Characterizing In-Air Eyes-Free Typing Movements in VR

Hyunjae Gil
UNIST
Ulsan, Republic of Korea

Yonghwan Shin
UNIST
Ulsan, Republic of Korea

Hyungki Son
ETRI
Daejeon, Republic of Korea

Inwook Hwang
ETRI
Daejeon, Republic of Korea

Ian Oakley
UNIST
Ulsan, Republic of Korea

Jin Ryong Kim
University of Texas at Dallas
Richardson, TX, USA

ABSTRACT

We empirically explore fundamental requirements for achieving VR in-air typing by observing the unconstrained eyes-free in-air typing of touch typists. We show that unconstrained typing movements differ substantively from previously observed constrained in-air typing movements and introduce a novel binary categorization of typing strategies: typists who use finger movements alone (FINGER) and those who combine finger movement with gross hand movement (HAND). We examine properties of finger kinematics, correlated movement of fingers, interrelation in consecutive key-strokes, and 3D distribution of key-stroke movements. We report that, compared to constrained typing, unconstrained typing generates shorter (49 mm) and faster (764 mm/s) key-strokes with a high correlation of finger movement and that the HAND strategy group exhibits more dynamic key-strokes. We discuss how these findings can inform the design of future in-air typing systems.

CCS CONCEPTS

• **Human-centered computing → Text input**.

KEYWORDS

In-Air Typing, Typing in VR, Text Entry

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1 INTRODUCTION

Virtual Reality (VR) is undergoing a renaissance: the emergence of high-fidelity, low cost Head Mounted Displays (HMDs) is transforming it from the province of the lab to that of the living room. VR now impacts a very broad range of application areas from media consumption through gaming [37] to simulation [12] and expressivity [4] or productivity [5] tools. As its reach spreads, more emphasis is being placed on the interactive aspects of VR - the majority of headsets ship with dedicated input controllers or advanced bare hand tracking systems. However, such systems still struggle to effectively support many fundamental input tasks, such as text-entry. We argue text-entry is of growing relevance to VR. Gamers need chat with peers, or perform administrative tasks like logging into accounts or configuring settings. In more productivity-oriented domains, tasks such as file manipulation, communication or browsing the Internet will all frequently require text input. Removing headsets to perform these tasks is, at best, laborious and unappealing. Reflecting this perspective, a number of text input systems for VR have been proposed. A simple approach is to rely on existing VR controllers (e.g. Cutie Keys, Punch Keyboard, etc), but input bandwidth is typically low. Physical keyboards can also be tracked and integrated into a virtual scene, superimposing the real on the virtual [34]. While this can offer good performance, it tethers a user to a single physical space [21].

Freehand text input can solve this problem - users simply type in the air. However, systems that implement virtual keyboards based on finger interaction are slow and cumbersome to use [6, 22] – hitting targets in mid-air is not the same as hitting targets on a real keyboard. A more promising approach is to capture high fidelity finger movements during in-air typing [33] [38] [39]. In this way, users can rely on their motor system [28] to type at high speed [30]. Furthermore, as no keyboard needs to be presented, users are free to move around and the VR scene remains clutter free.

While this idea is appealing, it remains difficult to implement – typing finger movements in mid-air are rapid and complex. Prior work targeting this space has tended to simplify the problem. For example, ATK [39] achieves reasonable recognition performance using a probabilistic tap detection algorithm based on the height of the stroking finger; to ensure each tap is clearly performed, users are instructed to issue a sequence of controlled, temporally separated motions with single fingers. We refer to this as *constrained* in-air typing and note that the movements it is based are highly simplified compared to the interleaved bi-manual activity that characterizes real-world typing. Here, we define *unconstrained* in-air typing as the uninstructed typing behaviors that users exhibit during in-air typing and which reflect their real-world typing behaviors. To achieve truly eyes-free typing in mid-air with unconstrained finger kinematics, it is important to fully understand how people naturally behave without any instruction when they are engaged in mid-air typing. This allows us to define fundamental requirements and guidelines for designing in-air typing systems in VR. To achieve this objective, we collect 25,932 in-air finger stroke traces of unconstrained typing in VR through an empirical study.

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We characterize this data and identify key properties and features including: different typing strategies among the users; finger kinematics; correlated movement of fingers; interrelation in consecutive keystrokes; and 3D end-point distribution. This analysis provides quantitative data that can support the development of in-air typing systems for VR based on unconstrained finger movement. This data is important as relaxing the constraints on typing motions will increase the difficulty of accurately classifying the keys they indicate. Only by understanding and detailing the behaviors involved in unconstrained in-air typing will we enable input that is rapid, accurate, fluid, and eyes-free.

The contributions of this paper are 1) empirical data characterizing unconstrained behavior during eyes-free in-air typing and contrasting it with prior data from studies of constrained in-air typing, 2) a description of how typing strategy impacts this data, 3) the development of features describing interrelated finger strokes that can support improved segmentation and recognition of a single finger stroke, and 4) design considerations for building in-air typing system and feasibility of finger classification based on our findings. Throughout the paper we contrast the data we report with existing data captured in constrained in air typing settings (ATK [39]).

2 RELATED WORK

2.1 Text Entry on HMDs

Authors have proposed a variety of approaches to text entry during HMD use including touchscreen typing via integrating a large input surface into an HMD [14]. Others have proposed systems based on handheld controller motions that describe text-entry gestures [17] or control a ray-based pointer that intersects a keyboard [32]. While these systems effectively support typing, their efficiency is lacking: performance ranges from 10 WPM or less [14] [17] through between 10 to 20 WPM [32]. A potentially more effective approach is to integrate physical keyboards into virtual scenes. Walker et al. [34] exemplify this approach. This work implemented a HMD-based text entry system that tracks a real keyboard. The VR system includes a virtual keyboard assistant to provide visual feedback inside the virtual scene. Performance reached 43.7 WPM with 2.7% error rate. Similarly, McGill et al. [27] report that typists on a physical keyboard can achieve 38.5 WPM with 1.07% uncorrected error rate while wearing a HMD. We note that while blending keyboards into the virtual scene provides high typing performance, it restricts VR simulations in other important ways: users are tethered to the keyboard and/or desk.

2.2 Ten Finger Typing on Flat Surfaces

The design of in-air typing systems can also be informed by the substantial literature on unconstrained text entry on flat surfaces such as mobile phones and tablets. This typically involves examining naturalistic typing patterns in order to propose the design of future touchscreen keyboards [2, 31]. For example, Findlater et al. [10] analyzed twenty typists' touch contact points and hand contours and reported that individual typists exhibit spatially consistent key press distributions. They also showed that typists could achieve up to 58.5 WPM mean typing speed without visual cues showing keyboard layout. In follow-up work, they showed that personalized ten-finger touchscreen typing models can improve both typing speed and subjective experience [9]. Haptic feedback has also been shown to be important in touch typing on flat keyboards. Kim et al. [19][18][20], for example, used piezoelectric discs under each key to create specific feedback for each keypress. Their results showed significant improvements to typing performance when haptic and auditory feedback were included.

2.3 In Air Typing in VR

Freehand typing techniques have the potential to combine two beneficial properties: input that is high bandwidth input and also not tethered to a physical device. Numerous authors have proposed systems to explore this potential. ARKB [22] relies on markers on the fingers to implement this approach. A more complex approach is to recognize finger strokes based on highly consistent movement schemes such as touch typing. TiTAN [38] attempts this, showing up speeds of up to 9.4 WPM with 10 fingers. ATK [39], a freehand-based mid-air typing system based on a Leap Motion's 3D hand tracking data, also implements this approach. It recognizes ten-finger typing by adopting a probabilistic tap detection algorithm and augmented version of Goodman's input correction model [13]. ATK achieves up to 29.2 WPM of typing speed after practice, showcasing the strong potential of this approach. Despite this performance, we note that the typing task of ATK involved "clearly performed tap[s]" on an "horizontal imaginary keyboard". The relatively low WPM, compared to real world touch typing, reflects the controlled nature of these typing movements and enabled the authors to use simple vertical finger motions to reliably classify stroking fingers and tapped keys. This enabled the authors to develop a final system with a word-level accuracy of 99.7%.

3 STUDY: UNDERSTANDING IN-AIR TYPING

The goal of this study was to characterize unconstrained finger kinematics and behaviors during in-air typing to provide insights and implications that can inform the design of in-air typing systems. To achieve this goal, we explored and analyzed the typing behaviors and strategies of mid-air typists in order to investigate the time at which a single stroke is executed, the finger that is issuing it and the location it is intended to indicate from a rapid, complex and interleaved sequence of unconstrained finger motion. Throughout our study, we compare our analysis with ATK [39], a closely related study that discusses the features needed to support in-air typing based on constrained finger motions—participants in ATK were instructed to clearly tap on each key with temporally separated individual finger movements. Our study involves an in-air typing task completed by touch typists. We collect a large number of unconstrained finger movement traces and characterize a range of key features from this data including finger kinematics, correlated movement of fingers, inter-relation in consecutive keystrokes, 3D end-point distribution, and typing strategies among the typists. This analysis provides quantitative engineering specifications and design insights that can support the development of in-air typing systems for VR that integrate rapid and fluid typing experiences based on unconstrained finger movement.

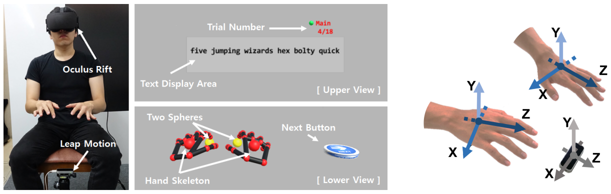

Figure 1: Experimental hardware setup with participant performing typing task (left) and typing test in a virtual scene (middle). Relative coordinate used palm position as the origin (blue axes) and absolute coordinate used the common origin of Leap Motion (gray axes) in 3D.

3.1 Participants

Sixteen typists (female=5; M=30.06; SD=7.76, two left-handed) were recruited for this study. Prior to the main experiment, we confirmed their typing performance and finger to key mapping with a physical keyboard using TextTest [36], a text entry evaluation tool. Mean typing speed was 62.68 words per minute (WPM) (SD=12.1) with 0.8% of uncorrected error rate using a physical keyboard. They were paid for their participation with a $3 coffee voucher.

3.2 Experimental Setup

Figure 1 shows the experimental setup and a virtual scene of typing test. Participants were asked to take a seat, wear a HMD device (Oculus Rift CV1) and reach out their hands above a Leap Motion finger tracking device (version 3.2.0+45899) to start the typing experiment. The Leap Motion has a deviation of below 0.2 mm (static) and 1.2 mm (dynamic) between a desired 3D position and the measured positions [35]. The Leap Motion device was placed 41 cm above from the floor using a tripod. The virtual scene was implemented using Unity3D (version 5.6.0.3f) displayed through the binocular displays in the HMD.

In the virtual scene, two hand skeletons were rendered from the Leap Motion to provide a visualization of the typing fingers. Two spheres were presented as indicators of initial finger positions that are similar to indicators on the F and J keys on physical keyboards. The two virtual spheres were placed 15 cm above the Leap Motion and the distance between them was 9 cm. We derived this spacing by starting with 6 cm, approximately the spacing between the two indicators of F and J on physical keyboards, and iteratively testing to find the most natural and comfortable distance. Subjective assessment by experimenters suggested that 9 cm was suitable for in-air typing. Participants were able to adjust the height of the virtual spheres to achieve a comfortable pose. Starting from the two spheres is important as they act as reference points for our measures. A next button with a diameter of 15 cm was placed 33 cm to the right of two indicators. This was used in order to move to subsequent trials. A text display area was placed in the visual field at 90 cm above the two spheres, approximately eye-height. This displayed the phrases to type. The current trial number was also displayed right above the text display area to communicate progress through the study.

There was no further visual content (e.g., a bounding box for hand placement, a visual keyboard layout) in the scene. In addition, visual feedback on finger strokes was not provided as the purpose of this study was to observe unconstrained finger motions. These choices were explicit. We argue it would be impossible to observe unconstrained typing finger movements while displaying a visual keyboard layout for several reasons. Firstly, people may look at the layout while making keystrokes. This visual constraint will further generate eye-gaze shifts between text and keyboard areas, reducing typing speed. As our goal is to characterize in-air eyes-free typing movements and most typists spend minimal time looking at the keys on a physical keyboard, providing minimum visual cues is the best way to elicit natural high speed typing behavior. Secondly, following [9] [10] we believe that typing behavior captured without a visually displayed keyboard provides ground truth about users' expected locations for keys that can be used to inform future virtual keyboard designs (e.g. key positions, sizes). Displaying a virtual keyboard will inevitably compromise this behavior. Finally, recent work on touchscreen keyboards demonstrates rapid performance without displayed keyboards [40]. Furthermore, we provided no auditory or haptic feedback to participants and also no constraints or guidance as to the location of the backspace key. By combining these unconstrained conditions and limited visual cues, we hoped to solicit unconstrained in-air typing motions.

All joint position data from finger stroking movements was captured in real time from the Leap Motion by C# scripts. The data includes 3D coordinate positions of all the joints between phalanx bones in thumb, index, middle, ring, and pinky fingers of both hands. We also collected the center position of each palm. This raw data describing finger stroking motions for all participants was then analyzed to build a ground-truth model for performance of in-air finger stroking for eyes-free typing in VR. We use two different 3D coordinate systems in our descriptions: absolute and relative (see Figure 1). Absolute is a global position measurement with its origin at the Leap Motion reference frame. In the relative coordinate system, the current palm position is defined as the origin.

The study was composed of four blocks of 20 trials. The first block was considered practice and the remaining three used for data collection. Each trial contained one phrase and the first two trials in all blocks were also treated as additional practice (as in [10]). A randomly selected phrase from either Mackenzie's phrase set [25] or one of 6 pangrams were used for each trial. In each block, the 6 pangrams were interleaved with phrases from Mackenzie's set to increase the occurrence rate of rarely used characters.

3.3 Procedure

A typing test with a physical keyboard was conducted prior to the main study. During this time, we closely monitored participants' behavior with a web camera to ensure their fingers follow the standard finger-to-key mapping. In the beginning of each study block, participants were asked to take a seat, wear a VR headset, and reach out their hands above the Leap Motion. They first completed an informal training session to get used to the input scenario, then began the first trial in main study by placing their index fingers into the two spheres. The spheres then disappeared, a text phrase was displayed and the color of hand skeletons turned white to indicate the start of a trial. Participants then typed the phrase as fast and accurately as possible. We recommended they hit backspace whenever they felt they made errors. When they felt that they completed the trial, they were instructed to press the next button to go on to the next trial, which again started by requiring they place their index fingers into the spheres to begin. Participants were requested to take a break after each block to minimize fatigue.

3.4 Data Processing

We collected and analyzed a total of 25,932 labeled finger strokes. The traces, containing data from the Leap Motion API, include positions, directions and velocity for all fingers and both hands. We use these to derive finger stroke amplitude, finger stroke start and end positions, finger movement directions, and also movement of the palms. Data analysis procedures were as follows. First, we processed the data to create ground truth typing behavior. We parsed the raw data and loaded it into a Unity3D based typing sequence visualiser. This system loads the 3D position data of all fingers' stroking movements and provides a visual environment to browse 3D depictions of typing actions and manually label each action with the appropriate character (e.g. the character that should have been typed). This procedure is inspired by that used in ATK [39] and was achieved through observation of finger acceleration and movement profiles to ascertain the 3D endpoint of each finger stroke. This time consuming process was required since there is currently no existing model of in-air finger stroking during unconstrained eyes-free typing.

After end-points were identified, we traced backwards to determine stroke start-points. Prior to the end-point the finger is moving at speed, so we simply categorized start points at the origin of these essentially ballistic motions – the most proximate local speed minima. To perform this task accurately, we used a relative coordinate frame (Figure 1) and applied linear interpolation to fill the gaps in the velocity data and a rolling average with a window size of five to eliminate noise. After segmenting all strokes, our subsequent analysis used this raw but delimited data. The final data set includes information of all 3D positions, directions, keystroke amplitudes, velocities, and accelerations of finger strokes for all ten fingers and two palms. We also measured typing speed in WPM and finger-level accuracy as the ratio of incorrect finger strokes (defined as use the wrong finger) to the total number of finger strokes.

4 GENERAL DESCRIPTION: IN-AIR TYPING

4.1 Typing Speed

Participants achieved up to 78.3% of their typing speed on a physical keyboard during in-air typing: 49.1 WPM in-air vs. 62.7 WPM keyboard. It is obvious that in-air typing is slower than physical keyboard typing. A number of factors likely contribute to this. Firstly, the lack of haptic feedback on finger strokes resulted in relatively deep stroking motions (49 mm, SD = 12 mm), which may reduce speed [19]. Secondly, prior work has suggested that fast typists keep their hands still and slower typists move their hands more [8]. We observed larger hand motion (16 to 31mm) compared to prior studies of typing on keyboards—these additional motions likely slowed participants down. Despite these factors, WPM that participants achieved suggests that unconstrained in-air typing speeds in VR may be relatively high in optimal conditions. It contrasts strongly with the speeds reported in prior work—ATK: 29.2 WPM and TiTAN: 9.4 WPM.

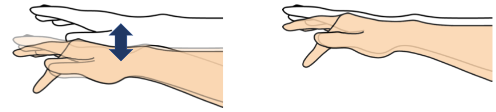

Figure 2: Typing strategy: Participants either move their entire hand and finger together (HAND strategy, left) or only finger (FINGER strategy, right) for single finger-stroke

4.2 Typing Strategy: HAND vs. FINGER

Global hand movement referring to motions of the entire hand expressed in absolute 3D coordinates, has been shown to support identification of different typing strategies during use of a physical keyboard [8]. We specifically investigate this issue in unconstrained in-air typing as the lack of explicit guidance as to key locations and feedback during key presses may increase the amount of hand movement that occurs. We therefore assumed that in-air typing would exhibit variations in typing strategies based on the different patterns of global hand movement reported in prior work.

4.3 Results & Discussion

Two distinct in-air typing strategies were observed during the study. Some typists tend to stroke the keys by moving their entire hand and finger together (HAND strategy) while other typists use only their fingers to reach keys, minimizing their hand movements (FINGER strategy). Figure 2 shows the two strategies. We examined the travel distance of the hand during finger strokes to categorize participants into the two strategies. For this, we considered a palm movement as a movement of the entire hand and calculated the position change in absolute 3D coordinates between the start and end of each finger-stroke. With a feature of palm movement, we adopted a K-means clustering method to cluster each participant into one of two strategies: HAND (N=6) and FINGER (N=10). The centroid of each cluster was 37.2 mm in HAND strategy and 14.1 mm in FINGER strategy, respectively. This indicates that HAND strategy group moved their hand greater distances than FINGER strategy group during the finger-stroking. We confirmed the clear distinction between two strategies through visual inspection.

As increased dynamic palm movement would affect the properties of finger-stroke generally, we identify typing strategy as a critical factor to understand unconstrained in-air typing behavior. Following typical processes, we will compare two groups and discuss how their typing behaviors and tendencies in each group affect other components in designing and developing in-air keyboards.

5 FINGER KINEMATICS

We examined finger kinematics to understand the structure and characteristics of finger-strokes in terms of their duration, amplitude, travel distance, and max velocity for both hands and all four fingers: index, middle, ring, and pinky. Each finger-stroke includes 'flexion' and 'extension' phases referring to, respectively, the fingertip displacement from the start point of the stroke to when the finger at its most bent and then back to its position when the finger is most fully stretched. We also measured the amplitude (finger stroke depth relative to the depth at the start of the stroke) and the max velocity of a fingertip in relative 3D coordinates. Finally, we measured the travel distance representing the total movement of the fingertips in the air in absolute 3D coordinates. We argue that the features showing statistical differences represent distinct kinematic behaviors that can be adopted for classifying fingers or strokes in the future.

5.1 Results & Discussion

Table 1 shows the kinematic features of fingers during flexion and extension phases, including duration, amplitude, travel distance, and max velocity for each finger. Table 2 shows the same kinematic features in each typing strategy group. Figure 3 provides a graphical illustration of the finger kinematics. Examining this data reveals that unconstrained typing shows faster finger velocities (764mm/s, SD=214), shorter finger-stroke times (322ms, SD=25), and lower amplitudes (49mm, SD=12) than the figures reported for ATK's constrained typing, respectively: 623mm/s, SD=262; 496ms, SD=170 and; 64mm, SD=24. Basically, in unconstrained typing, fingers move shorter distances more rapidly and, thus, reach their terminal destinations more quickly. These differences suggest that typists in our study performed with natural typing motions—with short, rapid finger movements. In Table 3, we compare stroke features in more detail. We argue that the short and fast finger strokes in unconstrained typing will increase the difficulty of detecting finger strokes accurately compared to the more constrained movements used in systems such as ATK. These qualities also alter the features that may be most salient. While times and distances traveled may be less useful, due to the fact they are smaller in magnitude, the faster finger velocities observed suggests this feature may be particularly important.

Table 1: Mean (SD) of kinematic features of fingers during flexion and extension phases, including duration, amplitude, travel distance, and max velocity for each finger. One-way ANOVA results show the main effect of the finger.

		INDEX	*MIDDLE*	*RING*	*PINKY*	*F*	*p-value*
Overall Duration (ms)		331 (30)	316 (27)	316 (22)	327 (27)	F(3,60)=1.241	0.303
Flexion	*Duration (ms)*	143.3 (12.0)	138.0 (10.93)	140.7 (9.9)	144.2 (11.6)	F(3,60)=1.006	0.397
	Travel Distance (mm)	69.7 (18.6)	62.3 (22.2)	63.4 (21.2)	62.8 (20.4)	F(3,60)=0.446	0.721
	Amplitude (mm)	54.0 (13.3)	47.6 (14.6)	48.9 (13.6)	47.3 (13.5)	F(3,60)=0.810	0.493
	Velocity (mm/s)	829.7 (227.4)	741.8 (256.1)	762.2 (215.6)	722.1 (238.8)	F(3,60)=0.635	0.595
Extension	*Duration (ms)*	187.2 (19.06)	177.86 (17.93)	175.6 (13.5)	182.6 (18.14)	F(3,60)=1.419	0.246
	Travel Distance (mm)	61.8 (16.1)	50.4 (14.1)	49.6 (12.45)	52.2 (13.0)	F(3,60)=2.818	0.0466
	Amplitude (mm)	45.8 (10.9)	39.0 (10.8)	38.8 (10.5)	41.9 (11.7)	F(3,60)=1.404	0.250
	Velocity (mm/s)	658.2 (179.06)	564.58 (232.8)	607.1 (225.9)	613.03 (272.2)	F(3,60)=0.445	0.722

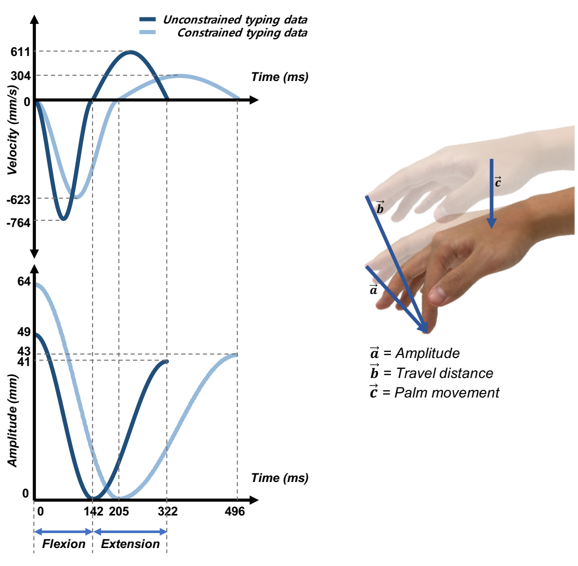

Figure 3: Finger kinematics (left). Dark blue indicates unconstrained typing from current study and light blue indicates constrained typing from ATK. Left-top shows velocity and left-bottom shows amplitude. Features of finger stroke (right); amplitude, travel distance and palm movement.

Data were further analyzed using one-way ANOVA on the variable of the finger. Tukey's test for Post-hoc testing was applied to reveal the differences among fingers. We found a significant main effect in travel distance during the extension phase (F(3,60)=2,818, p=0.0466). Post-hoc testing confirmed that the index finger moved longer distances than all other fingers (p<0.001) in the extension phase. There is no main effect on other features. However, we noticed that the index finger tended to move faster (velocity) and further (amplitude) than the other fingers. These variations are likely because each index finger is responsible for six keys, rather than three or fewer keys for other fingers, and this greater diversity requires larger but faster movements.

Table 2 shows the mean of kinematic features of fingers during flexion and extension phases in each typing strategy group. We performed a Mann-Whitney U test for a non-manipulation variable [29] with unpaired samples and unbalanced sample size. The HAND group showed faster velocity (p=0.0225) with longer travel distance (p=0.0002) and amplitude (p=0.016) in flexion phase and longer distance (p=0.001) in extension phase than the FINGER group; their hands are more mobile during the typing task. Our analysis indicates that the HAND group makes more substantial typing motion than the FINGER group, which can be a more clear trigger for keystroke detection. However, the larger finger motion in the HAND group could generate higher correlated movements in other fingers (passive fingers), possibly yielding the recognizer more complicated. We will discuss the correlated movement of fingers in Section 6.

An interesting finding is that, in the flexion phase, we observed a relatively long travel distance of 65 mm (SD=19.9) (similar to the amplitude of 64 mm in constrained typing). This may be due to the addition of hand movements since the mean distance covered by the palm is 23.0 mm (SD=16.1) and 23.5 mm (SD=11.5) for left and right hands, respectively. Since finger stroking in unconstrained typing leads to these marked movements of the palms, we suggest the travel distance may be particularly salient as a key feature for finger stroke detection in unconstrained typing.

Another interesting finding is the recovery ratio of movement amplitude in the flexion phase over that in the extension phase. We

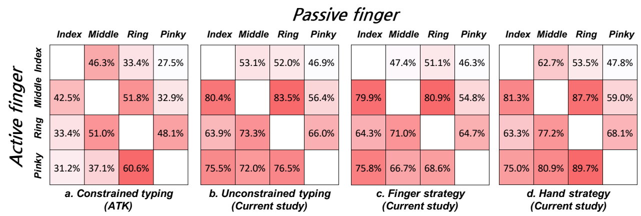

Figure 4: Amplitude ratio (AR) between active and passive fingers. a) Constrained typing (ATK [39]), b) Unconstrained typing, c) Finger strategy, and d) Hand strategy.

found that unconstrained typing achieved an 84% recovery ratio (flexion: 49mm and extension: 41mm) while constrained typing is reported to reach a ratio of 67% (flexion: 64mm and extension: 43mm) (see Figure 3). We interpret this as indicating that, in an unconstrained typing scenario, the previous finger stroke is quickly returned to its original position to yield smoother consecutive keystrokes. This leads to a higher recovery ratio. In contrast, the recovery ratio was lower in constrained typing since it emphasizes clearly individuating keystrokes rather than continuous typing. We speculate that the higher recovery ratio may help support clearer segmentation of finger strokes and recognition of the finger.

6 CORRELATED MOVEMENT OF FINGERS

Human fingers do not move alone—due to the arrangement of muscles and tendons in the palm, hand, and wrist, intentional movements of a single finger inevitably lead to unintended, but correlated, movements in other fingers. An accurate understanding of this correlated movement has been identified as an important factor to support accurate finger classification in in-air typing [39]. To analyze the correlated movement among the fingers in our data, we use the*Amplitude Ratio (AR)*. This is the ratio between the active finger's amplitudes, the one making the intended stroke, and all other fingers, which are termed passive fingers. Correlated movement among the fingers is calculated as: $AmplitudeRatio(AR) = (Amplitude_{passive\ finger} / Amplitude_{active\ finger}) \times 100\%$.

6.1 Results & Discussion

The AR of unconstrained typing (46.9-83.5%) (Figure 4-b) was higher than that of constrained typing in ATK (27.5-60.6%) (Figure 4-a). This suggests that unconstrained typing exhibits a higher correlation of finger movements. This is likely due to the fact that, in

Table 2: Mean (SD) of kinematic features of fingers during flexion and extension phases in each strategy group. A Mann-Whitney U test was applied for statistical analysis.

		FINGER (n=10)	*HAND (n=6)*	*Mean difference*	*p-value*
Overall duration (ms)		314.53 (19.96)	335.46 (28.49)	-22.94	0.1471
Flexion	***Duration (ms)***	138.25 (9.64)	147.1 (8.49)	-8.76	0.0727
	Travel Distance (mm)	51.56 (8.93)	86.22 (11.78)	-0.034	**0.0002**
	Amplitude (mm)	43.84 (10.13)	58.84 (10.55)	-0.02	**0.016**
	Velocity (mm/s)	672.22 (177.93)	916.86 (188.92)	-254.14	**0.0225**
Extension	***Duration (ms)***	176.28 (10.89)	188.36 (20.39)	-12.11	0.3132
	Travel Distance (mm)	45.33 (7.54)	67.17 (5.68)	-0.02	**0.001**
	Amplitude (mm)	38.57 (9.15)	46.06 (10.4)	-0.008	0.1806
	Velocity (mm/s)	572.29 (225.84)	674.78 (163.53)	-123.15	0.0934

Table 3: Comparison between constrained (ATK [39]) and unconstrained typing in duration, amplitude, and velocity.

	Flexion		*Extension*	
	ATK	*Current Study*	*ATK*	*Current Study*
Durtaion (ms)	205 (81)	141 (10)	291 (148)	181 (16)
Amplitude (mm)	64 (24)	49 (12)	43 (26)	41 (10)
Velocity (mm/s)	623 (262)	764 (214)	304 (136)	611 (205)

Table 4: Inter-key press timing with interrelation variables. Data were analyzed using Mann-Whitney U test for the unpaired and unbalanced samples.

Inter-keystroke interval (ms)		*Overall*	*FINGER (n=10)*	*HAND (n=6)*	*Mean difference*	*p-value*
Grand mean		279.1 (73.8)	239.5 (44.4)	345.2 (66.3)	-87.87	0.0047
Same-hand	***Normal***	321.6 (89.6)	278.4 (58.0)	393.7 (89.9)	-108.03	0.011
	Digraph	271.8 (75.6)	230.4 (44.3)	340.6 (67.3)	-108.83	0.003
Cross-hand	***Normal***	290.1 (71.6)	252.3 (42.4)	353.0 (67.3)	-89.22	0.0017
	Digraph	233.1 (65.5)	196.8 (42.6)	293.7 (50.6)	-90.08	0.003

ATK, participants were asked to perform a clear tap to capture the gesture of a finger stroke and see their hands during typing (i.e. they were not wearing an HMD). We argue that participants in the ATK data set made substantial effort to produce clear individuated input, resulting in reduced amounts of passive finger movements. In contrast, in the unconstrained task in the current study, participants exhibited greater movements of passive fingers due to study instructions requesting them to freely "type" in the absence of any cues indicating keyboard layout.

We note that the higher levels of correlated movement in unconstrained in-air typing may pose challenges for accurate finger classification—during any given key-press, more fingers were moving further. This is a particular problem for the HAND group (see Figure 4-d) as they showed stronger correlated movement (47.8-89.7%) than the FINGER group (46.3%-80.9%). We note this difference may be due to passive finger motions that occurred due to forces applied as an incidental but inevitable result of using more dynamic whole hand movements during typing. Regardless, the reduced finger individuation we observed during keystrokes indicates that relying on stroke amplitude for finger classification, as in ATK's constrained typing system, would likely lead to poor results.

7 INTER-KEYSTROKE RELATIONSHIP

It is essential to obtain a precise tapping movement for each finger stroke to achieve stable finger-stroke detection and finger classification. The prevalence of either overlap or very short intervals between strokes makes this hard—it reduces the clarity of stroke movements and adds uncertainty to measures of initial finger position. Furthermore, errors in one stroke can cascade into follow-up strokes. Thus, characterizing typical time interval between endpoints of consecutive finger strokes can support improved finger-stroke detection and finger classification. We examined this 'inter-keystroke interval' [9] over three key variables: 1) hand combination between previous and current hands (either same or different), 2) typing strategy (either HAND or FINGER) and 3) digraph frequency (either conventional or other). This last factor refers to the how often letter pairs co-occur—we use it to contrast performance with highly practiced pairs and less well-practiced pairs. The typical set included twelve digraphs for both same (in, er, on, re, at, es, ea, io, ou, ar, as, ve) and different (th, he, an, nd, ha, en, of, nt, ti, to, le, is) hands [24]. We excluded digraphs stroked with the same finger. We calculated overlap time between consecutive finger strokes as *"Overlap time = Keystroke duration - Inter-keystroke interval"*.

7.1 Results & Discussion

Table 4 shows inter-keystroke interval for all three variables. Data were analyzed using the statistical procedures similar to those used in prior analyses: two-way ANOVA followed by post-hoc tests for variables of hand combination and digraph frequency. The grand mean of the inter-keystroke interval was 279.1 ms (SD = 73.8 ms). Given that the average stroke extension duration is 181 ms (see Table 3), this reveals that keystrokes are overlapped by an average of 23.8%, or 43 ms. In other words, flexion during a keypress starts well before the extension of the prior keypress is complete. In terms of hand combination, the inter-keystroke interval for different hands (M=261.6 ms, SD=67.5) was not significantly difference with that for the same hand (M=296.7 ms, SD=81.3): ($F(1,60)=3.40$, $p = 0.07$).

Common digraphs (252.4 ms, SD=69.5) showed significantly reduced inter-keystroke intervals compared to other digraphs (305.8 ms, SD=79.8): ($F(1,60)=7.88$, $p=0.006$). Typists' habitual use of these key pairs on physical keyboards leads to very rapid key stroking behaviors. The relatively short intervals for digraphs could require a faster finger-stroke recognition system or digraph gesture recognition system in in-air typing.

Data were further analyzed using Mann-Whitney U test on the variable of the typing strategy. HAND strategy group (345.2 ms, SD=66.3 ms) showed longer inter-keystroke intervals than FINGER strategy group (239.5 ms, SD=44.4). This was further confirmed with a Mann-Whitney U test that typing strategy was statistically significant factor for inter-keystroke press timing. We argue that dynamic hand movement in HAND group leads to longer inter-keystroke intervals. Due to the shorter inter-keystroke intervals, FINGER group caused longer overlap time between consecutive finger strokes than that of HAND group. The relatively short keystroke duration (314.5 ms) and long overlap time (75.0 ms) of the FINGER group could yield the finger stroke detection more complicated.

8 INDIVIDUAL IN-AIR KEYS

We further analyzed finger stroke amplitude in terms of in-air finger travel. Figure 5 shows the amplitude and maximum velocity of active fingers from their initial state to their fully pressed point for each key. In addition, we examined the end point of participants' fully extended key strokes in absolute 3D coordinates. We averaged absolute coordinate positions and directions of the active fingers at the endpoint of a key press for each subject. Figure 6 shows 'xy' and 'xz' projections of the 3D positions and directions.

8.1 Results & Discussion

Amplitude and velocity for each in-air key. In Figure 5, in terms of keyboard rows (i.e. top, middle, and bottom rows), the active finger moved further to keys located in bottom (M=58.2mm, SD=1.5) than top (M=45.5mm, SD=4.2mm) and middle (M=54.8mm, SD=5.3) rows. The average maximum velocity also varied among rows: 734.7mm/s (SD=63.4), 809.4mm/s (SD=65.1) and 856.0mm/s (SD=45.0) for top,

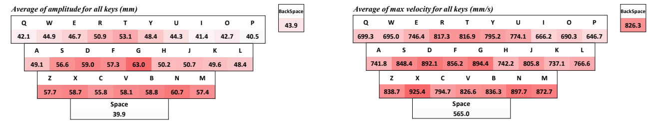

Figure 5: Amplitude (left) and max velocity (right) for each in-air key; towards the bottom of the keyboard, both features showed faster and deeper values.

middle, and bottom rows, respectively. This data shows that finger-strokes became faster and deeper towards the bottom of the keyboard. This may indicate that participants envisaged their fingers hovering near the top of the keyboard—as such, shorter, slower strokes would be sufficient to select keys there, while longer, faster strokes were required for keys on the center and bottom rows. These variations may help support accurate key classification, the final recognition step in an in-air typing system.

3D End-point Distribution. The deviations of fingertip end-positions were smaller in x-axis (M=12.26 mm, SD=2.38) than those in y-axis (M=15.67 mm, SD=2.09) and z-axis (M=16.67 mm, SD=2.16). Vertical and sagittal movements are essential to perform a finger stroke and change rows on the keyboard. Meanwhile, we do not need to move our fingers laterally except the left index finger, which covers two columns and the right pinky, which tends to press the backspace key. This observation is supported by the large position deviations of the backspace key: 21.03, 21.93, and 20.55 mm, in x, y, z, respectively. The averaged positions shown in Figure 6 are also relatively well aligned to the layout of a real keyboard. The mean distance between F and J keys (indicators in physical keyboards) was 97.1 mm, little different from the fixed 90 mm enforced at the beginning of each trial. While the y-positions of the most keys can be distinguished by their rows, the spacebar tended to be positioned in line with the keys on the bottom row. The locations of the air-keys were spread over approximately 250 mm in the x-axis and 100 mm in the z-axis, slightly exaggerated compared to typical physical keyboard sizes (200 mm by 70 mm). This larger horizontal size may have been due to greater initial horizontal hand spacing—F and J are typically separated by about 60 mm on a physical keyboard, rather than the 90 mm used in this study. The larger vertical size may simply reflect participants, possibly intentionally, use of exaggerated motions.

Participants' virtual keyboards were also conceptualized to be highly slanted in the z-axis, with a mean slope of 54.9°. This is much higher than the 0-10° slants common in physical keyboards. We suggest this is due to the fact the finger must be stretched forward to press a key in the top row, and this action reduces the depth of vertical movement that can be achieved by the finger joints. When the participants perform a finger stroke to the keys towards the center of the keyboard (around the F and J keys), the directions of fingertip strokes were close to vertical. Stroke directions were increasingly rotated towards the center with greater distance from the center. The space bar was the only exception from this tendency. It was typically pressed by the thumb with a stroke closely aligned to the forward direction of the participants.

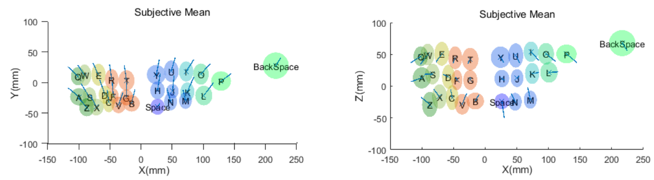

Figure 6: Averaged positions (cross marker) and directions (line) of fingertip when each of "virtual" keys is fully pressed (end point) in absolute coordinate. SD of positions for each participant were averaged and represented as lengths of axes on ellipsoids. Each ellipsoid was colored to show the dominant finger used to stroke the corresponding key.

9 FEASIBILITY OF FINGER CLASSIFICATION

To examine the feasibility of finger classification in unconstrained typing, we constructed a new classifier, including promising features from our analysis. The feature set for the classifier consisted of the absolute and relative 3D position of endpoints, maximum velocity and amplitude of the fingers at the endpoint. We applied this feature set to a RandomForest classifier with 10-fold cross-validation process using data from both all users and also in a per-user arrangement to assess the impact of individual differences.

As shown in Table 5, the static classifier achieved 83.3% and 84.0% finger classification accuracy for the left and right hands. The average accuracy of the per-user classifiers was 86.9% (SD=7) and 86.0% (SD=5.6). The highest accuracy among classifiers was 92.2% (right pinky), and the lowest accuracy was 80.3% (right middle). It is noticeable that the index and pinky fingers achieved higher accuracy of finger classification than middle and ring fingers. It is probably because features from finger movements in pinky and index fingers are distinct from their neighbor fingers, whereas middle and ring fingers are relatively not.

10 GENERAL DISCUSSION

This work investigates the fundamental requirements for developing in-air keyboards for unconstrained in-air eyes-free typing scenario in VR. It captures data in an unconstrained typing scenario and contrasts this with prior reports of data in constrained settings: ATK [39]. In general, we show that unconstrained typing involves faster, shorter and more interleaved and inter-correlated motions than studied in prior work. This means that recognition systems that have been successfully deployed in the past may not be applicable to real-world scenario. Here, we summarize the key findings of unconstrained in-air typing and discuss how they can impact the design of in-air keyboard system.

Table 5: Accuracy of finger classification with *RandomForest* using features from unconstrained typing system.

Finger	*Index*		*Middle*		*Ring*		*Pinky*		*Total*	
Hand	*L*	*R*	*L*	*R*	*L*	*R*	*L*	*R*	*L*	*R*
Accuracy of static (%)	85.5	90.2	79.7	74.9	77.8	79.6	88.1	91.5	83.3	84.0
Accuracy of per-user (%)	89.2 (6.5)	90.7 (3.9)	83.3 (8.4)	80.3 (9.1)	83.1 (10.2)	82.4 (8.8)	90.8 (6.0)	92.2 (8.2)	86.9 (7.0)	86.0 (5.6)

Typing speed is faster in unconstrained in-air typing. Our participants typed at 78.3% of their typing speed with a physical keyboard in unconstrained in-air eyes-free typing. This is a significant improvement since constrained in-air typing occurs at 44.4% of a user's typing speed on a physical keyboard. This improvement is due to the fact that unconstrained typing generates shorter (49 mm) and faster (764 mm/s) keystrokes with a high correlation of finger movement, yielding increased velocity, shorter duration, and overlapping fingers.

Finger stroke recognition is complex. Our analysis showed that there are multiple factors to consider for recognizing a finger stroke. We claim that increased velocity with a shorter amplitude of finger stroke in unconstrained in-air typing can add more difficulties in detecting a finger stroke. We further claim that a higher correlation of finger movements in unconstrained typing can lead to a higher ratio of false detection. In addition, the shorter inter-keystroke interval with longer overlap time and increased degree-of-freedom in finger movements will bring more complexity for finger stroke recognition. Furthermore, the typing strategy (HAND/FINGER) should be considered to optimize the recognizer in order to improve the recognition rate. More apparent and distinct features should be identified in order to detect and recognize a series of finger strokes accurately in unconstrained in-air eyes-free typing. This will be discussed in the following subsection.

Haptics can play a significant role. We argue that adding haptic feedback can enhance the in-air typing performance - the presence of both tactile feelings of the keyboard layout and confirmatory clicks will significantly improve the typing speed. In fact, several works have already demonstrated the benefits of adding haptic cues to virtual typing systems on, for example, touchscreens [1] [23] [15]. In fact, a mid-air haptics display using focused ultrasound waves [3] can provide the haptic cues in mid-air for each finger stroke [16]. We suggest that mid-air haptic feedback can provide a confirmation for each finger stroke, and this may lead to reduced finger movements in both active and passive fingers, yielding decreases in finger travel distance and increases in typing speed.

10.1 Takeaways

Based on a detailed characterization of unconstrained in-air eyes-free typing, we believe that researchers can adopt the analysis from our study as a ground-truth to construct an in-air typing system. To move towards this goal, we present the following data-based recommendations to achieve accurate recognition of unconstrained in-air typing, including time components, finger stroke detection, finger/key classification, and in-air keyboard layout.

Time components for in-air typing system. Given that the average finger flexion duration is 141 ms, the recognition processing should be completed within this time period. The recognizer should be able to detect the initial moment that triggers the finger stroke, retrieve all the features during the flexion finger motion, feed those features into the finger/key classification model, and determine the correct key with proper cues (i.e. visual, audio, haptic, etc).

An inter-keystroke interval is another important time factor to distinguish the sequential finger strokes during a rapid in-air typing. The overlapping between the previous and current finger strokes can lead to an unstable acquisition of necessary features for both finger strokes. We noticed that overlap time takes about 30% of the flexion and 24% of the extension, and this may cause additional false triggers. The overlap time becomes even larger with cross-hand digraphs. One possible solution that we suggest is to use the overlapping finger movements in the extension phase as a feature for the recognizer. Since the recovery movement of the previous keystroke in the extension phase can affect the movement of a current keystroke in flexion phase, the finger movements can be a good option to be a feature to improve the accuracy.

Typing strategy is an important factor. Typing strategy, split between HAND and FINGER in this work, is a key to understanding unconstrained in-air eyes-free typing behavior. The HAND typists tend to stroke the keys by moving their entire hands while the FINGER typists use only their fingers to reach keys. Our analysis revealed that the HAND strategy group moved all their fingers further than the FINGER strategy group. These variations in motor control behavior are likely transferred, and possible amplified, from participant's typing patterns on physical keyboards. On a physical keyboard, the range of movements for a given keystroke is constrained by the physical relationship between fingers, hands and keys. In mid-air, this relationship is relaxed, likely resulting in more diverse behaviors. In addition, the lack of physical terminators for motion (i.e., the physical travel depth of actual keys) and the haptic feedback associated with such impacts, likely contributed to the universal extensions to keystroke length we observed. Regardless, these variations in strategy will increase the challenges associated with accurate detection of finger strokes and, indeed, likely demand approaches specific to each strategy. For example. the HAND strategy group, showed stronger correlated movement among the fingers. This will increase the difficulty of accurate keypress detection. On the other hand, the FINGER strategy group exhibited shorter inter-keystroke intervals and greater overlap between strokes. This will also present challenges for finger stroke classification, albeit relating to the close temporal proximity of the strokes rather the increased quantities of unintentional finger motion. Based on this analysis, we argue that it will be necessary to model typing strategy to achieve accurate in-air typing systems based on unconstrained finger motions.

Finger stroke detection. Detecting a finger stroke in unconstrained in-air typing should consider other factors as features besides simply amplitudes in finger flexion. Since the unconstrained typing generates relatively lower amplitudes, the irrelevant finger movements from passive fingers can add more false triggers. We argue that the velocity of finger stroke can be one of the key features. We noticed that the velocity of the finger stroke was faster (764ms/s) than those from irrelevant movements in passive fingers. In addition, the palm movement can be an another important feature for finger stroke detection because the palm often moves before the finger stroke, indicating that a finger is about to be pressed.

Finger/Key classification. Unlike constrained in-air typing, it is difficult to use the amplitude alone as a feature in unconstrained in-air eyes-free typing due to its high amplitude ratio (AR) between active and passive fingers (46.9%-83.5%). Alternatively, other features can be adopted together with the amplitude. These include acceleration of finger stroke, direction of fingertip, angle of finger flexion, and 3D end-position.

In-air keyboard geometric features. Participants envisage an in-air keyboard to be large and slanted. Specifically, our data suggest 250 mm by 100 mm at a slope of 54.9°. In-air key depth (derived from stroke endpoints) increases from the top row (45.5mm, SD=4.2) to the bottom row (58.2mm, SD=1.5). We derive recommended sizes for in-air keys based on the standard deviation of fingertip end-positions over all keys (see Figure 6): 12.26mm (SD=2.38), 15.67mm (SD=2.09), and 16.67mm (SD=2.16) in x, y, and z (depth), respectively. The backspace key occupies a relatively large region (21.03mm, 21.93mm, and 20.55mm in x, y, z, respectively) compared to its size on a physical keyboard.

Typing is a fundamental input task across a wide range of device form factors. We believe in-air typing is therefore highly relevant to VR scenarios [7] [26]. Understanding finger movements during the unconstrained in-air typing will be essential for future designs. We contribute a discussion of the features that can be used to accurately recognize user input in this setting. This includes differences from prior work (e.g. correlated movement of fingers has weak discriminatory power) and a set of specific data and recommendations for how to detect finger strokes (duration during flexion and extension, inter-keystroke interval, amplitude, velocity) and recognize stroking fingers (amplitude ratio between active and passive fingers, end-point, layout of in-air keyboard-size, depth and skewed). This data is of direct use for researchers seeking to build in-air typing systems. Immediate future work is the validation of our current feature set through further empirical studies with a new set of typists. This new data will allow us to validate and refine our data, analysis and conclusions. A larger sample will also increase confidence in our measures and may suggest new features, in particular if further approaches to in-air typing strategies are uncovered. In addition, future work should apply approaches from bio-mechanics, or models of human movement, such as Fitts' law [11], to in-air finger typing movements. These models may provide additional insight into the relationships between users finger motions and the in-air keys they intend to select.

11 CONCLUSIONS

In summary, we explored the properties of unconstrained in-air eyes-free typing to determine the feasibility of, and requirements for, development of a real world in-air typing system. We also contrasted our data with that captured in a constrained typing setting. We contribute practical observations about basic finger kinematics, typing strategies, correlated movement of fingers, 3D endpoint distribution, and interrelation features of consecutive finger strokes that can support stable finger stroke detection and finger classification. We close by discussing design considerations for developing real-world in-air typing system based on our findings. These contributions can promote the development of more effective, practice in-air eyes-free typing systems in the future.

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