Predicting Stroke Gesture Input Performance for Users with Motor Impairments

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

Radu-Daniel Vatavu
MintViz Lab | MANSiD Research Center
University Ștefan cel Mare of Suceava
13 Universității
Suceava 720229, Romania
vatavu@eed.usv.ro

Luis A. Leiva
Sciling
Valencia, Spain
name@sciling.com

Daniel Martín-Albo
Independent researcher
Barcelona, Spain
dmartinalbos@gmail.com

MobileHCI '18 Adjunct, September 3–6, 2018, Barcelona, Spain

ACM ISBN 978-1-4503-5941-2/18/09.
https://doi.org/10.1145/3236112.3236116

Abstract

The performance of users with motor impairments with stroke gesture input on touchscreens has been little examined so far, despite the wide prevalence of mobile devices and the benefits they bring to increase users' quality of life. In this work, we present the first empirical results on this subject matter from 915 gestures collected from 10 participants with motor impairments (spastic tetraplegia and tetraparesis) and 10 participants without known impairments. We report that different motor abilities lead to different performance in terms of gesture production time. We also show that the production times of gestures articulated by users with motor impairments can be accurately predicted with an absolute error of just 150 ms and a relative error of only 3.7% with respect to actual times (user-independent tests), a result that will enable designers to estimate human performance *a priori* when prototyping gesture UIs for users with motor impairments.

Author Keywords

Touch gestures; gesture performance; stroke gestures; production time; motor impairments; touchscreens.

ACM Classification Keywords

H.5.2. [Information Interfaces and Presentation (e.g., HCI)] User Interfaces: *Input devices and strategies*; K.4.2. [Computers and Society] Social Issues: *Assistive technologies for persons with disabilities*.

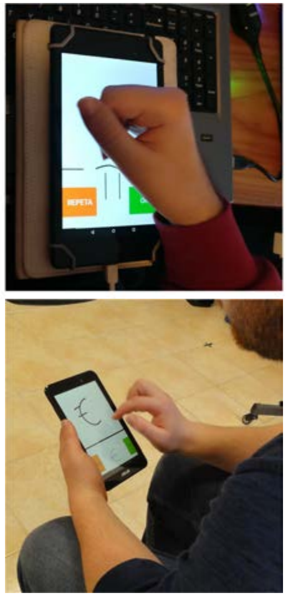

Figure 1: Snapshots captured during our gesture collection experiment showing a participant with motor impairments (top) and without known impairments (bottom) performing stroke gestures on a mobile touchscreen device.

Introduction

Input on smart mobile devices, such as smartphones, tablets, and smartwatches, is mostly constrained to touchscreen input, which requires precise motor coordination of the hand, wrist, and fingers to touch targets effectively [5,8] and articulate stroke gestures accurately [23,24]. Various user categories, such as children [27], elderly [7], or people with visual [11,26] or motor impairments [16,22] exhibit different performance with touch input and, consequently, adaptive design of touch interfaces is in order to accommodate varying abilities as well as their interplay [28].

For users with motor impairments, these abilities are affected by neuromotor conditions that may cause tremors, tiredness and muscle fatigue, numbness, or even pain during arm and hand movements. This leads to decreased performance for acquiring touch targets compared to users without impairments [4,16]. Moreover, this performance can only be attained by adopting coping strategies [1,16,22], such as using the knuckle of the little finger for input (see Figure 1, top), wearing hand straps, or keeping the fingers on the edge of the device to prevent spurious touches [4].

Stroke gesture input requires the ability to slide the fingers on the touch-sensitive surface following a specific geometrical path under the constraints of articulation accuracy [23,24], so that unistroke [31], multistroke [29], and multitouch [14] gesture recognizers would be able to interpret those touch paths correctly. However, investigations on gesture input for users with motor impairments have been neglected in the community until very recently [22], despite the attractive attributes of stroke gestures to execute commands efficiently [2,21,32]. In this work, we focus on the performance of users with motor impairments with gesture input on mobile devices, which we characterize in terms of production times and predict using the sigma lognormal model of the Kinematic Theory [12,13,18,19].

We are interested in predicting human performance so that practitioners would be able to inform gesture set design without recurring to actual experiments, at least in the first phases of their prototypes. We are specifically interested in production time as a key metric of human performance [2,32] that is strongly connected to users' perceptions of gesture difficulty [20,25].

Our contributions are as follows:

1. We provide the first analysis of the stroke gesture input performance of users with upper body motor impairments on mobile touchscreen devices by reporting empirical results on their gesture production times, which we contrast to the performance achieved by users without motor impairments.
2. We compute time predictions for gestures produced by users with motor impairments by using the Kinematic Theory to model stroke gesture input with log-normal velocity profiles of the finger touching the screen [9-11]. Specifically, we rely on the recent KeyTime and GATO techniques [12,13] to compute accurate time predictions for both unistroke [12] and multistroke [13] gestures, for which we report an average absolute error of just 150 ms and a relative error of only 3.7% from actual times.

Our work reveals aspects of stroke gesture input performance on touchscreens untapped so far for users with motor impairments. We hope that our empirical results will encourage further investigations in the community towards designing assistive techniques to enable effective input on touchscreen devices for users with all motor abilities.

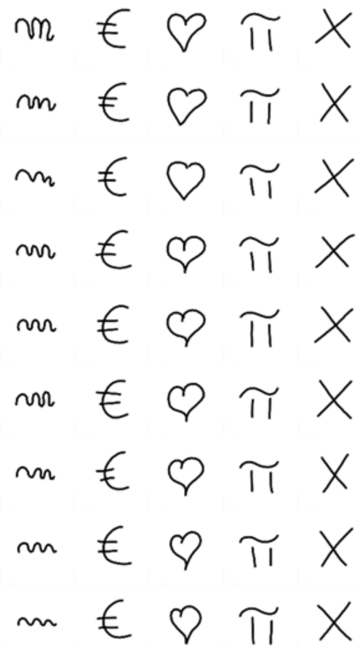

Figure 2: Stroke gestures collected from participant P_{14} (without any known motor impairments). From left to right, in order, a total of 45 gesture articulations: the "energy" and "Euro" symbols, "heart", letter "pi", and letter "X."

See Figure 3, on the next page, for visual illustrations of the same gesture types produced by a participant with motor impairments.

Related Work

Prior work examined the performance of people with motor impairments with various input devices and techniques [4,15,16], and reported on the accessibility challenges for touch input [1,17]. For instance, Anthony et al. [1] analyzed user-generated YouTube videos to understand how people with motor impairments employ touchscreens, and reported on their interaction styles, the use of direct and indirect input, body postures, and physical device adaptations. Regarding accessibility techniques, Mott et al. [16] found that people with motor impairments touch, on average, at about 10 cm from the intended target, and proposed "Smart Touch," a technique to increase their touch input accuracy.

To our knowledge, only one work has examined stroke gesture input for users with motor impairments: Ungurean et al. [22] were interested in the reliability of the Kinematic Theory [18,19] to accurately model gestures articulated by users with motor impairments. Their results revealed that people with motor impairments produce stroke gestures on touchscreens that meet the motor performance criteria set by the Kinematic Theory and, thus, recommended further investigations in this direction. In this paper, we follow up on the work of Ungurean et al. [22] to understand the practical differences in stroke gesture time performance between users with and without motor impairments.

Early prediction techniques for the production time of unistroke gestures were introduced by Isokoski [6] and Cao and Zhai [3]. Recently, those techniques were superseded in accuracy by the KeyTime [12] and GATO (Gesture Articulation Time predictOr) [13] approaches. While KeyTime [12] computes time predictions for unistrokes, GATO [13] is a generic approach that covers multistroke and multitouch gestures alike. In this work, we rely on GATO [13] to understand the feasibility of estimating the expected production time of gestures produced by users with motor impairments.

Experiment

Twenty (20) participants entered stroke gestures on a 7-inch tablet running Android and our custom software application. Ten participants (M=34.6, SD=9.8 years, one female) had various types of motor impairments; see Table 1. The other 10 participants (M=22.8, SD=4.5, 4 female) had no known impairments.

No	Age, Gender	Condition
P_1	37 yrs., M	Spastic tetraplegia (SCI - C6)
P_2	37 yrs., M	Spastic tetraplegia (SCI - C6)
P_3	53 yrs., M	Spastic tetraplegia (SCI - C7)
P_4	34 yrs., M	Spastic tetraplegia (SCI - C5)
P_5	28 yrs., M	Spastic tetraplegia (SCI - C6)
P_6	44 yrs., M	Spastic tetraplegia (SCI - C6)
P_7	34 yrs., M	Spastic tetraparesis (CP)
P_8	22 yrs., F	Spastic tetraparesis (CP)
P_9	21 yrs., M	Spastic tetraparesis
P_{10}	32 yrs., M	Spastic tetraparesis

Table 1: Demographic details for our 10 participants with tetraplegia and tetraparesis caused by spinal cord injury (SCI) at vertebrae C5 to C7 and cerebral palsy (CP).

We considered five gesture types for our data collection procedure ("heart", letter "X", Greek letter "Pi", the "Euro" and the "energy" symbols; see Figures 2 and 3) that we chose for their diversity in terms of (i) number of strokes (i.e., 1, 2, and 3), (ii) stroke types (straight lines and curves), and (iii) geometric complexity (between 2 and 7, evaluated using Isokoski's measure [6]). Participants were asked to repeat each gesture type for 10 times (gesture type was randomized across

Figure 3: Stroke gestures collected from participant P_8 (spastic tetraparesis caused by cerebral palsy). From left to right, in order, 44 gesture articulations: the "energy" symbol, the "Euro" symbol, "heart", letter "pi", and letter "X."

See Figure 2, on the previous page, for visual illustrations of the same gesture types produced by a participant without motor impairments.

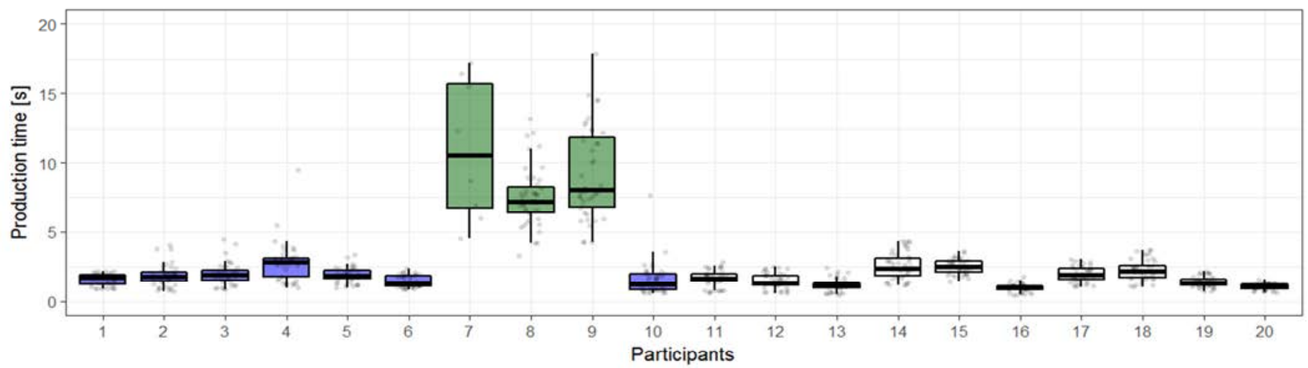

Figure 4: Production time boxplots for all participants. *Note*: P_1 to P_{10} are participants with motor impairments; see Table 1.

participants). We instructed participants to produce gestures at their normal speed with no restrictions in terms of the number of strokes, stroke directions or the fingers touching the screen. In total, we collected 915 gesture samples for a task completion rate of 91.5%.

Results

On average, participants with motor impairments performed stroke gestures in 3.57 seconds (SE=1.25), compared to 1.68 seconds (SE=0.18) for participants without motor impairments, which were 2 times faster. Since the distribution of production times for participants with motor impairments was not normal (Shapiro-Wilk's W=0.726, p=.002, skewness γ_1=1.032, kurtosis β_2=2.436) and heteroscedasticity was present (Levene's $F_{(1,18)}$=22.975, p<.001), we employed the Brunner-Munzel heteroscedastic analog of the Wilcoxon-Mann-Whitney test, which showed a marginally-significant effect of motor impairment on gesture production times ($W^{BF}_{(17.227)}$=2.055, p=.055). To find out more, we looked at the performance of each participant individually (Figure 4), which highlighted two distinct sub-groups: one sub-group (P_1-P_6, P_{10}) performed on par with participants without impairments (P_{11}-P_{20}), while the second sub-group (P_7-P_9) seemed to have struggled considerably more. Looking at the video footage of the experiment, we found that participants of the first sub-group (tetraplegia caused by spinal cord injury) employed the knuckle of the little finger (P_1, P_4) or the middle finger (P_3), the thumb (P_2, P_6), and even the index finger with the help of a hand strap (P_5) as gesture implementers, which resulted in fast articulations controlled by shoulder-elbow movements. Participants from the second sub-group (spastic tetraparesis) experienced involuntary contractions of the arm muscles, which affected their ability to produce steady input. As a form of coping strategy with the gesture input task, participants of the second sub-group deliberately took more time to draw the gestures.

Under these considerations, we re-ran our analysis with a 3×5 mixed design with MOTOR-IMPAIRMENTS as the between variable (3 groups) and GESTURE as the within variable (5 conditions). To deal with the non-normality and heteroscedasticity in the data, we employed a

Predictor	Without motor impairments (N=10 participants)					With motor impairments (N=10 participants)				
	Ground truth (s)	Predicted (s)	Absolute error (s)	Relative error	*t*-test	Ground truth (s)	Predicted (s)	Absolute error (s)	Relative error	*t*-test
Mean	1.80†	1.90	0.20	11.7%	$t_{(4)}$=-3.96, p=.017, r=1.00	**3.98†**	**3.83**	**0.15**	**3.7%**	**$t_{(4)}$=1.49, p=.212, r=1.00**
Median	**1.80†**	**1.77**	**0.07**	**4.1%**	**$t_{(4)}$=0.39, p=.717, r=.70**	3.98†	2.20	1.78	44.8%	$t_{(4)}$=8.37, p=.001, r=0.90
20%-trimmed mean	1.80†	1.83	0.13	7.6%	$t_{(4)}$=-1.18, p=.302, r=1.00	3.98†	2.68	1.30	32.5%	$t_{(4)}$=8.20, p=.001, r=1.00
20%-Winsorized mean	1.80†	1.86	0.16	9.4%	$t_{(4)}$=-1.63, p=.179, r=1.00	3.98†	3.55	0.43	10.7%	$t_{(4)}$=3.70, p=.021, r=1.00

Table 2: Prediction accuracy results for gesture production times. The most accurate predictor is highlighted in bold. † The mean times reported in this table are slightly different than those reported previously, because 35 gestures could not be reliably modeled as log-normal velocity profiles and, thus, had to be removed from this analysis.

robust method for comparing 20%-trimmed means for between-within designs; see Wilcox [30, p. 548]. Results showed a significant main effect of MOTOR-IMPAIRMENTS ($F_{(2,8.24)}$=20.293, p<.001) and GESTURE type ($F_{(4,8.60)}$=20.424, p<.001) on production time. We also found a significant interaction between the MOTOR-IMPAIRMENTS group and GESTURE type ($F_{(8,9.16)}$=4.302, p=.021): while the average production times of participants without impairments followed a descending trend from "energy" to "Euro", "heart," and letters "pi" and "X," the production times of participants with motor impairments increased from letter "X" to "energy", "Euro", "heart," and Greek letter "pi." These preliminary results show that different types of motor impairments (and coping strategies) impact gesture production differently, and distinct user sub-groups may be identifiable based on their motor abilities to produce stroke gestures. Our results recommend more investigation on larger samples of participants.

Predicting Production Times for Gestures Produced by Users with Motor Impairments

Data collection from users with motor impairments is laborious, takes time, and missing data are likely to occur, just like in our experiment. Such challenges hinder the repeated evaluation of UI prototypes or simply collecting enough data to inform gesture set design, such as to devise gesture shortcuts that are fast [2,32] or that are perceived easy to produce [20,25]. A lucrative alternative would be to use predictive models of human performance to inform design. In the following, we apply the principles and tools of the Kinematic Theory [18,19] to model the stroke gestures articulated by users with motor impairments as log-normal velocity profiles of the finger moving on the touchscreen. Then, we use the GATO technique [13] to compute time predictions for the gestures collected in our dataset.

We followed the same evaluation approach as Leiva et al. [12,13] to compute user-independent predictions of gesture production times with the following four predictors: (1) the mean production time (t_M); (2) the

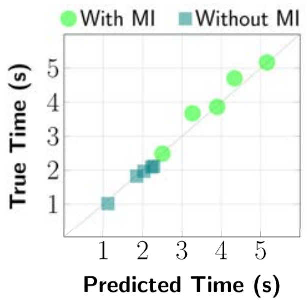

Figure 6: Predicted time (t_M) versus actual production time for each gesture type (the "energy" symbol, the "Euro" symbol, heart, Greek letter "pi", and letter "X") for participants with and without motor impairments. The closest the data points are to the diagonal, the more accurate the time predictions are.

median (t_{Mdn}); (3) the 20%-trimmed mean ($t_{.20}$); and (4) the 20%-Winsorized mean (t_W). We refer to Leiva et al. [12,13] for the mathematical formulae of these predictors as well as for the details of the user-independent evaluation methodology used to assess their estimation accuracy.

Prediction results are illustrated in Figure 6: the closer the data points to the diagonal, the more accurate the predictions. We found that the mean production time (t_M) delivered the highest accuracy for participants with motor impairments, with an absolute error of just |3.98-3.83|=0.15 s and a relative error of only |3.98-3.83|/3.98=3.7% with respect to actual times. A paired *t*-test between predicted and actual times revealed no significant differences between the two conditions; see Table 2 on the previous page. These results show that *a priori* user-independent estimation of human performance is reliable for stroke gestures articulated by people with motor impairments, which opens opportunities for practitioners to inform gesture set design, e.g., explorations towards identifying easy-to-produce gesture types [20,25], from just a few samples [12,13], without the need to dedicate considerable time and effort to run large data collection procedures.

Conclusion

We evaluated the performance of stroke gesture input for users with motor impairments, and we reported production times that were twice as long compared to users without impairments. We showed that predictions of stroke gesture production times can be computed accurately for gestures articulated by users with upper body motor impairments to be used by practitioners in the early design phases of their user interface prototypes. Future work will expand on such practical options to inform gesture set design [2,20,25]. Our empirical results also suggest that stroke gesture input on mobile touchscreens devices may be viable for people with motor impairments.

Acknowledgment

This work was supported by PN-III-P2-2.1-PED-2016-0688 (209PED/2017) financed by UEFISCDI, Romania.

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 *Proc. of CHI '13*. ACM, 1223-1232. https://doi.org/10.1145/2470654.2466158
2. Caroline Appert and Shumin Zhai. 2009. Using strokes as command shortcuts: cognitive benefits and toolkit support. In *Proc. of CHI '09*. ACM, New York, NY, USA, 2289-2298. https://doi.org/10.1145/1518701.1519052
3. Xiang Cao and Shumin Zhai. 2007. Modeling human performance of pen stroke gestures. In *Proc. of CHI '07*. ACM, 1495-1504. https://doi.org/10.1145/1240624.1240850
4. 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 *Proc. of CHI '17*. ACM, 6056-6061. https://doi.org/10.1145/3025453.3025603
5. Niels Henze, Enrico Rukzio, and Susanne Boll. 2011. 100,000,000 taps: analysis and improvement of touch performance in the large. In *Proc. of MobileHCI '11*. ACM, 133-142. https://doi.org/10.1145/2037373.2037395
6. Poika Isokoski. 2001. Model for unistroke writing time. In *Proc. of CHI '01*. ACM, New York, NY, 357-364. http://dx.doi.org/10.1145/365024.365299

7. Masatomo Kobayashi, Atsushi Hiyama, Takahiro Miura, Chieko Asakawa, Michitaka Hirose, and Tohru Ifukube. 2011. Elderly user evaluation of mobile touchscreen interactions. In *Proc. of the 13th IFIP TC 13 Int. Conf. on Human-computer interaction (INTERACT'11).* Springer-Verlag, 83-99. https://doi.org/10.1007/978-3-642-23774-4_9
8. Seungyon Lee and Shumin Zhai. 2009. The performance of touch screen soft buttons. In *Proc. of the SIGCHI Conf. on Human Factors in Computing Systems (CHI '09)*. ACM, New York, NY, USA, 309-318. https://doi.org/10.1145/1518701.1518750
9. Luis A. Leiva, Daniel Martín-Albo, and Réjean Plamondon. 2015. Gestures à Go Go: Authoring Synthetic Human-Like Stroke Gestures Using the Kinematic Theory of Rapid Movements. *ACM Trans. Intell. Syst. Technol. 7*, 2, Article 15 (Nov. 2015), 29 pages. https://doi.org/10.1145/2799648
10. Luis A. Leiva, Daniel Martín-Albo, and Réjean Plamondon. 2017. The Kinematic Theory produces human-like stroke gestures. *Int. with Comp. 29*(4), 552-565. https://doi.org/10.1093/iwc/iww039
11. Luis A. Leiva, Daniel Martín-Albo, and Radu-Daniel Vatavu. 2017. Synthesizing Stroke Gestures Across User Populations: A Case for Users with Visual Impairments. In *Proc. of the 2017 CHI Conf. on Human Factors in Computing Systems (CHI '17)*. https://doi.org/10.1145/3025453.3025906
12. Luis A. Leiva, Daniel Martín-Albo, Réjean Plamondon, and Radu-Daniel Vatavu. 2018. KeyTime: Super-Accurate Prediction of Stroke Gesture Production Times. In *Proc. of the 2018 CHI Conference on Human Factors in Computing Systems (CHI '18)*. ACM, New York, NY, USA, Paper 239, 12 pages. https://doi.org/10.1145/3173574.3173813
13. Luis A. Leiva, Daniel Martín-Albo, and Radu-Daniel Vatavu. 2018. GATO: Predicting Human Performance with Multistroke and Multitouch Gesture Input. In *Proc. of the MobileHCI '18, the 20th Int. Conf. on Human-Computer Interaction with Mobile Devices and Services.* ACM, New York, NY, USA. https://doi.org/10.1145/3229434.3229478
14. Hao Lü and Yang Li. 2012. Gesture coder: a tool for programming multi-touch gestures by demonstration. In *Proc. of the SIGCHI Conf. on Human Factors in Computing Systems (CHI '12)*, 2875-2884. http://dx.doi.org/10.1145/2207676.2208693
15. Kyle Montague, Hugo Nicolau, and Vicki L. Hanson. 2014. Motor-impaired touchscreen interactions in the wild. In *Proc. of the 16th Int. ACM SIGACCESS Conference on Computers & Accessibility (ASSETS '14)*. ACM, New York, NY, USA, 123-130. http://dx.doi.org/10.1145/2661334.2661362
16. 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 *Proc. of the 2016 Conf. on Human Factors in Computing Systems (CHI '16)*. ACM, 1934-1946. https://doi.org/10.1145/2858036.2858390
17. Martez E. Mott, Jane E., Cynthia L. Bennett, Edward Cutrell, and Meredith Ringel Morris. 2018. Understanding the Accessibility of Smartphone Photography for People with Motor Impairments. In *Proc. of the 2018 CHI Conf. on Human Factors in Computing Systems (CHI '18)*. ACM, New York, NY, USA https://doi.org/10.1145/3173574.3174094
18. Réjean Plamondon. 1995a. A kinematic theory of rapid human movements. Part I: Movement representation and control. *Biol. Cybern. 72*(4),

295-307. https://doi.org/10.1007/BF00202785

19. Réjean Plamondon. 1995b. A kinematic theory of rapid human movements. Part II: Movement time and control. *Biol. Cybern. 72*(4). https://doi.org/10.1007/BF00202786
20. Yosra Rekik, Radu-Daniel Vatavu, and Laurent Grisoni. 2014. Understanding Users' Perceived Difficulty of Multi-Touch Gesture Articulation. In *Proc. of the 16th Int. Conf. on Multimodal Interaction (ICMI '14)*. https://doi.org/10.1145/2663204.2663273
21. Quentin Roy, Sylvain Malacria, Yves Guiard, Eric Lecolinet, and James Eagan. 2013. Augmented letters: mnemonic gesture-based shortcuts. In *Proc. of CHI '13*. ACM, 2325-2328. https://doi.org/10.1145/2470654.2481321
22. Ovidiu-Ciprian Ungurean, Radu-Daniel Vatavu, Luis A. Leiva, Réjean Plamondon. (2018). Gesture Input for Users with Motor Impairments on Touchscreens: Empirical Results based on the Kinematic Theory. In *Proc. of CHI EA '18*. https://doi.org/10.1145/3170427.3188619
23. Radu-Daniel Vatavu, Lisa Anthony, and Jacob O. Wobbrock. 2013. Relative accuracy measures for stroke gestures. In *Proc. of ICMI '13,* 279-286. https://doi.org/10.1145/2522848.2522875
24. Radu-Daniel Vatavu, Lisa Anthony, and Jacob O. Wobbrock. 2014. Gesture Heatmaps: Understanding Gesture Performance with Colorful Visualizations. In *Proc. of ICMI '14*. ACM, 172-179. https://doi.org/10.1145/2663204.2663256
25. Radu-Daniel Vatavu, Daniel Vogel, Géry Casiez, and Laurent Grisoni. 2011. Estimating the perceived difficulty of pen gestures. *In Proc. of INTERACT'11).* Springer, 89-106. https://doi.org/10.1007/978-3-642-23771-3_9
26. Radu-Daniel Vatavu. 2017. Improving Gesture Recognition Accuracy on Touch Screens for Users with Low Vision. In *Proc. of CHI '17*. ACM, New York, NY, USA, 4667-4679. https://doi.org/10.1145/3025453.3025941
27. Radu-Daniel Vatavu, Gabriel Cramariuc, Doina Maria Schipor. (2015). Touch Interaction for Children Aged 3 to 6 Years: Experimental Findings and Relationship to Motor Skills. *Int. Journal of Human-Computer Studies 74*. Elsevier, 54-76. http://dx.doi.org/10.1016/j.ijhcs.2014.10.007
28. Radu-Daniel Vatavu, Lisa Anthony, Quincy Brown. (2015). Child or Adult? Inferring Smartphone Users' Age Group from Touch Measurements Alone. In *Proc. of INTERACT '15.* Springer. http://dx.doi.org/10.1007/978-3-319-22723-8_1
29. Radu-Daniel Vatavu, Lisa Anthony, and Jacob O. Wobbrock. 2012. Gestures as point clouds: a $P recognizer for user interface prototypes. In *Proc. of ICMI '12*. ACM, New York, NY, USA, 273-280. https://doi.org/10.1145/2388676.2388732
30. Rand Wilcox. 2012. Modern Statistics for the Social and Behavioral Sciences. Taylor & Francis Group, LLC, Boca Raton, FL, USA.
31. Jacob O. Wobbrock, Andrew D. Wilson, and Yang Li. 2007. Gestures without libraries, toolkits or training: a $1 recognizer for user interface prototypes. In *Proc. of UIST '07.* https://doi.org/10.1145/1294211.1294238
32. Shumin Zhai, Per Kristensson, Caroline Appert, Tue Andersen, and Xiang Cao. 2012. Foundational Issues in Touch-Surface Stroke Gesture Design: An Integrative Review. *Foundations and Trends in Human-Computer Interaction 5, 2* (Feb. 2012), 97-205. http://dx.doi.org/10.1561/1100000012