Self-supervised Learning of Visual Speech Features with Audiovisual Speech Enhancement

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Abstract

We present an introspection of an audiovisual speech enhancement model. In particular, we focus on interpreting how a neural audiovisual speech enhancement model uses visual cues to improve the quality of the target speech signal. We show that visual features provide not only high-level information about speech activity, i.e. speech vs. no speech, but also fine-grained visual information about the place of articulation. An interesting byproduct of this finding is that the learned visual embeddings can be used as features for other visual speech applications. We demonstrate the effectiveness of the learned visual representations for classifying visemes (the visual analogy to phonemes). Our results provide insight into important aspects of audiovisual speech enhancement and demonstrate how such models can be used for self-supervision tasks for visual speech applications.

Index Terms: audiovisual speech enhancement, lip reading, viseme classification, self-supervised learning

1. Introduction

The goal of monaural (single-channel) speech enhancement is to improve the quality and intelligibility of speech when the audio is recorded in a noisy environment from a single microphone. Enhancement models attenuate additive noise from a speech signal and can be used as pre-processors for various downstream applications, including automatic speech recognition (ASR) and speaker verification [1–5].

Previous research has shown that acoustic models used for speech enhancement benefit from the addition of visual cues [6–10]. Although neural audiovisual speech enhancement models have shown promising results, it is unclear how visual cues are utilized [6,11]. One hypothesis is that visual cues provide only high-level information about speech activity, i.e. speech vs. no speech, depending on whether the lips are moving or not. An alternative hypothesis is that visual cues provide fine-grained information about what is being articulated. The aim of our work is to interpret how visual cues are used by audiovisual speech enhancement models. Such analysis is not only necessary for understanding the mechanism by which an audiovisual enhancer uses visual cues, but also for understanding the performance gains obtained from the addition of visual cues.

We study the performance of audio-only speech enhancement models as a function of what is being articulated, where we use visemes as the basic unit of analysis. A viseme consists of a cluster of phonemes that share the same place of articulation, and so visemes represent visually indistinguishable phonemes [12]. For example, the phonemes /uh/ and /w/ both map to a rounded vowel viseme, while phonemes /b/ and /m/ map to a viseme representing bilabial consonants. We hypothesize that enhancement performance will vary depending on what is being said since certain sounds are more visually prominent than others. Given the per-viseme audio-only enhancement performance, we then quantify the performance gains obtained from the addition of visual cues to the enhancement model.

We also hypothesize that the visual representations implicitly learned by the audiovisual model can be used for other visual speech tasks. We show that these visual representations can be used to discriminate visemes during continuous speech, e.g. rounding lips, stretching lips, and visible teeth. Our results show that audiovisual speech enhancement can be used as a self-supervision task for learning meaningful visual speech representations without relying on manual annotations.

2. Related Work

Past work has shown that the introduction of visual cues can improve the robustness of various speech processing applications. These include automatic speech recognition (ASR), speaker recognition and diarization, speech enhancement, and emotion recognition [13–15]. This section covers recent relevant works on audiovisual speech enhancement, audiovisual source separation, and speech driven multi-modal self-supervised learning.

Gabbay et al. introduced an audiovisual speech enhancement model based on an encoder-decoder architecture [8]. The model they introduced takes in the log Mel-scale spectrogram representation of the speech segment and the corresponding gray-scale video frames containing the lips of the target speaker, and outputs an enhanced version of the input spectrogram. Although promising, the models were all speaker-dependent (i.e. the same target speakers were used during training and testing phases), which limits their generalizability.

Ephrat et al. introduced a speaker-independent approach for audiovisual speech enhancement [10]. Their models take in, as input, a complex-valued spectrogram of a three-second segment of speech and the corresponding video frames cropped to contain only the face, and outputs complex masks, which are used to reconstruct an enhanced speech signal. Concurrently, Afours et al. introduced an audiovisual speech enhancement approach to model both the magnitude and the phase components of the short-time Fourier transform (STFT) representation of the input signal [29]. In a follow-up study, they extended their original approach to make the enhancement model robust to partial occlusions by conditioning it on both visual cues and speaker representations [11].
The audiovisual speech enhancement system takes as input a mixture speech signal and the corresponding video containing the face of the speaker, and outputs a clean speech signal. The neural model (Figure 2) takes in two inputs, the mixture spectrogram and a video of the mouth region, and outputs an ideal ratio mask (IRM). The IRM is multiplied with the noisy spectrogram to give a clean spectrogram, which is used along with the noisy phase to reconstruct the clean speech signal.

Previous research looked at using correlation between acoustic and visual modalities as a self-supervisory training signal [17–21]. Cheng and Zisserman [17] trained a model to determine whether the audio and visual modalities of a speaker are temporally aligned or not. They created training examples by randomly introducing shifts in one of the modalities. The authors showed that the learned visual representations can be used as features for lip reading applications. Owens and Efros [18] trained a more general model to predict whether the visual and acoustics streams of a scene are temporally aligned or not, and then used the learned representations for three tasks: source localization, audiovisual action recognition, and audio source separation. To the best of our knowledge, our work in this paper is the first to investigate audiovisual speech enhancement as a self-supervisory signal for learning strong visual features.

In contrast to previous research, our work focuses on interpreting how audiovisual enhancers use visual cues to enhance the target signal. In particular, the novelty of our work is two-fold. Firstly, we show that the performance of audiovisual speech enhancers varies depending on what is being said, and we show that performance gains vary as a function of the place of articulation. Secondly, we demonstrate the effectiveness of the audiovisual speech enhancement task as a self-supervised way of learning useful visual embeddings that encode information about the place of articulation. In the self-supervised paradigm, we learn meaningful representations by training a model to solve a task with labels obtained from the data itself as opposed to labels obtained from manual annotation [22].

### 3. Audiovisual Speech Enhancement Model

Our architecture is shown in Figure 1. The neural enhancer receives two inputs: the squared magnitude of the STFT (i.e. power spectrum) of the noisy speech segment, and a video segment containing the corresponding pose-normalized gray-scale mouth images of dimension $w \times h \times t$. To produce an enhanced version of the input speech, the model predicts an ideal ratio mask (IRM), which we write as:

$$IRM(m, f) = \frac{|S(m, f)|^2}{|S(m, f)|^2 + |N(m, f)|^2}$$

where $|S(m, f)|^2$ and $|N(m, f)|^2$ represent the power spectrums of the speech and noise signals at frame $m$ and frequency bin $f$. Element-wise multiplying an IRM by the power spectrum of the noisy signal gives an optimal estimate, in the sense of the minimum mean square error (MMSE), of the power spectrum of the clean signal [23].

### 3.1. Audiovisual Neural Model

The audiovisual neural model, shown in Figure 2, consists of three sub-networks: (1) the audio encoder, (2) the video encoder, and (3) the mask predictor. The audio encoder induces a fixed-size embedding from a spectrogram segment and the video encoder induces a fixed-size embedding from a sequence of gray-scale images of the mouth region. The mask predictor outputs an ideal ratio mask (IRM) given the concatenated multimodal embedding.

### 4. Experimental Setup

#### 4.1. Dataset

We use an in-house audiovisual corpus containing around 68 hours (39,097 utterances) of speech from 600 gender-balanced speakers. The utterances are queries for a digital assistant spoken in English with an American accent. The audio is sampled at 16kHz using a 16-bit PCM encoding. The video has a frame rate of 60Hz and a resolution of $720 \times 1280$. We randomly split the dataset into gender-stratified partitions using a 80/10/10 rule. The resulting splits consist of 480 speakers (29,415 utterances, 52 hours) for training, 60 speakers (4,650 utterances, 8 hours) for validation, and 60 speakers (5,032 utterances, 8 hours) for testing.

#### 4.2. Details

Mixed utterances for training are created on-the-fly by mixing the target utterance with a random utterance from a different speaker in the training set. The mixtures used for the validation and test sets are fixed and are created using speakers from their...
The performance of the fully-connected (FC)-based encoders to that of LSTM-based encoders. We compare three regression-based loss functions: mean squared error (MSE), MAE, and a hybrid loss function that combines MAE with the cosine distance.

MSE is a common loss function used in regression problems. Minimizing the MSE is equivalent to maximizing the log-likelihood of data with a unimodal Gaussian distribution. Upon further inspection of the distribution of the training targets, i.e. the IRMs, we find that it does not resemble a unimodal Gaussian. Instead, the distribution of our training targets is bimodal, with a very large peak at zero (sparse labels) and a second smaller peak at one. The MSE solution in this case, which is the conditional mean of the distribution, will be between the two peaks, shifted toward the higher peak, at zero. This results in predicting blurry masks, which is consistent with observations about using the MSE loss in computer vision applications [22].

Using the MAE loss function can mitigate some of the limitations incurred from using the MSE loss function by encouraging the prediction of sharper IRMs [9,11]. One remaining limitation with using both MSE and MAE loss functions is the assumption that the individual components of the IRM vector are statistically independent. To address this limitation, we propose using a joint loss function that combines MAE with the cosine loss function. The cosine loss measures the distance between two *entire vectors* instead of measuring the distance between individual vector components. The cosine distance, however, cannot be used as a standalone loss, as it minimizes the angle between two vectors irrespective of their magnitudes. This can result in IRM vectors with magnitudes beyond the masks’ boundaries, i.e. zero and one. Therefore, we use the following hybrid loss of the MAE and cosine distance to optimize the angle between the ground truth and inferred IRM vectors while bounding their magnitude values to be between zero and one:

\[
L_{\text{hybrid}} = L_{\text{MAE}} + \alpha L_{\text{cos}}
\]

where \(\alpha\) is a trade-off parameter that we set to 0.5 in our experiments.

Table 1 gives a summary of the results obtained from our baseline experiment. The results show that considerable gains are achieved using an audio-only enhancer (columns labeled \(A\)), which was not expected a priori. One reason for this is that although the target mixture for the noisy signal was 0dB SNR, mixtures of 1dB emerged due to short pauses in the target and background speech. This 1dB difference between target and background acoustic speech gives the network a clue for enhancing the target speaker, even without visual cues. That said, the results show that the addition of visual cues still provides improvement in performance for all setups. The results also show that using an LSTM-based audio encoder yields better performance compared to FC-based encoders. This can be attributed to the temporal modeling of LSTMs. Finally, the results show that using the proposed hybrid loss function gives improvements over using MSE for the majority of the setups.

5.2. Viseme-specific Relative Improvements

In this section, we investigate whether the visual features improve the speech enhancement model by simply providing it with voice activity features, i.e. speech/silence, or by providing the model with more fine-grained information about what is being articulated. We compare the per-viseme improvements of the audio-only and audiovisual speech enhancement models in terms of the MAE between the inferred and ground truth

| Audio Encoder | Loss | SNR | PESQ |
|---------------|------|-----|------|
|               |      | A   | AV   | A    | AV   |
| FC            | MSE  | 4.21| 7.53 | 2.70 | 2.88 |
|               | MAE  | 4.28| 8.10 | 2.56 | 2.87 |
|               | MAE+Cosine | 4.62 | 8.07 | 2.67 | 2.90 |
| LSTM          | MAE  | 4.61| 8.42 | 2.67 | 2.92 |
|               | MAE+Cosine | 4.63 | 8.56 | 2.58 | 2.90 |
|               | MAE+Cosine | 5.17 | 8.87 | 2.73 | 2.95 |
5.3. Viseme Classification with Learned Visual Embeddings

In this section, we investigate whether or not we can use audiovisual speech enhancement as a self-supervised task for learning meaningful visual representations that can be used in other visual speech applications. Given the trained audiovisual speech enhancement model from our previous experiment, we disconnect the video encoder and use it as a general feature extractor. We use these extracted features to train a logistic regression model for viseme classification. For training the logistic regression model, we further split the test set used for evaluating the audiovisual speech enhancement model into training, validation, and test sets following a speaker-independent 80/10/10 split rule. This approach ensures two things: (1) speakers used for training the enhancement models are different from those used in analysis; and (2) the logistic regression model is trained, validated, and tested on speaker independent partitions. The hyper-parameter of the logistic regression model was tuned using the validation set. The performance is evaluated in terms of recall per viseme.

Table 3 shows the viseme classification performance obtained when using the visual embeddings as features for a simple logistic regression viseme classifier. We find that the visual embeddings are discriminative toward visemes, giving an overall unweighted accuracy of 33.5%, where 7.7% is the chance performance. We find that our classifier predicts apparent visemes, such as /Z/, /P/, and /SH/, relatively accurately compared to predicting visemes articulated more towards the back of the mouth, such as /T/ and /G/. The trends that we observe for viseme prediction performance using visual embeddings are similar to those observed in viseme classification tasks. As a benchmark, we were able to obtain an unweighted accuracy of 49.2% using a separate VGG-M neural network trained from scratch specifically to detect visemes, which suggests that our self-supervised visual features were able to close a large proportion of the performance gap. This demonstrates the efficacy of audiovisual speech enhancement as a self-supervised task for learning strong visual features.

6. Conclusion

In this paper, we shed light on how an audiovisual speech enhancement model utilizes visual cues to improve the quality and intelligibility of a target speech signal. We showed that the performance of enhancement models varies depending on what is being articulated; and we showed that the addition of visual cues provides non-consistent gains in performance depending on what is being articulated. Further, we demonstrated the effectiveness of audiovisual speech enhancement as a self-supervision task for learning meaningful visual representations for visual speech applications.
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