HeadText: Exploring Hands-free Text Entry using Head Gestures by Motion Sensing on a Smart Earpiece

SONGLIN XU, University of Science and Technology of China, China
GUANJIE WANG, University of Science and Technology of China, China
ZIYUAN FANG, University of Science and Technology of China, China
GUANGWEI ZHANG, University of Science and Technology of China, China
GUANGZHU SHANG, University of Science and Technology of China, China
RONGDE LU, University of Science and Technology of China, China
LIQUN HE, University of Science and Technology of China, China

Fig. 1. Application scenarios of HeadText. Fig. a shows that users could perform head gestures to respond to messages when they are eating and their hands are holding the cake. Fig. b presents that a user could use HeadText to input text on a smart watch, whose text entry is originally limited due to the small screen size. Fig. c shows that HeadText could be utilized to help users with motor impairments for text entry. Fig. d presents the application scenario where users could perform head gestures for text entry on the smart glass which is private and socially acceptable in public.

We present HeadText, a hands-free technique on a smart earpiece for text entry by motion sensing. Users input text utilizing only 7 head gestures for key selection, word selection, word commitment and word cancelling tasks. Head gesture recognition is supported by motion sensing on a smart earpiece to capture head moving signals and machine learning algorithms (K-Nearest-Neighbor (KNN) with a Dynamic Time Warping (DTW) distance measurement). A 10-participant user study proved that HeadText could recognize 7 head gestures at an accuracy of 94.29%. After that, the second user study presented that HeadText could achieve a maximum accuracy.
of 10.65 WPM and an average accuracy of 9.84 WPM for text entry. Finally, we demonstrate potential applications of HeadText in hands-free scenarios for (a). text entry of people with motor impairments, (b). private text entry, and (c). socially acceptable text entry.

CCS Concepts: Human-centered computing → Text input; Gestural input; Interaction techniques; Graphics input devices.

Additional Key Words and Phrases: hands-free input, text entry, wearable

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1 INTRODUCTION

Text entry is an important and common task for computing devices like computers, mobile phones and smart wearables in the daily life. Hands-free techniques provide a new interaction experience for text entry, which is especially useful for people whose hands are occupied with other tasks or people with motor impairments. Therefore, hands-free text entry has become an important problem to assist users for more flexible text input.

One apparent solution to realize hands-free text entry is speech input. However, this may be inappropriate in some social scenarios and may also leak the privacy of users. In addition, speech recognition may not work well in the noisy environment. To address this problem, researchers have explored various kinds of techniques for hands-free text entry. Non-vocalized speech input such as TongueBoard[24] and CHANTI[42] is a new way which could support hands-free text entry while also keeping users’ privacy in social situations. What’s more, facial movements could also be used for hands-free text entry. FaceInput[13] presented a hands-free and secure text entry system by facial vibration. Additionally, to achieve hands-free text entry, Eye movements[1] are investigated a lot using gaze paths(EyeSwipe[22]), blink gesture(BlinkWrite[29]) or even eyebrow movements[7].

In this paper, we report a new technique, HeadText, for hands-free text entry as well as solving private and socially acceptable issues. Instead of using head pointing techniques to select all keys on a QWERTY keyboard[54], HeadText allows users to perform four head gestures to trigger each key on a 2x2 keyboard in an alphabetical order to reduce head pointing errors and also improve user experience so that users do not have to point their heads towards all kinds of directions in the 3D space. Besides, our techniques are not only suitable for Head-Mounted Devices, but also for computers, mobile devices and smart wearables since our method does not rely on HMDs and our head gesture recognition system could also work well in noisy scenarios during walking, eating or speaking.

There are three main challenges that may prevent users from using head gestures for text entry. First, head movements may distract users from doing their own jobs. And users may not be able to focus on the keyboard if they rotate their heads with too much angle. To find a balance between recognition and distraction, we have conducted a user study to understand users’ head movements and explore how slight is enough for users to perform head gestures so that they could focus on the keyboard while performing head gestures. Second, text entry information may leak in public. HeadText solved this problem by allowing subtle head gestures and unknown gesture-text decoding mechanism. Third, general text entry behavior may be not socially acceptable in public, especially for users who are talking with others face to face. HeadText overcomes this challenge and our study shows that HeadText is more socially acceptable for spectators compared with smart phones while users are talking with others.

The contributions of this paper are as follows.
• A motion sensing pipeline on smart wearables to detect and recognize head gestures robustly and accurately, even in noisy scenarios including walking, eating, and speaking.
• A new hands-free text entry system using slight head movements on an earpiece through motion sensing.
• Three user studies to understand users’ head movements, evaluate text entry performance, and investigate socially acceptable text entry respectively.
• Hands-free application scenarios of HeadText in (a). text entry of people with motor impairments, (b). private text entry, and (c). socially acceptable text entry.

2 RELATED WORK

HeadText is a head gesture based text entry technique to support hands-free input. Therefore, we first introduce hands-free gesture input techniques. After that, we review existing work about gesture-based and hands-free text entry. Finally, we present previous research that are most related with our work and state our specific contributions compared with existing work.

2.1 Hands-free Gesture Input

Eye gesture input is the most frequently used method for hands-free input such as eye gesture recognition[31–33] and gaze interaction (Orbits[6], GazeTap[15]). And mouth-related interface (Whoosh[38], TieLent[20]) such as tongue interface[11, 24] and teeth interface (TeethTap[43], Bitey[2], EarSense[37]) also offers users a novel way for hands-free input. What’s more, ear-based interaction (EarRumble[39]), waist gestures (HulaMove[48]) and foot gestures (FootUI[17], FEETICHE[26]) are also explored by researchers. Compared with existing work, head gestures present another way for hands-free input like navigation in 3D space[5]. To recognize head gestures or orientations, researchers have explored various sensing techniques such as motion sensing[14], acoustic sensing (Soundr[53]), capacitive sensing[16], vision-based sensing[23, 35], and so on. Radi-Eye[40] is a hands-free radial interfaces for interaction in 3D space using both gaze and head crossing gestures. HeadCross[50] and HeadGesture[52] presented a hands-free interface using head movements for HMDs. In addition, Headbang[18] and HeadReach[45] used head gestures for discrete action triggering and reachability increasement on mobile devices. What’s more, Andrea Ferlini et al.[8] used in-ear wearables to track head motions, which is similar with our technique using an earpiece to recognize head gestures.

2.2 Hands-Free and Gesture-Based Text Entry

Eye movements[1] are investigated a lot for hands-free text entry, whether using gaze interaction (EyeSwipe[22]), blink gestures (BlinkWrite[29], BlinkWrite2[3]) or eyebrow movements[7]. Lu et al.[28] also examined the difference between DwellType, BlinkType and NeckType in virtual reality. Additionally, non-vocalized speech input is another useful method such as TongueBoard[24] and CHANTI[42]. Naoki Kimura et al.[19] used a SilentSpeller to realize mobile and hands-free silent speech texting by sensing tongue gestures. Facial movements could also be used for hands-free text entry by facial vibration detection (Facelinput[13]) or vision (Face Typing[10]). Yulia Gizatdinova et al.[9] examined the difference between text entry using eye tracking, head tracking, and facial gestures including mouth open and brows up gestures in a video-based interface and found that mouth interaction caused significantly fewer errors than brow interaction.

Additionally, head gestures could also be utilized for hands-free text entry. Usually, head gestures are used for pointing and assisting key selection in AR/VR Head-Mounted Displays[41, 46]. DepthText[27] leveraged head movements towards the depth dimension for hands-free text entry in mobile virtual reality systems. RingText[47] presented a dwell-free and
hands-free text entry technique for mobile head-mounted displays using head motions. Chun Yu et al. [54] explored the
difference of head-based text entry techniques using tap, dwell or gesture input method, i.e. TapType, DwellType and
GestureType. However, these head-based text entry techniques (RingText[47], DepthText[27], TapType, DwellType and
GestureType[54]) all focused on Head-Mounted Displays, which may not be suitable for general computing devices
such as computers, mobile phones, and smart wearables. What’s more, these techniques used built-in IMU sensor in
HMDs for head motion tracking, but they did not explore and evaluate the effect of users’ movements such as walking,
eating or speaking that may have an influence on their head-point techniques. Additionally, pointing each key of the
keyboard using head motion tracking may lead to apparent errors in some specific situations such as noise scenarios.

Our work, HeadText, is designed to provide hands-free text entry using head gestures which is suitable for general
computing devices including not only HMDs and computers, but also mobile devices and smart wearables. We employ
a 2×2 keyboard layout which is controlled by only four head gestures to reduce the errors that may be caused by head
pointing and also provide better user experience so that users do not have to point their heads towards too many
directions for key selection. In addition, we conduct a user study to understand users’ head movements and also explore
the private and socially acceptable text entry challenges. Our technique is also low-cost, as it only relies on an IMU
sensor on an earpiece, which could work with other computing devices such as smart watches, smart phones and
computers together for text entry.

3 DESIGN CONSIDERATIONS

We considered the following factors in the HeadText design.

| Gesture      | Gesture Performance                     | Plot |
|--------------|-----------------------------------------|------|
| Single-Left-Tap | Middle → Left → Middle                  |      |
| Single-Right-Tap | Middle → Right → Middle                |      |
| Double-Left-Tap | Middle → Left → Middle → Left → Middle |      |
| Double-Right-Tap | Middle → Right → Middle → Right → Middle |      |
| Single-Down-Tap | Middle → Down → Middle                 |      |
| Left-Slide   | Middle → Left → Middle → Right → Middle |      |
| Right-Slide  | Middle → Right → Middle → Left → Middle |      |

Fig. 2. Head gestures sets and gyroscope signals.
3.1 Learnability
Learnability is important during our design process. We need to make sure that users could learn our technique quickly and easily. There are several factors that are related to users’ learnability. First, the head gesture set should be designed carefully. Too many or complex head gestures may be hard for users to remember and perform. In addition, we also need to consider the design of keyboard layout, including the one following an alphabetical order or a QWERTY layout. Considering that some users may not be a master of QWERTY keyboard, we decide to adopt the alphabetical order so that most users could get used to our system as quickly as possible.

3.2 User Experience
The user experience here mainly refers to users’ feelings when they are using head gestures for text entry. Specifically, in the text entry process, some head gestures will be performed for many times. If the gestures are too complicated, users will feel pretty tired. Besides, the design of text entry system, such as mapping head gestures to the commands of text entry system, should be designed carefully. For instance, the direction of head gestures could be related to the position of keys on the keyboard. In this case, users will feel easy and intuitive to perform head gestures for text entry.

3.3 Accuracy and Efficiency
There are two types of accuracy: head gesture recognition accuracy ($E_1$) and text entry accuracy ($E_2$). Higher $E_1$ could speed up the text entry process and result in higher $E_2$. However, the text entry system could also tolerate certain level of head gesture recognition errors thanks to the auto-correct model in our text entry system. The lasting time of head gestures will affect text entry speed, and therefore has an impact on the efficiency of text entry process. Besides, $E_1$ will affect users’ text entry performance. If a head gesture is not recognized correctly, the user has to perform the gesture again, decreasing $E_2$. Word disambiguation appears if more than one letters are associated with an enlarged key (e.g. T9) which could be hard to tell which letter the user wants to enter [49]. Thus, a balance is required between word disambiguation and key size.

3.4 Privacy and Social Acceptability
To protect users’ private text entry information, head gestures should not be easily noticed. Even if head gestures are noticed, others should not be able to decode text entry information from head gestures. Socially acceptable text entry issue appears in public, especially when users are talking with others face to face. For instance, if users are talking with others while using phones for text entry at the same time, others may feel uncomfortable who may think phone users do not respect them enough. Similarly, head gestures should not be too obvious as well.

4 HEADTEXT: SYSTEM IMPLEMENTATION
4.1 Head Gesture Design
The design of head gesture set is inspired by HeadGesture[52]. In order to make sure our gesture set is easy to be memorized and performed by users, we choose four directions where users’ heads will perform: Left, Right, Up and Down. To enlarge the head gesture set, we introduce different combination of head gestures towards these four directions while also considering the design considerations in Section 3. Finally we have designed seven head gestures which are shown in Fig. 2.

- Single-Left-Tap. Turn left from the middle position, and turn right to return to the middle position.
Fig. 3. (a). HeadText prototype. (b)(c)(d): three sensor locations. (e): 3-axis (X, Y, and Z) direction of gyroscope.

Fig. 4. Gyroscope signals in three locations. Three rows stand for 3-axis of gyroscope. Seven columns present signal curves of seven head gestures repeated five times randomly.

- Single-Right-Tap. Turn right from the middle position, and turn left to return to the middle position.
- Double-Left-Tap. Perform Single-Left-Tap gesture twice.
- Double-Right-Tap. Perform Single-Right-Tap gesture twice.
- Single-Down-Tap. Turn down from the middle position, and turn up to return to the middle position.
- Left-Slide. Turn left from the middle position, and then turn right to the right side. Finally, turn left to return to the middle position.
- Right-Slide. Turn right from the middle position, and then turn left to the left side. Finally, turn right to return to the middle position.

4.2 Hardware Prototype

We utilize an inertial measurement unit (IMU) to capture motion signals while users are performing head gestures. IMU is a low-cost (less than 10 dollars) and highly sensitive motion sensor. The overall hardware system is shown in Fig. 3(a). The elastic band is used to fix IMU on the user’s head under the ear tightly enough. While users are performing head gestures, IMU will capture motion signals, which will be sent to the computer to process the data through Arduino.
The IMU sensor we used contains three circuits: ITG3200, ADXL345 and HMC5883L, corresponding to gyroscope, accelerometer, and magnetometer. After a pilot study, we finally decided to utilize gyroscope signals for head gesture recognition, which could capture motion signals of head gestures robustly. The direction of each axis in gyroscope is shown in Fig. 3(e). The gyroscope signal curves of seven head gestures are shown in Fig. 2. In the signal curves of seven head gestures, \( \text{gyro1} \), \( \text{gyro2} \) and \( \text{gyro3} \) stand for 3-axis of gyroscope data and the unit is degrees of angle per second (degrees/s) in the curves.

4.3 Sensor Location Exploration

Another problem is to decide the position where IMU is located. Theoretically speaking, IMU signal change should be similar on different positions around ear as long as IMU is fixed tightly enough, because IMU and the head constitute a rigid body and do not move relative to each other. We conducted a preliminary study to verify this assumption. Three locations are selected: on the ear canal (Position 1: Fig. 3(b)), behind the ear (Position 2: Fig. 3(c)), and under the ear (Position 3: Fig. 3(d)). We asked a participant to perform these seven head gestures mentioned above (Fig. 2) five times per gesture randomly in each sensor position scenario. Then we compared gyroscope signals which are shown in Fig. 4. We could find that all three locations have shown good repeatability across seven kinds of head gestures, which verify our assumption. We finally decided to put the IMU under the ear (i.e. Position 3: Fig. 3(d)) which is easier to fix IMU and also more comfortable for users.

4.4 Real Time Head Gesture Segmentation

Before gesture recognition, a head gesture is first segmented from real-time series data (Fig. 5), which should meet requirements below:

- All head gestures should be detected. Noise gestures could be filtered by a noise gesture classifier later.
- Head gestures should be segmented completely, instead of leaving broken gesture pieces.
- Current gesture should be segmented accurately, without pieces of the next gesture or the previous gesture.

To achieve this, we first calculated energy signal of the 3-axis gyroscope signals using the formula below:

\[
\text{Gyroscope}_{\text{Energy}} = \sqrt{\text{Gyroscope}_x^2 + \text{Gyroscope}_y^2 + \text{Gyroscope}_z^2}
\]  

(1)

Then we use the energy signal for gesture segmentation. As is shown in Fig. 5(c), there are four parameters responsible for gesture segmentation: \text{Peak Threshold}, \text{Left Buffer}, \text{Tolerance Range}, and \text{Right Buffer}. One segmented gesture is denoted as \text{Gesture Unit}.

Fig. 5(b) shows each step in gesture segmentation process. At first, if users are keeping still, the energy will not exceed \text{Peak Threshold}, which will not be recorded (\text{Gesture Unit} = \text{Blank}). After that, if the energy exceeds \text{Peak Threshold}, the system will recognize it as the start of one gesture and record the most recent gesture data (i.e. \text{Left Buffer}). At this time, \text{Gesture Unit} = \text{Left Buffer}. Then, if the energy is always larger than \text{Peak Threshold}, it will be added into \text{Gesture Unit} continuously. After that, if the energy is lower than \text{Peak Threshold}, the system will not stop collecting data immediately. Instead, there is a \text{Tolerance Range}, which means that the system will continue saving new data to \text{Gesture Unit}, unless the lower value data length is longer than \text{Tolerance Range}. This step aims to avoid segmenting gesture data into broken pieces and also distinguish if a gesture has ended or not. Finally, if energy value is lower than \text{Peak Threshold} for a longer data length than \text{Tolerance Range}, the gesture is recognized as being finished. And the \text{Right Buffer} (most recent data of gesture ending point) is added to \text{Gesture Unit} as the end of segmented head gesture.
4.5 Head Gesture Recognition

As is shown in Fig. 5(a), the segmented gesture is then recognized as specific head gestures using KNN (K-Nearest Neighbor) with a metric of DTW (Dynamic Time Warping). To demonstrate the algorithm, we denote two time series head gesture data as $M_1^{LM}$ and $N_1^{LN}$. $L_M$ and $L_N$ stands for their data length respectively. $M_i$ and $N_j$ is denoted as the i-th point and j-th point in $M_1^{LM}$ and $N_1^{LN}$ respectively. $\delta_{i,j}$ is denoted as the distance between $M_i$ and $N_j$. The time series data similarity measurement problem is then converted to find an optimal way from $\delta_{1,1}$ to $\delta_{LM,LN}$. We denote $\text{DTW}_{i,j}$ as the distance between $M_i^1$ and $N_i^1$ with the best alignment. $\text{DTW}$ is first initialized as a matrix full of infinity number with $L_M + 1$ columns and $L_N + 1$ rows. So we have:

$$\text{DTW}_{i,j} = \infty (0 < i < L_M + 1, 0 < j < L_N + 1)$$ (2)

$$\text{DTW}_{0,0} = 0$$ (3)

For $i \in [1, L_M + 1], j \in [1, L_N + 1]$, based on dynamic planning:

$$\text{DTW}_{i,j} = \delta_{i,j} + \min(\text{DTW}_{i-1,j} + \text{DTW}_{i,j-1} + \text{DTW}_{i-1,j-1})$$ (4)

Finally, the output, i.e. $\text{DTW}_{LM,LN}$, is the similarity measurement of the two time series head gesture data $M_1^{LM}$ and $N_1^{LN}$.
K-Nearest Neighbor (KNN) is a machine learning algorithm (implemented by scikit-learn\cite{36}) for gesture recognition based on distance measurement and voting. The basic idea of KNN is to find K most adjacent samples of a new sample. If most of the K samples belong to a certain gesture class, then the new sample also belongs to this gesture class. Therefore, there are four steps in our head gesture recognition algorithm:

- **Step 1**: Data preprocessing to make sure the new gesture data could be fed into our algorithm.
- **Step 2**: Calculating the distance between the new gesture data and existing training samples using DTW Measurement.
- **Step 3**: Ranking all distances from Step 2 and pick K samples with the smallest distance. Here we set K = 1.
- **Step 4**: The gesture class that the new sample belongs to is that most of the K samples belong to.

### 4.6 Noise Gesture Cancellation

We select three scenarios which are highly related to noise head movements and also may occur in text entry tasks: Walking, Eating and Speaking. We recruited one participant randomly and let him perform all kinds of noise gestures during these three scenarios. Each scenario lasted 2 to 3 minutes. Totally, 81 noise gesture samples were segmented including 72 walking samples, 8 eating samples and 1 speaking sample. The result also showed that compared with eating and speaking, walking will have a larger influence on head gesture recognition. This is reasonable because walking will cause larger head movements while eating and speaking will not have such affect apparently. The noise
data from three scenarios are shown in Fig. 6 and we could find that there are indeed a list of gesture samples that may be confused with head gestures. However, we find that time domain features of energy curves such as peak number is clearly different between noise gestures and head gestures. This provided us theoretical proof to distinguish them using energy signals. We also asked the participant to perform each head gesture for three times as the standard head gesture data set. Finally, we used energy signals of 81 noise samples and 21 head gesture samples for training (80% data) and testing (20% data) a binary SVM classifier. The testing result indicated that all gestures are classified correctly. This classifier also worked well in our following user study for head gesture recognition and text entry tasks.

5 UNDERSTANDING HEAD MOVEMENTS

In the text entry system, speed of head movements is a trade-off problem. On one hand, high speed head motions could result in high text entry speed. However, on the other hand, high speed head motions may generate noisy head gestures, result in decreases of head gesture recognition accuracy. Additionally, high speed head motions may lead to uncomfortable user experience, distracting users from focusing on the keyboard layout and even cause private and socially acceptable issues. Therefore, we conduct the first user study to understand users’ head movements and find the best suitable value, which is directly related to head motion speed (described in Section 4.4). The initial range of Peak Threshold is from 10 to 50 degrees/s, which is obtained from a pilot study. Then we select five value: 10, 20, 30, 40, and 50 for exploration. To find the best suitable value, we implement each one in each session and analyze head gesture recognition result in the study.

5.1 Participants

We recruited 10 right-handed participants (4 female) aged between 20 and 26 from the author’s institution. Each participant was asked to fill in a questionnaire and was paid with 10 USD for their time.

5.2 Apparatus

We utilized the prototype of HeadText which was described before in Fig. 3(a) to conduct the user study. A computer screen was in front of each participant to provide visual instructions such as which kind of head gesture the participant will do to the participant.

5.3 Study Design

There are five sessions for each participant totally, corresponding to five value settings of Peak Threshold. Participants do not know the different Peak Threshold value set. Also, the order of different sessions is shuffled randomly. In each session, there are two parts: training part and testing part. During each training part, participants need to perform 3 samples per head gesture randomly to train a head gesture recognition model, which will be used to recognize head gestures in the testing part, where participants are asked to perform 5 samples per head gesture randomly. Totally, for the ten participants, we collect \(10 \times 5 \times (3+5) \times 7 = 2800\) gesture samples.

5.4 Procedure

The researchers first introduced the study to participants and then instructed them to wear the prototype and explained visual instructions on the computer. Each participant was allowed to practice head gestures before they conducted actual tests until they felt confident to perform head gestures correctly. For each session, participants followed instructions
on the screen to perform head gestures. If they happened to make mistakes such as wrong gestures, they would tell experimenters to remove wrong samples. The groundtruth was recorded by the computer automatically. Participants did not know whether performed gestures were recognized correctly. The whole user study took about 1 hour for each participant, who would fill in a NASA TLX form after each session.

5.5 Result and Analysis

5.5.1 Head Gesture Recognition Accuracy. Fig. 7 shows recognition accuracy during different sessions (i.e. different Peak Threshold). We could find that most results are higher than 90%. However, compared with others, threshold = 30 performs best in most head gestures such as Double-Left-Tap, Double-Right-Tap, Left-Slide and Right-Slide. Although threshold = 30 performs worst in Single-Down-Tap, the recognition accuracy (96%) is still higher than 95%. Besides, threshold = 30 is the only threshold that accuracy of all gestures is higher than 90%. Additionally, as is shown in Fig. 8, threshold = 30 holds the highest gesture recognition average accuracy (i.e. 94%).

5.5.2 Head Gesture Lasting Time. The gesture lasting time means the time from when the gesture is detected to when the gesture is recognized to be finished in our system, which is shown in Fig. 7. We find that gesture lasting time will decrease with the increasement of threshold, which indicates that threshold = 50 holds the shortest gesture lasting time. However, in Fig. 7, we also find that the gap of lasting time between threshold = 30 and threshold = 50 is actually much lower than that between threshold = 10 and threshold = 50. In addition, as is shown in Fig. 8, the gap of average gesture time between threshold = 10 and threshold = 30 is 0.16s while that between threshold = 30 and threshold = 50 is only 0.08s. If taking both high gesture recognition accuracy and low gesture lasting time into considerations, threshold = 30 could be the best value.
5.5.3 Subjective Feedback. NASA TLX result is shown in Fig. 8. Surprisingly but reasonably, we found that threshold = 30 held the lowest score in all classes of NASA TLX form, indicating that threshold = 30 could provide the best user experience among all threshold. We got reasons after interviewing some participants. In the threshold = 10 or threshold = 20 sessions, users felt that some noise gestures were easy to be detected, distracting their focus on performing head gestures. While for the threshold = 40 or threshold = 50 sessions, it might took more efforts of them to perform head gestures so that gestures could be detected by the system.

Finally, considering the trade-off problem among gesture recognition accuracy, gesture lasting time, and subjective feedback from participants, which may affect both text entry speed and user experience, we decide to use 30 degrees/s as the Peak Threshold to provide fast yet also user-friendly text entry system.

6 TEXT ENTRY SYSTEM

6.1 Keyboard Layout Mapping

With design considerations in section 3 and user study results, we show our text entry system in Fig. 9. We adopt the alphabetical order of the keyboard layout so that most users could get used to it as soon as possible. The whole keyboard is divided into four blocks, with each block is mapped to a head gesture. For each word to input, users could trigger specific blocks by performing the corresponding head gestures. Then an auto-complete algorithm will produce three predicted words according to the blocks that are triggered by users, so that users do not have to input all letters. Users could select one word in turn from the three auto-complete words by performing Single-Down-Tap. We choose Single-Down-Tap for word selection in a reason that Single-Down-Tap holds the shortest lasting time compared with other gestures (results are from the first user study).

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The word will be committed automatically once the user starts typing the next word. A space will be inserted after the committed word automatically. We also have an auto-correct algorithm that could predict right words even if users make a mistake about their head gestures. Users could also cancel the last head gesture or the last word they have selected by performing Left-Slide. The difference between gesture cancellation (Fig. 9(c)) and word cancellation (Fig. 9(d)) is whether users have selected a word by Single-Down-Tap. This means if users have already committed a word by Single-Down-Tap, then when they perform Left-Slide, the system will delete the last word immediately. Otherwise, if users have not selected a word by Single-Down-Tap, then the system will delete the last gesture. After users have finished the current phrase, they could perform Right-Slide to start to input the next phrase (Fig. 9(e)).

6.2 Auto-Complete and Auto-Correct

Our auto-complete and auto-correct feature is based on WrisText[12]. A Bayesian model is utilized to predict a target word (denoted as W) based on users’ gesture input S = [s1, s2, s3, ..., sn] (i.e. a series of head gestures). We denote the word dictionary we use as L. We need to find a word W∗ in L that could satisfy:

\[ W^* = \arg \max_{W \in L} P(W|S) \]  

Additionally, according to the Bayes’ rule, we have:

\[ P(W|S) \times P(S) = P(S|W) \times P(W) \]  

Therefore,

\[ P(W|S) = \frac{P(S|W)P(W)}{P(S)} \]  

Because P(S) is an invariant across words, we have:

\[ P(W|S) \propto P(S|W) \times P(W) \]  

Therefore, Equation 5 could be converted to:
\[ W^* = \arg \max_{W \in L} P(S|W) \times P(W) \] (9)

In Equation 9, \( P(W) \) could be got from language model (LM) and \( P(S|W) \) could be obtained from spatial model (SM), so we have:

\[ P(S|W) = \prod_{i=1}^{n} P(S_i|W_i) \times \alpha^{m-n} \] (10)

We assume that users will not generate insertion or omission errors. Each key strike that is triggered by users’ head gestures is treat independently\cite{12}. In Equation 10, \( S_i \) stands for the \( i \)-th letter of the word which is entered by users and \( W_i \) refers to the \( i \)-th letter of \( W \) in the dictionary \( L \) whose length is between \( S \) and \( S + 8 \), where \( 8 \) is determined from both WrisText\cite{12} and our preliminary test. To prevent long words with high frequency to be ranked too high in our system and may dominate short words with low frequency, we introduce the penalty parameter \( \alpha^{m-n} (m \geq n) \), where \( m \) is the length of word \( W \) and \( n \) is the number of head gestures in \( S \). We finally set \( \alpha = 0.65 \) which performs best in our text entry system.

Auto-correct feature is mainly used to deal with cases where users fail to select a desired key, which is composed of two scenarios: 1. Our head gesture recognition system fail to recognize users’ right gestures; 2. users perform a wrong head gesture which is actually not the gesture they intend to perform. From the first user study we find that the head gesture recognition accuracy is 94%. Therefore, we set \( P(S_i|W_i) = 0.94 \) if \( S_i \) and \( W_i \) are from the same key. For \( S_i \) and \( W_i \) belonging to keys that are adjacent or diagonal to each other, we choose 0.025 and 0.01 respectively.

7 TEXT ENTRY EVALUATION

7.1 Participants

We recruited 5 right-handed participants (2 female) aged between 22 and 26 from the author’s institution (Covid-19 has limited further recruitment). Each participant was paid with 10 USD for their time.

7.2 Apparatus

We utilized prototype in Fig. 3(a) to conduct the study. A computer screen was in front of each participant to provide visual instructions such as which phrase for input to the participant. Also, top three candidates by auto-complete will be shown and participants could perform Single-Down-Tap to navigate the candidate list and commit words. Participants could also perform Left-Slide to delete the last letter or the last word. The keyboard layout was also shown on the screen to assist participants for text entry.

7.3 Study Design

There are six sessions in this study, each containing 8 phrases picked from the MacKenzie’s phrase set\cite{30} randomly. Each participant will input all phrases in each session and no phrase was repeated. Since different sessions contained different phrases, the order of sessions for each participant was also shuffled randomly. After entering a phrase, a participant could perform Right-Slide to proceed to the next phrase. Totally, we collected 5 participants × 6 sessions × 8 phrases = 240 phrases.

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7.4 Procedure

The researchers would first introduce the study to participants and instruct them to wear our prototype and explain the visual instructions on the computer screen. Each participant was allowed to practice performing head gestures for text entry before they conducted the actual test. When participants got familiar with our system, they would proceed to the following six sessions. The groundtruth of target phrases, participants’ actual input and text entry speed was recorded by the computer automatically. The user study took about 1 hour for each participant.

7.5 Result and Analysis

We analyzed the results through a one-way repeated measures ANOVA. Bonferroni corrections were used for pair-wise comparisons and a Greenhouse-Geisser adjustment was adopted for degrees of freedom for violations to sphericity.

7.5.1 Text Entry Speed. Mean WPM of each session was shown in Fig. 10(a). ANOVA yielded a significant effect of Session ($F(2.106, 8.424) = 20.456, \ p < 0.001$). Fig. 10(a) also demonstrated a performance improvement through users’ practice. In addition, Post-hoc pair-wise comparisons showed a significant difference between first and fifth session ($p < 0.001$), and also difference between first and sixth session ($p < 0.05$), second and sixth session ($p < 0.05$). Participants achieved 6.35 WPM (s.e. = 0.430) in the first session and the speed increased to 9.84 WPM (s.e. = 0.240) in the last session with an improvement of 55%. These results suggested potentials to continue increasing text entry speed for long-term learning. Additionally, the maximum speed in the last session is 10.65 WPM.

7.5.2 Error Rate. Two kinds of error rate are reported: uncorrected error rate (UER) and total error rate (TER). Uncorrected errors refer to errors that are found in the final input words after auto-correction. Total errors include both uncorrected errors and errors that have been corrected by the system. Overall, for both UER and TER, no significant effect was found in Session (UER: $F(1.925, 7.700) = 1.864, \ p > 0.05$; TER: $F(2.040, 8.161) = 2.517, \ p > 0.05$). Whereas UER and TER decreases with the increasement in text entry speed, suggesting that users increase text entry speed by decreasing mistakes. However, correcting errors was still one of the major sources preventing users from achieving faster speed. The average UER and TER was 16.28% and 18.78% respectively, indicating that our auto-correction feature was not fully utilized. Fig. 10(c)(d) showed results, where we found that average UER and TER in the first session (21.40%, 25.10%) improved by 34% and 37% in the last session (14.20%, 15.80%). Although error rate improvement is significant, we could find that there is still enough space to improve the error rate.
7.5.3 Auto-Complete Rate. The auto-complete rate of a word is calculated by dividing the number of automatically filled letters by the length of the word. Results were shown in Fig. 10(b). No significant effect was found in Session (F(1.563, 6.253) = 3.075, p > 0.05). Participants achieved 8.00% auto-complete rate (s.e. = 2.3%) in the first session which increased to 19.60% (s.e. = 1.2%) in the last session with an improvement of 145%. Additionally, we could find that text entry speed increases with the increase in auto-complete rate. These results indicated that users accelerated their text entry speed by increasing their auto-complete rate.

7.5.4 Subjective Feedback. We asked participants to express their opinions and suggestions. All participants agreed with our idea of using head gestures for text entry and some of them purposed that this technique could be used in the commercial products like smart earbuds. One participant said that HeadText is pretty cool and convenient for use. Another participant hoped that we could build a more flexible band to wear more comfortably. Overall, participants welcomed our technique and believed that this could have many potential applications in the future.

8 APPLICATION SCENARIOS

In addition to hands-free applications in Fig. 1, we demonstrate application scenarios in three points: text entry of people with disabilities, socially acceptable text entry and private text input.

8.1 Text Entry for People with Disabilities

The most direct application of this hands-free text entry technique is to help people with motor impairments for text input. Users could perform head gestures to trigger keys on a keyboard and commit the word to the system instead of using hands. Compared with HeadText, GazeSpeak[55] is another alternative technique for people with Amyotrophic Lateral Sclerosis (ALS) and other motor impairments by allowing users to use gaze directions for text input at an average speed of 80.9 seconds per sentence (around 3.71 WPM) and at a maximum speed of 51 seconds per sentence (around 5.88 WPM). Whereas our evaluation shows that users mean text entry speed is 9.84 WPM and maximum speed is 10.65 WPM, which is much faster than GazeSpeak. Additionally, HeadText is also able to be operated by people with ALS, Muscular Dystrophy and other motor impairments except for users whose heads could not move.

8.2 Socially Acceptable Text Entry

We conducted an extra study to demonstrate social acceptability for HeadText. Inspired by the survey of social acceptability in HCI[21], we utilized two dimensions for evaluation: (1). the user’s social acceptance and (2). the spectator’s social acceptance, according to Montero et al.[34]. There are two social situations that we consider: face-to-face conversation (one-to-one) and public situation (one-to-more). Theoretically we needed to connect the prototype to a computer and ask users to perform gestures for real text entry while running our algorithm. However, this requires a screen for visual feedback of auto-complete words and word selection, which is bulky and inconvenient and may have a bias for study results. We also anticipate that HeadText could be used with a speaker inside an earpiece or smart glasses to provide audio or visual feedback in the future. Therefore, we finally decided that HeadText did not have to be connected with a computer. Users just needed to wear the prototype and perform head gestures to simulate text entry. Because our purpose is to evaluate social acceptability for wearing the prototype and performing head gestures, this design could also meet our research target.

8.2.1 Face-to-face Conversation Study. We recruited 6 participants for the face-to-face conversation study of two sessions, who are divided into 3 pairs randomly. For each session, each pair was asked to have a 20-minute conversation.
Participants could talk anything they want. The difference of two sessions is the additional task: Wearing HeadText or Holding Phones for typing, which design is inspired by Logas et al. [25]. For each pair, we randomly selected one participant (technique user) and asked him/her to wear HeadText (session 1) or hold a smart phone (session 2). The user was also required to perform 20 head gestures naturally during the conversation to simulate inputting one phrase (around 5 words, 20 gestures) (session 1) or use fingers to input one phrase on a phone (session 2). Since we could not anticipate which words users want to input in the real life, the kind and order of head gestures or the content of words are not limited. Another participant (technique spectator) in one pair was not informed about tasks of the technique user. After the study, technique users were asked to score their acceptability to (a). wear HeadText/hold phones and (b). use head gestures/phones for typing during a conversation. Technique spectators were asked to score their acceptability for people who (a). wear HeadText/hold phones and (b). use head gestures/phones for typing while talking with them. Both technique users and spectators were encouraged to state their subjective feelings. The score of acceptability is presented through 1 to 7 rating. Score 1 means totally unacceptable while score 7 means totally acceptable. The result is shown in Table 1. We found that holding a phone owned higher acceptability score than wearing HeadText during a conversation, which was quite normal since users are more familiar with phones and therefore feel more natural to use a phone. However, the spectator owns more acceptability for people who wear HeadText for typing than those who use a phone. One participant told us that phone typing requires users to keep their eyes pointing at phones, instead of conversation partners. Therefore, spectators might not feel respected. However, using an earpiece for typing could make sure users’ eyes focusing on spectators, even if their heads are moving at an unobservable angle. Besides, all HeadText wearers showed their acceptability for wearing the prototype and they told us that it just felt like wearing a normal earphone.

8.2.2 Public Situation Study. The public situation (one-to-more) study is a semi-controlled study, where we designed two parts, focusing on evaluation of HeadText users and spectators respectively. For the first part, we recruited three participants who is asked to do whatever they originally should do respectively for 30 minutes in three places: basketball court, library, and dining hall. For instance, a participant in the library may read books, talk with others and so on. In the same time, each participant needed to wear HeadText prototype and perform 20 head gestures. Similar with face-to-face study, users’ performing gestures meet three conditions: (a). Which head gesture the participant is performed is not limited; (b). When the participant will perform each gesture is not limited; (c). The spectator (others who may notice the participant in public) is not informed of the participant’s tasks (i.e. wear and perform head gestures). After the study, participants were asked to state their personal feelings. The participant in the dining hall told us that he did not feel embarrassed because nobody noticed him except one person who swept the floor. The participant in the library gave us similar feedback, stating that everyone was doing their own work and therefore he did not have any uncomfortable feelings, just like usual work in the library. Interestingly, the participant in the basketball court said: “ When I was performing head gestures, I felt that other observers thought that I was just doing some muscle and bone exercises. So I didn’t feel embarrassed ”.
For the second part, we recruited one participant from the school and asked him to go to a cafeteria and do whatever he wants naturally. Additionally, the participant needed to wear HeadText prototype and perform 20 head gestures, whose performing gestures meet the three conditions described before. Overall, the participant bought a cup of coffee, played his phone and dealt with affairs work. There were totally 6 persons in the cafeteria except for the participant and including one salesman. We interviewed all the 6 spectators. Surprisingly, all spectators, including the salesman who sold the coffee to the participant, failed to notice that the participant was either wearing a prototype or performing head gestures. After an interview, the salesman told us that he was focusing on his work and therefore ignored the HeadText user. However, he said he might notice the user if he was not busy. When we asked his acceptability for the HeadText user, he said that he was tolerant of every guest’s behavior. When we interviewed other spectators, they told us that they all did not notice the HeadText user. Also, they did not care whether users wore the prototype. When we interviewed the HeadText user, he told us that he felt a little embarrassed at first. But when he found that almost nobody noticed him and started to do his own work, he did not feel embarrassed at all.

8.3 Private Text Entry

Existing work (PrivateTalk[51], FingerPad[4], ThumbRing[44]) on private input rarely has an evaluation study for their private feature. HeadText demonstrated feasibility of privacy-protection through a social study in both face-to-face conversation and public situations (described in Socially Acceptable Text Entry part). The results show that most people in public (such as cafeteria, library, dining hall) will not notice the one who wear HeadText. The most possible situation that others may notice users’ head movements is a face-to-face conversation. However, results also present that conversation partners rarely notice users’ head motions especially if they personally do not know users are using head gestures for typing. What’s more, even if others have noticed users’ head motions, it is still hard to leak text entry information, because it is hard to decode text information from head gestures. Here are the reasons.

- Our head gesture set is composed of four primitives: Left, Right, Up and Down. Observers may notice the primitives performed by users, but they could not infer which gesture the user is performing. For instance, if observers find that users are performing Left-Right-Left-Right, perhaps users are performing Double-Left-Tap or two Single-Left-Tap gestures. But observers do not know which one the user is performing.
- It is hard for observers to remember all head gestures performed by users. If one head gesture is missed by the observer, the head gesture order is interrupted and observers could not restore the text information.
- Observers do not know the mapping from head gestures to keyboard layout. They also do not know the word prediction candidates. Therefore, even if observers know users are selecting words using head gestures, they do not know which word the user has selected.

9 DISCUSSION AND FUTURE WORK

Although we have demonstrated the feasibility and robustness of our technique, we indeed admit that there are some limitations of this work and we could do more to further improve our technique.

9.1 Text Entry Speed

HeadText is a gesture-based system, whose efficiency highly relies on gesture detection and recognition time. Therefore, one method for increasing text entry speed is to speed up gesture segmentation and recognition process. One way is that the system does not have to wait until users have already finished a gesture. We could recognize the head gesture
using only the first half of the gesture to save time. Another way is that users do not have to turn their head back to the initial position after each gesture. Instead, they could directly perform the next head gesture. Last but not least, we could design faster and easier head gestures to speed up the text entry process.

9.2 Error Rate and Auto-Complete Rate
As is described in the result of the second user study, our auto-correct feature has not been fully utilized which could have better text entry performance. In our future work, we will optimize the parameter design in our auto-correct feature to help improve our text entry performance. We also notice that auto-complete rate increases with the increase of text entry speed, indicating that users speed up their text entry process by utilizing the auto-complete feature. Additionally, a long-term user study may have higher auto-complete rate and better text entry performance, which could be our future work for exploration.

9.3 Head Gesture Design and Mapping
Our head gesture design is inspired by both previous work[52] and our preliminary study. However, in the studies, we find that some gestures may bring extra burden to users and also may last more time which may affect text entry speed. Therefore, in our future work, we could further optimize our head gesture design and introduce more user-friendly and efficient head gestures for text entry. We will also optimize mapping specific gestures to the keys on the keyboard layout to speed up text entry process.

9.4 Keyboard Layout Design Improvement
HeadText follows an alphabetical order considering that some users may not be a master of QWERTY keyboard. However, for some users who are familiar with computers, it may be much easier for them to use QWERTY board. Therefore, in the future, we may explore the performance of QWERTY keyboard. The number of keys on the keyboard could also be optimized. The current key design is a reasonably designed keyboard layout to demonstrate the feasibility of HeadText. However, we see it as a long-term research process to keep improving our keyboard layout design. For instance, we could reduce the size of keys and increase the number of keys to further reduce text input ambiguity. What’s more, head gesture recognition result could be improved using a static decoder like TipText[49], and therefore text entry speed could also be improved.

9.5 Sensor and Prototype Form Factor
Our prototype aims to demonstrate the feasibility of our idea. There is enough space for us to further improve our form factor such as decreasing the size of our prototype and using more flexible material to improve user experience of wearing the prototype. In addition, HeadText prototype is based on a motion sensor – Inertial Measurement Unit, which already exists in the COTS(Commercial Off-the-Shelf) device like smart earbuds. Therefore, there is potential that our technique could be used in existing electronic devices directly. Additionally, we could explore other sensing techniques like acoustic sensing for hands-free text entry in the future.

9.6 User Study
Although using head gestures to simulate text entry is reasonable and necessary in the social study, we admit that it is still better to have a real text entry study. In the future, we may use a wireless prototype to connect to the computer and use smart glasses to provide visual feedback or a speaker in the earbud to provide audio feedback to participants for
auto-complete words notification and word selection. In this case, we could compare the difference of social acceptability of real or simulated text entry.

Additionally, we have a noise gesture classifier which works well in our study. However, our text entry evaluation is in a sitting scenario. Whether users’ walking or eating may affect text entry performance continues to be unknown, since these noise scenarios may distract users from focusing on their current text entry and therefore nonstandard gestures may be recognized by mistake. Therefore, we will ask participants to evaluate text entry in a more complicated scenario which is more closed to the real life.

10 CONCLUSION

In this paper, we present a gesture-based hands-free technique to support users utilizing head gestures for text input wearing a smart earpiece using motion sensing. A 10-participant user study is conducted to understand users’ head movements and a second study for text entry proves the feasibility of HeadText. Moreover, we investigate the social acceptability and privacy-protection ability of HeadText through a social study. We finish our paper with discussions about limitations and future work of our system. We believe that our technique may serve as important groundwork for future text entry on smart devices.

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