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The Effect of Attention Saturating Task on Eyes-Free Gesture Production on Mobile Devices

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Touch screens are popular input methods for mobile devices, but they compete for visual attention with users' real-world tasks, leading to performance hindrances. In this study, we investigated the effect of an attention-saturating task on eyes-free gestures. A user study was conducted with 13 participants who performed eyes-free gestures on a smartphone using their dominant or non-dominant hand, alone or while performing a primary task that saturates attention. The results indicated that performing another task while drawing a gesture shortened the length and size of the gesture, reduced the duration of gesture entry, while the finger maintained the same speed across the touchscreen. Additionally, drawing a gesture with the nondominant hand increased the length of the gesture but generated less directional movements around the z-axis.

CCS Concepts: • **Human-centered computing** → **Touch screens**.

Additional Key Words and Phrases: Eyes-free gestures, attention saturating task, gestures features, phone movements, mobile device

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1 INTRODUCTION

Touch screens are rapidly growing in popularity as a means of input for smart phones and other mobile devices. Direct-touch interaction on mobile phones revolves around screens that compete for visual attention with users' real-world tasks and activities, including situations where interaction complements another task that either needs full attention (*e.g.*, driving) or is cognitively demanding (*e.g.*, receiving a notification when typing a text). This increase in the cognitive load of the user has been shown to hinder the performance of touch interactions [15]. In the literature, these types of temporary reductions in user performance due to context are referred to as situationally induced impairments and disabilities (SIIDs) [18]. The term situationally-induced impairments (also known as situational impairments) was first introduced by Sears [16], to establish the relationship between the user, the nature of tasks that the user is engaged in, the surrounding environment where the task is performed, and the design of technology used to complete the task. Multitasking has been considered an effective way of fragmenting attentional or cognitive resources when interacting with touchscreens.

In these scenarios, people often choose to use their mobile device without eyes on the screen, with one hand without lowering their head to the screen, due to varying environmental, social, device-specific, and personal factors (*e.g.*, extreme lighting conditions, being in a meeting, tiny screen, self-enthusiasm) [11]. In such scenarios, the thumb of the hand holding the device is normally the only finger available for touch input [4]. However, mainly due to the biomechanical limitations of the thumb, only a subregion of the touch screen is comfortable to access by the thumb [10],

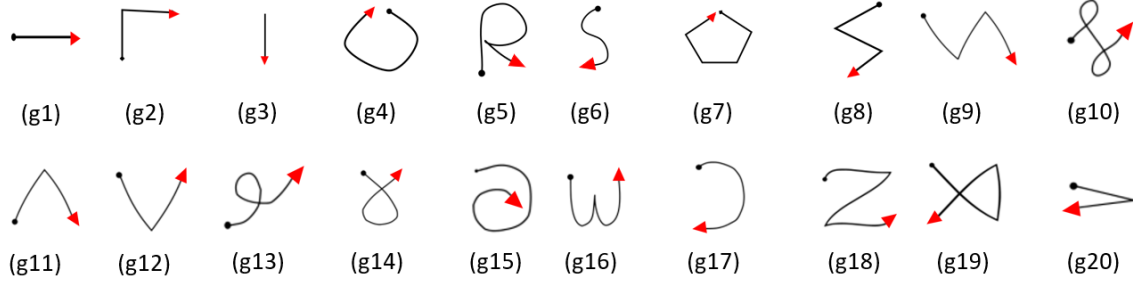


Fig. 1. Gesture set.

and gestures without eyes can provide a solution to these challenges. They can reduce attentional load [5], can be committed to muscle memory, helping users focus on their task [12], generally do not require dedicated screen space [5], and can be used in single-hand configuration.

In this work, we study the effect of an attention saturating task on eyes-free gestures production. We conducted a user study with 13 participants. Each participant performed eyes-free gestures on smartphone using their dominant or non-dominant hand, alone or while performing a primary task. Our results showed that drawing gestures while performing another task shortens the length and size of the gesture. On the other hand, drawing the gesture with the non-dominant hand increases the length and size of the gesture. We found that engaging in another task while drawing gesture decreases the duration of gesture entering, but the finger moves across the touchscreen with same speed.

2 EXPERIMENT

We conducted an experiment to evaluate the effect of an attention saturating task on eyes-free gesture articulation on a mobile device.

2.1 Participants and apparatus

13 right-handed participants (7 males and 6 females) volunteered to participate in our experiment. The ages of the participants ranged from 20 to 31 years ($mean = 24.3$, $sd = 3.5$). All participants had been using smartphones for several years. We collected stroke gestures using our custom software on a Samsung Galaxy S7 smartphone running Android 6.0.1. The smartphone screen size is 5.65"×2.78" with a display resolution of 1440×2560 pixels and a pixel density of 227 pixels per cm.

2.2 Design and gesture set

The set of gestures used in this study included 20 gestures. These gestures were selected from previous work (e.g., [2, 5, 19]) and were composed of operands, letters, mark segments, rationally invariant, and mnemonic gestures. All were simple to perform, distinct enough and can be drawn imprecisely [5] (see Figure 1).

The experiment used a 2×2 within-subject design with two factors: *activity* and *used hand*. *Activity* presents if the participant is doing the attention saturating task, i.e., *centering the ball (CB)* or just waiting for the notification that we name here the *control condition (Ctrl)*. The *used hand* presents the hand used for the secondary task (i.e., the used hand to hold the phone and draw the gesture without eyes) and covered two conditions: right hand (RH) and left hand (LH).

2.3 Task & Procedure

After participants comfortably sat at a desk with laptops, they completed a demographic questionnaire. Next, we explained the experiment and its requirements, including primary and secondary tasks. The participants then engaged in the experiment: performing a secondary laptop task and drawing eye-free gestures on a smartphone (primary task) upon laptop notifications. (see Figure 2). In the control condition, participants only had to wait for the notifications displayed on the laptop screen to perform the gaze-free gesture. The rationale for adding the control condition is to better understand the effect of the attention-saturating task on eyes-free gesture production.

For the primary task that saturates the attention, we followed [9] and used the same task that saturates the attention. Our attention-saturating task featured a circle that randomly moved according to a two-dimensional Perlin noise function. Participants were asked to keep the circle centered over a cross-hairs displayed in the center of the square as the best they could, and this by contracting its movement using the arrow keys of the laptop keyboard. The participants were told that keeping the circle centered on the crosshair was the most important task and that their performance was measured for both the primary and secondary task.

In the right-hand scenario, participants held the phone with their right hand, using their right thumb to draw gestures on the screen without looking. Similarly, in the left-hand scenario, they used their left hand. In both cases, the free hand was used to interact with the laptop during attention-saturating tasks. All gestures were single strokes; a new gesture appeared as soon as the finger left the screen. For corrections, participants could use the back button of the phone.

In the experiment phase, the two activity conditions were randomly presented to the participants. For each activity condition, the two hand conditions were also randomly presented. Each participant in total performed 400 gestures ($=2 \text{ activities} \times 2 \text{ hand} \times 20 \text{ gestures} \times 5 \text{ repetitions}$). For each activity condition and hand condition, the gestures were presented to the participant in random order. The experiment took 20 minutes on average to complete.

3 RESULTS

Our results include gesture features, smartphone directional movements, and questionnaire responses.

3.1 Gesture Features

We selected six geometric features: (a) gesture length, (b) gesture height, (c) gesture width, (d) gesture area, (e) gesture duration, and (f) gesture speed. These features have been employed in the literature on gesture recognition and analysis literature [1, 3, 14, 17] in order to characterize how users produce strokes.

The Shapiro-Wilk normality test was conducted to determine whether the six gesture features data are normally distributed. The results indicate that we must reject the null hypothesis for all six gesture features data ($p = 0.000$) and conclude that all gesture features data are not normally distributed. So, we used separate 2×2 (*activity* and *used hand*) ANOVAs with Aligned Rank Transforms for each main subjective measure - a test more appropriate for the Likert scale data than a standard ANOVA. Since the dependent variables did not meet the normality assumptions, repeated measures ANOVA with the Aligned Rank Transform (ART) was used for nonparametric factorial analysis. Tukey tests were used post hoc when significant effects were found. Only significant results are reported in the following.

3.1.1 Gesture length. Gesture length is the cumulative path distance from the first touch event registered to the last. We found a significant main effect of *activity* ($F_{1,12} = 41.135, p < 0.001$) and *used hand* ($F_{1,12} = 5.323, p = 0.040$) on *gesture length*. *Centering the ball condition* ($\text{mean} = 6.82\text{cm}, \text{sd} = 3.22\text{cm}$) led participants to enter gestures with shorter lengths than *the control condition* ($\text{mean} = 7.44\text{cm}, \text{sd} = 3.51\text{cm}$). The drawing gesture with the left hand

($mean = 7.47cm, sd = 3.50cm$) led the participants to enter gestures with lengths longer than the drawing gesture with the right hand ($mean = 6.79cm, sd = 3.23cm$).

3.1.2 Gesture height. Gesture height is the height of the bounding box that contains the gesture ($max_y - min_y$). We found a significant main effect of *activity* ($F_{1,12} = 34.327, p < 0.001$) on *gesture height*. *Centering the ball condition* ($mean = 2.40cm, sd = 1.02cm$) led participants to enter gestures with a shorter height than *the control condition* ($mean = 2.64cm, sd = 1.19cm$).

3.1.3 Gesture width. Gesture width is the width of the bounding box that contains the gesture ($max_x - min_x$). We found a significant main effect of *activity* ($F_{1,12} = 17.998, p = 0.001$) on *gesture width*. *Centering the ball condition* ($mean = 2.33cm, sd = 0.88cm$) led participants to enter gestures with smaller width than *the control condition* ($mean = 2.49cm, sd = 0.97cm$).

3.1.4 Gesture area. Gesture area is the surface area of the bounding box containing the gesture (height \times width). We found a significant main effect of *activity* ($F_{1,12} = 38.801, p < 0.001$) on *gesture area*. *Centering the ball condition* ($mean = 7.07cm^2, sd = 4.72cm^2$) led participants to enter gestures with smaller area than *the control condition* ($mean = 7.17cm, sd = 5.87cm$).

3.1.5 Gesture duration. Gesture duration is the time elapsed while entering the gesture, that is, the timestamp of the last touch event registered for the gesture minus the timestamp of the first touch event registered. We found a significant main effect of *activity* ($F_{1,12} = 7.422, p = 0.019$) on *gesture duration*. *Centering the ball condition* ($mean = 0.96seconds, sd = 0.65seconds$) led participants to enter gestures with duration shorter than *the control condition* ($mean = 1.05seconds, sd = 0.67seconds$).

3.1.6 Gesture speed. Gesture speed is the average speed recorded on all touch events belonging to a gesture (length/duration). We did not find any significant main effect of *activity* or *used hand* on gesture speed.

3.2 Mobile Directional Movement

Previous work showed that hand use and body posture affect smartphone movement as users' perception of the smartphone device could be boosted [8]. Therefore, it is important to understand how eye-free interaction may influence the tilt and rotation of the smartphone during gesture production. We then consider the same dependent variables as in [8] to characterize the phone's movement: Alpha (z axis), Beta (x axis), and Gamma (y axis) using the built-in accelerometer and gyroscope (see Figure 3). For each of the directional axes, we captured the total deviation made around this axis, calculated as the difference between the largest and the smallest value. Repeated measures ANOVA with the Aligned Rank Transform (ART) was used for nonparametric factorial analysis. Tukey tests were used post hoc when significant effects were found. Only significant results are reported below.

3.2.1 Alpha deviation – deviation around z axis. We found significant main effect of *used hand* ($F_{1,12} = 7.675, p = 0.017$) on *alpha deviation*. Using the right hand to manipulate the phone caused significantly more deviation in alpha ($mean = 5.14^\circ, sd = 4.71^\circ$) compared to using the left hand ($mean = 3.40^\circ, sd = 4.48^\circ$).

3.2.2 Beta deviation – deviation around x axis, and Gamma deviation – deviation around y axis. No significant main effect of *used hand* or *activity* was found on *beta deviation* ($mean = 5.83^\circ, sd = 4.84^\circ$) or *gamma deviation* ($mean = 2.83^\circ, sd = 2.84^\circ$).



Fig. 2. The setup used for the experiment. The smartphone was held under the table to maintain eyes-free condition.

3.3 Subjective results

Our participants were also asked to rate the task after each condition in terms of performance, temporal demand, physical demand, mental demand, frustration, effort. Table 1 shows the responses to the questionnaire. Friedman tests, followed by Conover post hoc analysis revealed that only physical demand, frustration, and effort were significantly

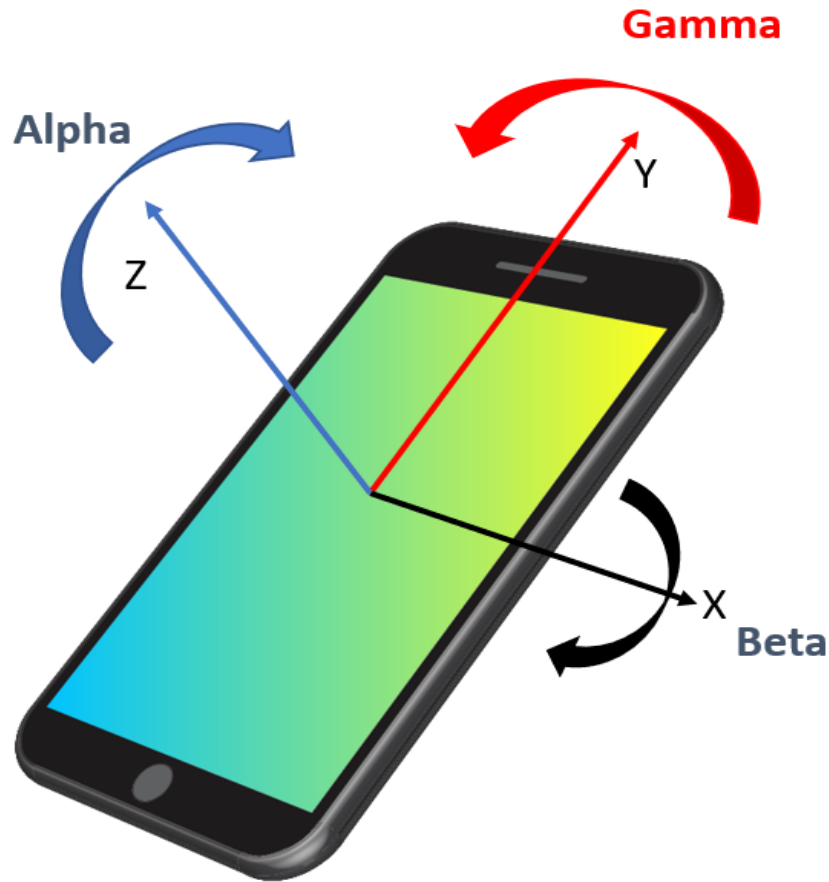


Fig. 3. Axes and orientations of the smartphone.

higher than three other conditions when the participant was performing two tasks simultaneously and holding the phone in the left hand ($p < 0.05$).

4 DISCUSSION AND NEXT STEPS

Our key finding is that the attention-saturating task had an impact on the geometric features of the eyes-free gesture, but not on the kinematic features. For example, when centering the ball, the gestures have shorter lengths and smaller height, width, and area than the control condition. It also led to gestures produced in a shorter time without compromising speed. It is important to note here that the speed was not affected as both gesture length and duration are reduced. We found no significant interaction ($p > .05$), suggesting that these findings are consistent across different hand conditions. Consequently, when performing an attention-saturating task while entering eyes-free gestures on mobile devices, recognizers that rely on geometric gesture descriptors, such as [14] (p. 335) should be used with caution.

	<i>RH+Ctrl</i>		<i>LH+Ctrl</i>		<i>RH+CB</i>		<i>LH+CB</i>		Friedman
	mean	sd	mean	sd	mean	sd	mean	sd	$\chi^2(3)$
Performance	6.15	1.81	6.23	1.59	6.61	2.02	6.53	1.76	4.18
Temporal demand	2.23	1.42	2.31	1.60	2.54	1.45	2.00	1.68	6.95
Physical demand	3.08	1.66	3.06	1.71	3.15	2.27	4.23	2.71	16.70
Mental demand	3.84	1.95	3.74	2.26	3.38	1.76	3.69	1.97	0.57
Frustration	2.69	1.55	3.54	1.66	3.23	2.17	5.46	2.54	21.70
Effort	4.30	2.25	4.38	2.06	3.92	2.78	5.46	2.10	16.01

Note: Friedman tests are reported at significance levels $p=.05$ (*) significance levels. The significant tests are highlighted.

Table 1. Mean and s.d Nasa TLX questionnaire responses, with 1=very low, and 10 = very high.

Our findings also indicate that the length of the gesture was affected by the hand used with the left hand, leading to longer gesture paths than when using the right hand, but generated less directional movements around z axis.

Our results indicate that, during attention-saturation tasks, using the left hand for eye-free gestures is more frustrating and physically demanding than the other three conditions. Thus, right-handed users should prioritize using their right hand for eye-free gestures on mobile devices when simultaneously tackling attention saturation.

Like any study, our study has limitations. For example, in our study, the participants were younger than the population average and were right-handed. Undoubtedly, older people, children, or left-handed participants would behave differently. Also, during the experiment, only one phone was used and tested for all participants independently of their hand sizes or OS preferences. Maybe other phone sizes or form factors may produce different results or observations. These issues are worthy of investigation, but are beyond the scope of the current work.

Future work will also consider more challenging scenarios where participants are encumbered (e.g., holding objects such as shopping bags [13]) or had to focus their attention on some other primary task that could be cognitively or/and visually demanding (e.g., writing a text [6, 9] or driving [7]). Finally, future work will investigate the effect of adding haptic feedback during eyes-free gesture production.

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REFERENCES

- [1] Lisa Anthony, Quincy Brown, Jaye Nias, and Berthel Tate. 2013. Examining the Need for Visual Feedback during Gesture Interaction on Mobile Touchscreen Devices for Kids. In *Proceedings of IDC'13* (New York, New York, USA). ACM, New York, NY, USA, 157–164.
- [2] Caroline Appert and Shumin Zhai. 2009. Using Strokes as Command Shortcuts: Cognitive Benefits and Toolkit Support. In *Proceedings of the SIGCHI Conference on Human Factors in Computing Systems* (Boston, MA, USA) (*CHI '09*). ACM, New York, NY, USA, 2289–2298.
- [3] Rachel Blagojevic, Samuel Hsiao-Heng Chang, and Beryl Plimmer. 2010. The Power of Automatic Feature Selection: Rubine on Steroids. In *Proceedings of the Seventh Sketch-Based Interfaces and Modeling Symposium* (Annecy, France). Eurographics Association, Goslar, DEU, 79–86.
- [4] Sebastian Boring, David Ledo, Xiang 'Anthony' Chen, Nicolai Marquardt, Anthony Tang, and Saul Greenberg. 2012. The Fat Thumb: Using the Thumb’s Contact Size for Single-Handed Mobile Interaction. In *Proceedings of MobileHCI'12* (San Francisco, California, USA). ACM, 207–208. <https://doi.org/10.1145/2371664.2371711>
- [5] Andrew Bragdon, Eugene Nelson, Yang Li, and Ken Hinckley. 2011. Experimental analysis of touch-screen gesture designs in mobile environments. In *Proceedings of the SIGCHI Conference on Human Factors in Computing Systems*. 403–412.
- [6] Qin Chen, Simon T. Perrault, Quentin Roy, and Lonce Wyse. [n. d.]. Effect of temporality, physical activity and cognitive load on spatiotemporal vibrotactile pattern recognition. In *Proceedings of AVI '18* (Castiglione della Pescaia, Grosseto, Italy, 2018). ACM, 1–9.

- [7] Andy Cockburn, Dion Woolley, Kien Tran Pham Thai, Don Clucas, Simon Hoermann, and Carl Gutwin. [n. d.]. Reducing the Attentional Demands of In-Vehicle Touchscreens with Stencil Overlays. In *Proceedings of AutomotiveUI '18* (Toronto, ON, Canada, 2018). ACM Press, 33–42.
- [8] Rachel Eardley, Anne Roudaut, Steve Gill, and Stephen J. Thompson. 2017. *Understanding Grip Shifts: How Form Factors Impact Hand Movements on Mobile Phones*. ACM, New York, NY, USA, 4680–4691.
- [9] Adnane Guettaf, Yosra Rekik, and Laurent Grisoni. 2021. Effect of Attention Saturating and Cognitive Load on Tactile Texture Recognition for Mobile Surface. In *Human-Computer Interaction – INTERACT 2021: 18th IFIP TC 13 International Conference, Bari, Italy, August 30 – September 3, 2021, Proceedings, Part IV* (Bari, Italy). Springer-Verlag, Berlin, Heidelberg, 557–579.
- [10] Amy K Karlson and Benjamin B Bederson. 2007. ThumbSpace: generalized one-handed input for touchscreen-based mobile devices. In *Proceedings of INTERACT 2007*. Springer, 324–338.
- [11] Taslim Arefin Khan, Dongwook Yoon, and Joanna McGrenere. 2020. Designing an Eyes-Reduced Document Skimming App for Situational Impairments. In *Proceedings of CHI'20* (Honolulu, HI, USA) (*CHI '20*). Association for Computing Machinery, New York, NY, USA, 1–14. <https://doi.org/10.1145/3313831.3376641>
- [12] Gordon Paul Kurtenbach. 1993. *The design and evaluation of marking menus*. Citeseer.
- [13] Alexander Ng, John Williamson, and Stephen Brewster. [n. d.]. The Effects of Encumbrance and Mobility on Touch-Based Gesture Interactions for Mobile Phones. In *Proceedings of the 17th International Conference on Human-Computer Interaction with Mobile Devices and Services - MobileHCI '15* (Copenhagen, Denmark, 2015). ACM, 536–546.
- [14] Dean Rubine. 1991. Specifying Gestures by Example. In *Proceedings of the 18th Annual Conference on Computer Graphics and Interactive Techniques (SIGGRAPH '91)*. ACM, New York, NY, USA, 329–337.
- [15] Bastian Schildbach and Enrico Rukzio. 2010. Investigating Selection and Reading Performance on a Mobile Phone While Walking. In *Proceedings of MobileHCI '10* (Lisbon, Portugal). ACM, New York, NY, USA, 93–102. <https://doi.org/10.1145/1851600.1851619>
- [16] Andrew Sears, Min Lin, Julie Jacko, and Yan Xiao. 2003. When computers fade: Pervasive computing and situationally-induced impairments and disabilities. In *HCI international*, Vol. 2. 1298–1302.
- [17] Radu-Daniel Vatavu, Daniel Vogel, Géry Casiez, and Laurent Grisoni. 2011. Estimating the Perceived Difficulty of Pen Gestures. In *Proceedings of INTERACT 2011*, Pedro Campos, Nicholas Graham, Joaquim Jorge, Nuno Nunes, Philippe Palanque, and Marco Winckler (Eds.). Springer Berlin Heidelberg, Berlin, Heidelberg, 89–106.
- [18] Jacob O Wobbrock, Shaun K Kane, Krzysztof Z Gajos, Susumu Harada, and Jon Froehlich. 2011. Ability-based design: Concept, principles and examples. *ACM Transactions on Accessible Computing (TACCESS)* 3, 3 (2011), 1–27.
- [19] Jacob O. Wobbrock, Andrew D. Wilson, and Yang Li. 2007. Gestures without Libraries, Toolkits or Training: A \$1 Recognizer for User Interface Prototypes. In *Proceedings of UIST '07* (Newport, Rhode Island, USA). ACM, New York, NY, USA, 159–168.

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