Towards a Perceptual Model for Estimating the Quality of Visual Speech

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Abstract

Generating realistic lip motions to simulate speech production is key for driving natural character animations from audio. Previous research has shown that traditional metrics used to optimize and assess models for generating lip motions from speech are not a good indicator of subjective opinion of animation quality. Yet, running repetitive subjective studies for assessing the quality of animations can be time-consuming and difficult to replicate. In this work, we seek to understand the relationship between perturbed lip motion and subjective opinion of lip motion quality. Specifically, we adjust the degree of articulation for lip motion sequences and run a user-study to examine how this adjustment impacts the perceived quality of lip motion. We then train a model using the scores collected from our user-study to automatically predict the subjective quality of an animated sequence. Our results show that (1) users score lip motions with slight over-articulation the highest in terms of perceptual quality; (2) under-articulation had a more detrimental effect on perceived quality of lip motion compared to the effect of over-articulation; and (3) we can automatically estimate the subjective perceptual score for a given lip motion sequences with low error rates.

Index Terms: speech animation, audio-visual speech, lip sync, human-computer interaction

1. Introduction

Animating faces from speech has applications in interactive systems, including virtual reality, entertainment, and accessibility. Most recent approaches for automatically generating these animations use neural networks, especially recurrent neural networks (RNNs) [1–6], where a model is trained to replicate ground-truth reference facial motion that accompanies speech. Training such models involves optimizing a metric, such as the mean squared error (MSE), between the ground-truth reference motion and the predicted motion. However, these objective measures capture errors globally and it has been shown that they can fail to capture perceptually significant errors [7–9]. Thus, the assessment of trained models typically involves some form of subjective assessment, using pairwise preference testing or mean opinion score (MOS) aggregation [4,9–16], which is time-consuming and difficult to replicate due to its subjective nature.

Previous works have highlighted the disconnect that exists between objective measures and human evaluations for assessing face animation quality. For instance, [7] studied the relationship between several objective measures and subjective opinion and found that Pearson’s correlation and root-mean-square error (RMSE), the two most commonly used objective measures, were not the most indicative of perception quality. Similarly, in [8] it was shown that sequences which had very little difference according to MSE varied considerably in terms of the subjective opinion of quality. Consequently, several approaches have been proposed to address the limitation of traditional objective metrics. In [13], a collection of metrics were proposed to evaluate the dynamics of facial animations. In [17], a pre-trained SyncNet model was used to quantify the quality of lip motion. In [18], the distance between embeddings extracted from a pre-trained lip reading model was used as a metric for evaluating animation performance. Although the approaches proposed in previous works mitigate the limitations of traditional metrics, none of them directly estimate the perceived quality of lip motion as measured via human judgement.

The goal of this work is to reduce the need for running repetitive subjective tests during the development and evaluation of lip motion generation models by learning perceptual models for estimating the perceived quality of lip motion sequences. The trained perceptual model can be incorporated in a loss function to mitigate perceptually significant errors during model training. We first collect subjective ratings from crowd-sourced individuals for lip motion sequences that have undergone varying degrees of under- and over-articulation. We then train models to predict the annotators’ score for sequences that have undergone some known degree of articulation adjustment. To ensure the focus is on lip motion (and not on rendering artifacts), we extract animations of facial landmarks from videos akin to point-lights [19]. Our results provide insights into human perception of visual speech and show that we can automatically estimate the perceptual scores given a visual speech animation.

2. Dataset and Features

We use the GRID corpus [20], which contains multimodal recordings of 34 native English speakers (16 female and 18 male) reciting fixed grammar sentences of the form, command-color-preposition-letter-number-adverb, where each token in the grammar has a limited number of options (see [20] for details). An example utterance might be “place bin blue at A three now”. The dataset contains all combinations of the colors, letters, and digits. Each speaker recited a total of 1000 sentences, and each video is three seconds long recorded at frame rate 25 Hz.

We use Dlib [21] to extract 68 facial landmarks from each video frame and then reduce the effects of tracking noise by convolving the sequence across time with an averaging window of width three. We then align the facial landmarks to a common reference following the approach described in [1] to remove translation, rotation, and scaling variation. To ensure we focus exclusively on the motion of the lips and jaw when assessing the quality of speech animation, we remove landmarks that correspond to the eyes, nose, and eyebrows. As a result, each frame is represented by 31 landmarks, where each landmark is a pair of x-y points.
We focus our study on one speaker from GRID to remove the effects of inter-speaker variability from our initial analyses. Specifically, we select speaker s-25 since they have the largest variance in the distance between the mid-points of the upper and lower lips. In total, we have 996 sequences available for speaker s-25 since the landmark extraction failed for the following four videos: prat5a, pwin2n, bbwq4n, and brwk8p.

3. Crowd-sourcing the Perceptual Scores

We generate variations of the 996 ground-truth sequences from GRID by varying the degree of under-articulation (damped) and over-articulation (exaggerated) in the speech motion. Specifically, we measure the impact of scaling the degree of articulation on the perception of the speech motion using a user-study, and then train a model using the scores collected from our user-study to learn to predict the subjective quality of an animated sequence. Such a model reduces the need for future user-studies for assessing the quality of visual speech animations subjectively.

3.1. Changing the Degree of Articulation in Visual Speech

The effects of over- and under-articulation can be achieved by first projecting the facial landmarks onto a set of low-dimensional basis vectors using principal components analysis (PCA) to capture correlated motion, then scaling the PCA values of the facial landmarks by some desired amount, and finally reconstructing the landmarks from the scaled values. An advantage of using this approach for controlling the degree of visual articulation is that the strength of articulation is parameterized by a single scalar value. Specifically, multiplying the PCA values with a scalar that is greater than 1 results in speech that is visually over-articulated, while multiplying the PCA values with a scalar that is less than 1 results in speech that is visually under-articulated. Figure 1 shows examples of the effect of scaling the PCA values using multiple scaling factors on the same video frame.

We fit a PCA model to the landmarks of the selected speaker (s-25) and retain sufficient components to describe 95% of the variance present in the data, which requires 11 components. To ensure that the reconstructed landmarks result in valid face shapes, we clip the scaled PCA values to remain within defined bounds to prevent artifacts, e.g., crossing of the upper and lower lips. The resulting rendered frames are then written out to video files for our user-study.

3.2. The Crowd-sourcing Experiment

We generate our dataset by randomly sampling four scaling factors per utterance from speaker s-25 and then scaling the PCA values of the utterances accordingly. As a result, our dataset contains 3984 utterances and scaling factors are sampled from the following set: \( \{0.1, 0.3, 0.5, 0.7, 0.9, 1.0, 1.1, 1.3, 1.5, 1.7, 1.9, 2.1\} \). These scaling factors were chosen to have a paired value for under- and over-articulation. For example, the values of 0.9 and 1.1 are equivalently scaled either side of no scaling (1.0). The scaling factor 2.1, however, does not have an equivalent under-articulation as this would correspond to \(-0.1\). So although stimuli from the scaling factor 2.1 were shown to viewers (and so are included in Figure 2), we remove them from our analysis in Section 3.3. Each sequence is annotated by five annotators to account for the subjective nature of the task, resulting in a total of 19,920 annotations.

Annotators completed two tasks. The first task served as a qualification task to assess the annotators’ suitability, and the second task was the main task from which we derived the labels for the videos. At the start of the study, annotators were presented with a brief description of the two tasks they were asked to complete. Annotators were not told that the first task was accessing their suitability.

The qualification task. This task provided quality control over the annotators who were allowed to complete the annotation task. Annotators were asked via a multiple choice question to identify the words spoken in a given audio-visual sequence. We purposefully picked a qualification task that is different from the main task of assessing the quality of lip motions so as to not bias the annotator pool by only choosing individuals who are sensitive to differences in the lip motions.

The annotation task. Annotators were shown two audio-visual sequences and were asked to indicate the relative difference in quality between the two. The reference video (no scaling) was on the left and the scaled video on the right. Annotators were asked to indicate their preference using a seven-point Likert scale by choosing one of following options: \{Extremely Worse, Moderately Worse, Slightly Worse, The Same, Slightly Better, Moderately Better, Extremely Better\}

We collected annotations from 300 unique crowd-sourced individuals using an in-house crowd-sourcing platform. All annotators were English speakers (determined by the crowd-sourcing platform’s screening process and confirmed for this specific task through our qualification test) and they came from the following countries: U.S. (49.0% of the annotators), Great Britain (17.5%), Canada (15.7%), Australia (6.2%), Philippines (4.0%), Ireland (3.7%), India (2.9%), and Singapore (0.9%). We used Krippendorff’s alpha to measure the degree of agreement between the annotators and obtained \(\alpha = 0.32\), which suggests that there is moderate agreement between the annotators despite the subjective nature of the task [22].

3.3. Results

We analyzed annotator perceptual judgements using linear mixed effect regression.\(^1\) For this analysis, we decomposed the scaling factor into two categorical variables: articulation type, representing the direction of scaling (under- vs. over-articulation, sum-coded) and scaling step (1-5, sliding differ-

\(^1\)We followed the recommendation by [23] on using linear regression for ordinal scale data.
Specifically, we predicted the perceptual score from articulation type, scaling step, and their interactions. The model included the maximal random effects structure for the task design: a random intercept for annotator ID and a random intercept for item nested within a ground truth animation (relating to the version of the ground truth animation). Trials with a scaling factor of 1.0 (ground truth) were removed from this analysis since scaling step did not apply.

The analysis revealed a main effect of articulation type ($\hat{\beta} = -0.472$, $t = -53.53$, $p < 0.0001$; see Figure 2), suggesting that annotators provided lower scores (i.e., dispreferred) to under-articulated animations compared to the mean across all scaling steps. Every scaling step increase resulted in a lower score compared to the previous step (step 2 vs. step 1: $\hat{\beta} = -0.09$, $t = -3.07$, $p = 0.002$; step 3 vs. step 2: $\hat{\beta} = -0.27$, $t = -9.75$, $p < 0.0001$; step 4 vs. step 3: $\hat{\beta} = -0.56$, $t = -20.19$, $p < 0.0001$; step 5 vs. step 4: $\hat{\beta} = -0.58$, $t = -21.21$, $p < 0.0001$). These results tell us that the more the degree of speech articulation is modified, the more impact it has on viewer perception of quality. Furthermore, articulation type interacted with every scaling step contrast, suggesting that an increase in scaling had a more pronounced effect on under-articulation compared to over-articulation (step 2 vs. 1 * articulation type: $\hat{\beta} = -0.16$, $t = -4.43$, $p < 0.0001$; step 3 vs. 2 * articulation type: $\hat{\beta} = -0.18$, $t = -6.39$, $p < 0.0001$; step 4 vs. 3 * articulation type: $\hat{\beta} = -0.32$, $t = -11.75$, $p < 0.0001$; step 5 vs. 4 * articulation type: $\hat{\beta} = -0.43$, $t = -15.76$, $p < 0.0001$). Interestingly, over-articulation was rated as high as the ground truth, or even better, at all but the highest scaling steps (step 1: 0.14 mean, 95% CI [-0.09, 0.19]; step 2: 0.22 mean, 95% CI [0.13, 0.30]; step 3: 0.09 mean, 95% CI [-0.02, 0.20]; step 4: -0.12 mean, 95% CI [-0.25, 0.01]; step 5: -0.32 mean, 95% CI [-0.47, -0.16]).

These findings suggest that while humans are sensitive to scaling levels, scaling has less of an effect for over-articulation than it has for under-articulation, and that viewers prefer over-articulation to under-articulation overall.

4. A Perceptual Model for Visual Speech Quality Assessment

The results in Section 3.3 demonstrate how the perceived naturalness of lip motion varies with the degree of visual articulation. In this section, we ask: can a model estimate the perceptual scores for a given sequence of landmarks? Learning a perceptual model can streamline the building of lip motion generation models by reducing the need for running repetitive subjective tests for every iteration of development, which can both be time-consuming and difficult to replicate.

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2 Sliding difference coding compares the mean of the dependent variable for one level of the categorical variable to the mean of the dependent variable for the preceding adjacent level (e.g., scaling step of 2 to scaling step of 1).
Table 1: Perceptual score prediction performance. We report the performance of predicting the mean perceptual score from the sequence of augmented landmarks alone and from both the augmented and reference sequences as described in Section 4.1. Statistical prior baseline always predicts the mean score computed on the training set. We report the means and the standard deviations on the test set from 100 runs.

| Setup                  | MAE       | ρ        |
|------------------------|-----------|----------|
| Statistical Prior      | 0.73 (±0.02) | –        |
| Augmented Only         | 0.47 (±0.06) | 0.76 (±0.04) |
| Augmented & Reference  | 0.47 (±0.09) | 0.79 (±0.03) |

connected layers (reduce the size by 2 for the first layer; reduce the size by 4 for the second layer; reduce the size to 1 for the final layer), the number of epochs (50), and the non-linearity in the regression module (tanh).

Recipe. We randomly split the 3984 annotated samples into train/validation/test partitions following a 0.7/0.15/0.15 split rule. The resulting partitions are utterance independent (i.e., augmented versions of the same ground-truth animation are unique to each partition). We learn a PCA transform on the training partition such that we retain sufficient components to describe 95% of the variance present in the data and apply the same transform on all three partitions. We use a combination of MAE and Pearson correlation coefficient (PCC) losses to optimize the parameters of the model using the Adam optimizer [24]. We pick the hyper-parameters that yield the lowest mean validation MAE over 10 runs, where each run uses a random split of the data, and report both the mean and standard deviation of the evaluation metrics on the test sets computed over 100 runs to account for variation from data splits and random initialization.

4.2. Results

Table 1 shows the performance of estimating the perceptual scores using the described models. We compared the performance of our models to the performance of a simple baseline that predicts the mean perceptual score computed from the training set. The results show that our models improve MAE over baseline by lowering it from 0.73 to 0.47. The results also show that the estimates made by our models have a strong positive correlation with the ground-truth perceptual scores (0.76 for the Augmented Only model and 0.79 for the Augmented & Reference model), suggesting that our models can estimate the relative perceptual score for the given lip motion sequence.

The results in Table 1 also show that providing the model with the reference landmark sequence (in addition to the augmented landmark sequence) only provides a small improvement in the PCC (from 0.76 ± 0.04 to 0.79 ± 0.03). One explanation for this is that the data we used in our experiments only has one speaker and the models learned a reference (baseline) for this speaker during training. Figure 2 shows a comparison of the mean perceptual scores (grouped by scaling step) obtained from the annotators and the mean perceptual scores estimated by our trained model (Augmented & Reference). The figure shows that although our model’s estimates follow the general trends generated through human perception for under-articulated speech, the estimates are less accurate for over-articulated speech.

5. Conclusion

In this work, we investigated the building of a perceptual model for estimating the perceived quality of lip motion without the requirement for running repetitive manual subjective assessments. Such a model lays the groundwork for bridging the gap between the objective and subjective measures of performance used in the literature.

We focused our investigation on the relationship between the degree of articulation and the perceived quality of lip motion and studied how varying the strength of over- and under-articulation affects the perceived quality of the animations. We found that individuals consistently preferred visually over-articulated speech to visually under-articulated speech for all scaling steps. We also found that while the perceptual score goes down for high scaling steps, the reduction in the score is more pronounced for visually under-articulated speech. In addition, we found that human annotators preferred animations that are slightly over-articulated over the ground-truth animations. We followed the perceptual study with a modeling study and showed that we can train a model to automatically estimate the perceptual scores of quality for lip animations with relatively high performance. The findings from this work impact lip animation models in two aspects. First, the findings from our perceptual studies can be incorporated into training algorithms to yield more natural animations. Specifically, loss functions for neural-based lip-sync systems can be re-weighted to account for the perceived effects of articulation errors (i.e., err on the side of over-articulation for the best perceived outcome). Second, the findings from our modeling experiments suggest that perceptual models can streamline the building of lip animation models by reducing the need for running repetitive subjective tests.

Future work will investigate the effect of other common augmentations (e.g., jitter, synchronization) on the perceived quality of lip motion and will also investigate incorporating the perceptual model in a loss function to capture perceptually significant errors during model training.

6. Acknowledgements

The authors would like to thank our colleagues Vikram Mitra, Russ Webb, and Ahmed Hussen Abdelaziz for their insightful feedback on this work. The authors would also like to thank Lukas Michelsen, the annotation team, and the annotators for their help conducting the perceptual studies.

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