9,10]. The goniometer, an inexpensive alternative, measures joint ROM through manual measurements. While less precise, this is seen as the gold standard for assessing finger joint ROM due to its portable and economical nature [9–11]. For MS, physical assessment of the hands is infrequently performed and, when done, relies on subjective clinical judgment and the patient's self-report of symptoms [12]. Smartphones recently emerged as a potential solution to increase the frequency of objective health monitoring in various conditions [13]. We investigate whether simple smartphone screen gestures provide information to infer hand tremor and finger joint ROM.

Smartphone quantification of finger joint ROM previously focused on using internal measurement units (IMU) or computer vision. IMUs replicate the measurement of individual joint angles by statically placing the phone on different phalanges with results matching a goniometer [9,10,14]. This method is not easily operated [9] and requires the hands to be rigidly held in static positions. Using computer vision algorithms, images of the hands are analyzed for joint angles, with comparable results to the goniometer [2,15,16]. However, this requires mounts to position a smartphone at the required distance and instructions for keeping the hand in the camera's view frame. Finger joint ROM has not yet been correlated with touchscreen-tracked swiping trajectories.

Smartphones for people with MS have been used to investigate fatigue using tapping gestures [17], dexterity through pinching motions [18], and general progression of the condition through non-invasive keyboard gestures [19]. To the best of the authors' knowledge, force control for people with MS has not been investigated using smartphone screen measurements.

II. Methods

A. Participants

Individuals over the age of 18 were recruited from the University of California, Berkeley (UCB) and the local community through digital flyers. A total of seventeen participants took part in the study. Three participants self-reported as having MS with two reporting they had hand tremors. One normative participant did not follow study instructions during the tapping task and was removed from the tapping related analysis. The two participants with MS and hand tremors were unable to complete the swiping gesture task. A total of sixteen participants completed the tapping task (mean age: 33.6 ±16.1), while fifteen completed the swiping task (mean age: 32.4 ±15.0).

Joint angles were measured using a goniometer with 1° resolution. To measure index finger ROM, participants actively flexed their metacarpophalangeal joint (MCPj), then their proximal interphalangeal joint (PIPj), and distal interphalangeal joint (DIPj). The MCPj abduction was measured with the participant's hand on a table, while actively abducting the MCPj. Zero pose is defined as the natural position of the fully extended joint with relative flexion reported as positive values. For the individuals who completed the swiping task, the mean voluntary joint flexion of the joints is as follows: MCPj is 83.40°±11.20°, PIPj is 94.37°±10.39°, DIPj is 70.43°±9.11°, and mean abduction of the MCPj is 37.57°±4.80°.

B. Smartphone Test Bed and Procedures

An iPhone X (5.7x2.79x0.3 in) running iOS 14.4.2 (Apple Inc.) with a screen resolution of 2436 × 1125 pixels was used in this study. This smartphone samples touch input at 120Hz, capturing touchscreen interactions including the x and y position of the touch. It can also measure the radius of touch, or z, which is the circular approximation of the contact area of the fingertip with the touchscreen with 0.1 cm resolution. This phone model also uniquely measures on-screen normal forces using a parallel plate capacitor [20], characterized in Ref. [21]. These captured metrics can be seen in Fig. 1.

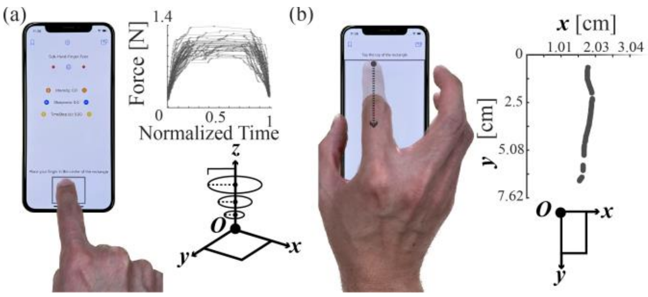

Fig. 1. Smartphone gestures can be used to capture various hand functionality parameters. (a) shows the tap and hold task that participants performed, and the forces generated over time during various trials of the tap and hold gesture for a normative participant. (b) shows the downward swiping task used in this study, and a single tested trajectory example. Both tasks (a) and (b) measure the x and y contact coordinates, with (a) additionally measuring z, representing the radius of touch.

1) *Tapping Task*: In a study preprint published [21], we found a correlation between participant cutaneous sensation and the detection of smartphone vibrational feedback. During this experiment, participants used their dominant index finger to tap and hold onto the 2.5 × 2.5 cm square at the bottom of the touchscreen (Fig. 1(a)). They were instructed to use as much force as they typically applied when opening an app on their smartphone. A minimum of 21 tapping trials were conducted for each subject. Here, we present the normal force and radius of touch applied during these tap-and-hold gestures.
2) *Swiping Task*: For the swiping task, participants were asked to first hold the phone such that their palm was touching the chin of the smartphone and to hold the sides of the phone with the first and fifth digits of their dominant hand (Fig. 1(b)). The swiping gesture occurred on the touchscreen on a 5.08 × 7.62 cm interaction area. To start the gesture, participants double-tapped the furthest top point of this area as an initialization step. They were then instructed to try and swipe downwards, along the y direction, in a straight line from their starting point. Three trials per subject were completed.

C. Swipe Data Metric Generation

The swiping task produced motion traces as shown in Fig. 2(a) from initial contact to finger lift-off. We consider how to parameterize these trajectories and whether motion artifacts produced at the start and end of the swipe must be trimmed using either force or time thresholds. For the force trim, any point with force lower than 90% of the trial median force is removed (Fig. 2(b)). For the time trim, the data points generated in the first 30% and last 20% of the trial gesture are removed, leaving 50% of the gesture time (Fig. 2(c)). Cut-off asymmetry reflects how more data points are generated during the initialization step than during lift-off.

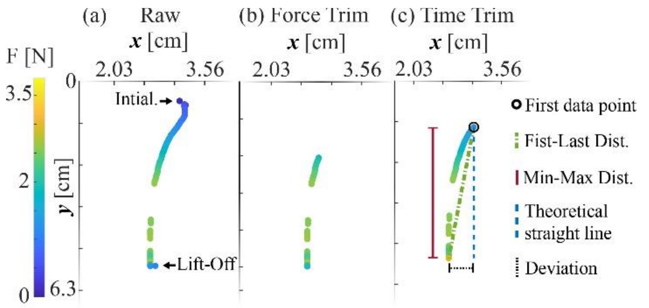

Fig. 2. A sample graph for a participant's swiping gesture including the applied forces. (a) shows the un-edited gesture with traces from initial contact to finger lift-off. (b) shows the force trim. (c) shows the time trim along with the various distance metrics used to quantify a swipe.

For the raw gesture, force trim, and time trim, we extract (1) the path length, (2) the vertical distance from the smallest y coordinate to the largest y coordinate (Min to Max Line Distance), (3) the straight line distance from the first to last data points generated (First to Last Distance), (4) the sum of the absolute value of the x distance from each data point to the line created from the first and last point (First to Last Line Deviation Sum), and (5) the absolute value of the deviation in x from the theoretical straight line (TSL) (Deviation from TSL). TSL is the line that would be generated if the participant drew a perfectly straight line from the first point of contact until the end of the gesture. A sample of this is shown overlaid atop the time trim in Fig. 2(c). Metrics (1)-(3) are hypothesized to correlate with finger flexion while (4) and (5) are hypothesized to correlate with abduction.

III. Results

A. Tapping Task Results

For participants without hand tremors, the forces generated follow a parabolic shape as shown in Fig. 1(a). At touch-down, forces rise to a plateau and eventually tap off during lift-off. Participants with tremors demonstrate more variability in this pattern. All of the force readings during the tapping tasks are amalgamated and binned for each subject. Figure 3(a) shows the percent of data points generated (%DPG) for each of the bins. The two participants with MS and tremors (15 and 16 as designated with a T) have a wider distribution of points across the different bins, reaching as high as 3N. Figure 3(b) shows a similar graph using the radius of touch, z; there is less difference between subjects with and without tremors as compared with force measurement. Figure 3(c) shows the volume of the 3D shape encompassing all x, y, and z generated points, calculated using the boundary function in MATLAB with a shrink factor of 0.1. Two sample 3D shapes are provided for a normative participant and one with MS and hand tremors. The volume metric shows more separation between people with and without tremors, as compared with z alone.

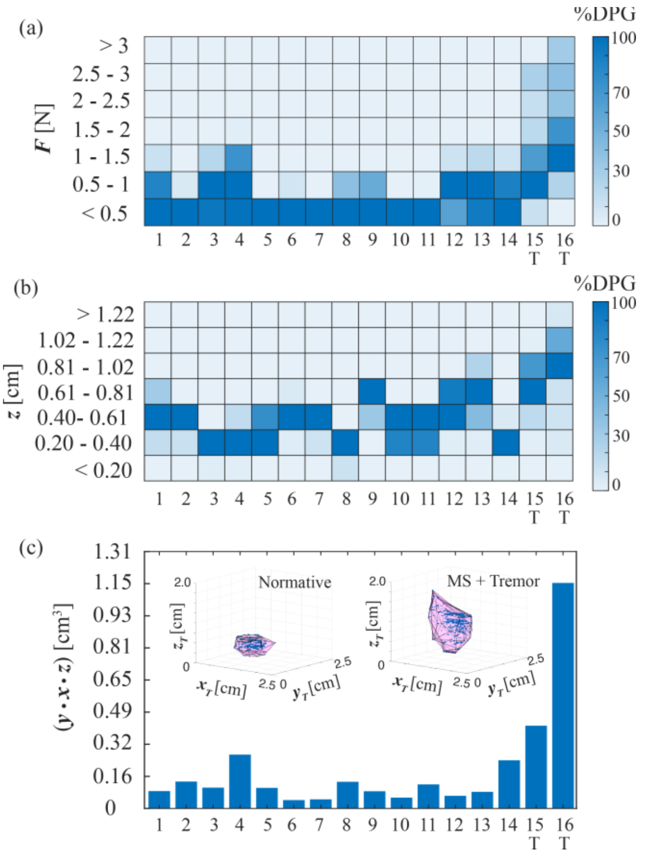

Fig. 3. N = 16 (a) A heatmap of the normal forces (F) applied to the smartphone touchscreen as a percentage of data points generated (%DPG). (b) a heatmap of the radius of touch of touchscreen interaction as a %DPG. The volume of the 3D shapes created that encompass all x, y, and z points as well as sample 3D shapes for a normative and an MS + Tremor participant

B. *Swiping Task results*

Table I shows the three trial average metrics for the different distance parameters obtained in the raw, time trim, and force trim methods. The time trim method provides the smallest distance metrics with the smallest standard deviation. The sum of the deviations from the First to Last Line are largest in the raw gesture as these include more data points than the trim methods. Deviations from the TSL are similar across the raw and two trim methods.

TABLE I. PHONE METRICS (N=15)

	Raw		Time Trim		Force Trim	
	Mean	STD	Mean	STD	Mean	STD
Avg. Path Length (cm)	4.89	1.72	2.72	1.35	3.50	1.48
Avg. Min to Max Line Distance (cm)	4.57	1.72	2.59	1.30	3.41	1.52
Avg. First to Last Distance (cm)	4.57	1.74	2.69	1.36	3.44	1.51
Avg. Deviation from TSL (cm)	0.30	0.21	0.21	0.15	0.24	0.18
Avg. First to Last Line Deviation Sum (cm)	14.92	10.39	4.98	4.72	6.51	3.83

Table II shows the Speraman's rank correlation between distance metrics for the different trim methods and the active maximum flexion angles of the MCPj, PIPj, and DIPj at a significance level of 0.05. The PIPj flexion angle is moderately to highly positively correlated for all distance metrics for all trim methods. The MCPj flexion angle is moderately correlated only in the time trim method. The MCPj abduction angle is not significantly correlated to any of the deviation metrics for either the raw or two trim methods.

TABLE II. CORRELATION BETWEEN PHONE METRICS AND JOINT ROM N = 15

		Raw		Time	Trim	Force	Trim
		r	p	r	p	r	p
Avg. Path Length	MCP Flex	0.30	0.282	0.54*	0.037	0.47	0.074
	PIP Flex	0.58*	0.023	0.71*	0.003	0.66*	0.007
	DIP Flex	0.07	0.800	0.36	0.183	0.27	0.340
Avg. Min to Max Line Distance	MCP Flex	0.36	0.190	0.61*	0.016	0.47	0.075
	PIP Flex	0.57*	0.026	0.72*	0.002	0.64*	0.010
	DIP Flex	0.11	0.698	0.45	0.090	0.32	0.247
Avg. First to Last Distance	MCP Flex	0.30	0.276	0.54*	0.037	0.46	0.082
	PIP Flex	0.54*	0.037	0.72*	0.003	0.66*	0.007
	DIP Flex	0.07	0.805	0.45	0.183	0.24	0.389
Avg. Deviation From TSL	MCP Abduct	-0.10	0.728	0.13	0.655	0.05	0.846
Avg. First to Last Line Deviation Sum	MCP Abduct	-0.25	0.374	0.09	0.755	0.05	0.859

IV. DISCUSSION

We present data from tapping and swiping as an initial study of using these simple gestures for smartphone-enabled detection of hand health metrics. Tapping results show how force measurements from the smartphone screen capture variations in contact loads due to known hand tremors. Such variation is expected because tremors are associated with a reduction in force control [4]. The iPhone X is one of the last models to incorporate the ability to measure touchscreen forces. Therefore, we also explore alternative ways of replicating force reading. While the radius of touch is sometimes associated with force, the results show less separation between subjects with and without tremors. This results from an individual's fingertip deforming nonlinearly with force, or the low-resolution measure of radius of touch from the phone. Combining the position of touch with the radius of touch into a 3D volume, however, amplifies the differences between those with and without tremor. This study includes only two participants with MS and tremors, and the standard characterization of subject tremor severity is not quantified. Regardless, this experiment motivates further study into smartphone tapping gestures for force control deviations due to tremors.

We find that the vertical swiping gesture is consistently correlated with PIPj ROM in all data post-processing methods and metrics hypothesized to depend on finger flexion. Using the time trim post-processing method only, the MCPj flexion angle shows a significant correlation. This methodology highlights the center portion of the gesture, and future work is needed to explore further this relationship.

While the MCPj abduction angle is not significantly correlated with any of the deviation metrics, this is reasonable given that the tested gesture explicitly asks participants to limit lateral movement. While natural gestures are captured in health metrics including tremors and joint ROM in the future, this study restricted the individual's interaction area and movement on the screen to reduce variability and test for the presence of a measurable effect. Therefore, we cannot extrapolate these results to unstructured common smartphone use. The smartphone also does not guarantee consistent contact detection and can produce data gaps, e.g., in the middle of the swipe in Fig. 2. This is due to the participant's fingernail preventing them from making fleshy contact with the touchscreen. While the current study is limited to a controlled laboratory setting and specific tasks, it demonstrates the potential of smartphones to capture metrics for detecting differences in hand tremors and joint ROM. Future studies will look at more natural interactions with the smartphone and how these alter the results.

ACKNOWLEDGMENT

This research was supported by the Johnson & Johnson Women in STEM^{2}D award (Sponsor Award #051062) and the Hearts to Humanity Eternal (H2H8) Association Graduate Research Gift.

REFERENCES

[1] G. I. Bain, N. Polites *et al.*, "The functional range of motion of the finger joints," *J of Hand Surgery (European Volume)*, vol. 40, no. 4, pp. 406–411, May 2015.

[2] H. Dong, E. Ho *et al.*, "'DIGITS' app - smartphone augmented reality for hand telerehabilitation," *Computer Methods in Biomechanics and Biomedical Engineering: Imaging & Visualization*, vol. 10, no. 4, pp. 375–382, Jul. 2022.

[3] V. Iyengar, M. J. Santos *et al.*, "Grip Force Control in Individuals With Multiple Sclerosis," *Neurorehabilitation and Neural Repair*, vol. 23, no. 8, pp. 855–861, Oct. 2009.

[4] W. W. Spirduso, K. Francis *et al.*, "Quantification of Manual Force Control and Tremor," *J of Motor Behavior*, vol. 37, no. 3, pp. 197–210, May 2005.

[5] A. Gopal, W.-Y. Hsu *et al.*, "Remote Assessments of Hand Function in Neurological Disorders: Systematic Review," *JMIR Rehabilitation and Assistive Technologies*, vol. 9, no. 1, p. e33157, Mar. 2022.

[6] A. Conte, G. Leodori *et al.*, "Somatosensory temporal discrimination threshold in Parkinson's disease parallels disease severity and duration," *Clinical Neurophysiology*, vol. 127, no. 9, pp. 2985–2989, Sep. 2016.

[7] A. Conte, E. M. McGovern *et al.*, "Temporal Discrimination: Mechanisms and Relevance to Adult-Onset Dystonia," *Frontiers in Neurology*, vol. 8, p. 625, Nov. 2017.

[8] G. Ferrazzano, S. G. Crisafulli *et al.*, "Early diagnosis of secondary progressive multiple sclerosis: focus on fluid and neurophysiological biomarkers," *J of Neurology*, vol. 268, no. 10, pp. 3626–3645, Oct. 2021.

[9] H. H. Lee, K. St. Louis *et al.*, "Accuracy and Reliability of Visual Inspection and Smartphone Applications for Measuring Finger Range of Motion," *Orthopedics*, vol. 41, no. 2, Mar. 2018.

[10] K. Miyake, H. Mori *et al.*, "A new method measurement for finger range of motion using a smartphone," *J of Plastic Surgery and Hand Surgery*, vol. 54, no. 4, pp. 207–214, Jul. 2020.

[11] G. F. Hamilton and P. A. Lachenbruch, "Reliability of Goniometers in Assessing Finger Joint Angle," *Physical Therapy*, vol. 49, no. 5, pp. 465–469, May 1969.

[12] L. Sigcha, I. Pavo´n *et al.*, "Automatic Resting Tremor Assessment in Parkinson's Disease Using Smartwatches and Multitask Convolutional Neural Networks," *Sensors*, vol. 21, no. 1, p. 291, Jan. 2021.

[13] G. N. Graham, M. Ostrowski *et al.*, "Population health-based approaches to utilizing digital technology: a strategy for equity," *J of Public Health Policy*, vol. 37, no. S2, pp. 154–166, Nov. 2016.

[14] Harrison Theile, Sara Walsh *et al.*, "Smartphone goniometer for reliable and convenient measurement of finger range of motion: a comparative study," *Australasian J of Plastic Surgery*, vol. 5, no. 2, 2022.

[15] F. Gu, J. Fan *et al.*, "Automatic range of motion measurement via smartphone images for telemedicine examination of the hand," *Science Progress*, vol. 106, no. 1, p. 003685042311527, Jan. 2023.

[16] J. Z. Zhao, P. E. Blazar *et al.*, "Range of Motion Measurements of the Fingers Via Smartphone Photography," *HAND*, vol. 15, no. 5, pp. 679–685, Sep. 2020.

[17] L. Barrios, P. Oldrati *et al.*, "Smartphone-Based Tapping Frequency as a Surrogate for Perceived Fatigue: An in-the-Wild Feasibility Study in Multiple Sclerosis Patients," *Proceedings of the ACM on Interactive, Mobile, Wearable and Ubiquitous Technologies*, vol. 5, no. 3, pp. 1–30, Sep. 2021.

[18] X. Montalban, J. Graves *et al.*, "A smartphone sensor-based digital outcome assessment of multiple sclerosis," *Multiple Sclerosis J*, vol. 28, no. 4, pp. 654–664, Apr. 2022.

[19] A. Hoeijmakers, G. Licitra *et al.*, "Disease severity classification using passively collected smartphone-based keystroke dynamics within multi- ple sclerosis," *Scientific Reports*, vol. 13, no. 1, p. 1871, Feb. 2023.

[20] J. V. Chamary, "3D Touch In iPhone 6S Isn't Just A Gimmick. Here's How It Works," section: Science.

[21] W. Torres, M. Abbott *et al.*, "Cutaneous perception identification using smartphone haptic feedback," preprint, Aug. 2022.