Typing on Split Keyboards with Peripheral Vision

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ABSTRACT

Split keyboards are widely used on hand-held touchscreen devices (e.g., tablets). However, typing on a split keyboard often requires eye movement and attention switching between two halves of the keyboard, which slows users down and increases fatigue. We explore *peripheral typing*, a superior typing mode in which a user focuses her visual attention on the output text and keeps the split keyboard in peripheral vision. Our investigation showed that peripheral typing reduced attention switching, enhanced user experience and increased overall performance (27 WPM, 28% faster) over the typical eyes-on typing mode. This typing mode can be well supported by accounting the typing behavior in statistical decoding. Based on our study results, we have designed *GlanceType*, a text entry system that supported both peripheral and eyes-on typing modes for real typing scenario. Our evaluation showed that peripheral typing not only well coexisted with the existing eyes-on typing, but also substantially improved the text entry performance. Overall, peripheral typing is a promising typing mode and supporting it would significantly improve the text entry performance on a split keyboard.

CCS CONCEPTS

• **Human-centered computing** → **Text input**; *Touch screens*; User studies;

KEYWORDS

Split keyboard; peripheral vision; gaze.

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1 INTRODUCTION

Split keyboards are specially designed to account for the form factor of tablet computers (e.g., Samsung Galaxy Tab, Apple iPad, and Microsoft Surface). It split the conventional QWERTY keyboard into two halves and positions them on the left and right of the touchscreen respectively. Users hold the device with two hands and type with both thumbs. Compared with regular keyboards, this allows for a steadier grip during walking, sitting or lying, saves precious screen real estate [17], and potentially improves typing performance due to two-thumb use [3, 12, 21, 24]. Despite these advantages, a split keyboard suffers from a weakness in the conventional eyes-on typing mode: users have to frequently switch visual focus back and forth between two keyboard halves. This not only causes eye/neck fatigue but also limits the typing speed [5, 16].

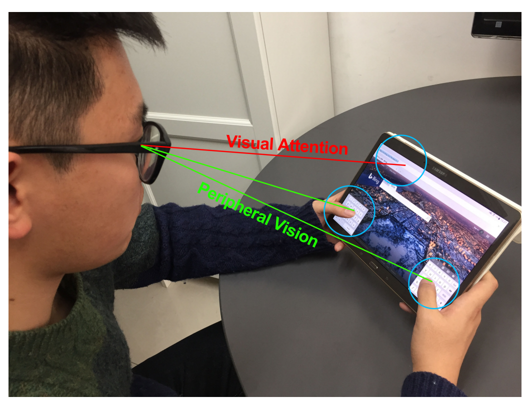

Figure 1: A user types with the split keyboard on a tablet computer. He needs to see three locations when typing (marked in blue circles): the text feedback (URL bar in this figure), and the left and right keyboard halves. When he is focusing on the field of text feedback, two split keyboard halves are located in his peripheral vision.

In this paper, we investigate typing with peripheral vision (*peripheral typing*), in which a user focuses her visual attention on the output text and keeps the keyboard in her peripheral vision (Figure 1). This mode does not require the user to switch visual attention frequently between different parts of the interface. Peripheral typing assumes users are familiar with two-thumb typing (e.g., on a smartphone) and can type with spatial and muscle memory when the keyboard is located in peripheral vision. Unlike touch typing [18] and invisible keyboard [39] that the keyboard feedback vanishes in typing process, a user still gains partial visual feedback of the keyboard when typing with peripheral vision, which contrasts and complements recent progress of text entry research. We believe interaction with peripheral vision is a promising paradigm where more and more interaction tasks [10, 27, 34] are competing for users' visual attention.

We follow an iterative approach to validate the feasibility of peripheral typing on a split keyboard. We first conduct a Wizard-of-Oz experiment to collect touch data and compare it with two baseline modes: eyes-on and no-keyboard. Results show peripheral vision can indeed provide a certain degree of visual feedback for controlling thumb tapping. The touch accuracy of peripheral typing is lower than eyes-on but significantly higher than no-keyboard setting. We then combine the derived touch model and a unigram word-level language model to develop an input decoder. Both simulation and real-user studies show that the decoding is effective. When entering in-vocabulary words, peripheral typing (27 WPM) improves the input speed by 28% over the typical eyes-on typing (21 WPM). It also reduces the attention switching and increases user satisfaction.

To support real use that involves typing out-of-vocabulary words (e.g., uncommon names or addresses), we further propose a new design of text entry interface that features two candidate lists: one beneath the output text associated with peripheral typing and the other above the keyboard halves associated with the default split keyboard output. With this design, users can spontaneously choose between peripheral typing and eyes-on typing with no explicit mode switching operation. This design allows peripheral typing to be easily incorporated with the current typing approach (e.g., the commercial keyboard) with little conflict. We also evaluate our prototype - *GlanceType* in a real corpus with out-of-vocabulary words and non-alphabetic characters. Results show that *GlanceType* increase the input speed by 7.0% compared with the commercial keyboard.

Our major contributions are two-folded. First, we have studied an unexplored typing mode - peripheral typing. Our investigation showed that it was not only feasible but also promising and even superior over the typical eyes-on typing. The reasons are 1) users can to a degree control thumb tapping with peripheral vision; and 2) accounting for the peripheral typing behavior in statistical decoding is effective in resolving the noise generated in this typing mode. Second, we have designed a two-candidate-region mechanism supporting spontaneously choosing between eyes-on and peripheral typing with no need for an explicit mode switch. We have incorporated this mechanism into a text entry system called *GlanceType*. A user study showed that *GlanceType* improved the performance over a commercial split keyboard.

2 RELATED WORK

Our work is related to text input, split keyboard and peripheral vision. To our knowledge, no work has been done to investigate the effect of peripheral vision in text input task.

Typing on QWERTY Layout with Visual Constrains

Touch typing, that the user performs ten-finger typing without looking at the physical keyboard, is a well-known solution to input text efficiently in desktop PC scenario. After long-term training, touch typing speeds of everyday typists can achieve 34-79 WPM [8]. The typing performance of blind people [22] or able-bodied people in blind environments (e.g., virtual reality) [35] has also been researched. As the QWERTY keyboard layout has been implemented in most touchscreen devices like smartphones, smart tabletops, tablets, etc., many works have tried to bring the touch typing from the physical keyboard to the soft keyboard.

Typing with ten fingers on touchscreens has been extensively studied. When typing on a tabletop touchscreen surface [9], touch points without the visual keyboard were relatively noisier than that with the visual keyboard. Splitting and rotating the whole keyboard on the back of the tablet with the finger-to-key assignment remaining enables ten-finger typing when gripping the tablet. Both the physical version (RearType [26]) and the virtual version (Sandwich Keyboard [25]) of the keyboard have been proposed.

In order to type on a small keyboard (e.g., smartphones), thumb-based typing postures, including one thumb and two thumbs, are generally used. Previous works have found it possible for keyboard users to use thumbs to type eyes-freely on mini physical keyboards [6] or soft keyboards [18, 33]. Users are also able to type on an invisible keyboard [39] with the speed close to that on a visible keyboard. That is, the users possess the ability to seek keys with thumbs in limited visual condition when they were well trained on the keyboard layout (so-called spatial memory and muscle memory). Peripheral vision, one kind of important visual influences, is worth to be explored in this area.

Improving Split Keyboards

To our knowledge, only two works have been done to improve the performance of split keyboards. In both these works, typing on split keyboards follows an eyes-on mode where users need to frequently switch visual attention among the text feedback and the two keyboard halves.

A new split keyboard layout - KALQ was designed to improve two-thumb text entry on tablet devices [23]. The layout of keys on both sides of the keyboard was rearranged and optimized. Input speed of this keyboard can achieve 37 WPM with only 5% error rate after weeks of training. However, the new keyboard layout would be a barrier to new users, preventing immediate and efficient use.

Bimanual gesture keyboard [5] was proposed to enable two-thumb gesture input on the split keyboard. This work designed two methods for gesture interaction and a multi-stroke gesture recognition algorithm. The typing speed of bimanual gesture keyboard achieved 30 WPM, a little lower than unimanual gesture keyboard.

New keyboard layouts or typing methods may sacrifice learnability for higher input speed. On the contrary, peripheral typing balances this trade-off, allowing users to type faster in the original way and the familiar layout with the only requirement of focusing on the text field.

Input and Output with Peripheral Vision

Peripheral vision is a part of vision that occurs outside the very center of gaze [36]. The visual field 4° away from direct gaze is called peripheral vision [29], while the combined visual field of a pair of human eyes can be up to 130-135° vertical and 200-220° horizontal [7]. Visual acuity declines by about 50% every 2.5° from the center up to 30°, then it declines more steeply [4]. Humans are weak in distinguishing details, colors, and shapes with peripheral vision [28].

Peripheral vision was considered as the feedback to help users complete some input tasks in previous researches, like rotating a knob [34], pressing tactile buttons on a keypad [27], and pointing indirectly on a touchpad [10]. Results consistently showed the performance with peripheral visual feedback is worse than that with direct visual feedback, and is better than that without visual feedback. These results indicate that peripheral vision can be well employed to enhance input tasks compared with the totally eyes-free condition. We expect the split keyboard in peripheral vision would be positive visual feedback to help users for typing tasks.

Some researches studied visual output issues in human's peripheral vision. The research about motion processing [31] pointed out that users' reaction time of the motion increased when the target velocity declined in users' peripheral vision. Two researches [14, 19] pointed out that the motion was a very strong stimulus to improve the perception in peripheral vision, while other stimuli (e.g., color, luminance, shape) were not easy to perceive. We expect users' moving thumbs tapping on the keyboard would be also helpful to the perception of the keyboard and key positions.

3 STUDY 1: TOUCH MODEL WITH PERIPHERAL VISION

The goal of this study is to collect the touch data of peripheral typing on the split keyboard for analysis and understanding. We expected the data would provide support for the feasibility of two-thumb typing with peripheral vision, and provide insights of different typing modes.

Participants

We recruited 18 participants (15 males and 3 females, aged 18-25) from the university campus. They were all right-handed and had daily experience of typing on QWERTY keyboards on their personal mobile phones. All of them had experience with tablets. All of them focused their attention on the keyboard when typing on tablets before.

Apparatus and Experiment Platform

We used Samsung Galaxy Tab SM-T800 tablet as the device. The touchscreen dimensions were 228mm×142mm with a resolution of 2560×1600. The weight was 465g. We developed an Android application as the software of our experiment platform. The interface was designed in landscape mode and consisted of two main components: the split keyboard and the text field (Figure 2).

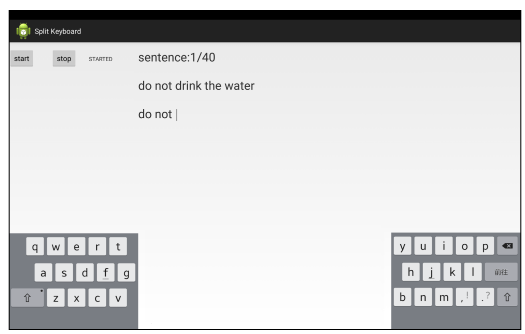

Figure 2: Experiment interface on the tablet.

The split keyboard was rendered using a screenshot of the commercial landscape split keyboard on Samsung tablet. The effective size of one key was 9.25mm×11.50mm. The two halves of the split keyboard were located at the bottom left and right corner of the touchscreen respectively, which is the default setting of the tablet. The placement of the split keyboard was confirmed by participants as a comfortable setting so it was easy for participants to tap on the keyboard while gripping the tablet.

The text field was placed at the top middle part of the tablet. It contained a sample sentence and an editing bar. Participants were required to type the sample sentence in the editing bar. Sentences consisted of lowercase letters and spaces. We also designed a right swipe gesture to substitute the space key, and a left swipe gesture to substitute the backspace key, with the aim to distinguish them with letter-tapping. After finishing the current sentence, a right swipe would lead to the next sentence.

Similar to previous works [3, 9, 11, 39], we designed a Wizard-of-Oz experiment to mimic a real typing scenario. In this way, the interface always displayed the correct character no matter where the participant tapped on the touchscreen [18]. An asterisk would appear when the platform detected a mismatch of a letter and space, and participants were required to correct it. Participants were notified the output text was rigged. For the purpose of collecting more realistic typing data, we informed participants to imagine that the keyboard algorithm would be intelligent enough to perfectly comprehend their input.

Experiment Design

During the experiment, we set the distance between the text field and the split keyboard to be 8-18cm, and the distance between the tablet and the user's eyes to be 35-50cm. The corresponding visual angle between the text field and the split keyboard is 9.1-28.8°, which falls into a human's near peripheral vision [36]. Participants reported they were not able to avoid catching a glimpse of the keyboard in typing when focusing on the text field.

As the goal of the experiment is to collect participants' typing data with and without gazing at the keyboard, we also controlled the keyboard visibility as a factor to test the effect of peripheral vision. We designed a within-subject experiment with *mode* being the only factor, each participant was required to type in all the three modes:

Eyes-on: In this mode, we ask users to look at the desired key when tapping it, which means the gaze needs to switch between the text feedback field and the two keyboard halves. This is the typical way when typing on split keyboards in daily lives.

Peripheral: In this mode, the keyboard is visible, but users were required not to look at it directly. That is, participants only stare at the text field during typing, while the keyboard is visible in their peripheral vision. In this mode, users type on split keyboards without attention switching.

No-Keyboard: In this mode, the keyboard is completely invisible, so that users only look at the text field and rely on their spatial and muscle memory to input text.

Peripheral and *No-keyboard* are both gaze-fixed modes where participants are required to type without gazing at the keyboard or their thumbs. In these two modes, participants partially leverage their familiarity with the QWERTY layout to input. We did not control the visual angle of the keyboard in participants' peripheral vision, but we recorded videos to monitor participants' eyeballs to ensure they did not gaze at the keyboard.

Procedure

We first introduced the goal of this experiment to participants. Before the experiment, participants were required to familiarize themselves with typing in the three modes. We did not stipulate participants' ways of gripping the tablet as long as their thumbs could tap on the split keyboard comfortably. According to the expertise of two-thumb typing on QWERTY keyboard, this warm-up phase took 3-5 minutes.

The experiment consisted of three sessions, with each session corresponding to one mode. The order of the three modes was counterbalanced. In each session, the participant was required to type 40 phrases randomly chosen from the MacKenzie and Soukoreff phrases set [20]. We told the participants to type as naturally as possible, and correct errors if they were aware of. We recommended the participants to take a break between two sessions. In total, the experiment for each participant took about 25-35 minutes.

Results

Across all participants, we collected 16,992, 17,161 and 16,997 touch points from transcribed typing data in *Eyes-on*, *Peripheral* and *No-keyboard* modes, respectively. Touch points which were more than three times standard deviation away from the observed key centroid in either X or Y dimension were regarded as outliers and removed. Outliers accounted for 2.65%, 2.02% and 2.09% of letter-point pairs in our data for three modes, respectively. We also checked the videos to confirm all participants followed our requirements for gaze.

Table 1: The mean standard deviation and offset (mm) of touch point distributions of keys.

		Eyes-on	*Peripheral*	*No-keyboard*
Standard Deviation	**X**	1.24±0.34	2.81±0.90	3.62±1.37
	Y	1.05±0.29	1.96±0.53	3.18±1.14
Offset	**X**	-0.08±0.50	0.68±2.56	-0.29±2.33
	Y	1.18±0.60	-1.46±1.65	-8.30±1.36

The standard deviation of the touch point distribution upon a key reflects how precise users' touches on the key are. The mean standard deviation across all keys is given in Table 1. RM-ANOVA found a significant effect of typing modes on the mean standard deviation on X-axis ($F_{2,34} = 118$, $p < .0001$) and Y-axis ($F_{2,34} = 147$, $p < .0001$). Post hoc analysis showed that two gaze-fixed typing modes were significantly noisier than *Eyes-on* mode on both X- and Y-axes, which caused the difficulty of interpreting participants' target keys. We also found the visibility of keyboard in participants' peripheral vision influenced their typing behavior. Post hoc analysis found a significant difference between the mean standard deviations of *Peripheral* and *No-keyboard* on

X-axis ($F_{1,17} = 25.0$, $p < .0001$) and Y-axis ($F_{1,17} = 70.7$, $p < .0001$). Figure 3 showed the collected touch point in different typing modes, where a remarkable difference in the size of spread can be observed.

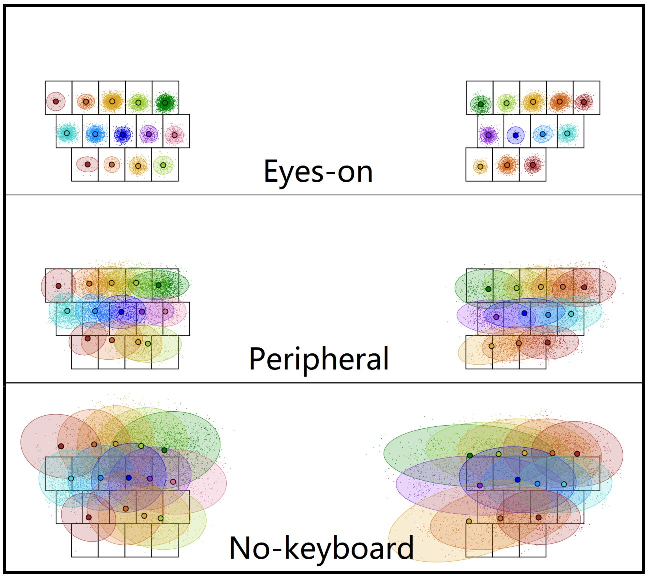

Figure 3: Collected touch points across all participants in three modes. The ellipse covers 90% of touch points corresponding to an individual key.

The offset between the centroid of the observed distribution and the actual centroid of a key reflects whether there is a tendency of performing biased tapping for participants. The mean offset of keys is given in Table 1. Results showed participants tended to tap a little below (positive offset) the key centroid in *Eyes-on* mode, a little above (negative offset) the key centroid in *Peripheral* mode, and far above the key centroid in *No-keyboard* mode (Figure 3).

Discussion

As expected, touch points in *Peripheral* mode appeared to be more accurate than *No-keyboard* mode. This can be explained by the positive effect of peripheral vision. Associated with peripheral vision, there is an actual frame reference for participants to position their thumbs around the desired key. While in *No-keyboard* mode, there was no reference so that participants would tap more sloppily.

The result on touch offsets showed that the visible keyboard effectively constrained participants' tapping within the keyboard, while without the visual feedback participants tended to tap away from the original location of the keyboard. That indicates peripheral vision in the typing task indeed helped the participant to limit her thumbs around the approximate location of the split keyboard.

4 ALGORITHM AND PERFORMANCE SIMULATION

Before conducting an evaluation with real techniques, we first conducted a simulation to provide a preview of the input prediction performance in each mode of study 1. In this section, we introduce our decoding algorithm of predicting the target word from the user's touch points and report the simulation results.

Decoding Algorithm

We used a unigram Bayesian algorithm based on Goodman et al.'s method [13], with which given tap location sequences $I = \{(x_i, y_i)\}_{i=1}^{n}$ we can compute the posterior probability of a word $w = w_1 w_2 \ldots w_n$ in the corpus as follows [12, 18]:

$$p(w|I) = p(w) * p(I|w)/p(I) = p(w) * \prod_{i=1}^{n} p(I_i|w_i)$$

where $p(w)$ represents the possibility of occurrence of w, and $p(I)$ is regarded as a constant and ignored. We used two Gaussian distributions [3, 18, 38] for X and Y axes to model one key and compute the probability of one tap as follows:

$$p(I_i|w_i) = p(x_i|X_{w_i}) * p(y_i|Y_{w_i})$$

where X_{w_i} and Y_{w_i} follow the Gaussian distributions of key w_i. For each typing mode, the mean and standard deviation of the Gaussian distribution of each key in touch model can be derived from our collected data in study 1.

Simulation Result

We used the top 10,000 words with the corresponding frequencies from ANC [1] as our corpus. We performed leave-one-out cross-validation for the three modes, respectively, and computed the prediction accuracy. In each iteration, we trained parameters of the touch model using the data of 17 participants and tested it on the data from the remaining participant. Finally, we averaged the accuracy. We reported top-1, top-5 and top-25 accuracy as the result, where top-K means the target word is within first K candidates ranked by the algorithm according to the probability.

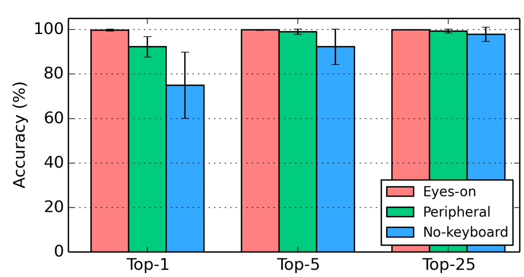

Figure 4: Top-1, top-5 and top-25 accuracy of three modes. Error bars represent standard deviations.

Top-1 accuracy indicates the algorithm recommends exactly the target word after participants finish their taps. Top-1 accuracy in *Eyes-on*, *Peripheral* and *No-keyboard* modes was 99.7%, 92.3% and 75.0%, respectively (Figure 4). RM-ANOVA showed a significant difference between modes ($F_{2,34} = 41.5$, $p < .0001$). Post hoc analysis showed *Peripheral* mode significantly outperformed *No-keyboard* mode ($F_{1,17} = 30.5$, $p < .0001$) but was significantly worse than *Eyes-on* mode ($F_{1,17} = 45.4$, $p < .0001$).

Top-5 and top-25 accuracy emerged similarly as top-1 accuracy, *Eyes-on* mode was the best and *No-keyboard* mode was the worst. In addition, top-5 accuracy in *Peripheral* mode was over 99%, which significantly outperformed the top-5 accuracy in *No-keyboard* mode ($F_{1,17} = 13.8$, $p < .001$). There was no significant difference between *Peripheral* and *No-keyboard* on top-25 accuracy.

5 STUDY 2: PERFORMANCE OF PERIPHERAL TYPING

In this study, we implemented a text input technique which enables typing with peripheral vision. This technique incorporates the decoding algorithm mentioned above and the touch model derived from typing data collected in study 1.

The goal of this study is to examine the performance of peripheral typing in text entry tasks. We expect results would draw the benefit of peripheral typing compared with the conventional eyes-on one, and prove if peripheral typing is a promising mode for two-thumb text input on tablets.

Participants and Apparatus

We recruited 18 participants (15 males and 3 females, aged 19-26) from the university campus. They were all familiar with QWERTY keyboard on mobile phones.

We used the same tablet as study 1. The user interface and the swipe gestures remained the same, except we integrated the decoding algorithm into the software this time.

To observe users' gaze movement during typing, we also used a Pupil-Labs eye tracker for tracking the gaze of participants. We attached markers on the tablet to define the surface, and the eye tracker automatically determined the position of gaze point on the surface. The gaze point data were recorded at 30Hz.

Experiment Design

We designed a within-subject experiment with the only factor *typing mode*. Two modes were evaluated in this study: *Eyes-on* and *Peripheral*. Both were introduced in study 1.

We integrated the decoding algorithm into the experiment platform, so participants could see real-time prediction results and select target words from the candidate list. The touch model for the decoding algorithm in each mode was trained individually from the corresponding data in study 1.

According to our simulation result, the top-5 words could cover 99% of users' intended word in both *Eyes-on* and *Peripheral* modes. Therefore, we showed 5 candidates with the highest probabilities in the candidate list for the participant to choose when the participant finished her touch input. Due to the difference of the areas participants needed to gaze at, the location of the candidate list and its corresponding selection method were different in two modes. We will illustrate the impact of different settings of selection in the result.

In *Eyes-on* mode, two candidate lists are located above the two split keyboard halves respectively, showing the same content. The participant directly taps on the target word shown in the candidate list to select it. This setting follows the current commercial text entry on tablets.

In *Peripheral* mode, to avoid attention switching in the selection phase, the candidate list is located exactly beneath the word in the output text. When selecting, the participant can still fix her visual attention around the output text and perform a drag-release method to select top-5 candidates from the list. The participant first drags either thumb horizontally on the touchscreen to alter the highlighted target word in the candidate list, then releases the thumb to confirm the selection. In addition, a quick right swipe (less than 100ms) is enabled for a quick selection of the top-1 word. This indirect selection method with in-situ thumbs was shown to be efficient [15, 18].

Procedure

In the beginning, we introduced the goal of the experiment and the requirements of each mode. In addition, we introduced the selection methods in two modes and required participants to get used to the methods. We told participants to believe in the prediction power and allowed them to practice for 3-5 minutes in each mode. In *Peripheral* mode, participants were easy to follow our instruction for gaze due to the convenience of the gaze-fixed feature, and they would find it not difficult to enter a correct word because of the high accuracy of prediction. Then participants were required to input 40 phrases chosen randomly from MacKenzie's phrases set [20] in each mode. We required participants to type as fast as possible in the premise of leaving no error. In each mode, the task was divided into 5 blocks and participants were required to take a break between two blocks. The order of presented modes was counterbalanced. After the whole experiment, participants were required to fill a NASA-TLX questionnaire to score for the two typing modes. The whole experiment lasted 30-40 minutes.

Result

Input Speed. The input speed was reported as

$$WPM = \frac{|S| - 1}{T} \times 60 \times \frac{1}{5}$$

where S is the transcribed string and T is the time in seconds [9]. Average input speeds in *Eyes-on* and *Peripheral* modes were 21.02 (SD=2.90) WPM and 26.83 (SD=4.76) WPM, respectively. RM-ANOVA showed typing in *Peripheral* mode significantly outperformed typing in *Eyes-on* mode ($F_{1,17} = 58.0$, $p < .0001$) with an increase in speed of 27.6%. This was because participants typed more freely in *Peripheral* mode. In *Eyes-on* mode, participants had to calibrate and aim at a key each time before they tapped it. In *Peripheral* mode, instead, they did not take time to execute this process.

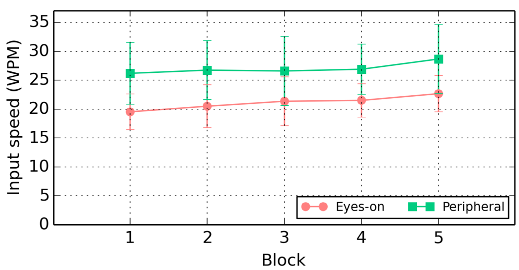

Figure 5: Input speed across blocks. Error bars represent standard deviations.

RM-ANOVA also found a significant effect of blocks on input speed in *Eyes-on* mode ($F_{4,68} = 5.21, p < .01$), but not in *Peripheral* mode ($F_{4,68} = 2.09, p = .09$). Results showed there was a slight learning effect from block 1 to block 5 with a speed increase of 16.0% in *Eyes-on* mode and a speed increase of 9.4% in *Peripheral* mode (Figure 5). After 5 blocks, the input speed achieved 22.66 WPM and 28.66 WPM in *Eyes-on* and *Peripheral* modes, respectively. Although both speeds kept increasing in the last few blocks, peripheral typing yields a relatively higher typing speed than eyes-on typing.

We also calculated the time consumption of the selection phase. The right swipe and the drag gesture consumed 5.4% and 3.5% of the total time in *Peripheral* mode, while selection with tapping only consumed 3.0% of the total time in *Eyes-on* mode. This confirmed that the higher input speed in peripheral typing than eyes-on typing was not caused by the selection method.

Input Accuracy. Top-1 rate reflects the percentage of entering a target word without the selection phase, which is especially important since the selection phase takes much more time than a swipe gesture for confirmation. Top-1 rates of the decoding algorithm were 99.8% (SD=0.3%) and 90.0% (SD=7.3%) in *Eyes-on* and *Peripheral* modes, respectively. The result was in line with the simulation result (Figure 4). Top-1 rate above 90% in *Peripheral* mode indicates that although the user typed "casually", basic decoding algorithm and the language model are still able to predict from user's noisy input.

We calculated Word Error Rate (WER) to measure the input accuracy. We reported both corrected error (an error was made but corrected later) and uncorrected error (an error was made and remained in the final phrase) [37]. Corrected WER in *Eyes-on* and *Peripheral* modes were 1.3% and 4.7%, respectively, while uncorrected WER was 0.2% and 0.4%, respectively. RM-ANOVA showed *Peripheral* mode contained significantly more corrected errors ($F_{1,17} = 28.8, p < .0001$), which reflects typing in *Peripheral* mode is less accurate than typing in *Eyes-on* mode. However, no significant difference was found on uncorrected error ($F_{1,17} = 2.46, p = .14$).

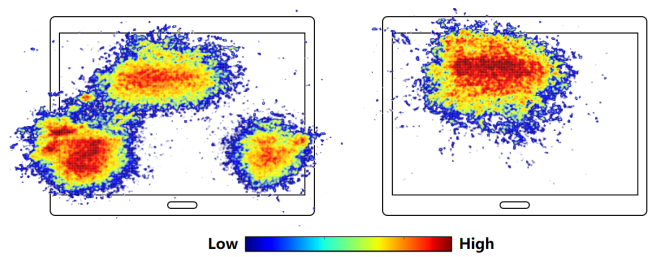

Figure 6: Heat maps of gaze points on the tablet while typing in *Eyes-on* mode (left) and *Peripheral* mode (right).

Gaze Behavior. We recorded 1,181,988 and 862,571 gaze points from the eye tracker in *Eyes-on* and *Peripheral* modes, respectively. We visualized the data as heat maps in Figure 6. The gaze data confirmed participants followed the requirement of each mode and pointed out the active areas of gaze in each mode. We found participants gazed more at the left keyboard half (43.6%) rather than the text field (37.5%) and the right keyboard half (18.9%) in *Eyes-on* mode. This is because over 95% of tapping selections in *Eyes-on* mode were performed on the candidate list above the left keyboard half. Contrarily, participants mostly fixed their gaze at the text field in *Peripheral* mode.

We also calculated the moving distance of the gaze point per second as a metric for attention switching. Gaze moving distance per second in *Eyes-on* and *Peripheral* modes was 37.01cm (SD=11.71cm) and 11.62cm (SD=4.12cm), respectively. This result proved peripheral typing could indeed reduce attention switching on the usage of the split keyboard.

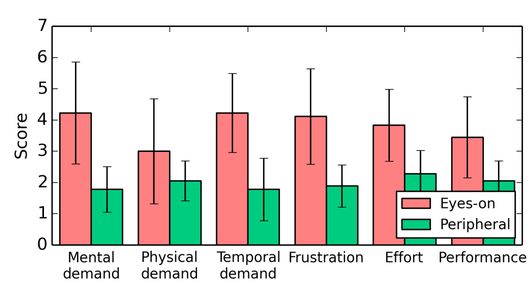

Figure 7: Participants' subjective feedback. Error bars represent standard deviations. The higher the score, the more demanding a person believed the mode to be.

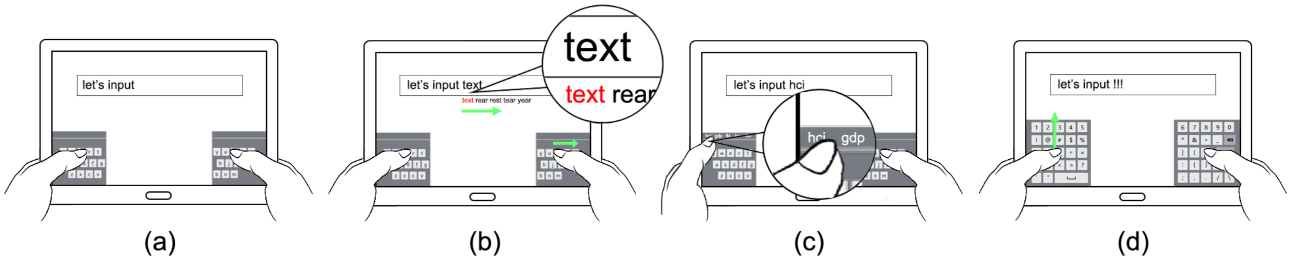

Figure 8: Interactions of *GlanceType*. (a) Tap on both sides of the split keyboard to input letters in either peripheral or eyes-on mode. (b) When performing peripheral typing, gaze fixes at the text field. Swipe right to select the first candidate or drag indirectly to select top-5 candidates from the list beneath the text. The target is highlighted in red. (c) When performing eyes-on typing, direct tap on the candidate to select OOV words from the list above the keyboard. (d) Swipe upward to trigger an additional keyboard for entering punctuation symbols and digits.

Subjective feedback. Wilcoxon signed-rank test showed there were significant differences on mental demand ($Z = -3.568$, $p < .0001$), physical demand ($Z = -2.316$, $p < .05$), temporal demand ($Z = -3.671$, $p < .0001$), effort ($Z = -3.373$, $p < .001$), frustration ($Z = -3.539$, $p < .0001$) and performance ($Z = -3.252$, $p < .001$) between two modes. Typing in *Peripheral* mode was rated as the better one on all dimensions (Figure 7). All 18 participants reported they preferred typing in *Peripheral* mode.

6 *GLANCETYPE*: SUPPORTING EYES-ON MODE IN PERIPHERAL TYPING

One limitation of the decoding algorithm for peripheral typing in study 2 is the user cannot input out-of-vocabulary (OOV) words (e.g., uncommon names) because the algorithm relies on a predefined word vocabulary. In addition, entering arbitrary characters like punctuation symbols is also important for realistic keyboard techniques. Aim at these problems, we improved the design to support eyes-on mode in peripheral typing to allow users to input OOV words and non-alphabetic characters.

We implement *GlanceType*, a keyboard technique that combines both peripheral and eyes-on typing. We design a two-candidate-region mechanism to support both typing modes at the same time: one candidate region is just beneath the output text (e.g., a URL container or a search box) on the top of the screen (Figure 8b) to avoid attention switching when typing with peripheral vision; the other candidate region is displayed just above the two split keyboard halves (Figure 8c) to enable tap-based selection like conventional eyes-on typing.

As mentioned in study 2, we design a drag-release gesture to select candidates from the list beneath the output text in peripheral typing mode, so that the user does not need to switch visual attention when selecting candidates. The user drags either thumb horizontally anywhere on the touchscreen to trigger the selecting phase, moves the thumb to alter the highlighted target word, and finally releases the thumb to confirm the selection (Figure 8b). This indirect selecting method with in-situ thumbs was shown to be efficient [15, 18]. In addition, we extend right swipe (less than 100ms) for a quick selection of the top-1 word, since swipe gesture is clearly faster than drag-release operation.

Our technique allows the user to freely choose eyes-on or peripheral typing mode without an explicit switching operation. Two candidate regions are visible simultaneously, therefore, the candidate region the user selects depends on the user's attention. When the user chooses to type in peripheral mode, a list of candidate words is generated by the algorithm and displayed beneath the output text. The user keeps her attention fixed at the output text region and drags to select the intended word (Figure 8b). When the user is looking at the keyboard and performing eyes-on typing, the candidate region just above the split keyboard halves displays the literal character string input by the user. She directly taps on this region to input the content (Figure 8c).

With eyes-on mode supported, the user can not only input OOV words but also input punctuation symbols and digits. To achieve this, we allow the user to swipe upward on the keyboard to switch to a secondary keyboard containing special characters (Figure 8d). The user swipes downward to return to the alphabetic keyboard. In addition, we also allow the user to input uppercase letters with a 300ms thumb press. A vibration occurs to signal the input.

7 STUDY 3: EVALUATION IN MORE PRACTICAL TEXT ENTRY TASKS

The goal of this study is to show that peripheral typing can well co-exist with the eyes-on typing in real use and improve the input performance. In this study, we will evaluate our design - *GlanceType* in a more practical task of tablets including complex contents like OOV words and punctuation symbols. We will also observe user behaviors when users are free to determine typing with and without peripheral vision.

Participants and Apparatus

The experiment of study 3 was conducted weeks after the experiment of study 2. We recruited 12 participants (10 males and 2 females, aged 19-25) who participated in the experiment of study 2. All of them also had the experience of using commercial split keyboards on tablets.

We used the same tablet in study 2 as the platform. We also used the same eye tracker to record participants' gaze.

Experiment Design and Procedure

We chose sending email, chatting and using social media as typical scenarios using tablets, and arbitrarily selected 50 phrases each from the email [32], dialogue [2] and Twitter [30] corpus as the phrases for our experiment. Every phrase includes at least one of the following components: OOV words, punctuation symbols or digits. Some of the phrases include uppercase letters. Punctuation symbols and digits make up 6.48% of total characters. OOV words make up 8.59% of all words, which is more than the existing work [24].

We designed a within-subject experiment with the only factor *technique*. Participants were required to input 30 randomly selected phrases each with three techniques:

GlanceType: is introduced in section 6.

No-peripheral: is the control technique of *GlanceType*, which only shows one candidate region above the split keyboard. That is, it remains the same appearance and interaction as *GlanceType* except the candidate region beneath the text field for peripheral typing.

Samsung-keyboard: is the default split keyboard text entry provided by Samsung tablets. It has auto-correction and auto-completion with a larger vocabulary and functional buttons for entering arbitrary characters, which represents a state-of-the-art commercial text entry. The candidate list is also shown above the split keyboard.

No-peripheral and *Samsung-keyboard* have only one candidate region which is located right above split keyboard halves. *GlanceType* and *No-peripheral* share the same decoding algorithm, vocabulary and interactive design, while *Samsung-keyboard* is different.

For the sake of observing the real behavior of users with peripheral typing, we did not force the typing strategies in this study. That is, the users were free to choose peripheral typing, eyes-on typing or some other strategies when using each technique.

Before the experiment, we first introduced the goal of this study and all three techniques. We showed all potential situations participants would meet (e.g., uppercase letters, OOV words or punctuation symbols), and introduced the way to deal with them. Since all participants have experienced peripheral typing and commercial split keyboard, they were required to familiarize with each technique for 3-5 phrases. Then participants were required to finish the task as fast as possible in the premise of leaving no error. The presented order of the three techniques was counterbalanced. There was a break between two techniques.

Result

We recorded 341,076 gaze points from the eye tracker and 4,243 touchscreen operations of users when participants used *GlanceType*. We synchronized gaze points with users' touch events, and manually assigned labels: peripheral or non-peripheral, for each time span of typing between two successive touch events to represent if the participant fixes the gaze at the text field in this time span. The label is determined by the amount of gaze points fallen around two keyboard halves and the tendency of gaze movement within the time span. Time span in which the user's gaze only fixed around the text field was labeled peripheral, otherwise, it was labeled non-peripheral. Manual labels were used instead of automatically extracted labels since gaze movement was a continuous procedure with non-negligible noises.

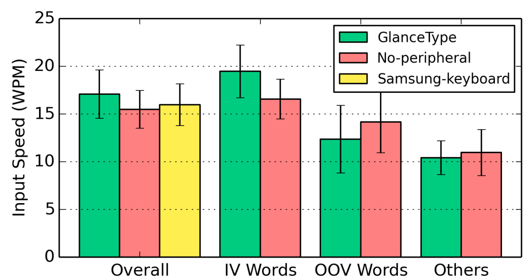

Figure 9: Input speed of three techniques. Error bars represent standard deviations.

Input Speed. We still reported WPM defined in study 2 as the metric for evaluating the input speed. The average input speed of *GlanceType*, *No-peripheral* and *Samsung-keyboard* was 17.08 (SD=2.52), 15.48 (SD=1.97) and 15.97 (SD=2.18) WPM, respectively. Input speed of *GlanceType* was 10.3% higher than that of *No-peripheral*, and RM-ANOVA shows there was a significant difference between two techniques ($F_{1,11} = 10.4$, $p < .01$). Input speed of *GlanceType* was also 7.0% higher than that of *Samsung-keyboard*, but no significant difference was found between two techniques ($F_{1,11} = 2.06$, $p = .18$).

We divided the whole corpus into IV (in-vocabulary) words, OOV words and others (non-alphabetic contents) and measured the input speed when entering each of these components to examine the detailed performance (Figure 9). Since the vocabulary in *Samsung-keyboard* was not controlled, we only compared *GlanceType* and *No-peripheral* here. The average input speed of *GlanceType* when entering IV words, OOV words and others was 19.47 (SD=2.76), 12.36 (SD=3.55) and 10.42 (SD=1.77) WPM, respectively, while these of *No-peripheral* were 16.56 (SD=2.09), 14.16 (SD=3.23) and 10.97 (SD=2.42) WPM, respectively. RM-ANOVA showed *GlanceType* had a significantly higher speed than *No-peripheral* when entering IV words ($F_{1,11} = 30.3$, $p < .001$), but there was no significant difference between two techniques when entering OOV words ($F_{1,11} = 0.66$, $p = .43$) and others ($F_{1,11} = 0.40$, $p = .54$).

The input speeds of *GlanceType* and *No-peripheral* were close when entering OOV words and non-alphabetic contents. We explain that participants mainly used eyes-on typing. On the other hand, participants could use peripheral typing to enter IV word, so the input speed of *GlanceType* was higher. In general, typing speed can be increased by enabling peripheral typing for IV words, even compared to a commercial keyboard.

Behaviors of GlanceType for IV words. According to the labeled data of touchscreen operations, we analyzed word-level behaviors of entering IV words. 89.7% of IV words were entered with peripheral typing entirely (gaze fixed at the text field). 1.8% of IV words were entered with attention switching. The remaining 8.5% of IV words were entered with the gaze first at the keyboard but later with peripheral typing. We explain this behavior as a "pre-glance" before peripheral typing, which often took place when participants just finished an OOV word or a non-alphabetic character. A "pre-glance" might promote mastering the positions of keys, and help participants to perform the first tap confidently.

Participants reached 19.94 WPM with entire peripheral typing. The input speed dropped to 16.29 WPM with a "pre-glance", and we explain this as a boot process to enter the fluent peripheral typing. Moreover, participants had only 12.04 WPM with attention switching. This result indicated that participants had relatively high typing speed with fluent peripheral typing. The input speed of IV words dropped down after interrupts took place (e.g., enter a digit).

Totally 98.2% of IV words were entered with peripheral typing. This result showed that participants were willing to use the gaze-fixed feature of *GlanceType* to enter IV words. Considering individual participants, the highest ratio of entering IV words with peripheral typing was 100%, and the lowest was 85%.

Behaviors of GlanceType for OOV words. On average, 10.7% of OOV words was entered with the gaze fixed at the text field. This result was somewhat beyond our expectation since we expected OOV words could only be entered in eyes-on mode. We further analyzed the data, and we found sometimes participants treated an OOV word as an IV word and tried to enter it with peripheral typing. This behavior also slowed down the speed of *GlanceType* for entering OOV words. When using peripheral typing in real scenarios, how to identify a word as OOV or not is an important problem for users. We will discuss it in the limitation.

8 LIMITATION

There were some limitations of our approach. First, the proportion of peripheral vision was not controlled in our experiments. Visual acuity [4] which affects the capability of peripheral vision may be different in some other conditions using tablets, like walking, portrait posture, etc. Second, our approach of decoding noisy touch input can be improved. Bigram or even sentence-level language model can be employed for better interpreting user's intention. Third, how to be aware of OOV words when using *GlanceType* influences the user experience by retyping. Personalizing a user's vocabulary is one solution since an OOV word will become IV after the first input.

9 CONCLUSION

In this paper, we investigate an unconventional typing mode for text input on tablets - typing with peripheral vision, to enable fast and comfortable typing with two thumbs on the split keyboard. With peripheral typing, users focus on the output text feedback only, meanwhile, they perform typing on the keyboard in their peripheral vision. Our first study showed a visible keyboard in participants' peripheral vision was helpful to decrease typing noise. An empirical control study proved peripheral typing could achieve 27 WPM with over 90% top-1 accuracy, and significantly outperformed conventional eyes-on typing. Peripheral typing also reduced attention switching on the split keyboard and was preferred by the participants. Then, we designed *GlanceType*, a text entry supporting both peripheral typing and eye-on typing for entering OOV words and arbitrary characters. Our real-scenario study showed *GlanceType* had a competitive input speed of entering any content in real use, which was 7.0% faster than a commercial split keyboard. Participants also preferred to use peripheral typing to improve the input performance of IV words.

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