Looking into Your Speech:
Learning Cross-modal Affinity for Audio-visual Speech Separation
-Supplementary Materials -

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https://caffnet.github.io/

In this document, we describe architecture details of CaffNet and CaffNet-C, details of implementation and training, and provide more quantitative and qualitative results on LRS2, LRS3, and VoxCeleb2 datasets.

1. Network

1.1. Complex-valued Networks

Here we present a brief review of complex-valued networks, which can handle complex computations in deep networks [1, 2, 3]. The complex-valued convolution operation on the intermediate feature representation \( h = h_r + ih_i \) with a complex-valued convolutional filter \( w = w_r + iw_i \):

\[
w * h = (h_r * x_r - h_i * w_i) + i(h_r * w_i + h_i * w_r),
\]

where \( w_r, w_i \) are real-valued matrices of filter and \( h_r, h_i \) are real-valued matrices of complex feature representation. In practice, complex convolutions can be implemented as two different real-valued convolution operations with shared real-valued convolution filters as follows [1], and activation functions like ReLU were also adapted to the complex domain. To establish the complex-valued convolutional layer in our networks, we modified 2D complex-valued convolutional layers [1] into 1D complex-valued convolutional layers.

1.2. Network Architecture

Our networks are based on V-Conv [4] architecture, which consists of encoder-decoder architecture. For the audio-visual encoder, it contains two coupled encoders; an audio encoder and a visual encoder. In Tab. 1, CaffNet follows basic configuration of V-Conv [4]. Different from that, the affinity module is added for audio-visual fusion considering global and local correspondence between cross-modal streams. As demonstrated in Tab. 2, CaffNet-C leverages complex-valued convolutional layers (Conv) in audio encoder and mask decoder. For the simplicity, we denote \( \Pi(\mathcal{E}_f(I^{1:5}), \cdots, \mathcal{E}_f(I^{T-4:T})) \) as \( \mathcal{E}_f(I) \) in Tab. 1 and Tab. 2.

2. Implementation and Training Details

Visual Feature Extraction. Visual features for audio-visual speech separation represent implicit information corresponding to target speech, i.e. linguistic representation on lip movements, called viseme. We train the feature extractor using the strategy of audio-to-video synchronization in self-supervision. In [5, 6], they build two-stream networks to embed audio and visual sequences onto a latent space. In their strategies, when input audio and visual segments are taken from the same timestamps, the distance between audio-visual embeddings is minimized, whereas it is maximized for the segments from different offsets. As a result, the embedding learns linguistic information commonly existing on speech sound and lip movements. Especially, we adopt \( M \)-way matching method proposed in [6, 7] for the representation learning by providing multiple negative samples over a single positive input,

\[
E = \frac{1}{2N} \sum_{n=1}^{N} \sum_{m=1}^{M} y_{n,m} \log(p_{n,m})
\]

\[
p_{n,m} = \frac{\exp(d_{n,m}^{-1})}{\sum_{m=1}^{M} \exp(d_{n,m}^{-1})}
\]

where \( d_{n,m} = ||v_{n,m} - a_{n,m}||_2 \) is similarity distance between embedding pairs and \( y_{n,m} \in \{0, 1\} \) denotes simi-
Table 1: Network configuration of CaffNet. ‘K’, ‘S’ and ‘P’ represents the kernel, stride, and padding size of convolution layer, and ‘Ch. I/O’ represents channels of input and output relative to the input, respectively. ‘B.N’ is the batch normalization layer and ‘Act.’ is the activation function.

| Module       | Layer       | K. | Ch. I/O      | S. | P. | B.N. | Act. | Input | Output |
|--------------|-------------|----|--------------|----|----|------|------|-------|--------|
| Visual Encoder | V-Conv1D    | 5  | 512/1536     | 1  | 2 | ✔    | ReLU | v-feat1 | v-feat1 |
|              | V-Conv1D (x8) | 5  | 1536/1536    | 1  | 2 | ✔    | ReLU | v-feat1 | v-feat9 |
|              | V-Conv1D    | 5  | 1536/1536    | 1  | 2 | -    | -    | v-feat9 | V      |
| Audio Encoder | Decompose   | -  | 257/257      | -  | - | -    | -    | X      | X      |
|              | A-Conv1D    | 5  | 257/1536     | 1  | 2 | ✔    | ReLU | a-feat1 | a-feat1 |
|              | A-Conv1D (x3) | 5  | 1536/1536    | 1  | 2 | ✔    | ReLU | a-feat1 | a-feat4 |
|              | A-Conv1D    | 5  | 1536/1536    | 1  | 2 | -    | -    | a-feat4 | S      |
| Affinity Module | V-Nonlocal (x2) | 5  | 1536/1536    | 1  | 2 | ✔    | ReLU | V      | V      |
|              | A-Nonlocal (x2) | 5  | 1536/1536    | 1  | 2 | ✔    | ReLU | S      | S      |
|              | AV-Aff.     | -  | 1536/1536    | -  | - | -    | -    | S̅, V̅ | V̅     |
|              | Concat. (II)| -  | 1536/3072    | -  | - | -    | -    | S̅, V̅ | Ψ     |
| Mask Decoder  | Conv1D      | 5  | 3072/1536    | 1  | 2 | ✔    | ReLU | m-feat1 | m-feat1 |
|              | Conv1D (x13) | 5  | 1536/1536    | 1  | 2 | ✔    | LReLU | m-feat1 | m-feat14|
|              | Conv1D      | 5  | 1536/257     | 1  | 2 | ✔    | Sigmoid | m-feat14 | M    |
|              | Mult. (⊙)  | -  | -           | -  | - | -    | -    | |       |

Table 2: Network configuration of CaffNet-C. ‘K’, ‘S’ and ‘P’ represents the kernel, stride, and padding size of convolution layer, and ‘Ch. I/O’ represents channels of input and output relative to the input, respectively. ‘B.N’ is the batch normalization layer and ‘Act.’ is the activation function. ‘LReLU’ indicates LeakyReLU function with a slope 0.2. ‘Conv’ denotes complex-valued convolutional layer. At the last layer of mask decoder, we adopt tanh activation for the magnitude of the estimated mask.

| Module       | Layer       | K. | Ch. I/O      | S. | P. | B.N. | Act. | Input | Output |
|--------------|-------------|----|--------------|----|----|------|------|-------|--------|
| Visual Encoder | V-Conv1D    | 5  | 512/1536     | 1  | 2 | ✔    | ReLU | v-feat1 | v-feat1 |
|              | V-Conv1D (x8) | 5  | 1536/1536    | 1  | 2 | ✔    | ReLU | v-feat1 | v-feat9 |
|              | V-Conv1D    | 5  | 1536/1536    | 1  | 2 | -    | -    | v-feat9 | V      |
| Audio Encoder | Decompose   | -  | 257/257      | -  | - | -    | -    | X      | X      |
|              | A-Conv1D    | 5  | 257/1536     | 1  | 2 | ✔    | LReLU | a-feat1 | a-feat1 |
|              | A-Conv1D (x3) | 5  | 1536/1536    | 1  | 2 | ✔    | LReLU | a-feat1 | a-feat4 |
|              | A-Conv1D    | 5  | 1536/1536    | 1  | 2 | -    | -    | a-feat4 | S      |
|              | Decompose   | -  | -           | -  | - | -    | -    | -      | -      |
| Affinity Module | V-Nonlocal (x2) | 5  | 1536/1536    | 1  | 2 | ✔    | ReLU | V      | V      |
|              | A-Nonlocal (x2) | 5  | 1536/1536    | 1  | 2 | ✔    | ReLU | | S̅, V̅ | |       |
|              | AV-Aff.     | -  | 1536/1536    | -  | - | -    | -    | | S̅, V̅ | |       |
|              | Concat. (II)| -  | 1536/3072    | -  | - | -    | -    | | S̅, V̅ | | Ψ     |
|              | Reconstruct | -  | -           | -  | - | -    | -    | | S̅, V̅ | | e<sup>θ</sup> |
| Mask Decoder  | Conv1D      | 5  | 3072/1536    | 1  | 2 | ✔    | LReLU | m-feat1 | m-feat1 |
|              | Conv1D (x13) | 5  | 1536/1536    | 1  | 2 | ✔    | LReLU | m-feat1 | m-feat14|
|              | Conv1D      | 5  | 1536/257     | 1  | 2 | -    | Tanh | m-feat14 | M    |
|              | Mult. (⊙)  | -  | -           | -  | - | -    | -    | | X, M  | | Y     |
Training and Optimization  We use PyTorch library [8] and single RTX 24GB to train our networks. The network parameters are optimized using the mini-batch stochastic gradient descent (SGD) method. All networks are trained from scratch and we applied the Adam optimizer [9] with learning rate $1 \times 10^{-5}$, beta1 $\beta_1 = 0.9$, beta2 $\beta_2 = 0.999$ and batch size 32. We use PyTorch’s ReduceLROnPlateau learning rate scheduler with a reduction factor of 0.8 and a patience parameter of 2 to adapt the learning rate during training. At each training iteration, we randomly sampled one audio-video pair and another audio that has a different identity. We randomly take segments from each audio signal and add them to make mixture input. Hence, we use 64K training samples for each epoch and all networks are trained for a total of 50 epochs.

3. More Results

3.1. Quantitative Results

We provide more quantitative results for AVSS performance regarding SDR improvement (SDRi) metric concerning varying delay in Fig. 1 on LRS3 and VoxCeleb2 datasets. The results are obtained from CaffNet-C using predicted magnitude and phase. On the top of Fig. 1, we report the average SDRi of unseen 1000 speaker samples on LRS3 dataset. In this experiment, we train CaffNet-C using LRS2 dataset only, so the network cannot see any samples of LRS3 at the training stage. At the bottom of Fig. 1, we provide the average SDRi of unseen 1000 speaker samples on VoxCeleb2 dataset.

Figure 2: Qualitative evaluation of affinity matrices and spectrograms with respect to jitter effect on LRS2 dataset. The results are obtained from CaffNet-C.
3.2. Qualitative Results of Spectrograms

We provide more qualitative results of spectrograms. Fig. 2 shows the examples with and without jitter. Fig. 3 includes the spectrogram results of three different testing samples. In this experiment, we sample by immobilizing the audio stream at a certain time and moving the video segment according to the degree of delay. Although the video stream does not synchronize exactly with the audio stream, the results are similarly predicted. In Fig. 4, we compare the results with V-Conv [4]. These results validate that the CaffNet are flexible and interpretable for the delay, thus widely applicable on real-world videos. Fig. 5 demonstrates the results of spectrograms on VoxCeleb2 dataset. At the last column in Fig. 5, colored image means the target speaker and gray-scale image indicates the interfering speaker. The target speaker’s speech is isolated while the other’s interfering speech is suppressed.

3.3. Video

Our demo video\(^1\) includes the examples of videos on LRS2 dataset, and the examples from real-world news videos.

\(^1\)https://youtu.be/9R2qQ7dGTp8
Figure 5: Examples of speech separation results on VoxCeleb2 dataset. From left to right, each column notes mixed speech, target speech and separated output. These are randomly selected samples of CaffNet-C with full prediction of magnitude and phase components.
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