Abstract

Physical contact-based typing interfaces are not suitable for people with upper limb disabilities such as Quadriplegia. This paper, thus, proposes a touch-less typing interface that makes use of an on-screen QWERTY keyboard and a front-facing smartphone camera mounted on a stand. The keys of the keyboard are grouped into nine color-coded clusters. Users pointed to the letters that they wanted to type just by moving their head. The head movements of the users are recorded by the camera. The recorded gestures are then translated into a cluster sequence. The translation module is implemented using CNN-RNN, Conv3D, and a modified GRU based model that uses pre-trained embedding rich in head pose features. The performances of these models were evaluated under four different scenarios on a dataset of 2234 video sequences collected from 22 users. The modified GRU-based model outperforms the standard CNN-RNN and Conv3D models for three of the four scenarios. The results are encouraging and suggest promising directions for future research.

1 Introduction

Assistive-technologies have attracted the attention of several Human-Computer Interaction (HCI) researchers recently. People with limited physical abilities find it difficult to interact with traditional typing equipment, including keyboard, mouse, and joysticks as they require consistent physical interactions. For example, a person with a physical condition such as Quadriplegia (all four limbs are paralyzed) cannot use any of the off-the-shelf-devices for typing. Recent advancements in motion tracking, computer vision, and natural language processing have enabled researchers to develop techniques that assist people in typing. For example, touchless interaction such as lip reading [Salik et al., 2019; Uttam et al., 2019; Shrivastava et al., 2019], speech recognition [Hinton et al., 2012], Brain-Computer Interface (BCI) [Saha and Fels, 2019; Nguyen et al., 2018], eye tracking [Hansen and Pece, 2004], and head operated interfaces [Yu et al., 2017; Nowosielski and Forczmański, 2018] have been utilized for assistive typing.

The previously proposed touchless technologies are either intrusive, less accurate, language and vocabulary dependent, underdeveloped, expensive, or apply to very specific application scenarios. For example, lip-reading systems have a significant performance discrepancy to speech recognition due to the ambiguous nature of lip actuation, which makes it very challenging to extract useful information [Zhao et al., 2019]. Speech recognition involves the use of voice cues which are not helpful for a person with speaking disabilities. Although it is one of the most used methods, the speech recognition system is language-dependent and affected by surrounding noise.

BCI-based methods utilize EEG signals generated from a person’s brain activity to infer what word/phrase a person was thinking [Saha and Fels, 2019]. The capturing of EEG signals is a tedious task as it requires the user to wear a device with several electrodes. The BCI devices are expensive, limited to research labs, and are not yet available for common use. The readily available BCI headbands such as Muse2 possess only four electrodes and are generally used for monitoring sleep. Eye tracking-based methods [Hansen and Pece, 2004] require consistent eye movements which could be strenuous for the user and may cause health problems. Head movements-based interfaces have also been explored in the past for controlling a cursor on the screen [Takami et al., 1996] as well as typing [Nowosielski and Forczmański, 2018]. Face-movement patterns have been studied for controlling a cursor, selecting keys, and scrolling over rows of the keyboard [Gizatdinova et al., 2012]. The scope of these works, however, was limited to moving cursor for selecting keys on modified keyboards. Typing on a modified keyboard could be tedious at times and generally require multiple clicks.

Motivated from the previous studies, we propose a novel touchless typing interface that utilizes head movement patterns captured via an inexpensive smartphone Samsung M10 camera. The proposed method does not require any expensive tracker or device. Although the data was collected in a lab setting, the focus was on usability and cost. These were the reasons for using an on-screen QWERTY keypad and only one camera that is generally available with laptops or notebooks. The proposed method makes use of a virtual

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The division of on-screen keyboard into nine color-coded clusters (see the keyboard in Figure 1).

To type a letter sequence, the user makes a series of gestures by looking at the letters one by one on the virtual QWERTY keyboard. The sequence of gestures captured by the camera is then mapped to a sequence of clusters using deep learning models for sequential data. This predicted sequence of clusters can be used to suggest valid dictionary words that can be formed out of this sequence to the user.

Figure 1: An overview of the system. The clustered and color-coded keys of the on-screen QWERTY keyboard. The clusters are numbered in top-bottom and left-right manner. For example, “QWE” is cluster 1, “RTYU” is cluster 2, and so on.

We develop a dataset of head movement patterns recorded via a central-view camera. The data was collected from a total of 22 users in a lab environment. Each user typed twenty different words, ten different phrases, and five different sentences with average length (number of characters) 4.33, 10.6 and 18.6, respectively. The dataset and code would be shared publicly for fostering research in this field, further.

We propose a GRU based model that uses pre-trained embedding rich in head pose features and compare its performance with CNN-RNN and Conv3D, which are widely used for sequential data under four different scenarios.

The rest of the paper is organized as follows. Related works, dataset, details of the proposed system and the experimental design is presented in Section 2, Section 3, and Section 4, respectively. Section 6 describes results followed by Section 7 that concludes the work beside listing future research directions.

2 Related work

The closely related works can be divided into selection-based text entry and gestural input [Markussen et al., 2014]. Each of these is discussed as follows:

1The dataset and code are available upon request. Please contact the last author.

[Nowosielski, 2017b] suggested that typing with head movements is possible by the fusion of a camera mouse (or additional mechanism) and an on-screen keyboard [Tu et al., 2007; Nabati and Behrad, 2012]. The additional mechanism includes eye blink, open mouth, etc. and compliments the selection process. The selection-based text entry, however, suffers from the precision problem and is considered time-consuming as they use limited directional (e.g., Left, Right, Up, and Down) movements, in turn, requires many steps to reach the intended letter, and often uses a modified keyboard. The time consumption can be reduced by reducing the interaction with the keyboard [Nowosielski, 2017a]. [Nowosielski, 2017a] proposed a text entry method in which each letter can be entered with three steps. The individual step consisted of movement of the head in one of the four directions and the return. The text-entry process makes use of a modified keyboard in which the English alphabets were arranged chronologically. The author further improved the system with a two-step entry process [Nowosielski, 2017b] and later using a thermal camera to reduce the effect of lighting conditions on the text entry process [Nowosielski and Forczmański, 2018].

Word-gesture keyboards (WGK) [Zhai and Kristensson, 2012] enable fast text entry by allowing users to draw the shape of a word on the input surface. Such keyboards have been used extensively for touch devices, for example in smartphones swipe keyboards have been incorporated for a long which are based on this technology. [Markussen et al., 2014] presented a relatively faster mid-air (touchless) typing technique than the selection-based methods. The technique offered comparable accuracy to gesture-based text entry on touch-based input surfaces. The user of the system had to wear a glove with reflective markers that tracked the position of its hands and fingers. To write a word, a user placed the cursor on the first letter, made a pinch gesture using the index finger and the thumb, which followed tracing the remaining letters of the word, and finally releasing the pinch. The authors suggested that the user could select a word from the list of suggestions or continue typing, implicitly confirming that the highlighted word was a match. The user could also undo the suggested word in the text input field by selecting backspace or delete previously typed words by multiple selections of backspace. In other words, they used four basic interaction steps of a match, select, undo, and delete. The authors report that the touchless gesture entry process was 40% slower than the gesture-based text entry on touch surfaces and mentally demanding.
Hand movement-based gestures have also been studied in the context of smartphone security. [Shukla et al., 2014; Ye et al., 2017; Shukla and Phoha, 2019] have established that hand movements recorded by a front-facing camera can be used to reconstruct smartphone users’ PIN, pattern, and password.

One can also use a Virtual Reality Headset (VRH) based method proposed by [Yu et al., 2017] instead of hand gloves. The users using the VRH generally control a pointer on a virtual keyboard using head rotation. Another interesting way of touchless typing is through eye-tracking. The eye tracking-based systems detect and track the movement of the pupil to move a cursor [Cáceres et al., 2018] or control a key selector. For example, [Zhang et al., 2018] proposed a system in which they use eye gaze to select keys on a TV keyboard. Accurate eye gaze systems require sophisticated eye trackers and are also not suitable for long typing sessions as eyes need to be open for a long period.

Our work differs from the aforementioned works as it uses a standard QWERTY keyboard, a single mobile camera (does not require the user to wear an external device) for recording the head movement-based gestures, and applies deep learning-based sequence to sequence models for translating the recorded gestures to a cluster sequence that can be used to recommend valid words for typing.

### 3 Dataset

In this section, we describe the data collection setup and the dataset.

#### 3.1 Data Collection Setup

The dataset used in this paper was collected as part of a larger data collection exercise following the approval of the Institutional Review Board (IRB) of IIIT Delhi. The overall goal of the data collection was to capture the head-movements of the participants via camera and motion sensors while the users instinctively looked at the cluster one by one (see the keyboard in Figure 1). Specifically, the data collection setup consisted of three cameras placed at -45°, 0°, and 45°, a virtual keyboard displayed on a 17” screen, and a headband (Muse 2) worn by the participants. The camera placed at 0°(facing the participants). The headband consisted of accelerometer and gyroscope sensors. The three cameras captured the visual aspect of the participant’s head movement, whereas accelerometer and gyroscope sensors captured the acceleration and rotation, respectively. Our work, however, utilizes only the information recorded via a central view camera (the one placed at 0°). The central camera-view setup represents a realistic setup as most of the laptops, notebooks, and phones consist of at least one camera nowadays. On the other hand, the use of multiple cameras and a headband symbolizes a futuristic setup as we envision that the use of Brain-Computer Interfaces (BCI) headbands would be common for tech-savvy.

The keyboard in Figure 1 demonstrates the color-coded clusters. Each color represents a cluster (a group of nearby keys). The clusters were numbered from 1 to 9. To type a sequence of letters, the participants pointed to the corresponding clusters that consisted of those keys by moving his/her head. For example, if the participant wanted to type the word ‘god’, the participants would point to the cluster sequence [5, 3, 4]. The use of virtually clustered QWERTY keypad had multiple advantages. First, the participants were already familiar with the keyboard. Second, they did not have to spend much time in locating the keys. They just had to point to the clusters by moving their head. Finally, it simplified the problem from predicting 27 keys to predicting just 9 clusters.

An analysis was conducted to find out how many unique words can be formed from each possible sequence. It was observed that for the 10,000 most common English words there are 8529 unique cluster sequences with each sequence having an average 1.17 different words. So once we predict the cluster sequence, it can be translated to 1-2 valid words on an average which is comparable to character level prediction.

#### 3.2 Data Description

A total of 25 volunteers participated in the data collection, of which 19 were male, and six were female university students. Out of these, data for three participants were discarded after inspecting manually. Each participant typed 20 words, ten phrases, and five sentences. Some examples are presented in Table 1. The exercise was repeated three times for each participant which resulted in 105 recordings per user. The number of recordings, thus, totaled to 2234, which is less than 2310 (=20+10+5)*22) because some of the samples of two users were not recorded fully. The average lengths of words, phrases, and sentences were 4.33, 10.6 and 18.6 letters, respectively. The words were chosen manually ranging from three to six characters long, such that each of the 8 clusters representing 26 English alphabets is included in at least one word, and the unique transitions between the clusters in a given word are maximized. The phrases were chosen from OuluVS dataset [Zhao et al., 2009] and

| Category | Text Typed | Cluster Sequence |
|----------|------------|------------------|
| Word     | live       | 6, 3, 7, 1       |
|          | box        | 9, 3, 7          |
| Phrase   | thank you  | 2, 5, 4, 9, 6, 8, 2, 3, 2 |
|          | see you    | 4, 1, 1, 8, 2, 3, 2 |
| Sentence | i never gave up | 3, 8, 9, 1, 7, 1, 2, 8, 5, 4, 7, 1, 8, 2, 3 |
|          | best time to live | 5, 4, 7, 1, 8, 4, 8, 5, 3, 3, 4, 8, 2, 3, 9, 1 |

Table 1: Examples of word, phrase, sentences, and corresponding cluster sequences.
sentences from TIMIT [Zue et al., 1990]. Considering every head movement from one cluster to another a gesture (or a letter entry), the users inputted 49.26 gestures per minute with a standard deviation of 5.3. The gesture entry rate would only increase with more practice on the proposed system.

4 Proposed System

In this section, we present the entire pipeline of our system, along with the deep learning model architecture and its various sub-modules.

4.1 System Overview

The system overview is presented in Figure 1. First, the region of interest, are extracted from the video using face detection DNN provided in OpenCV [Bradski, 2000]. Second, the processed video frames are fed into the deep learning models that output the cluster sequence the user was looking at. A set of valid words are recommended based on the predicted cluster sequence.

4.2 Head Pose Feature Embedding

End to end training of a joint CNN-RNN model is not suitable for a small dataset and might make the model not learn the desired characteristics. For our proposed model, we precompute the features denoting the head pose of a user for each frame separately and train only the RNN model. HopeNet [Ruiz et al., 2017] is a CNN based landmark-free head pose estimation model for computing the intrinsic Euler angles (yaw, pitch, and roll) from an RGB image of a person’s face in an unconstrained environment (Figure 2(b)). The Euler angles are the three degrees used to represent the orientation of a rigid body in 3-dimensional Euclidean space. For predicting the Euler angles, classification, as well as a regression approach, is applied. The angles in the range of $\pm 99^\circ$ are divided into 66 bins. The network outputs the bin in which the angle lies and this angle value for the bin is taken as the predicted value for the regression loss. As illustrated in Figure 2(a), the method uses a ResNet50 as a backbone network augmented with three fully connected layers of size 66. These three layers use the same ResNet50 backbone with shared weights. HopeNet network uses three loss functions for the three angles. Each one is composed of a coarse-bin classification loss and regression loss. The ground truth feature vector is prepared by the actual Euler values.

For bin classification, softmax cross-entropy loss is used, and for regression loss, the regular mean squared error loss is computed. The final loss function becomes

$$ L = H(y, \hat{y}) + \beta \cdot MSE(y, \hat{y}) \quad (1) $$

here $\beta$ represents the weight of regression loss.

Since this model is suitable to form the feature embedding for our task, we use the softmax outputs of size 66 (figurearch) for all three Euler angles and concatenate them to form our embedding of dimension $3 \times 66 = 198$.

4.3 Model Architecture

The task of generating cluster sequences using head movement video can be seen as a sequence to sequence modeling task in which the input sequence is a sequence of RGB frames and output sequence is a sequence of clusters the user was looking at. Recurrent Neural Networks (RNN) such as LSTM [Hochreiter and Schmidhuber, 1997], GRU [Cho et al., 2014] are widely used for a sequence to sequence modeling tasks. However, it might be the case that the number of video frames is not equal to the number of clusters in the target sequence, and hence an input frame cannot be aligned to a corresponding cluster. For this, we use Connectionist Temporal Classification (CTC) Loss [Graves et al., 2006], which solves the non-alignment problem of input and output. For forming the feature embedding, we use the output from the HopeNet model as described in the previous section. Our model consists of a four-layered Bi-Directional GRU network. The embedding dimension is 198 (concatenation of 66 dimension softmax output for all three Euler angles) and the hidden dimension of the GRU cell used is 512.

The model architecture is shown in Figure 3. Features along with the forward and backward directions, each of size 512, are added to give a $T \times 512$ size feature matrix. We apply 1D Batch Normalization followed by a fully connected layer with softmax activation, which reduces the 512 features to ten features. At each timestep, the final output of the model is a softmax vector of size ten consisting of probability at time $T$ for the nine clusters and a blank (for CTC loss). To generate the cluster sequence, we use Beam Search Decoding [Wiseman and Rush, 2016], a widely used decoding algorithm used in the field of natural language processing.

5 Training and Performance Evaluation

In this section, we describe the set of experiments and our training procedure.

5.1 Training

We use a 70:10:20 split for train, validation and test set. Instead of training on all $N$ frames of a video, we select every tenth frame, which helps in better capturing the actual directional change during head motion. We use SGD optimizer with nesterov set to true. We use an initial learning rate = 0.0025 and momentum = 0.9 and set max norm of 400 for tackling gradient explosion. We use a batch size of four for training. We use this experimentation for all three models. For the CNN-RNN model, we used a four-layered bidirectional GRU network stacked over Resnet18 CNN architecture. For Conv3D, 50 frames were uniformly sampled from the video sequence, which is passed into convolution layers followed by fully connected layers, eventually giving us a prediction among 35 classes.

5.2 Performance Evaluation

The performance of the standard, as well as the proposed model, were evaluated under the following scenarios:

1. Different Users Same Cluster Sequences (DU-SCS): In this scenario, the models are trained on a set of users $S_1$ and tested on a different set of users $S_2$ such that $S_1$ and $S_2$ are mutually exclusive. The cluster sequences are kept the same for train and test sets.
2. Different Users Different Cluster Sequences (DU-DCS): In this scenario, the models are trained on a set of user $S_1$ and a set of cluster sequences $T_1$ and tested on a set of users $S_2$ and a set of cluster sequences $T_2$ such that $S_1$, $S_2$ and $T_1$, $T_2$ are mutually exclusive.

3. Same User Different Cluster Sequences (SU-DCS): In this case, the models are trained on a set of cluster sequences $T_1$ and tested on another set of cluster sequences $T_2$ such that $T_1$ and $T_2$ are mutually exclusive. The users are kept the same in the train and test set.

4. Same User Same Cluster Sequences (SU-SCS): Since we had recorded three iterations for each cluster sequence from each user, we trained the models on the first two iterations of each sequence and tested it on the third keeping the users the same in train and test set.

For Conv3D based model, the problem is formulated as prediction out of the 35 sequences whereas, for CNN-RNN based model and our proposed model, we formulate the problem as a sequence generation task. We use the following metrics for evaluating the performance of the model:

1. Accuracy: The accuracy measures how many decoded sequence is an exact match to the target sequence.

2. Modified DTW: Besides Accuracy, we present Modified Dynamic Time Warping (M-DTW) distance [Choi and Kim, 2018] that is specifically designed to compare the sequence of gestures. M-DTW calculates the distance function using a linear combination of Euclidean and Directional distances. Formally, the function in Equation 2 is modified as mentioned in Equation 3.

$$\alpha(w) = \alpha(i, j)$$

M-DTW was preferred over Standard DTW [Bellman and Kalaba, 1959] because the standard DTW does not consider the directional changes in 2D space. We consider the keyboard as 2D space and the clusters as coordinates, as shown in Figure 4. Let $P = [7, 5, 1]$, and $Q = [9, 5, 3]$ are two predicted sequences and $A = [8, 4, 2]$ be the actual sequence. The standard DTW distances AP and AQ turned out to be the same. However, in reality, AP should be smaller than AQ as A is more similar to Q than P (see Figure 4).
The performance of the three models are presented in Table 2 under all four experimental scenarios. Conv3D-based models are evaluated only under the Same Cluster Sequence scenarios because it could not be tested on sequences (classes) other than the ones it was trained for. The accuracy indicates that the proposed model outperforms both the CNN-RNN and Conv3D based models in all but the Same User Same Cluster Sequence (SU-SCS) scenario. More specifically, the proposed model achieved 14.93% and 35.18% better accuracy than the CNN-RNN and Conv3D-based models respectively under Different User Same Cluster Sequence (DU-SCS) scenario. On the other hand, the CNN-RNN based model achieved the best (91.81%) classification accuracy closely followed by proposed (89.80%) and Conv3D (75.04%) for SU-SCS. The M-DTW distances suggest that the proposed method was as good as CNN-RNN-based for SU-SCS and performed significantly better in the rest of the scenarios. The results suggest that the presented models did not do well under the "Different Cluster Sequence" scenarios. We, therefore, aim to investigate that further.

The presented results are preliminary as they are based on data collected from a limited number of users under a controlled lab environment. Even though our proposed model with pre-trained embedding generalizes better, with more data end to end trained CNN-RNN models might adapt better to that data. Nonetheless, the results are encouraging, and it would be interesting to investigate how would the presented models perform for a much diverse population of users and under a real-world setup (instead of a lab-based setup). Factors that would likely affect the performance of the systems include the size of the on-screen keyboard, the extent of head-movements by the users during typing, the distance of the user’s head from the keyboard, and the quality of the camera in use among others.

### Table 2: Performance of the models based on CNN-RNN, conv3D, and the proposed architecture under various scenarios.

| Scenarios          | Proposed Accuracy | M-DTW | CNN-RNN Accuracy | M-DTW | Conv3D Accuracy |
|--------------------|-------------------|-------|------------------|-------|-----------------|
| DU-SCS             | 73.63             | 0.47  | 58.70            | 1.24  | 38.45           |
| SU-SCS             | 89.80             | 0.15  | 91.81            | 0.15  | 75.04           |
| SU-DCS             | 6.22              | 3.00  | 3.56             | 5.00  | N/A             |
| DU-DCS             | 6.67              | 3.23  | 3.81             | 5.76  | N/A             |

Table 2: Performance of the models based on CNN-RNN, conv3D, and the proposed architecture under various scenarios. The proposed architecture achieved the best performance in all but the Same User Same Cluster Sequence (SU-SCS) scenario. Overall, the models good performance for Same Cluster Sequence scenarios.

\[
\alpha(w) = (1 - \theta) \cdot \alpha(i,j) + \theta \cdot s(i,j) \cdot \alpha(i,j)
\]

where \(\theta\) represents the weight for directional distance. From our preliminary experiments we found out the value of \(\theta = 0.5\) gives the best measure. Directional distance, \(s\), between two direction vectors is calculated using the cosine similarity measure as follows:

\[
s(i,j) = 1 - \frac{\langle \vec{a}_i \times \vec{b}_j \rangle}{\|\vec{a}_i\| \|\vec{b}_j\| + \varepsilon}
\]

where \(\vec{a}_i\) and \(\vec{b}_j\) respectively represent the direction vector at cluster index \(i\) in sequence \(a\) and cluster index \(j\) in sequence \(b\). The vectors are computed as follows:

\[
\begin{align*}
\vec{a}_n & = (a_n - a_{n-1}) + ((a_{n+1} - a_{n-1})/2) \\
\vec{b}_n & = (b_n - b_{n-1}) + ((b_{n+1} - b_{n-1})/2)
\end{align*}
\]

where \(a_n\) represents the coordinates of cluster at cluster index \(n\) in sequence \(a\).

Figure 4: Comparison of DTW and Modified DTW (M-DTW) algorithms. The lesser the distance is the better the match.

### 6 Results and Discussion

The performance of the three models are presented in Table 2 under all four experimental scenarios. Conv3D-based models are evaluated only under the Same Cluster Sequence scenarios because it could not be tested on sequences (classes) other than the ones it was trained for. The accuracy indicates that the proposed model outperforms both the CNN-RNN and Conv3D based models in all but the Same User Same Cluster Sequence (SU-SCS) scenario. More specifically, the proposed model achieved 14.93% and 35.18% better accuracy than the CNN-RNN and Conv3D-based models respectively under Different User Same Cluster Sequence (DU-SCS) scenario. On the other hand, the CNN-RNN based model achieved the best (91.81%) classification accuracy closely followed by proposed (89.80%) and Conv3D (75.04%) for SU-SCS. The M-DTW distances suggest that the proposed method was as good as CNN-RNN-based for SU-SCS and performed significantly better in the rest of the scenarios. The results suggest that the presented models did not do well under the "Different Cluster Sequence" scenarios. We, therefore, aim to investigate that further.

The presented results are preliminary as they are based on data collected from a limited number of users under a controlled lab environment. Even though our proposed model with pre-trained embedding generalizes better, with more data end to end trained CNN-RNN models might adapt better to that data. Nonetheless, the results are encouraging, and it would be interesting to investigate how would the presented models perform for a much diverse population of users and under a real-world setup (instead of a lab-based setup). Factors that would likely affect the performance of the systems include the size of the on-screen keyboard, the extent of head-movements by the users during typing, the distance of the user’s head from the keyboard, and the quality of the camera in use among others.

### 7 Conclusion and Future Work

This paper presented a touchless typing interface that uses head movement-based gestures. The proposed interface uses a single camera and a QWERTY keypad displayed on a screen. The gestures captured by the camera are mapped to a sequence of clusters using a GRU based deep learning model that consists of pre-trained embedding rich in head pose and gaze-based features. The performance of the interface was evaluated on 2234 video recordings collected from twenty-two users. The presented interface achieved an accuracy of 91.81%, and 73.63% under the Same User Same Cluster Sequence and Different User Same Cluster Sequence scenarios, respectively. However, the performance declined under scenarios in which the sequence of clusters was different in train and test set. In the future, the aim is to improve the performance issue by (1) using more training
data containing a variety of meaningful sequences, and (2) combining video feeds from multiple cameras, brainwaves recorded via EEG sensors, acceleration, and rotation of the user's head recorded via accelerometer and gyroscope built into Muse 2 which were collected concurrently during the data collection.

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A.1 Devices and Configurations

Figure 5 depicts the data collection environment. To participate in the data collection, users wore a Muse 2 headband, sat on a chair in front of the monitor on which the virtual keyboard was displayed. Muse 2 consists of three sensors, namely, electroencephalogram (EEG), accelerometer, and gyroscope. The EEG sensor recorded the brain activity, whereas, accelerometer and gyroscope sensors recorded the acceleration and rotation of the participants head while typing. Other than Muse 2, three smartphone cameras were used to record the head movement-gestures. These cameras were placed on tripods at -45°, 0°, and 45°. The camera placed in the middle (see Camera-2 in Figure 6 recorded the head movements of the participant from the front. While Camera-1 placed at -45° and Camera-2 placed at 45° recorded the head movements from the left and right sides of the participant, respectively. The recording devices (cameras and the Muse 2) were connected and controlled using another laptop (see moderator’s laptop in Figure 5).

The videos were recorded at 30 frames per second with a resolution of 1920 × 1080 pixels. The focus was to record the area above the shoulder of the participant. A script running on the moderator’s laptop broadcast a message to the OpenCamera Remote Apps installed on each of the phones to start and stop the recording simultaneously.

Figure 5: The data collection environment consisting of a monitor on which the virtual keyboard was displayed, three cameras placed on tripods recording the head movement-based gestures of the participant, in addition to Muse 2 which was worn by the participant on his/her forehead as shown in Figure 6, a moderator’s laptop, and a laser light. All three cameras were facing the participant.

A.2 Protocol

A moderator guided the participants across the data collection process as per the need. Specifically, the participants were asked to sit on a chair and rehearse to make themselves familiar with the keyboard and the text entry method. The time of rehearsal varied from participant to participant as they were told to make themselves comfortable with the setup. The participants were asked not to spend more than half a second on a letter during the typing process. The specific steps that were followed are listed below:

1. The moderator reminded the user of the word, phrase, or sentence that was to be typed. The participants were encouraged to rehearse before starting each typing session to avoid mistyping.
2. A key (Enter) was pressed on the keyboard connected to the moderator’s laptop to start the recording.
3. The moderator then started the Muse-Monitor App installed on the smartphone that records the Muse 2 headband data, and the moderator then flashed a laser light at the center of the forehead of the participant.
4. To begin with the participants looked at the center of the virtual keyboard then started moving their head in direction of subsequent letters that were to be typed.
5. The recording was stopped once the participant finished by moving their head.
6. The above steps were repeated three times for each of the words, phrases, and sentences.

A.3 Synchronization

One of the major challenges that researchers face in designing multi-sensory data collection is synchronization. In our case,
we wanted to synchronize the recording such that lag between the video frames recorded by different cameras was minimal. Audio cues can be used to synchronize videos, however, they suffer from background noise issue [Adobe Systems, Inc.][Anina et al., 2015] used periodic flash for synchronization for their multi-view lip reading dataset. The flashes helped minimize the time difference between the periodic signals captured between the multiple view videos. However, they had to manually and roughly mark the frames where the flash occurred which could easily introduce some unwanted error.

In our data collection, we introduce an automatic laser-point based video synchronization method. The laser projects a highly concentrated beam of light that can be detected automatically.

Before starting the actual recording session, red-colored laser light is flashed such that it is captured by all three cameras. The problem of synchronization then boiled down to detecting the first frame from each video that had the laser point. Following algorithm was used to find the first frame in each of the three recordings:

1. The frames were converted from RGB color space to HSV. HSV because that is how humans perceive color.
2. Two binary masks $b_1$ and $b_2$ were formed using the two ranges of hue values $0 – 20$ and $170 – 180$ respectively, along with a high saturation range $100 – 255$ since the laser light is highly saturated red color. Hue values generally lie in the range of $0 – 360$. However, the use of OpenCV restricted it to the range of $0 – 180$. The two masks were then bitwise ORed to obtain the final mask.
3. A threshold of non-zero values is chosen. The frame is chosen as the marker of the first flash captured if the non-zero values in the final mask are more than the threshold.
4. Let $s_1$, $s_2$, $s_3$ denote the start and $e_1$, $e_2$, $e_3$ denote the end time of the 3 views respectively. The flash marker frames $f_1$, $f_2$, $f_3$ denote the frames with first flash cue. Initially, the $s_1$, $s_2$, $s_3$ are set to 1 and $e_1$, $e_2$, $e_3$ are set to the number of frames in respective video.
5. The goal of synchronization is to make $f_1 = f_2 = f_3$ by shifting and padding the videos. We take a reference view, consider view 2. The start and end time has to be shifted to make the flash frames equal. Therefore, for any view $i$,

\[
s_i = s_i + (f_2 - f_i)
\]
\[
f_i = f_i + (f_2 - f_i) = f_2
\]
\[
e_i = e_i + (f_2 - f_i)
\]
6. The videos were padded as the flash frame position was now similar in all the views. Let $front_{pad_i}$ and $back_{pad_i}$ represent the empty frames needed to pad in front and back of the video respectively, for view $i$. The values are calculated as follows:

\[
front_{pad_i} = s_i - \min(s_1, s_2, s_3)
\]
\[
back_{pad_i} = \max(f_1, f_2, f_3) - f_i
\]

![Figure 6: A view from the backside of the participant. The participant is wearing a Muse 2 headband and looking at the virtual keyboard displayed on the screen in front of it, and three cameras recording the head-movement gestures. Laser light was used to synchronize the data collection from different cameras as explained in Section A.3.](image1)

![Figure 7: The coverage (share) of each cluster across the dataset.](image2)