Stroke-Gesture Input for People with Motor Impairments: Empirical Results & Research Roadmap

Radu-Daniel Vatavu
MintViz Lab | MANSiD Research Center
University Ştefan cel Mare of Suceava
Suceava 720229, Romania
radu.vatavu@usm.ro

Ovidiu-Ciprian Ungurean
MintViz Lab | MANSiD Research Center
University Ştefan cel Mare of Suceava
Suceava 720229, Romania
ungurean.ovidiu@gmail.com

Figure 1. Snapshots of 35 people with motor impairments articulating stroke-gestures on a tablet. Note the accessibility challenges and coping strategies. In this work, we analyze 9,681 gestures from 70 people *with* and *without* motor impairments.

ABSTRACT

We examine the articulation characteristics of stroke-gestures produced by people with upper body motor impairments on touchscreens as well as the accuracy rates of popular classification techniques, such as the $-family, to recognize those gestures. Our results on a dataset of 9,681 gestures collected from 70 participants reveal that stroke-gestures produced by people with motor impairments are recognized less accurately than the same gesture types produced by people without impairments, yet still accurately enough (93.0%) for practical purposes; are similar in terms of geometrical criteria to the gestures produced by people without impairments; but take considerably more time to produce (3.4 s *vs.* 1.7 s) and exhibit lower consistency (−49.7%). We outline a research roadmap for accessible gesture input on touchscreens for users with upper body motor impairments, and we make our large gesture dataset publicly available in the community.

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CCS CONCEPTS

• **Human-centered computing** → **Touch screens**; **Accessibility technologies**.

KEYWORDS

Gesture input; Motor impairments; Touchscreens; Dataset.

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1 INTRODUCTION

The prevalence of touchscreen devices, such as smartphones and tablets, has led to the adoption of a direct and fast way to interact with computers via simple touches, flicks, and swipes. Beyond touches and swipes, stroke-gesture input enables users with even more flexibility to execute tasks efficiently [34,84] and with low cognitive effort [6,55]. However, even the simplest action of a touch or a swipe demands precise finger, hand, wrist, and arm movements to implement highly-skilled neuromotor action plans that users with no functional impairments in those body parts take for granted. In fact, touch input poses many challenges to users *with* upper body motor impairments [19,20,43,50], which need to adapt to devices and adopt coping strategies to be able to use those devices effectively; see Figure 1 for a few examples.

To improve the accessibility of touchscreen devices for users with motor impairments, the assistive technology community has documented interaction challenges, coping strategies, and contexts of use [2,25,38,41,42,45], introduced new input devices toward more effective touch input [11–13], and designed assistive techniques for more accurate touch target selection [43,50,86]. However, research on stroke-gesture input for users with upper body motor impairments has been practically neglected, being restricted to empirical examinations of simple directional swipes [20,46] or to engineering practical solutions that use directional strokes for input, such as for text entry [81]. However, the rich potential of stroke-gesture input, including symbolic gesture shortcuts [34,55], has not been examined for users with motor impairments. In the context of modern paradigms of inclusive design that focus on abilities rather than disabilities [78], *the current lack of knowledge on how people with motor impairments articulate stroke-gestures on touchscreens prevents effective understanding of their gesture input abilities and, thus, effective design of assistive technology better matched to those abilities.*

The need for such an understanding is important if we want to design inclusive technology for all motor abilities. In this work, we perform an in-depth examination of the stroke-gesture articulation performance of people with upper body motor impairments. Our contributions are as follows:

(1) We conduct the first analysis in the literature regarding the gesture articulation performance of users with upper body motor impairments on touchscreens, which we contrast to the performance of users without impairments on multiple levels of analysis: gesture structure, kinematics, shape geometry, and gesture articulation consistency.
(2) We conduct the first evaluation of the recognition accuracy rates of stroke-gestures produced by users with motor impairments and report results for a wide palette of popular gesture recognizers, such as the $-family.
(3) Informed by our empirical results, we outline a research roadmap for accessible stroke-gesture input on touchscreens for people with upper body motor impairments.
(4) To foster advances in the directions set in our roadmap, we release our dataset of 9,681 stroke-gestures collected from 70 people, of which 35 with motor impairments. To this date and to the best of our knowledge, our dataset is the first and only publicly available data on gestures produced by people with upper body motor impairments.

2 RELATED WORK

We review in this section prior work on accessible touch input for people with motor impairments. We also discuss generic gesture recognition and analysis techniques that we use in this work to examine stroke-gestures produced by users with upper body motor impairments on touchscreens.

Assistive Touch for Users with Motor Impairments

Studies conducted to understand interaction challenges [2, 19,26,28,38] have led to more effective touch UI designs, including new input devices and techniques. For example, Plaumann *et al.* [50] proposed a method to correct touch input affected by hand tremor by analyzing device motion, which led to 40% fewer missed targets. Martez *et al.* [43] introduced "Smart Touch," a technique based on point-cloud matching [67] to increase the accuracy of touch target selection for people with motor impairments; Smart Touch predicted the coordinates of the intended targets three times more accurately than conventional approaches. New input devices were also invented. For example, Carrington *et al.* [12] introduced "Gest-Rest," an input device featuring a pressure-sensitive surface that fits over a standard power wheelchair armrest. Gest-Rest detects taps, directional swipes, and pressure-based gestures, such as squeezing. The "Gest-Rest family" [11] is a suite of extended "chairable" designs [13] for power wheelchairs.

Stroke-Gesture Input for Motor Impairments

Very few works have addressed stroke-gesture input for users with motor impairments. Probably the most notable contribution is "EdgeWrite" [81], a unistroke text entry method and alphabet [76] consisting of symbols made up of straight lines. To assure the physical stability of motion, EdgeWrite requires an assisting piece of hardware to guide stroke input, such as a joystick, a trackball, or a touchpad with prominent edges [80]. As physical edges are the *raison d'être* of EdgeWrite, trying to extend EdgeWrite gestures to smartphones without prominent edges [75] would make little sense. Unfortunately, research on unconstrained stroke-gesture input for motor impairments is lacking. Only two recent studies [63,64] published preliminary results, yet adopting a different perspective than ours and on smaller datasets (7 and 10 participants, respectively). In those studies, the authors were interested in the "quality" of gestures produced by people with motor impairments from the perspective of the Kinematic Theory [49].

No prior work has examined in detail the articulation characteristics of stroke-gestures, including symbolic gestures, produced by users with motor impairments. In this work, we address this aspect by relying on techniques from the gesture recognition and analysis literature, which we overview next.

Stroke-Gesture Recognition and Analysis

Prior work has introduced many techniques to recognize stroke-gestures. These include generic machine learning approaches borrowed from the pattern recognition community and applied to gesture data, such as Hidden Markov Models [58] and neural networks [14], but also new approaches, developed inside and for the HCI community to assist UI designers to readily deploy gesture recognition on any platform. Techniques from the later category have been known as the "$-family" gesture recognizers to denote that they are easy to understand and implement even by novice programmers [82]. The canonical members of the $-family [77] include $1 [82], $N [4], $P [67], and $Q [70], designed to recognize stroke-gestures with high accuracy. Other approaches include $P+[66], a variant of $P for gestures produced by people with low vision, speed-ups Protractor [35] and Penny Pincher [60], or the modality-agnostic Jackknife [62].

Prior work in gesture analysis introduced a variety of techniques and tools to evaluate user performance. For example, Vatavu *et al.* [68] introduced "relative accuracy measures" to evaluate the articulation accuracy of stroke-gestures with respect to canonical forms; Anthony *et al.* [3] introduced the "Gesture Clustering Toolkit" to report users' consistency of gesture articulation; and the "Gesture Heatmaps Toolkit" [69] renders gesture visualizations that highlight the variation in articulation localized on the gesture path. These tools have been applied to evaluate gestures produced by children [59], people with low vision [66,71], blind people [9], and to validate gesture synthesis approaches [31,61]. We use these tools to report on the articulation characteristics of stroke-gestures produced by people with upper body motor impairments.

3 EXPERIMENT

We conducted an experiment to collect stroke-gestures from people *with* and *without* upper body motor impairments.

Participants

Seventy (70) participants were involved in the experiment, of which 35 with various motor impairments; see Table 1. The age range was 14–67 years (M = 30.6, SD = 11.0 years), and 20 participants were females (28.5%). Four participants (less than 18 years old) had their guardian's consent to participate.

Apparatus

A custom Android application was developed to implement the experiment design and to collect stroke-gestures; see Figure 1 on the first page. Gestures were collected in two locations with the same app running on two 10-point multi-touch ASUS tablets (Nexus 7 and MeMO Pad 7) with the same 7-inch diagonal size and 323 and 169 dpi, respectively. All pixel-based measurements were converted to centimeters.

Design

The design was mixed with two independent variables:

(1) Motor-Impairment, nominal, two conditions: *yes*, *no*.
(2) Gesture, nominal, 16 conditions: four directional swipes (left, right, up, and down) and twelve symbols, in alphabetical order: *Greek letter "alpha", checkmark, the "energy" symbol, the "Euro" symbol, heart, letters "M" and "R", paper clip, Greek "pi", six-point star, spiral,* and *"X"*; see Figure 2.

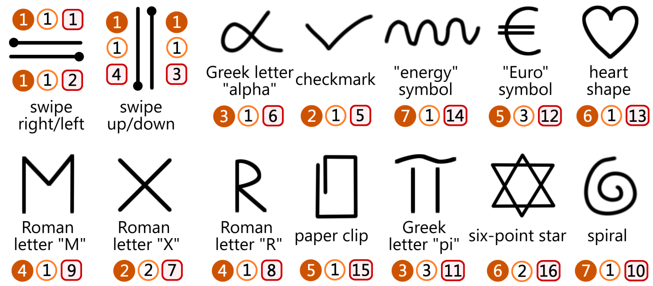

Figure 2. Stroke-gesture types used in our experiment. Numbers next to each gesture quantify its shape complexity [22], the minimum number of strokes to produce the gesture, and an estimated rank of the gesture's articulation difficulty [72]; larger values denote more complexity/difficulty.

We put considerable thought into the design of our gesture set. Gestures were chosen to be representative of letters, symbols, and generic geometric shapes, commonly used for stroke input and similar to the gesture types employed in other studies [5,66,72,82]. We also wanted gestures that could be articulated with as few touch up/down actions as possible and, thus, the majority of our gesture types require one stroke only, but we included four multi-stroke gestures as well. Gestures were also chosen for their different shape complexities, evaluated between 1 and 7 according to Isokoski's definition [22],[1] as well as for their different difficulty levels, from 1 to 16, estimated using the ranking rule[2] of Vatavu *et al.* [72] (p. 101). Figure 2 shows numbers next to each gesture type that show these characteristics.

Task

The gesture to produce was displayed at the bottom of the screen (with the tablet in portrait mode) and participants could draw on the upper side of the screen. After each trial, two actions became available: "Next" to advance to the next trial and "Undo," in case participants noticed an error from their part and wished to redo the gesture. There were no constraints with respect to how stroke-gestures had to be produced in terms of stroke count, stroke order, stroke direction, or the finger(s) touching the screen. In total, 16 (gesture types) × 9 (repetitions) = 144 articulations were expected from each participant. The order of Gesture was randomized across participants. A training phase preceded the experiment and consisted in entering each gesture type twice. On average, the experiment lasted 8.0 minutes (SD=1.9) for participants without motor impairments and 15.6 minutes (SD=7.1) for participants with motor impairments.

[1] The Isokoski complexity of a shape represents the minimum number of lines to which the shape can be reduced, yet still be recognizable by a human observer [22]; e.g., the complexity of Greek letter "alpha" is 3.
[2] Gesture A is likely to be perceived more difficult to produce than gesture B if the production time of A is greater than that of B [72].

Participant	Condition	Since	Finger used to enter stroke-gestures	Completion
P_1 (37 yrs., male)	Spinal Cord Injury (C6)†	2003	Little finger (knuckle); cannot move fingers	100%
P_2 (37 yrs., male)	Spinal Cord Injury (C6)	2002	Thumb; other fingers fixed to the physical edges of the device	100%
P_3 (53 yrs., male)	Spinal Cord Injury (C7)	1997	Middle finger (knuckle)	97.9%
P_4 (40 yrs., male)	Cerebral Palsy	1996	Index finger (fingertip)	99.3%
P_5 (34 yrs., male)	Spinal Cord Injury (C5)	2000	Little finger (knuckle); no wrist control, wears a hand strap	100%
P_6 (28 yrs., male)	Spinal Cord Injury (C6)	2017	Index finger (fingertip); cannot move fingers, wears a hand strap	97.9%
P_7 (44 yrs., male)	Spinal Cord Injury (C6)	1994	Thumb; cannot move fingers; fingers fixed to the device edges	99.3%
P_8 (34 yrs., male)	Cerebral Palsy	1983	Index finger (fingertip)	21.5%
P_9 (34 yrs., male)	Spinal Cord Injury (C6)	2015	Little finger (knuckle); no finger control, wrist gets tired quickly	99.3%
P_{10} (14 yrs., male)	Spinal Cord Injury (C5)	2017	Little finger (knuckle); weak or absent wrist movement	100%
P_{11} (54 yrs., male)	Spinal Cord Injury (C5)	2017	Little finger (knuckle); weak or absent wrist movement	64.6%
P_{12} (48 yrs., male)	Spinal Cord Injury (C5)	2017	Index finger (fingertip); weak or absent wrist movement	91.0%
P_{13} (37 yrs., female)	Meningitis	1980	Index finger (fingertip)	99.3%
P_{14} (45 yrs., male)	Spinal Cord Injury (C6)	2013	Thumb; cannot move fingers	100%
P_{15} (14 yrs., male)	Spinal Cord Injury (C5)	2016	Middle finger (fingertip); weak or absent wrist movement	100%
P_{16} (14 yrs., male)	Spinal Cord Injury (C5)	2016	Little finger (knuckle); weak or absent wrist movement	100%
P_{17} (42 yrs., male)	Spinal Cord Injury (C4-C5)	1996	Index finger (fingertip) of a rigid hand moved from the shoulder	93.8%
P_{18} (15 yrs., female)	Spinal Cord Injury (C6)	2015	Index finger (fingertip); cannot move fingers	100%
P_{19} (28 yrs., male)	Spinal Cord Injury (C7)	2006	Index finger (fingertip)	100%
P_{20} (22 yrs., male)	Spinal Cord Injury (C5)	2017	Uses a pen attached to the palm with a hand strip	28.5%
P_{21} (26 yrs., male)	Spinal Cord Injury (C7)	2018	Index finger (fingertip)	100%
P_{22} (29 yrs., male)	Spinal Cord Injury (C5)	2016	Little finger (knuckle); weak or absent wrist movement	100%
P_{23} (42 yrs., male)	Spinal Cord Injury (C6)	1995	Thumb; cannot move fingers	100%
P_{24} (43 yrs., male)	Spinal Cord Injury (C6)	2003	Index finger (fingertip) blocked by hand in fixed position	100%
P_{25} (23 yrs., male)	Phocomelia	1995	Middle finger (fingertip)	100%
P_{26} (22 yrs., female)	Cerebral Palsy	1996	Index finger (fingertip)	88.9%
P_{27} (21 yrs., male)	Spastic Tetraparesis	1997	Index finger (fingertip)	93.8%
P_{28} (32 yrs., male)	Spastic Tetraparesis	1986	Index finger (fingertip)	88.2%
P_{29} (42 yrs., male)	Spinal Cord Injury (C5)	2006	Thumb; weak or absent wrist movement	100%
P_{30} (30 yrs., male)	Spinal muscular atrophy (Kugelberg Welander type III)	1990	Index finger (fingertip)	100%
P_{31} (31 yrs., male)	Spinal Cord Injury (C5)	2010	Thumb; weak or absent wrist movement	100%
P_{32} (22 yrs., female)	Muscular Dystrophy (Limb-girdle)	2004	Index finger (fingertip)	87.5%
P_{33} (34 yrs., male)	Muscular Dystrophy (Duchenne)	1996	n/a (video recording lost)	100%
P_{34} (67 yrs., male)	Parkinson's disease	2014	Index finger (fingertip)	87.5%
P_{35} (23 yrs., male)	Spastic Tetraparesis	1995	Index finger (fingertip)	99.3%

† The code following in the parentheses denotes the affected vertebra(e), e.g., "(C6)" refers to traumatic injury at the 6th cervical vertebra.

Table 1. Demographic description of the 35 participants with upper body motor impairments and their completion rates.

4 RESULTS: STROKE-GESTURE ARTICULATION PERFORMANCE

We collected a total number of 9,681 valid stroke-gestures (of the expected 10,080), of which 4,662 from people with motor impairments. The completion rate was 92.5% for participants with motor impairments[3] and 99.6% for participants without impairments. The causes for the incomplete/invalid trials were fatigue and inability to produce certain gesture types; see Table 1 for completion rates for each participant with motor impairments, which varied from 21.5% (P_8) to 100% (18 participants). In this section, we are interested in differences in gesture articulation between people with and without motor impairments, which we report on several levels.

Evaluation Procedure, Measures, and Statistical Tests

Before reporting results, we present our evaluation approach. We are interested in the effect of Motor-Impairment on various performance measures of stroke-gesture articulation to answer questions such as *do people with motor impairments need more time to produce stroke-gestures than people without impairments?*, or *are people with motor impairments less consistent in their gesture articulations?*, etc. We are not specifically interested in the effect of the Gesture variable, which we treat as a random effect and aggregate our performance measures over all the gesture types. We define our dependent variables in the corresponding subsections where we discuss their effects, and we make distinction between *absolute* and *relative* measures. An *absolute* measure can be computed for each gesture independently, such as path length or production time. A *relative* measure evaluates a gesture with respect to some reference, such as the absolute deviation of a gesture's production time from the average production time of all the other gestures of the same type.

We employ the t-test for independent groups as the default test to evaluate the effect of Motor-Impairment, and use Welch's variant of the t-test when data are normal, but heteroscedastic. However, when the normality condition is not met, we use Yuen's robust method for 20%-trimmed means, described in Wilcox [74, p. 329] that reports the T_y statistic.[4] For t-tests, we report the r-value (Rosenthal, 1991), cited in Field [18, p. 341], as a measure of effect size, for which *small*, *medium*, and *large* effects are interpreted according to thresholds .10, .30, and .50. For Yuen's method, we report

[3] 4,662 valid gestures collected from 35 (participants with motor impairments) × 16 (distinct gesture types) × 9 (repetitions) = 4,662/5,040 = 92.5%.

[4] Yuen's method reduces to Welch with no trimming, but it is trimming and Winsorized variances that make it robust to deviations from normality [74].

the heteroscedastic measure ζ [74, p. 381] with limits .15, .35, and .50 for *small*, *medium*, and *large* effects, respectively.

Directional Swipes

We start our analysis with directional swipes due to their prevalence in touch UIs. A total of 1,098 swipes were collected from the participants with upper body motor impairments (completion rate 87.1%) and 1,240 swipes from the participants without impairments (98.4%).[5] For swipe gestures, supposed to be simple and fast, we are interested in the following measures of performance, for which we also state the corresponding research questions (*RQ*):

(1) Path-Length represents the physical length of the swipe on the screen, defined as the sum of Euclidean distances computed between consecutive points on its path. *RQ: Do motor impairments affect the length of swipes?*
(2) Production-Time is the time required to produce a swipe, from the moment when the first finger lands on the screen and the moment when the last finger lifts off. *RQ: Do motor impairments affect the duration of swipes?*
(3) Line-Steadiness evaluates the similarity of the swipe path to a straight line as the ratio between Path-Length and the length of the line segment defined by the first and last points; unitless, always larger than 1. *RQ: Do motor impairments affect the shape of swipe gestures?*

Results are shown in Table 2, rows 1-3, including means and statistical significance tests. We found no significant effect of Motor-Impairment on Path-Length, but we found that participants with motor impairments produced swipes that took twice as long (0.9 s *vs.* 0.4 s) and that deviated significantly more from a straight line (1.21 *vs.* 1.09) than the swipes produced by participants without impairments.

Symbolic Gestures

Participants with motor impairments produced 3,564 symbolic gestures with a completion rate of 94.3%, while the completion rate of participants without impairments was 99.9%. In the following, we report our participants' gesture articulation performance on multiple levels: geometric accuracy, kinematics, structure, and articulation consistency.

Geometric Accuracy. We evaluated the geometric accuracy of stroke-gestures using the following absolute and relative measures from the gesture literature [8,26,36,56,68,69]:

(1) Path-Length, absolute measure, defined as before. *RQ: Do motor impairments affect the length of stroke-gestures?*
(2) Length-Error, relative measure, defined as the absolute deviation of a gesture's path length with respect to the length of the gesture task axis. The task axis was introduced by Vatavu *et al.* [68, p. 281] as the centroid of a set of gestures of the same type. Depending on whether the gestures come from the same participant or not, Length-Error is measured *within* or *between* participants. *RQ: Do users with motor impairments vary the length of their strokes more than users without impairments?*
(3) Size, absolute measure, represents the area size of the axis-aligned bounding box of a stroke-gesture. *RQ: Do motor impairments affect the size of stroke-gestures?*
(4) Size-Error, relative measure, defined as the absolute deviation of a gesture size with respect to the size of the task axis [68, p. 281]. Just like Length-Error, Size-Error is evaluated both *within* and *between* participants. *RQ: Do users with motor impairments vary the size of their strokes more than users without impairments?*
(5) Total-Turning-Angle, absolute measure, is the sum of absolute turning angles on the gesture path, reflecting the total amount of bending required to produce the geometric shape of the gesture. *RQ: Do motor impairments affect the shape of stroke-gestures during articulation?*
(6) Bending-Error, relative measure, defined as the absolute average of the differences between corresponding turning angles at each point on the gesture and the task axis [68, p. 281]. As any relative measure, Bending-Error is evaluated both *within* and *between* participants. *RQ: Do users with motor impairments vary the shape of their strokes more than users without impairments?*

Table 2, rows 4-12, shows the effect of Motor-Impairment on the geometric accuracy of articulated gestures. Just like for swipes, we found no significant effect on Path-Length, but the between-users Length-Error was significantly larger for participants with motor impairments (5.6 *vs.* 3.3 cm). This result shows that, although the within-users variations seem to be roughly equivalent, participants with motor impairments produced gestures that were more different from each other compared to the gestures produced by participants without impairments. These results were corroborated by the Size measures (Table 2, rows 7-9). We also found that gestures produced by participants with motor impairments were less smooth, as reflected by larger Total-Turning-Angles (75.6 *vs.* 30.9 rad) and by larger variations in shape bending compared to participants without impairments (0.65 *vs.* 0.44 rad). All the effect sizes were large ($\zeta \geq .556$, $r \geq 649$).

Kinematic Performance. We evaluated the kinematic aspects of the stroke-gestures produced by our participants with the following measures from Vatavu *et al.* [68,69]:

(1) Production-Time, absolute measure, defined as before. *RQ: Do motor impairments affect gesture duration?*
(2) Time-Error, relative measure, defined as the absolute deviation of a gesture's production time with respect

[5] The 98.4% completion rate for the participants without motor impairments was caused by some participants mistaking the direction of the swipes, e.g., a left swipe was performed instead of a swipe to the right, etc.

	Measure	Type	Unit	Mean		20%-trimmed Mean		Test‡	p-value	Effect§
				with MI†	no MI	with MI	no MI			
❶ Directional swipes: Geometric and kinematic measures of performance										
1	Path length	*absolute*	cm	5.3	5.4	5.2	5.3	$T_{y(35.984)} = 0.340$	$p = .736$	$\zeta = .062$
2	Production time	*absolute*	s	0.9	0.4	0.6	0.4	$T_{y(26.314)} = 2.892$	$p = .008$	$\zeta = .681$
3	Line steadiness	*absolute*	·	1.21	1.09	1.07	1.01	$T_{y(20.015)} = 3.203$	$p = .004$	$\zeta = .789$
❷ Symbolic gestures: Geometric measures of performance										
4	Path length	*absolute*	cm	16.5	17.1	14.6	16.3	$t_{(68)} = 0.624$	$p = .534$	$r = .075$
5	Length Error, within	*relative*	cm	2.5	1.8	1.8	1.6	$T_{y(31.562)} = 1.923$	$p = .063$	$\zeta = .363$
6	Length error, between	*relative*	cm	5.6	3.3	3.6	2.5	$T_{y(22.668)} = 3.063$	$p = .006$	$\zeta = .556$
7	Size	*absolute*	cm^2	23.3	24.5	18.7	21.5	$T_{y(31.345)} = 0.596$	$p = .596$	$\zeta = .097$
8	Size error, within	*relative*	cm^2	6.1	4.6	4.3	3.8	$T_{y(27.866)} = 1.925$	$p = .064$	$\zeta = .449$
9	Size error, between	*relative*	cm^2	13.6	8.8	12.8	7.3	$T_{y(25.213)} = 3.370$	$p = .002$	$\zeta = .580$
10	Total turning angle	*absolute*	rad	75.6	30.9	60.7	29.8	$T_{y(25.260)} = 4.115$	$p < .001$	$\zeta = .863$
11	Bending error, within	*relative*	rad	0.5	0.3	0.4	0.3	$t_{(37.831)} = 5.253$	$p < .001$	$r = .649$
12	Bending error, between	*relative*	rad	0.65	0.44	0.63	0.44	$T_{y(23.563)} = 6.568$	$p < .001$	$\zeta = .921$
❸ Symbolic gestures: Kinematic measures of performance										
13	Production time	*absolute*	s	3.4	1.7	2.7	1.7	$T_{y(29.902)} = 4.352$	$p < .001$	$\zeta = .779$
14	Time error, within	*relative*	s	1.0	0.4	0.5	0.3	$T_{y(28.095)} = 3.849$	$p < .001$	$\zeta = .721$
15	Time error, between	*relative*	s	2.3	0.7	1.8	0.7	$T_{y(31.467)} = 13.020$	$p < .001$	$\zeta = .926$
❹ Symbolic gestures: Articulation preference measures										
16	Number of strokes	*absolute*	·	2.0	1.7	1.8	1.6	$T_{y(34.545)} = 2.777$	$p = .008$	$\zeta = .523$
17	Stroke error, within	*relative*	·	0.4	0.1	0.3	0.1	$T_{y(26.573)} = 4.700$	$p < .001$	$\zeta = .757$
18	Stroke error, between	*relative*	·	0.5	0.2	0.3	0.2	$T_{y(31.737)} = 2.135$	$p = .041$	$\zeta = .421$
❺ Symbolic gestures: Articulation consistency										
19	Consistency, within	*relative*	·	.630	.834	.674	.837	$T_{y(23.478)} = 3.446$	$p = .002$	$\zeta = .792$
20	Consistency, between	*relative*	·	.233	.468	.225	.458	$t_{(22)} = 3.034$	$p = .006$	$r = .543$

†MI abbreviates "Motor Impairments"; §Statistically significant differences ($p < .05$) and large and medium effect sizes ($\zeta > .35$ or $r > .50$) are highlighted.

Table 2. Performance measures for stroke-gestures articulated by participants with and without motor impairments.

to the production time of the task axis [68, p. 281]. As any relative measure, Time-Error can be evaluated both *within* and *between* participants. *RQ: Do users with motor impairments vary the duration of their stroke-gestures more than users without impairments?*

Table 2, rows 13-15, shows that stroke-gestures produced by participants with motor impairments took twice as long to articulate compared to the same gesture types produced by participants without impairments (3.4 s *vs.* 1.7 s), and had significantly larger time errors, both within (1.0 s *vs.* 0.4 s) and between participants (2.3 s *vs.* 0.7 s). All the effect sizes were large ($\zeta \geq .721$).

Gesture Structure. We evaluated the structure of stroke-gestures using the following dependent variables [68]:

(1) Number-of-Strokes, absolute measure, represents the number of strokes that make up a gesture articulation. *RQ: Do motor impairments affect the structure of a stroke-gesture in terms of its stroke count?*
(2) Stroke-Error, relative measure, defined as the absolute deviation of a gesture's number of strokes with respect to the task axis [68], *within* and *between* participants. *RQ: Do users with motor impairments vary the number of strokes more than users without impairments?*

Table 2, rows 16-18, shows that participants with motor impairments produced stroke-gestures with a significantly larger number of strokes than participants without impairments (2.0 *vs.* 1.7) and with more variation, both within (0.4 *vs.* 0.1) and between participants (0.5 *vs.* 0.2). All the effect sizes were medium to large ($\zeta \geq .421$).

Articulation Consistency. We measured the consistency of our participants' gesture articulations using the Gesture Clustering Toolkit[6] of Anthony *et al.* [68] that implements the agreement rate measure of Vatavu and Wobbrock [73]. Participants with motor impairments were significantly less consistent in their articulations compared to participants without impairments (.630 *vs.* .834 within-users consistency), but also in terms of other participants with motor impairments (.233 *vs.* .468 between-users); see Table 2, rows 19-20.

Key Takeaway

Our empirical results show that people with motor impairments can produce stroke-gestures on touchscreen devices, yet they take considerably more time to produce them, exhibit lower consistency in their articulations, and show more deviations from the geometric shapes of the intended gesture forms, such as in terms of path length, area size, and the bending of strokes within a gesture. In the next section, we look at how accurately gestures produced by people with

[6] Available at http://depts.washington.edu/madlab/proj/dollar/gecko.html

motor impairments can be recognized using popular classification techniques compared to the same stroke-gesture types articulated by people without impairments.

5 RESULTS: RECOGNITION ACCURACY RATES FOR STROKE-GESTURES

We report user-independent recognition rates for stroke-gestures by considering the popular Nearest-Neighbor (NN) classification approach and a wide palette of gesture dissimilarity functions commonly employed in the literature, such as the Euclidean shape distance [4,29,82], the Angular Cosine metric [5,35], or approaches based on matching point-clouds [52,66,67,70]. These dissimilarity functions constitute the basis of popular stroke-gesture, sketch, and shorthand writing recognizers, such as $1 [82], $N [4], $P [67], Protractor [35], $N-Protractor [5], and SHARK[2] [29], to name just a few. We also consider Dynamic Time Warping (DTW) due to its popularity and effectiveness for generic time series classification [51], including stroke-gestures [51,82]; the Hausdorff [57] and the modified Hausdorff shape distance functions [17], popular in the Computer Vision community for matching geometric shapes, while also effective for stroke-gesture recognition [27]; and two variants of the flexible $P point-cloud gesture recognition approach, i.e., $P+ [66], a highly accurate recognizer tailored to gestures produced by people with visual impairments, and $Q [70], a major speed-up of $P with a slight increase in accuracy as well.

Experiment Design

For this experiment, we employed three independent variables in a 2×8×7 mixed design (between-by-within-by-within):

(1) Motor-Impairment, nominal, 2 conditions: *yes* and *no*.
(2) Recognizer, nominal, 8 conditions, representing a NN recognition technique that uses one of the following dissimilarity functions: Euclidean ($1), Angular Cosine, $P, $P+, $Q, DTW, Hausdorff and modified Hausdorff.
(3) P, ordinal, 7 conditions, representing the number of participants from which gesture templates are selected for training, ranging from 1 to 30 in increments of 5, i.e., 1, 5, 10, 15, 20, 25, and 30 training participants, respectively.

Evaluation Procedure and Statistical Tests

We implemented a full cross-validation procedure for computing user-independent recognition rates [66,67], as follows. Each gesture from the dataset was treated as a candidate for classification. For each candidate, we selected P participants at random, different from the participant that provided the candidate, from which we randomly selected P templates for each Gesture type, one from each training participant. We computed the accuracy rate of each Recognizer by repeating the selection procedure for 100 times for each candidate and each P value. Overall, we present recognition results for 7,310 candidates from 69 participants.[7] We also restricted our analysis to the twelve symbolic gestures (see Figure 2), because directional swipes cannot be recognized by dissimilarity functions that were designed to be direction-independent in the first place, such as $P, $P+, $Q, and the two Hausdorff shape distances. (Directional swipes were analyzed in a previous section and they are straightforward to recognize by verifying their compliance to straight lines using geometric measures, such as Line-Steadiness.) Overall, we report results from 8 (Recognizers) × 7 (conditions for the number of training participants P) × 100 (repetitions for each P) × 7,310 (candidates) = $4.09 \cdot 10^7$ classification trials.

Because recognition rates data were not normal (as indicated by Shapiro-Wilk tests) and heteroscedasticity was present (according to Levene's test), we employed a robust ANOVA technique for 20%-trimmed means. The technique is described in Wilcox [74, p. 561] as an extension of Johansen's method [23] and uses Winsorized covariances and the F distribution with corrected degrees of freedom.[8] Post-hoc tests were conducted using a robust linear contrasts procedure for dependent groups based on the $\hat{\Psi}$ statistic and the t distribution with the family-wise error controlled with Rom's method for $\alpha = .05$; see Wilcox [74, p. 606] for details.[9]

Recognition Accuracy Rates

Figure 3 illustrates the mean recognition rates for each combination of the three independent variables. On average, there was a 12% difference in recognition accuracy between participants with and without motor impairments. We found a statistically significant main effect of Motor-Impairment on Recognition-Rate ($F_{(1,0.183)}$=18.351, p<.001): all recognizers considered, gestures produced by participants with motor impairments were recognized less accurately (M=83.7%, $M_{.20}$=88.6%)[10] than the same gesture types produced by participants without impairments (M=95.6%, $M_{.20}$=98.3%).

We found a significant main effect of Recognizer on Recognition-Rate ($F_{(7,0.137)}$=4.477, p<.001), with the $P+ recognizer delivering the highest accuracy for gestures produced by participants with motor impairments (M=89.5%, $M_{.20}$=94.1%) as well as for participants without impairments (M=99.3%, $M_{.20}$=99.9%). $P+ was followed, in order, by $Q, $P, the two Hausdorff shape distances, DTW, the Euclidean

[7] We had to remove participant P_{20} (spastic tetraparesis, cerebral palsy) from this analysis, because their data did not meet the requirement of the cross-validation procedure of at least one sample per gesture type.

[8] The test is implemented by the R function `bwwtrim()`, available from Rand Wilcox's home page, https://dornsife.usc.edu/labs/rwilcox/software/

[9] The test is implemented by the R function `rmmcp()`, available from Rand Wilcox's home page, https://dornsife.usc.edu/labs/rwilcox/software/

[10] Due to the non-normality and heteroscedasticity of the data, we run the statistical analysis on 20%-trimmed means, following the robust methods described in Wilcox [74]. However, to be as informative as possible, we report both the mean (M) and the 20%-trimmed mean ($M_{.20}$) in the text.

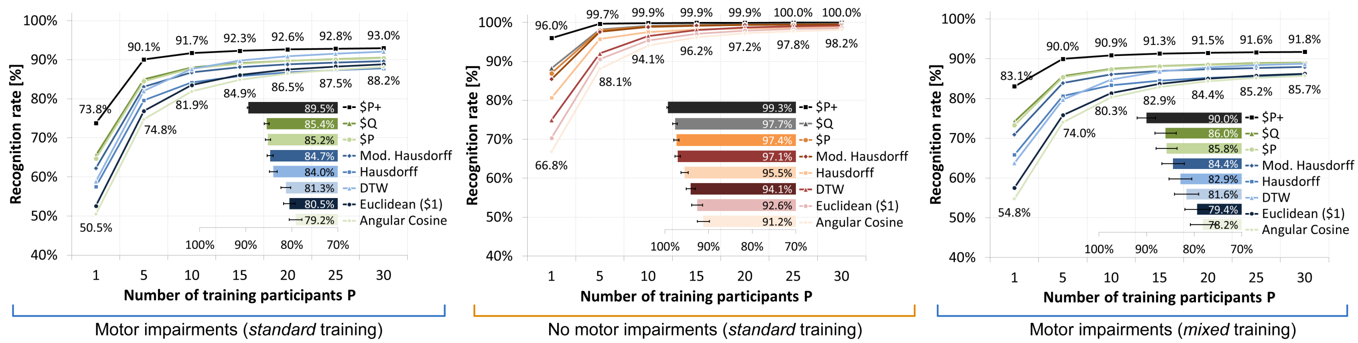

Figure 3. Recognition accuracy rates for stroke-gestures articulated by participants with motor impairments (left) and without impairments (middle) under *standard* training, and recognition rates for participants with motor impairments (right) under *mixed* training (see text for description), function of the number of training participants P. *Note:* error bars show 95% CIs.

shape distance, and the Angular Cosine metric; see Figure 3. Linear contrasts showed that \$P+ was significantly more accurate than the second-best recognizer, \$Q, for both participants with motor impairments ($\hat{\Psi}$=0.036, t=7.661, p<.001) and without impairments ($\hat{\Psi}$=0.016, t=9.788, p<.001). Recognizers improved their performance with more templates, as indicated by a significant main effect of the number of training participants P on Recognition-Rate ($F_{(6,0.139)}$=65.239, p<.001). For example, the best recognizer, \$P+, improved its performance for participants with motor impairments from 73.8% with one training template per gesture type to 93.0% when using templates from P=30 participants. Contrasts between consecutive P conditions showed significant improvements from 1 to 5 templates, 5 to 10, 10 to 15, 15 to 20, 20 to 25, and from 25 to 30 templates (p < .001).

There was no significant interaction between Motor-Impairment and Recognizer (p=.976), but we found a significant Motor-Impairment × P interaction ($F_{(6,0.139)}$=4.291, p<.001) indicating that using more templates increases recognition accuracy at different rates for gestures articulated by people with and without motor impairments; see Figure 3 for the evolution of Recognition-Rate function of P.

The Effect of Mixed Training on Accuracy Rates

So far, we know that stroke-gestures produced by people with motor impairments can be recognized with relatively good accuracy, i.e., 93.0% using \$P+. We want to learn whether the accuracy rates would improve if templates came from participants *without* motor impairments. Figure 3, right shows the results from 8 (Recognizers) × 7 (conditions for the number of participants P) × 100 (repetitions for each P) × 4,662 (candidate gestures from 35 participants[11] with motor impairments) = $2.61 \cdot 10^7$ classification trials. We can compare these results with those reported previously by adding a new independent variable to our experiment design: Training-Type, nominal with two conditions: *standard* and *mixed* training.

[11]For this test, P_{20} can be included as well.

On average, recognition rates were of similar magnitude for the two Training-Type conditions: M=83.7%, $M_{.20}$=88.6% and M=83.5%, $M_{.20}$=87.1%, respectively. A robust ANOVA on 20%-trimmed means did not detect any significant effect of Training-Type on Recognition-Rate ($F_{(1,0.188)}$=0.119, p=.730) and no interaction between Training-Type and Recognizer ($F_{(7,0.141)}$=0.039, p=.999). However, we did find a significant Training-Type × P interaction ($F_{(6,0.143)}$=2.153, p=.045), which can be observed in Figure 3: an increase in recognition accuracy for one template per gesture type in the *mixed* condition (e.g., 83.1% for \$P+ *vs.* 73.8% for *standard* training) is accompanied by a decrease in accuracy when using more templates (e.g., 91.8% *vs.* 93.0% for \$P+).

Key Takeaway

Our empirical results show that stroke-gestures produced by people with motor impairments can be recognized with relatively good accuracy, i.e., 93.0% using the \$P+ recognizer, feasible for practical purposes. However, the recognition performance is nevertheless suboptimal given that the same recognizer delivers 100% for people without impairments. New techniques are needed to remove this gap in recognition accuracy between users with and without motor impairments.

6 DISCUSSION, ROADMAP, AND DATASET

Our empirical results suggest that stroke-gestures may represent a viable input modality on touchscreens for users with motor impairments. Despite inherent geometric and kinematic inaccuracies or inconsistencies in articulation, stroke-gestures produced by people with upper body motor impairments were recognized effectively by popular classification algorithms, such as the members of the "\$-family" [77], e.g., the \$P+ recognizer delivered 93% user-independent accuracy. These results deliver great promise for accessible gesture input for people with upper body motor impairments.

Our initial plan for this section was to distill the empirical results into a set of guidelines for practitioners, a common

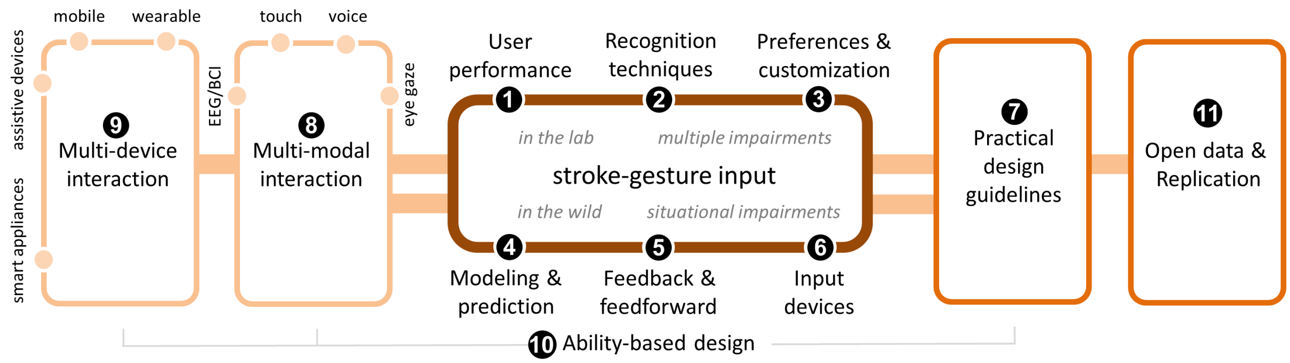

Figure 4. Sketch of a research roadmap for accessible stroke-gesture input for users with upper body motor impairments.

practice in our community [2,3,6,20,26,71], to inform the design of accessible stroke-gesture input. However, we realized that a much larger goal is at stake and that we could deliver a much more significant contribution. Given the lack of research in stroke-gesture input for people with motor impairments, we inspired from recent initiatives [16,44,87] and decided to draw a Research Roadmap for accessible stroke-gesture input that we hope to foster critical analysis, constructive discussion, and shape future research.

A Research Roadmap for Accessible Stroke-Gesture Input for Users with Upper Body Motor Impairments

Figure 4 presents a visual illustration of the key items of our research roadmap, as follows:

❶ *Toward an in-depth understanding of user performance with stroke-gesture input with new measures.* Our empirical exploration revealed the gesture articulation performance of users with motor impairments on many levels, including gesture structure, geometry, kinematics, and articulation consistency. To this end, we relied on measures and tools representing the state-of-the-art in stroke-gesture analysis [2,8,68,69]. However, we believe that this understanding can be further enriched with new measures, more specific and relevant to motor impairments. Studies from the literature (on other user groups) can be invoked to support this direction, e.g., Kane *et al.* [26] designed specific measures to characterize gestures articulated by blind people, such as the "form closure" or the "average angular acceleration" measures; or Woodward *et al.* [83], who analyzed children's touch input with the "input drag" and "holdovers rate" measures. For example, measures that look more closely at the steadiness of strokes may reveal more differences between users with and without impairments than our line steadiness measure (Table 2, row 3). Also, our current understanding of user performance needs to be completed with evaluations "in the wild" [41], involving users with multiple impairments [25], and by addressing situationally-induced impairments [1].

❷ *More accurate gesture recognition techniques.* Although the recognition accuracy of gestures produced by people with motor impairments was relatively high (max 93%), it was lower than the 100% rate reached for people without impairments. Future work is needed to remove this unnecessary gap in recognition accuracy rates between the two groups. We expect this to be achieved by a careful analysis of the gesture articulations of people with motor impairments to inform new recognition approaches or improvements of existing ones, e.g., similar to Vatavu [66], who achieved a 10% increase in the accuracy of the $P recognizer [67] for stroke-gestures produced by people with visual impairments.

❸ *Understanding users' preferences for stroke-gestures they are able to produce or would like to use.* We are currently unaware of the preferences of users with motor impairments for stroke-gestures they would like to use. Conducting gesture elicitation studies [73,79] will not only reveal such preferences, but also users' mental models of gesture interaction for various applications and contexts of use. For example, the fact that significantly more strokes were produced by our participants with motor impairments compared to participants without impairments (Table 2, rows 16-18) likely reflects their ability to produce stroke-gestures, but this may also be a coping strategy disguised as a matter of preference.

❹ *Toward modeling and prediction of user performance.* Collecting data from participants with disabilities is not easy, takes time and effort. For example, the data reported in this work was collected over a period of five months. Tunning generic models of user performance with stroke-gesture input, such as models of production time [10,32,33] or the user-perceived difficulty of gesture articulation [53,72], or creating entirely new models to explain and predict the stroke-gesture input performance of people with motor impairments (such as the large production times reported in Table 2, row 13) would provide valuable information to designers without the need to run actual experiments.

❺ *Suitable feedback and feedforward for stroke-gesture input.* The question of how to provide proper feedback during gesture input has been examined in the literature with the goal to teach users new gestures [24] or to help users transition from novices to experts [7]. In the accessibility literature, Oh *et al.* [47,48] proposed audio-based feedback techniques, i.e., "gesture sonification," for people with visual impairments. However, without validation data, it is not clear how these techniques will work for users with motor impairments, such as to help make their articulations faster (see Table 2, rows 13-15) or more consistent (rows 19-20).

❻ *New input devices for stroke-gesture input* to foster physical stability of motion during gesture articulation. Successful examples include EdgeWrite [76,81] for gestures made up of directional strokes and Gest-Rest [12] for taps, swipes, and pressure-based input. New ways to support stable implementers for gesture input with the thumb or the knuckle (see Table 1 and Figure 1) should be investigated to provide assistance during articulation according to the specific hand pose used to touch the screen, e.g., distinct gesture recognizers trained with different data according to the hand pose.

❼ *Formulation of practical design guidelines and recommendations for accessible stroke-gesture input.* Empirical results and observations on how people with upper body motor impairments produce stroke-gestures should be compiled into practical guidelines to assist practitioners, a common practice in our community to create design knowledge [2,3,6,20,26,71]. Examples of guidelines include using recognizers that are invariant to how users articulate stroke-gestures, because of the observed low articulation consistency for users with motor impairments (Table 2, rows 19-20), or favoring gesture shapes that can be articulated efficiently with small production times (rows 2 and 13). We also recommend new studies to confirm and strengthen such guidelines and inform new ones, e.g., by understanding the relationship between gesture articulation characteristics, such as path length or production time, and recognition rates to inform gesture sets that are performed effectively and efficiently by users with motor impairments, while also recognized with high accuracy.

❽ *Multi-modal interaction including stroke-gesture input.* Although research on stroke-gesture input for people with motor impairments has been scarce, other input modalities, such as voice [21,54], eye gaze [30,85], and direct brain-computer input [15] have been examined extensively. Combining gesture input with other modalities may lead to better user performance and satisfaction, e.g., providing personalized feedback for gesture input by analyzing the cognitive and emotional state of the user revealed by EEG measurements.

❾ *Stroke-gesture input and multi-device interaction.* Recent work has started to examine the performance of people with motor impairments with the newest input devices, such as head-mounted displays [38,39] and wearables [37,40], next to traditional studies comparing, e.g., mouse and touch input [19]. Wearable gadgets, such as smartbands, smartwatches, rings, glasses, and earbuds, can be worn and interacted with concurrently and alongside input on smartphones and tablets, creating thus the premises for casual multi-device input. Given the recent boom in wearables, looking into accessible stroke-gesture input for multi-device interactions is a step that the community will soon have to take. The small form factors of these devices and their touch pads may demand entirely new gesture recognition approaches than those evaluated in this work (see Figure 3) to extract meaning from tiny strokes of little dimensionality and cardinality [65].

❿ *Ability-based design for stroke-gesture input.* Last but not least, ability-based design [78] touches many of the items above. Implications regard customization of gesture sets, preferred feedback modalities, accessible gesture implementers and input devices better matched to the specific motor abilities of each user, or recognition algorithms tailored to users' motor abilities and specific ways to produce stroke-gestures, e.g., using the thumb or the knuckle; see Table 1 and Figure 1. While a core principle of ability-based design is the use of commodity hardware to accommodate users' abilities, we believe that this direction should be investigated alongside item ❻ (new input devices) as each direction can potentate the other, e.g., challenges in operating commodity hardware can inform innovations in input devices, while new devices present new opportunities for ability-based design.

Dataset

We can add one last item to the above list: *open data.* Advancing technology for users with motor impairments involves testing and evaluations, and having access to data will benefit this endeavor considerably. By releasing our large dataset, we make one step in this direction, enabling the community to contribute further analyses, invent more accurate recognizers, and distill design requirements for UIs. Our dataset is freely available at http://www.eed.usv.ro/~vatavu.

7 CONCLUSION

We examined stroke-gestures produced by people with upper body motor impairments and reported that simple recognition approaches, such as the $-family recognizers, are powerful enough to recognize those gestures with 93% accuracy. Our results enabled us to outline a research roadmap for accessible stroke-gesture input on touchscreen devices, which we hope to foster developments toward more accessible touch and gesture input for users with all motor abilities.

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