Design and Evaluation of a Silent Speech-Based Selection Method for Eye-Gaze Pointing

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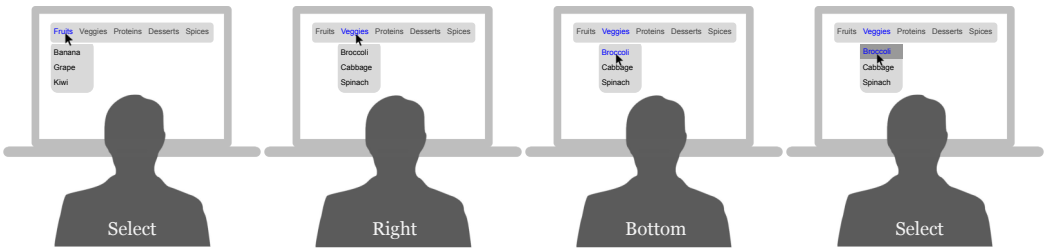

Fig. 1. A menu selection scenario with the proposed method. To select "Broccoli", the user starts scanning the horizontal menu from the left. The system locks the cursor on the first item when the gaze is within 10 pixels of the item. The user silently speaks the command "Select" to expand the current menu (display the sub-menu). The user silently speaks "Right" to move the cursor horizontally to the next item. The user locates the target, silently speaks "Bottom" to move the cursor to the target below the current item, then silently speaks "Select" to select the target.

We investigate silent speech as a hands-free selection method in eye-gaze pointing. We first propose a stripped-down image-based model that can recognize a small number of silent commands almost as fast as state-of-the-art speech recognition models. We then compare it with other hands-free selection methods (dwell, speech) in a Fitts' law study. Results revealed that speech and silent speech are comparable in throughput and selection time, but the latter is significantly more accurate than the other methods. A follow-up study revealed that target selection around the center of a display is significantly faster and more accurate, while around the top corners and the bottom are slower and error prone. We then present a method for selecting menu items with eye-gaze and silent speech. A study revealed that it significantly reduces task completion time and error rate.

CCS Concepts: • **Human-centered computing** → **Pointing**; *Natural language interfaces*; User interface design.

Additional Key Words and Phrases: Fitts' law, multi-modal, speech, silent speech, lip reading, dwell, eye tracking, pointing, selection

ACM Reference Format:
Laxmi Pandey and Ahmed Sabbir Arif. 2022. Design and Evaluation of a Silent Speech-Based Selection Method for Eye-Gaze Pointing. *Proc. ACM Hum.-Comput. Interact.* 6, ISS, Article 570 (December 2022), 26 pages. https://doi.org/10.1145/3567723

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2573-0142/2022/12-ART570
https://doi.org/10.1145/3567723

1 INTRODUCTION

Eye-gaze-based interaction is a promising modality for faster and seamless hands-free (also known as contactless or touchless) interaction [108]. It enables people with limited motor skills to interact with computer systems without using the hands [5, 16, 26, 57, 71]. It is also beneficial in Situationally-Induced Impairments and Disabilities (SIID) [104, 125], when the hands are incapacitated due to reasons such as performing a secondary task, minor injuries, or unavailability of a keyboard [101]. Hands-free interaction is also of a particular interest in situations when touching public devices is to be avoided to prevent the spread of an infectious disease [53].

Eye tracking technologies measure a person's eye movements and positions to understand where the person is looking at any given time. In the past, eye tracking required expensive, often non-portable extramural devices, which were slow and error prone [69, 127]. Recent developments have made eye tracking more affordable, portable, and reliable. Modern algorithms can track eyes using webcams almost as fast and accurately as commercial tracking technologies [69, 106, 126]. The most common application of eye tracking is to direct control a mouse cursor using eye movements [127]. While the idea of performing tasks simply by looking at the interface is empowering, eye tracking has yet to become a pervasive technology due to the "Midas Touch" problem [55], which refers to the classic eye tracking problem where the system cannot distinguish between users simply scanning the items versus their intention to select them, resulting in unwanted selections wherever the user looks, making the system unusable. One solution to this problem is to use a different action to activate selection. The most commonly used selection method with eye tracking is dwell, where users look at a target for 100–3,000 ms [42] to select it. It is, however, difficult to pick the most effective dwell time for a population since a short dwell time makes the system faster but increases false positives, while a long dwell time makes the system slower and causes users physical and cognitive stress [14, 42]. Many alternatives have been proposed to substitute dwell, including head and gaze gestures, blinking, voluntary facial muscle activation, brain signals, and foot pedals. Most of these approaches either use external, invasive hardware that are not yet scalable in practical situations or exploit unnatural behaviors that can cause users irritation and fatigue [56]. Speech is promising but not reliable in noisy places (e.g., when listening to music). Users are also hesitant to use speech when in public places (e.g., in a library) [30–32, 99]. Besides, speech does not work well with people with severe speech disorders since it relies on the sound produced by the users [5, 16].

In this work, we investigate silent speech as an alternative selection method for eye-gaze pointing. Silent speech is an image-based language processing method that interprets users' lip movements into text [89]. We envision several benefits of using silent speech commands as a selection method. First, it does not require the use of external hardware since both eye tracking and silent speech recognition can occur through the same webcam. Second, silent speech does not rely on acoustic features, thus can be used in noisy places or in places where people do not want to be disturbed [90]. Although outside the scope of this work, silent speech can also accommodate people with speech disorders. The contribution of our work is three-fold. First, we propose a stripped-down image-based model that can recognize a small number of silent commands almost as fast as state-of-the-art speech recognition models. Second, we design a silent speech-based selection method and compare it with other hands-free selection methods, namely dwell and speech, in a Fitts' law experiment. We follow-up on this by conducting another study investigating the most effective screen areas for eye-gaze pointing in terms of throughput, pointing time, and error rate. Finally, we design a silent speech-based menu selection method for eye-gaze pointing and evaluate it in an empirical study.

2 RELATED WORK

There is a rich body of work on selection methods for gaze pointing. Most of these works, however, explore manual approaches that require the use of the hands, particularly mid-air gesture (e.g., [18, 97, 102]) and physical keys, buttons, and controllers (e.g., [70, 71, 83, 121]). In this section, we only cover hands-free selection methods that are accessible to people with limited motor skills.

2.1 Hands-Free Selection Methods

Dwell is the most commonly used hands-free selection method in gaze pointing. It enables users to look at a target for a predetermined period of time to trigger selection [42]. This method is popular due to its simplicity and because it does not require the use of additional sensors like microphones, depth cameras, or motion sensors. However, it is difficult to maintain a sensible balance between speed and accuracy when selecting a dwell time. A short dwell time makes a system faster but increases the chance of unwanted selections, while a long dwell time makes the system slower and can cause users physical and cognitive stress [14, 42]. To address this, several works have enabled users to adjust the dwell time [76] or automatically adjusted dwell time based on user experience [82, 128]. While these approaches improved the performance of dwell, it remains a time-consuming and error prone selection method in gaze pointing.

Many alternatives have been proposed to substitute dwell. Drewes and Schmidt [29] explored gaze gestures with eye tracking, where users performed specific eye movements for target selection. Studies suggested users can perform complex gaze gestures intentionally [29, 50]. A follow-up study showed that gaze gestures can enable people with motor impairments to play online games [54]. Some have used specific types of gaze gestures (e.g., reverse crossing [34] and single gaze gestures [84]) and blinking [8] for target selection. However, performing intentional gaze gestures and blinking are unnatural [56], thus can cause users irritation and fatigue. Several works, in contrast, studied target selection through voluntary facial muscle activation [77, 117], brain signals [47], and foot pedals [79]. These methods use external and invasive hardware, thus not yet scalable in practical situations. Some have also attempted head gestures for target selection [79, 109, 110], which performed well in short-term use, but can cause fatigue in extended use. Many have combined gaze with speech, which is potentially a more natural and efficient mode of interaction [93, 112]. These works either use a single command to confirm selection [15] or multiple commands to facilitate both pointing and selection [81, 107]. Speech is promising but unreliable in noisy places and users are often hesitant to use speech in public places [30–32, 99]. Besides, speech does not work well with people with severe speech disorder [5, 16].

2.2 Gaze-Based Menu Selection

Not much work has focused on gaze-based menu selection methods. Menu selection is different than individual target selection (e.g., virtual keys, buttons, or links) since the former involves the selection of a sequence of horizontal and vertical targets. Error in one selection task results in an incorrect output, forcing the user to correct the mistake, then re-perform all tasks in the sequence. Menu selection, thus, has a much higher error correction overhead. Almost all gaze-based menu selection methods use a “zooming” approach that dynamically increases the size of a potential target to facilitate precise selection [12, 80, 111, 129]. These methods, however, do not provide an effective mechanism for controlling the zooming behavior, which can cause frustration when the method does not behave as expected. Expanding the menu items can also occlude the content in the background, causing inconvenience. Murata and Karwowski [83] positions the cursor at the center of a target by suppressing cursor movements caused by involuntary eye movements. Kammerer et al. [61] enable users to select a target my making a “click” sound when the cursor is over it.

Murata and Karwowski [83] enable users to speak the items in a menu to select them. Some also explored different menu designs (e.g., radial, semi-circular, etc.) for gaze pointing [61, 119].

2.3 Interaction with Silent Speech

Silent speech has not been well explored in user interfaces, presumably due to technological limitations, as the existing recognition models use expensive, invasive, or non-portable hardware, including electromagnetic articulography (EMA) [33, 38, 44], real-time magnetic resonance imaging (rtMRI) [91], electroencephalogram (EEG) [96], electromyography (EMG) [58–60, 62, 75, 105, 123], ultrasound imaging [27, 28, 35, 38, 44, 48, 49, 66], vibrational sensors of glottal activity [86, 94, 100, 118], speech motor cortex implants [10], and non-audible murmur microphones [45, 46, 85]. Recently, there have been some attempts to recognize speech from videos of mouth and tongue movements [3, 6, 9, 13, 20, 21, 21–23, 89, 95, 115, 116]. But these models are slow (takes ~5 seconds to recognize one word) and error prone (4–47% error rate) [89]. To the best of our knowledge, none have explored the possibility of using silent speech with gaze pointing.

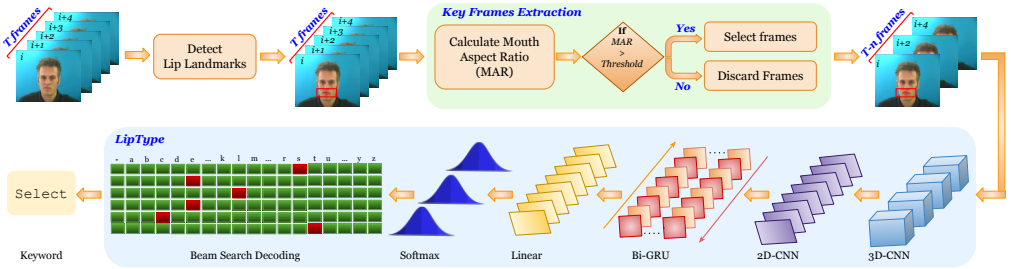


Fig. 2. The architecture of the proposed silent command recognition model. It pre-processes a sequence of T frames for mouth-centered cropped images to extract key frames. The key frames are fed to a 1-layer 3D CNN, followed by a 34-layer 2D SE-ResNet for spatiotemporal feature extraction. The features are then processed by two Bi-GRUs, a linear layer, and a softmax. Finally, the softmax output is decoded with a left-to-right beam search using the Stanford-CTC decoder.

3 A MODEL FOR SILENT COMMAND RECOGNITION

We customized an existing silent speech recognition model LipType [89] to recognize silent commands. We did not use an off-the-shelf recognizer since they are optimized for recognizing phrases, thus trained on large corpora (≥1,000 phrases [25]). This increases the variability and ambiguity in lip movements (similar movements for different characters), which are disambiguated in post-processing using language models [9, 89]. This affects both speed and accuracy. State-of-the-art silent speech recognition models can take up to 5,000 ms to recognize one word with accuracy rates between 53–96% [89]. Since voice assistants usually use a small number of words as commands, we used a smaller set of words that can be distinguished based on mouth aspect ratios (MAR) and scraped off all word and phrase-level language models. The proposed model consists of three sub-modules: a *key frames extraction* frontend that takes a sequence of video frames and extracts key frames to create a compact representation, a *spatiotemporal feature extraction* module that takes a sequence of key frames and outputs one feature vector per frame, and a *sequence modeling* module that inputs the sequence of per-frame feature vectors to recognize a keyword. The model is capable of mapping variable-length video sequences to text sequences. Fig. 2 illustrates the architecture of the model.

Module 1: Key frames extraction. This module crops one w:100 × h:50 pixels mouth-centered image per video frame to extract key frames. The module pre-processes each video clip with the DLib face detector [67] and the iBug face landmark predictor [103] with 68 facial landmarks (L) and Kalman filtering (Fig. 3, left). Then, mouth-centered cropped images are extracted by applying affine transformations. These images are used to measure MAR by dividing the distance between the upper and the lower lips (h) with the distance between the left and the right corners of the mouth (w) (Eq. 1). All frames with a MAR greater than 20 are considered as key frames and the remaining frames are discarded to reduce computation time. This threshold was picked based on an ablation study that revealed that a MAR greater than 20 is sufficient to distinguish between words in a corpus with 10 words (Fig. 3, right).

$$MAR = \frac{\|L_{61} - L_{56}\| + \|L_{60} - L_{57}\| + \|L_{59} - L_{58}\|}{2 * \|L_{44} - L_{50}\|} \quad (1)$$

Module 2: Spatiotemporal feature extraction. This module passes the extracted key frames to a 3D-CNN with a kernel dimension of T:5 × W:7 × H:7, followed by Batch Normalization (BN) [52] and Rectified Linear Units (ReLU) [4]. Then, the extracted feature maps are passed through a 34-layer 2D SE-ResNet to gradually decrease the spatial dimensions with depth until the feature becomes a single dimensional tensor per time step.

Module 3: Sequence modeling. This module processes the extracted features using two Bidirectional Gated Recurrent Units (Bi-GRUs) [19]. Each time-step of the GRU output is processed by a linear layer and a softmax layer over the vocabulary, and an end-to-end model is trained with connectionist temporal classification (CTC) loss [41]. The output is then decoded with a left-to-right beam search [24] using the Stanford-CTC decoder [72] to recognize spoken keywords.

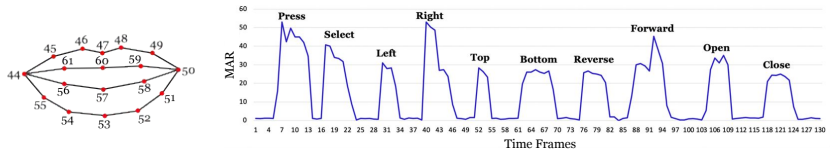


Fig. 3. From left, lip landmarks detected by DLib and iBug [67], and average mouth aspect ratios (MAR) of the ten keywords.

3.1 Training and Implementation

We trained the model for ten keywords: *Press*, *Select*, *Left*, *Right*, *Top*, *Bottom*, *Reverse*, *Forward*, *Open*, *Close*, with the data collected from 20 participants: 9 female, 11 male, average age 26.95 years (SD = 3.03). The data collection process occurred remotely. Participants sat in front of their computers and silently spoke each keyword in a random order for 50 times (20 participants × 10 keywords × 50 repetitions = 10,000 samples). We enabled them to use the embedded cameras to increase the variability of the dataset. They were instructed to take 1–2 minutes breaks between the words and ~3 seconds breaks between the repetitions to reduce the effects of fatigue. A researcher guided them and observed the whole process via a videotelephony system. Before training, we pre-processed the data by applying a horizontally mirrored transformation, color space augmentations, and random cropping on the cropped mouth images, resulting in 42,981 samples in total (4,290/keyword). We augmented the dataset with simple transformations to reduce overfitting. The number of frames was fixed to 75. Longer image sequences were truncated and shorter sequences were padded with

Table 1. Average recognition time (seconds) and accuracy rates (%) for the investigated models. "Sp." represents "Speech" and "Com." represents "Command".

Unit	Method	*Press*	*Select*	*Left*	*Right*	*Top*	*Bottom*	*Reverse*	*Forward*	*Open*	*Close*
Time	*Google Sp.*	1.73	1.64	1.65	1.54	1.69	1.82	1.82	1.68	1.65	1.61
	Kaldi Sp.	2.27	2.17	2.30	2.19	2.10	2.02	2.08	2.13	2.33	2.14
	Silent Com.	1.99	1.96	2.04	1.90	2.09	2.03	1.88	1.76	2.04	1.96
	LipType	3.09	3.28	2.95	3.24	3.02	3.09	3.18	3.15	3.09	3.38
Accuracy	*Google Sp.*	97.92	97.71	98.11	98.36	98.18	97.42	98.15	98.53	97.97	97.82
	Kaldi Sp.	88.05	88.65	90.19	87.48	89.04	88.41	85.83	88.04	89.62	88.02
	Silent Com.	77.12	79.36	73.44	72.48	72.37	71.91	71.84	72.76	79.52	76.18
	LipType	87.51	87.55	85.89	86.86	88.57	89.06	87.31	88.24	86.04	88.86

zeros. We applied a channel-wise dropout [114] of 0.3. The model was trained end-to-end by the Adam optimizer [68] for 60 epochs with a batch size of 50. The learning rate was set to 10^{-3}. The network was implemented on the Keras deep-learning platform with TensorFlow [2] as the backend. Wll models were trained and tested on an NVIDIA GeForce 1080Ti GPU board. The source code[1] and the training dataset[2] are freely available to download.

3.2 Performance Evaluation

We conducted a study to compare the performance of the proposed silent command model with a state-of-the-art speech (Google Speech-to-Text API [40], Kaldi (Api.ai) [98]) and silent speech (LipType [89]) recognition models to determine if it is reliable enough as a selection method in gaze-based interfaces. Twelve volunteers participated in the study (M = 27.67 years, SD = 2.77). Six of them identified themselves as female and six as male. None of them took part in the data collection process. In the study, participants either spoke or silently spoke (counterbalanced) each keyword for 12 times in a random order (12 participants × 2 methods × 2 models × 10 keywords × 12 repetitions = 5,760 samples). A custom web application, developed with HTML5, CSS, PHP, and JavaScript, presented one keyword at a time, processed and displayed the recognized word on the screen, then presented the next keyword. The application was loaded on a Chrome web browser v92.0.4515.131 running on a MacBook Pro 16″ laptop with 2.6 GHz Intel Core i7 processor, 16 GB RAM, 3072×1920 at 226 ppi. Its built-in FaceTime HD webcam (1.2 megapixel with 1,280×720 pixel resolution) was used to track lip movements. The application automatically calculated and recorded *recognition time* (seconds): the average time to recognize a word and *accuracy rate* (%): the average percentage of words accurately recognized by a model.

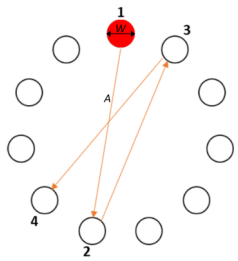
3.2.1 Results. On average, Google Speech-to-Text and Kaldi took 1.68 seconds (SD = 0.27) and 2.17 seconds (SD = 0.42), respectively, to recognize the keywords, whereas LipType and Silent command took 3.14 seconds (SD = 0.39) and 1.97 seconds (SD = 0.34), respectively. The differences were statistically significant ($F_{3,11} = 159.65, p < .0001$). The average accuracy rates for Google Speech-to-Text and Kaldi were 97.91% (SD = 1.15) and 88.32% (SD = 5.11), respectively, whereas 87.58 (SD = 5.22) and 73.47% (SD = 7.33) for LipType and Silent command, respectively. The differences were statistically significant ($F_{3,11} = 506.53, p < .0001$). Table 1 presents recognition time and accuracy rates for all keywords with each method. Within the investigated models, we selected the relatively best-performed models for speech and silent speech recognition: Google Speech-to-Text and Silent

[1]Source code: https://github.com/theiilab/Eye-Gaze-Pointing
[2]Dataset: https://www.theiilab.com/resources/Keywords_Data.zip

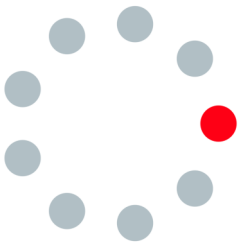
command. Silent command was almost as fast as Google Speech-to-Text (1.97 vs. 1.68 seconds) but was about 24% more error prone. However, this rate was recorded in a quiet room, while research showed that the accuracy rate of speech drops by 45–55% in presence of a background noise (42–58 db) [89]. The performance of silent speech, in contrast, is unaffected by this. Besides, an ablation study showed that the accuracy rate of the proposed model further improves with a much smaller corpus or a larger training dataset. The model reached a 100% accuracy rate with 1 keyword and close to 95% accuracy rate with 6 keywords, which are acceptable in the context of speech and silent speech input [90]. In this work, we use 1 keyword: *Select*, during the Fitts' law study, and the 6 most relevant keywords: *Select*, *Left*, *Right*, *Top*, *Bottom*, *Close*, in the menu selection study.

4 EYE TRACKING

This work uses the GazeCloudAPI for real-time eye-tracking using a webcam [36]. It tracks eyes in three stages: facial features extraction, eyes features detection, and point of gaze estimation. The process starts with capturing RGB color space images with a web camera and converting them to grayscale. These images are then normalized with histogram equalization to enhance facial feature accuracy [39]. Afterward, a Haar-like feature classifier is used to classify the images into face and non-face regions [122]. The classifier further classifies the face into subregions, such as the eyes, the nose, the lips, etc. Once the eye region is detected, the system first identifies the position of the pupil by detecting the iris from the eye region. Then, locates the pupil as the center of the iris using a Hough circle transform [65]. Finally, the point of gaze is estimated using the pupil location [37]. In an empirical evaluation [120], the API yielded 0.9°, 1° accuracy on the x, y coordinates with a Logitech Pro 9000 Webcam at 1600×1200, where participants could freely move their head. Note that eye tracking accuracy is measured in angles, representing the deviation in degrees between the actual and the predicted gaze directions. An average below 1.2° is considered to be a good measurement of accuracy in free head conditions, while an accuracy below 0.8° is desired when the head is fixed using a chinrest [120].



(a) The 2D Fitts' law task in ISO 9241-9



(b) A screenshot of the web application ($A = 780, W = 140$ pixels)

Fig. 4. (a) The target is highlighted in red. The arrows and the numbers demonstrate the sequence in which the targets are selection. (b) The custom web application also highlights the intended target in red and uses the same selection sequence as ISO 9241-9.

5 FITTS' LAW PROTOCOL

Fitts' law is a well-established method for evaluating target selection on computing systems [74]. In the 1990s, it was included in the ISO 9241-9 (revised: ISO 9241-411) standard for evaluating non-keyboard input devices by using Fitts' throughput as a dependent variable [113]. The most

common multi-directional protocol evaluates target selection movements in different directions. The task is 2D with targets of width W equally spaced around the circumference of a circle (Fig. 4a). Participants select the targets in a sequence moving across and around the circle, starting and finishing at the top target. Each movement covers an amplitude A, which is the diameter of the layout circle. A *trial* is defined as one target selection task, whereas completing all tasks with a given amplitude is defined as a *sequence*. Throughput cannot be calculated on a single trial because a sequence of trials is the smallest unit of action in ISO 9241-9. Traditionally, the difficulty of each trial is measured in bits using an index of difficulty (ID), calculated as follows:

$$ID = log_2(\frac{A}{W} + 1)$$

The movement time (MT) is measured in seconds for each trial, then averaged over the sequence of trials. It is then used to calculate the performance throughput (TP) in bits/second (bps) using the following equation:

$$TP = \frac{ID}{MT}$$

The revised ISO 9241-9 (9241-411) used here [51] measures throughput using an effective index of difficult ID_e, which is calculated from the effective amplitude A_e and the effective width W_e to make sure that the real distance traveled form one target to the next is measured. It also takes into effect how far the participants were from the target center.

$$TP = \frac{ID_e}{MT} \qquad\qquad ID_e = log_2(\frac{A_e}{W_e} + 1)$$

The effective amplitude is the real distance travelled by the participants and the effective width is calculated as follows, where SD_x is the standard deviation of the selection coordinates projected on the x-axis for all trials in a sequence. This accounts for any targeting errors by the participants, assuming that they were aiming at the center of the targets.

$$W_e = 4.133 * SD_x$$

6 EXPERIMENTAL SYSTEM

We developed a custom web application[3] with HTML5, CSS, PHP, and JavaScript for the Fitts' law experimental protocol (Section 5). It enables users to control a cursor with eye-gaze by translating gaze position into x, y coordinates of the cursor on the display. It uses the GazeCloudAPI for eye-tracking with a webcam (Section 4). We used it instead of other APIs [92, 126] due to its robustness [124]. The application uses the following free-hand target selection methods.

- **Dwell.** Users point at a target then fixate (or hold the sight) for 500 ms to select the target. The threshold was picked based on studies identifying 500 ms as the most effective dwell time for novice eye-gaze users [18, 73, 82].
- **Speech Command (Google).** Users point at a target then speaks the voice command *Select* to select the target.
- **Silent Speech Command.** Users point at a target then silently speaks the command *Select* (without vocalizing the word) to select the target.

7 USER STUDY 1: FITTS' LAW

We conducted a Fitts' law experiment to investigate the performance of different hands-free selection methods (dwell, speech, silent speech) with eye tracking.

[3]Based on an existing application: http://simonwallner.at/ext/fitts.

7.1 Participants & Apparatus

Twelve volunteers participated in the user study. Their age ranged from 24 to 40 years (M = 29.01, SD = 4.78). Four of them identified themselves as women and eight as men. Four of them wore corrective eyeglasses and one wore corrective contact lenses. One participant had experience working with the MediaPipe Iris API, but none used eye tracking to interact with their computer systems. Each of them received US $15 for volunteering in the study. We used the web application described in Section 6 (Fig. 4b) and the apparatus described in Section 3.2.

Fig. 5. Three participants taking part in the first user study.

7.2 Design

The experiment was a 3 × 3 × 4 within-subjects design. The independent variables and the levels were as follows:

- Selection method (*Dwell*, *Speech*, *Silent Speech*) counterbalanced
- Amplitude (260, 520, 780 pixels)
- Width (35, 70, 140, 220 pixels)

The three amplitudes were selected based on the minimum and maximum distance possible on the experimental device's 16″ display. Likewise, the four widths were selected since 35 pixels is one of the smallest widths used in prior eye tracking research [80], 70 pixels is the recommended width in eye tracking applications [121], while targets with widths over 220 pixels are unrealistic. The dependent variables in the experiment were as follows:

- **Throughput** (bps) as described in Section 5.
- **Selection time** (seconds) represents the average time users took to perform a selection task, measured from the moment the cursor entered the target (including re-entries, when the cursor mistakenly left the target, then re-entered) to the moment it was selected. This metric does not include **pointing time** (seconds) that signifies the time to move the cursor over a target as all selection methods used the same eye tracking method for pointing.
- **Error rate** (%) signifies the average percentage of incorrect target selections per trial (%), where users performed a selection action outside the target.

7.3 Procedure

The study was conducted in a quiet room. Upon arrival, we explained the research and demonstrated the application to the participants. They then signed an informed consent form and completed a short demographics questionnaire. We then calibrated the eye tracking system for each participant by using a 4-point calibration method. The display was located about 65–75 cm in front of the participants' eyes (Fig. 5), as recommended in eye tracking research [120]. After calibration, we

enabled participants to practice with the application by using the three selection methods for ~5 minutes. They could extend the practice period on request. Once familiar with the methods, they started the study by performing point-select tasks by pointing at a target using eye tracking, then selecting it using either dwell, speech, or silent speech. As per ISO 9241-411, the targets were highlighted one-by-one clockwise for all levels, starting from the top target. The amplitude and width values were selected randomly. As a target was selected, the next target was highlighted. We did not instruct participants to fix their head, thus could freely move their heads during the study. We enforced a 2-minute break after each four sequences and a 5-minute break after each condition to avoid the effect of fatigue. Upon completion of the study, participants completed a short questionnaire to rate their willingness to use and perceived physical and mental efforts of the methods on a 5-point Likert scale. All researchers involved in this study were fully vaccinated for COVID-19, wore face covering, and maintained a 3″ distance from the participants at all times. Participants were pre-screened for COVID-19 symptoms during recruitment and on the day of the study. They wore face coverings at all times, except for when taking part in the study. All study devices and all surfaces were disinfected before and after each session. This protocol was approved by the Institutional Review Board (IRB).

7.4 Results

A complete study session took about 60–80 minutes, including demonstration, questionnaires, and breaks. A Shapiro-Wilk test revealed that the response variable residuals were normally distributed. A Mauchly's test indicated that the variances of populations were equal. Hence, we used a repeated-measures ANOVA for all quantitative within-subjects factors (described in Section 7.2). We used a Friedman test for the questionnaire data [7]. We did not identify any effects of the between-subjects factors, namely age, gender, and the use of corrective eyeglasses or contact lenses.

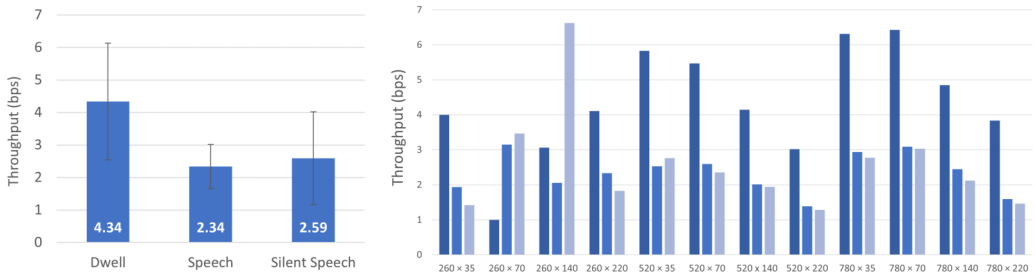
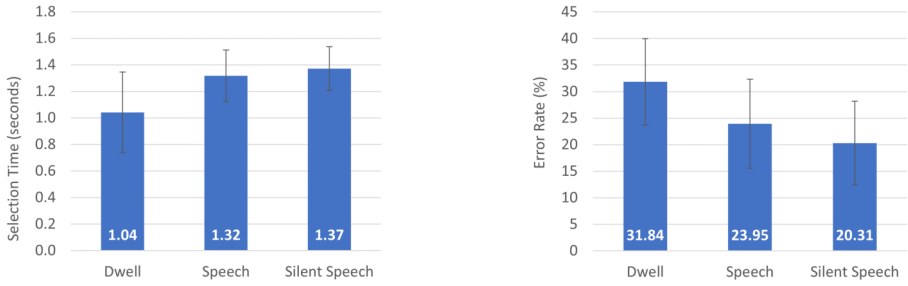


Fig. 6. Average throughput (bits/second) by (a) selection method and (b) selection method, amplitude, and width. Error bars represent ±1 standard deviation (SD).

7.4.1 Throughput. An ANOVA identified a significant effect of selection method on throughput ($F_{2,22} = 2367.84, p < .0001$). Average throughput for dwell, speech, and silent speech were 4.34 (SD = 1.79), 2.34 (SD = 0.68), and 2.59 bps (SD = 1.43), respectively (Fig. 6a). A Tukey-Kramer test found the three selection methods significantly different from one another. There was also a significant effect of amplitude ($F_{2,22} = 189.88, p < .0001$) and width ($F_{3,33} = 487.72, p < .0001$). The method × amplitude × width interaction effect was also statistically significant ($F_{12,132} = 225.83, p < .0001$). Fig. 6b illustrates average throughput by selection method, amplitude, and width.



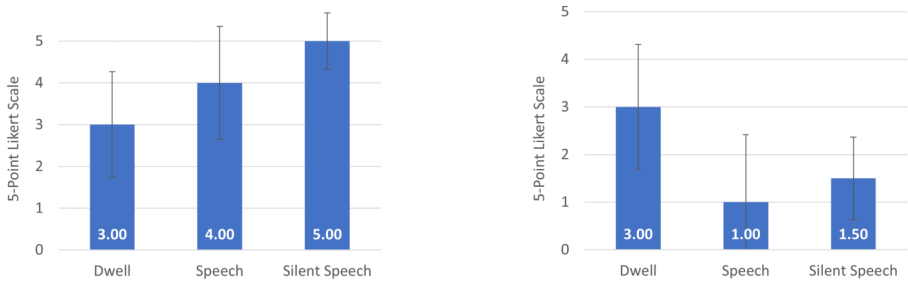
(a) Selection time (seconds)

(b) Error rate (%)

Fig. 7. Average selection time and error rate by selection method. Error bars represent ±1 standard deviation (SD).

7.4.2 Selection Time. An ANOVA identified a significant effect of selection method on selection time ($F_{2,22} = 1001.30, p < .0001$). Average selection time for dwell, speech, and silent speech were 1.04 (SD = 0.30), 1.32 (SD = 0.20), and 1.37 seconds (SD = 0.17), respectively (Fig. 7a).

7.4.3 Error Rate. An ANOVA identified a significant effect of selection method on selection time ($F_{2,22} = 3932.24, p < .0001$). Average error rate for dwell, speech, and silent speech were 31.84% (SD = 8.15), 23.95% (SD = 8.38), and 20.31% (SD = 7.88), respectively (Fig. 7b).



(a) Willingness-to-use

(b) Physical and mental effort

Fig. 8. Median willingness-to-use and physical and mental effort. Error bars represent ±1 standard deviation (SD).

7.4.4 User Feedback. A Friedman test identified a significant effect of selection method on willingness-to-use ($\chi^2 = 8.31, df = 2, p < .05$). However, no significant effect was identified on physical and mental effort ($\chi^2 = 3.33, df = 2, p = .11$). Fig. 8 presents median willingness-to-use and perceived physical and mental effort ratings of the three methods.

7.5 Discussion

Results confirmed that target amplitude and width influence the selection methods in accordance to the Fitts' law (Fig. 6b), except for dwell's unusual throughput for A:260 × W:140, which we identified as an outlier. Dwell was the best performed selection method in terms of throughput. Its 4.34 bps throughput was 85% and 68% higher than speech and silent speech (2.34 and 2.59 bps), respectively. However, it was also the most unreliable, which is reflected in its average selection

time (Fig. 7a) and error rate (Fig. 7b). Participants took on average 1.04 seconds to select targets with dwell. Since the dwell time was set at 500 ms, this suggests that there were many target re-entries, where the cursor left the target before selecting it, thus had to re-enter, forcing participants to spend extra time with the method. Fig. 9 illustrates cursor traces from a random participant for the three selection methods, where one can see that dwell required much more target re-entries than speech and silent speech. Dwell also yielded a 33% and 57% higher error rates than speech and silent speech, which suggests that participants frequently dwelled outside the targets. Dwell's unreliability had an impact on user preference. Participants were least willing to use the method and found it to be the most physically and mentally demanding (Fig. 8). One participant (male, 28 years) commented, *"Dwell was the most difficult because it was causing eye fatigue"*. This suggests that dwell can be useful in short-term use, but is likely to affect user performance, preference, and comfort in extended use. Silent speech was the second best performed selection method in terms of throughput. A Tukey-Kramer test found its throughput to be significantly better than speech. Silent speech was also the most accurate. A Tukey-Kramer test identified its error rate to be significantly lower than both dwell and speech (36% and 15% lower, respectively). Participants were also willing to use the method the most on their computers. They found it slightly more physically and mentally demanding than speech (Fig. 8b), but this effect was not statistically significant. These results identify silent speech as an effective selection method in eye-gaze pointing.

(a) Dwell (b) Speech (c) Silent speech

Fig. 9. Cursor trace examples for the three selection methods (A:520 × W:70 pixels).

8 USER STUDY 2: SCREEN LOCATION

We conducted a user study to inform the design of the final study. Its purpose was to identify the most effective screen areas for eye-gaze pointing, in terms of throughput, pointing time, and error rate, which can essentially help designing more effective interactive systems for eye tracking.

8.1 Participants

Twelve volunteers (M = 27.75 years, SD = 4.11) participated in the second study (Fig. 10b). None of them participated in the first study. Six of them identified themselves as women and six as men. Four of them wore corrective eyeglasses. None of them had experience with an eye-gaze-based system. They all received US $15 for volunteering.

8.2 Apparatus, Design, & Procedure

The study used the apparatus described in Section 3.2. To investigate the most effective screen areas, the 1792×1041 display area (excluding the dock and the menu bar) was divided into 12 equal 448×347 pixels zones (Fig. 10a). The application displayed circular targets (35 pixels in diameter) at random locations in the zones for the participants to select using silent speech command. The study used the following within-subjects design: 12 participants × 12 zones × 12 targets per zone

(a) (b)

Fig. 10. (a) The twelve zones used in the second study and (b) two participants taking part in the study.

= 1,728 targets. The independent variable was "zone" and dependent variables were throughput, pointing time, and error rate (Section 7.2). This study used the same procedure as the first study (Section 7.3) except for the task. In this study, participants performed the point-select tasks by pointing at a target using eye tracking then selecting the target using the silent speech command *Select*. A sequence of trials consisted of 12 circular targets (35 pixels in diameter) per zone. The targets were presented at random locations in the zones (Fig. 10b). Hence, all trials had the same width (W) but different amplitudes (A). Upon completion of all trials, participants completed a short questionnaire where they could rate the difficulty levels of the 12 zones on a 5-point Likert scale.

2.51	2.72	2.81	2.63
2.52	2.76	2.70	2.61
2.63	2.58	2.42	2.41

(a) Throughput (bps)

0.62	0.41	0.43	0.45
0.42	0.39	0.40	0.41
0.48	0.50	0.51	0.60

(b) Pointing time (seconds)

10.00	3.00	2.00	9.00
8.00	6.00	1.00	13.00
17.00	15.00	10.00	14.00

(c) Error rate (%)

Fig. 11. Average throughput, pointing time, and error rate per zone.

8.3 Results & Discussion

A complete study session took about 40–60 minutes, including demonstration, questionnaires, and breaks. A Shapiro-Wilk test revealed that the response variable residuals were normally distributed. A Mauchly's test indicated that the variances of populations were equal. Hence, we used a repeated-measures ANOVA for the quantitative within-subjects factors. We did not identify any effects of the between-subjects factors, namely age, gender, and corrective eyeglasses.

An ANOVA identified a significant effect of zone on throughput ($F_{11,121} = 4.37, p < .0001$). A Tukey-Kramer test identified three distinct groups: {1, 11, 12}, {4, 5, 7, 8, 9, 10}, and {2, 3, 6}, from the worst to the best performed zones. There was also a significant effect of zone on pointing time ($F_{11,121} = 8.93, p < .0001$). A Tukey-Kramer test identified three distinct groups: {1, 10, 11, 12}, {2, 3, 4, 5, 8, 9}, and {6, 7}, from the slowest to the fastest performed zones. An ANOVA also identified a significant effect on error rate ($F_{11,121} = 4.16, p < .0001$). A Tukey-Kramer test identified three distinct groups: {9}, {1, 4, 5, 8, 10, 11}, and {2, 3, 6, 7}, from the least to the most accurate zones. Fig. 11 illustrates these.

In summary, the study identified the central zones {2, 3, 6, 7} as the most accurate and the fastest. The top corners and bottom zones {1, 4, 9, 10, 12} were the most error prone and the slowest. The remaining zones {5, 8, 11} performed moderately well. User responses to the post-study questionnaire mirrored the quantitative data. We speculate, this is due to the increase in

participants' viewing angle when looking at the top corners and bottom zones. Prior work showed that eye tracking systems achieve the best accuracy at narrow visual angles and even a slight increase in visual angles can increase gaze errors significantly [63]. Participants also expressed their enthusiasm about the system. One participant (male, 29 years) wrote, *"The technology felt good. It will be helpful to disable people to simplify their life"*. Another participant (female, 28 years) commented, *"This could be useful in self-checkout kiosk"*.

9 MENU SELECTION WITH EYE-GAZE AND SILENT SPEECH

We designed a method for menu selection with silent speech and gaze pointing. It facilitates the selection of small targets from a grid by adopting the *target gravity* metaphor from traditional graphical user interfaces [11, 88] and using six silent speech commands for cursor positioning and target selection. Target gravity uses a snap-to effect [88] that automatically moves the cursor to a target's center when it is within 10 pixels of the target, and then remains locked on the target until the gaze path exceeds 10 pixels or the user silently speaks the release command. We used this behavior because cursor drift and jitter during fixation due to involuntary eye movements causes irritation and affects performance [83]. The 10 pixels threshold was used because it felt the most natural in multiple lab trials. The method uses two silent commands to select and close/release targets, and four commands for directional movements of the cursor (Table 2). Fig. 1 illustrates a menu selection scenario with the proposed system.

Table 2. The six silent commands and corresponding actions used in the proposed menu section method.

Command	Direction	Action
Select		Selects the current item
Right	Horizontal	Moves the cursor to the right item. If there are no items on the right of the current item, the cursor is moved to the first item in the menu
Left	Horizontal	Moves the cursor to the left item. If there are no items on the left of the current item, the cursor is moved to the last item in the menu
Top	Vertical	Moves the cursor one item above the current item. If there are no items above the current item, the cursor is moved to the last item in the menu
Bottom	Vertical	Moves the cursor one item below the current item. If there are no items below the current item, the cursor is moved to the first item in the menu
Close		Unlocks the cursor by releasing target gravity

10 USER STUDY 3: MENU SELECTION

We conducted a study to compare the silent speech-based selection method with and without menu selection commands.

10.1 Participants & Apparatus

Twelve volunteers took part in the study. Neither of them participated in the first study. Their age ranged from 22 to 36 years (M = 28.25, SD = 4.63). Six of them identified themselves as women and six as men. Two of them wore corrective eyeglasses. None of them had experience with an eye-gaze-based system. Each of them received US $15 for volunteering in the study. The study used the apparatus described in Section 3.2.

10.1.1 Task Selection. We customized the web application to display four menus (one at a time) categorizing different types of animals, food, popular books, and famous people. Simple categories

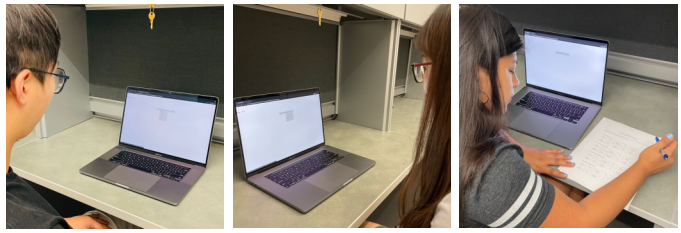


Fig. 12. Three participants taking part in the final user study.

were used to assure that the selection tasks do not require specialized knowledge. All categories had five vertical menu items. The vertical sub-menus under the horizontal menus had either three, four, or seven items. We did not use more than seven items per sub-menu to avoid memory overload [78]. Fifteen random targets were selected per category: five with target distances between 2–5, five between 6–7, and five between 8–12. Target distance signifies the total number of horizontal and vertical items before the target. Horizontal items are counted from left to right and vertical items are counted from top to bottom since research revealed that users tend to scan items from left-to-right and top-to-bottom [17]. The menus were designed following the macOS guidelines [1] to provide a familiar look-and-feel. Each menu item was 150×38 pixels. Current items were highlighted in a blue font (Fig. 13) and selected items were highlighted in a dark gray background (Fig. 1).

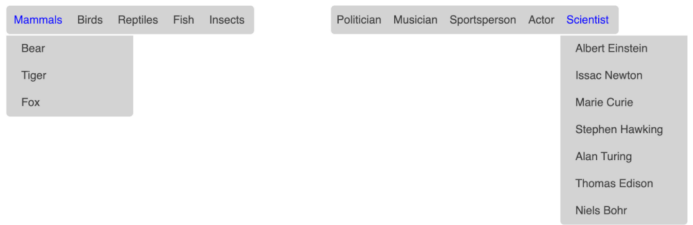


Fig. 13. Examples of two menus categorizing different types of animals and famous people.

10.2 Design & Procedure

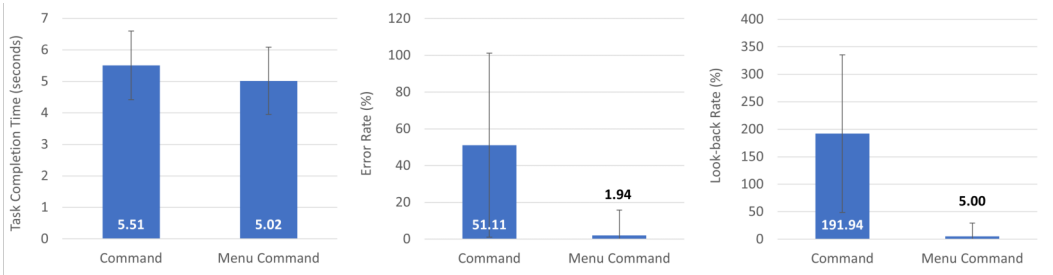
The study used the following within-subjects design: 12 participants × 2 methods (command, menu command, counterbalanced) × 2 unique menus per method × 15 tasks per menu = 720 menu selection tasks. The independent variable was "method" and dependent variables were as follows:

- **Task completion time** (seconds) represents the average time users took to perform a menu selection task.
- **Look-back rate** (%) represents the average percentage of times users entered a correct sub-menu, then left to explore the other sub-menus. This occurred when users were unable to locate a target despite entering the correct sub-menu, thus explored other sub-menus to find the target.
- **Error rate** (%) signifies the average percentage of incorrect menu selections per method (%), where users either selected an incorrect item or performed a selection task outside the menu.

The study used the same procedure as the previous studies (Section 7.3). During practice, participants selected two items using both methods (with and without menu commands) from a menu that was not used in the study. Once they were familiar with the methods, they started the main study, where they performed 15 target selection tasks per menu category with both methods. In the menu command condition, participants used the commands presented in Table 2 for navigation and selection. In the command condition, they used eye-gaze exclusively for positioning the cursor and the "Select" command to select a target. Tasks with different distances were presented on the screen in a random order. Considering some participants could be more familiar with the categories than the others, the application also displayed the complete target path. For example, for the scenario depicted in Fig. 1, the application displayed the task as "Select Veggies > Broccoli", indicating that the participants first have to go to the "Veggies" sub-menu then select "Broccoli". Two menu categories were assigned to each method in a counterbalanced order. We did not use the same menu categories with both methods to avoid any potential effects of knowledge (using the knowledge acquired in one condition to achieve the goals in another). Participants were instructed to select the targets as fast and accurate as possible. Error correction was not required. Timing started from the moment they lifted their gaze from the presented task to the moment a sub-menu item was selected. We enforced a 2-minute break after each menu category and a 5-minute break after each condition to avoid the effect of fatigue. Upon completion of the study, participants completed a custom and the NASA-TLX questionnaire [43] to rate the methods' perceived performance, usability, and workload.

10.3 Results

A complete study session took about 40–60 minutes, including demonstration, questionnaires, and breaks. A Shapiro-Wilk test revealed that the response variable residuals were normally distributed. A Mauchly's test indicated that the variances of populations were equal. Hence, we used a repeated-measures ANOVA for the quantitative within-subjects factors. We used a Wilcoxon Signed-Rank test for the questionnaire data. [7] We did not identify any effects of the between-subjects factors, namely age, gender, and the use of corrective eyeglasses.



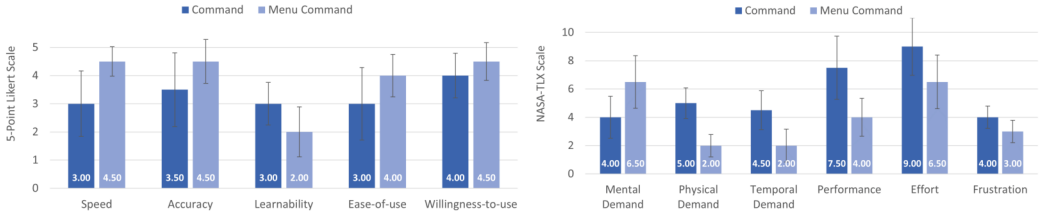
(a) Task completion time (seconds) (b) Error rate (%) (c) Look-back rate (%)

Fig. 14. Average task completion time, error rate, and look-back rate for the two investigated methods. Error bars represent ±1 standard deviation (SD).

10.3.1 Task Completion Time. An ANOVA identified a significant effect of method on task completion time ($F_{1,11} = 18.84, p < .005$). Average task completion time for command and menu command were 5.51 (SD = 1.09) and 5.02 seconds (SD = 1.07), respectively (Fig. 14a).

10.3.2 Error & Look-Back Rates. An ANOVA identified a significant effect of method on error rate ($F_{1,11} = 265.30, p < .0001$). Average error rate for command and menu command were 51.11% (SD =

50.06) and 1.94% (SD = 13.83), respectively (Fig. 14b). An ANOVA also identified a significant effect on look-back rate ($F_{1,11} = 1113.35, p < .0001$). Average look-back rate for command and menu command were 191.94% (SD = 143.25) and 5.00% (SD = 24.24), respectively (Fig. 14c).



(a) Usability questionnaire (b) NASA-TLX questionnaire

Fig. 15. Median willingness-to-use and physical and mental effort of the examined selection methods. Error bars represent ±1 standard deviation (SD).

10.3.3 User Feedback. A Wilcoxon Signed-Rank test identified a significant effect of method on perceived speed ($z = -2.45, p < .05$), perceived accuracy ($z = -2.16, p < .05$), and ease-of-use ($z = -2.22, p < .05$). However, there was no significant effect on learnability ($z = -1.06, p = .29$) and willingness-to-use ($z = -1.3, p < .19$). Fig. 15a presents median perceived performance and usability ratings of both methods.

10.3.4 Perceived Workload. A Wilcoxon Signed-Rank test identified a significant effect of method on mental demand ($z = -2.61, p < .01$), physical demand ($z = -2.82, p < .01$), temporal demand ($z = -2.83, p < .01$), performance ($z = -2.62, p < .01$), effort ($z = -2.95, p < .005$), and frustration ($z = -2.98, p < .005$). Fig. 15b presents median perceived workload ratings of both methods.

10.4 Discussion

Eye-gaze with menu command yielded about 9% faster task completion time than the baseline (the method without menu command). Most impressively, it reduced error rates by 96%. The baseline's 51% error rate (compared to menu command's 2%) suggests that roughly one in every two targets were incorrectly selected (Fig. 14b). Menu command also yielded 97% lower look-back rate than the baseline (Fig. 14c). The baseline yielded a 192% look-back rate, which suggests that most of the times participants were not confident that they were in the correct sub-menu, thus left to explore the other sub-menus. This behavior is particularly interesting since the experimental tasks did not require participants to explore the sub-menus to locate a target, instead displayed the exact path. The fact that participants did not look-back as much while using the menu command suggests that it increased their confidence in performing the tasks. A deeper analysis failed to identify an effect of horizontal and vertical (sub-)menu items on performance. This contradicts a prior work that found horizontal pointing to be about 18% more error prone than vertical pointing [64]. We also failed to identify any relationship between target distance and performance. This contradicts a prior finding that users' response time is an approximately linear function of serial position in the menu [87]. Our findings, however, are in line with a follow-up work that failed to replicate Nilsen [87]'s findings and argued that visual search and cursor movement strategies employed by actual users cannot be characterized easily [17].

Participants perceived the proposed method significantly faster and more accurate than the baseline (Fig. 15a). A participant (female, 25 years) commented, *"I think with commands [gaze-based menu selection] is more reliable"*. They also found the method significantly easier to use. They felt

that both methods were easy to learn. Interestingly, their ratings were also comparable in terms of willingness to use. We believe, the exclusion of error correction from the study protocol influenced this—their response could have been different if they were forced to correct all incorrect selections. Participants found the proposed method mentally, physically, and temporally less demanding than the baseline (Fig. 15b). They also felt that the method was better performed, required less effort, and caused less frustration than the baseline.

10.5 Limitations

Although the proposed approach is aimed at people that are unable use the hands due to a permanent or situational impairment, the studies recruited non-disabled people. While it is very likely that the quantitative findings are generalizable to the target population [130], it cannot be claimed with utmost certainty that the subjective feedback are also generalizable as people with disabilities might prefer a different method more due to lived experiences. Another limitation is that the study did not explore the effects of error correction on performance and preference. We decided not to force error correction in the study as it would have substantially increased the task completion time of the baseline condition, causing much frustration among the participants.

11 KEY FINDINGS AND DESIGN RECOMMENDATIONS

Below, we summarize the key findings of this work and make design recommendations.

- Silent command is a fast and effective alternative to dwell and speech-based selection methods in eye-gaze pointing, especially when the vocabulary is relatively small. We recommend designers to present a small number of options at a time to limit the total number of possible user responses to ten or less.
- We recommend against using dwell for tasks that require using the eyes for extended period of time since it tend to affect both user performance, preference, and comfort.
- When designing eye-gaze-based interactive systems, we recommend placing the most important and frequently used interactive elements at the center or around the two sides of the display. Avoiding the top corners and the bottom is recommended as they are usually the slowest and the most error prone.
- We recommend using silent command for menu selection with eye-gaze pointing as it is a more private and secure option and significantly increases users' confidence in selecting the correct option. Besides, vertical and horizontal menus are equally effective in eye-gaze pointing with silent speech.

12 CONCLUSION

In this work, we systematically studied the feasibility of using silent speech as a hands-free selection method in eye-gaze pointing. First, we proposed a stripped-down image-based model to recognize silent speech commands. An evaluation revealed that the model can recognize ten keywords almost as fast as a state-of-the-art speech recognition model. Second, we compared the method with other hands-free selection methods, namely dwell and speech, in a Fitts' law study, where both eye tracking and silent speech recognition used a webcam. Results showed that speech and silent speech are comparable in throughput and selection time, but the latter is significantly more accurate than the other methods. Besides, participants were significantly more enthusiastic about using silent speech than the other methods. We then conducted a follow-up study, which revealed that target selection around the center of a display is significantly faster and more accurate, while around the top corners and the bottom are slower and error prone. Finally, we presented a new method for selecting menu items with eye-gaze and silent speech commands. In a comparative evaluation, the

method was significantly faster and more accurate than the baseline. Participants also found the method significantly better in terms of performance, usability, and perceived workload.

13 FUTURE DIRECTIONS

In the future, we will extend the work to support more than ten silent speech commands. We will also investigate the possibility of using targeted commands, where the user silently speaks a specific menu item to select it rather than using directional commands. Finally, we will explore different error correction mechanisms to enhance the usability of the method. We envision numerous opportunities for future extension of this work. The proposed mouth aspect ratio-based model could be trained with people with muteness and speech disorders to enable hands-free interaction with computer systems using a set of custom commands or even lip gestures. The model could also be used with conversational agents, e.g., chatbots. Since they usually ask close-ended questions to limit the number of possible answers, the system has to disambiguate the input from a small number of samples at a time, comparable to the menu selection concept presented here. Eye tracking and silent commands could also be used in other application domains, such as in virtual reality or in automotive user interfaces.

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