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# MFFCN: Multi-layer Feature Fusion Convolution Network for Audio-visual Speech Enhancement

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**Abstract**—The purpose of speech enhancement is to extract target speech signal from a mixture of sounds generated from several sources. Speech enhancement can potentially benefit from the visual information from the target speaker, such as lip movement and facial expressions, because the visual aspect of speech is essentially unaffected by acoustic environment. In order to fuse audio and visual information, an audio-visual fusion strategy is proposed, which goes beyond simple feature concatenation and learns to automatically align the two modalities, leading to more powerful representation which increase intelligibility in noisy conditions. The proposed model fuses audio-visual features layer by layer, and feed these audio-visual features to each corresponding decoding layer. Experiment results show relative improvement from 6% to 24% on test sets over the audio modality alone, depending on audio noise level. Moreover, there is a significant increase of PESQ from 1.21 to 2.06 in our -15dB SNR experiment.

**Index Terms**—speech enhancement, audio-visual, multi-layer feature fusion convolution network (MFFCN)

## I. INTRODUCTION

Speech enhancement aims at improving speech quality and intelligibility when audio is recorded in noisy environment. This step is important for applications involving voice commands, especially in far-field conditions where Automatic Speech Recognition (ASR) may be affected by noise and interference, such as radio, TV, or other speakers [1]. Speech enhancement has been the subject of extensive research [2]–[4] and has recently benefited from advancements in lip reading [5], [6], and speech reading [7], [8].

Advanced audio-only speech enhancement algorithms makes noisy signal more audible, but the deficient in restoring intelligibility is remained. Consequently, the multi-modal speech enhancement algorithms are demanded that simulate the audio-visual speech processing mechanism in human contexts, amplify the target speaker, or filter out acoustic clutter. The model for audio-visual speech enhancement algorithms is shown in Fig. 1.

Recently, a large amount of research has been shown that the fusion of visual and audio information is beneficial for various speech perception tasks, e.g., [9]–[11], but several studies substantiates the belief that the audio-visual speech enhancement still being less investigated than audio-only speech enhancement. The overview article by Rivet et al. [12] surveys audio-visual speech separation techniques, but

it is up to 2014 when deep learning was not adopted for the task. Although audio-visual speech enhancement has been recently addressed in the framework of deep neural networks (DNNs), several interesting architectures, and well-performing algorithms were developed, e.g., [13], [14], the majority of the existing systems have a common disadvantage that one modality (not necessarily the most reliable in a given scenario) tends to dominate the other, causing performance degradation.

To tackle the above problems, this paper proposes an audio-visual deep Convolution Neural Networks (CNNs) based speech enhancement model that integrates audio and visual cues into a unified network. Moreover, the proposed model adopts a novel fusion technique named multi-layer audio-visual fusion strategy, instead of concatenating audio and visual modalities only once in the whole network, the proposed model extracted audio and visual feature in every encoding layers and fuses the audio-visual information in each layer. When two modalities in each layer are concatenated, the system applies them as an additional input to feed the corresponding decoding layer.

The method is evaluated on an audio-visual speech enhancement task involving the two largest publicly available audio-visual datasets, TCD-TIMIT [15] and GRID corpus [16], which contain complex sentences of both read speech and in-the-wild recordings. Using both of these datasets offers repeat-ability and allows other researchers to compare their systems directly to ours. The training data videos are added with synthetic background noise taken from the noise dataset collected in our lab.<sup>1</sup>

The reminder of the paper is organised as follows. Section II reviews related work in the field of audio-visual speech enhancement. Section III introduces the framework and audio-visual fusion strategy of proposed model. Section IV illustrates the employed datasets and audio-visual feature extraction method. In Section V experimental results are presented, and a discussion is shown in Section VI.

## II. RELATED WORK

Related work in the areas of speech enhancement and audio-visual signal processing is briefly reviewed in this section.

<sup>1</sup>Speech samples are available at: <https://XinmengXu.github.io/MultilayerFFCN>

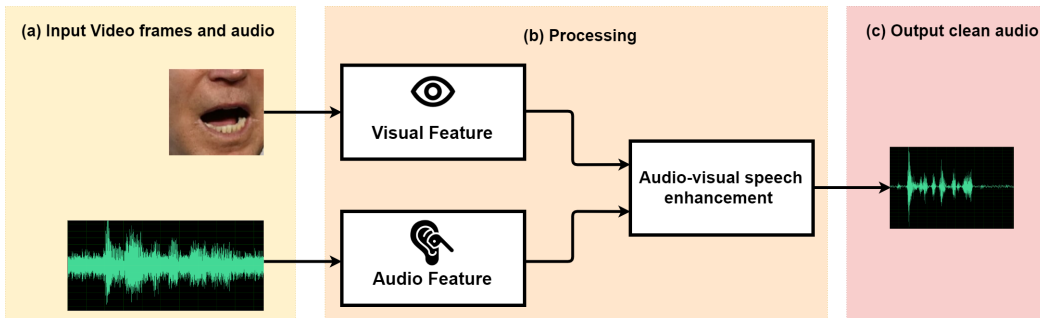


Fig. 1. The model for audio-visual speech enhancement. (a) The input is a video (frames and audio track) with the target speaker speaking, where the speech of interest is interfered by background noise. (b) Both audio and visual features are extracted and fed into the proposed audio-visual speech enhancement models. (c) The output is enhanced speech of target speaker.

### A. Audio-only based speech enhancement

Traditional single-channel-based speech enhancement methods were derived based on the characteristics and statistical assumptions of clean speech and noise signals. Classical methods use spectral subtraction [17], linear estimator, often referred to as the frequency domain Wiener filter [18], [19], and non-linear estimator [20], e.g., OM-LSA [2]. Another category of successful SE approaches is subspace-based methods [21], which aim to separate noisy speech into two subspaces, one for clean speech and the other for noise components.

Not surprisingly, speech enhancement has been recently addressed in the framework of DNNs [22]. Formulated as a supervised learning problem, noisy speech can be enhanced by neural networks either in the time-frequency domain or directly in time-domain where the discriminative patterns of speech, speakers, and background noise are learned from training data [23], [24].

In the past few decades, many speech enhancement approaches have been proposed and shown to provide better sound quality. However, despite their decent overall performance, deep learning based audio-only approaches are still not commonly accepted by industrial, because people always spend more resources to build a deep neural model but with only minor improvements when compared with traditional methods.

### B. Visually-derived speech processing

There is increased interest in using neural networks for the multi-modal fusion of audio and visual signals to solve various speech-related problems. These include audio-visual speech recognition [25], detecting and classifying sound events [26], voice activity detection [27], and unsupervised learning of language from visual and speech signals. The above methods leverage natural synchrony between simultaneously recorded visual and auditory signals.

### C. Audio-visual speech enhancement

Speech processing based on audio-visual multi-modal learning has been done on speech enhancement and separation [28]. Furthermore, a fully connected network, proposed by Hou et al. [13], was used to jointly process audio and visual inputs

to perform speech enhancement. Since the fully connected architecture cannot effectively process visual information, the audio-visual speech enhancement system in Hou’s approach is only slightly better than its audio-only speech enhancement counterpart. In addition, Gabbay et al. proposed a model [29] which feed the video frames into a trained speech generation network, and predict clean speech from noisy input, which has obtained a better performance when compared with the previous approaches.

The audio-visual multi-modal learning present significant performance mainly reflected in audio-visual features fusion approaches. These fusion approaches aims at one-time data fusion, which not only request a large multi-modal training dataset, but also cause the data feature wasting.

## III. MODEL ARCHITECTURE

In this section, the presented MFFCN architecture involves the encoder component, fusion component, and decoder component, and its architecture is shown in Fig. 2.

### A. Audio encoder

As previous approaches in several convolution neural network based audio encoding models [30]–[32], the audio encoder is thus designed as a convolution neural network using the spectrogram as input.

Each layer of an audio encoder block is followed by batch normalization, Leaky-ReLU for non-linearity, and strided convolutions for temporal sequence maintaining. The network layer structure of the audio encoder is described in Table I.

### B. Video encoder

The video encoder part is used to process the input face embedding. In our approach, the video feature vectors and audio feature vectors take concatenation access at every step in the encoding stage, and the size of visual feature vectors after convolution layer have to be the same as the corresponding audio feature vectors is shown in Fig. 2.

Consequently, the first encoding layer is used to regulate the size of video input equal to audio input, and the following video encoding blocks take the same structure with audio encoder, which has illustrated in Table I. Each layer in a video

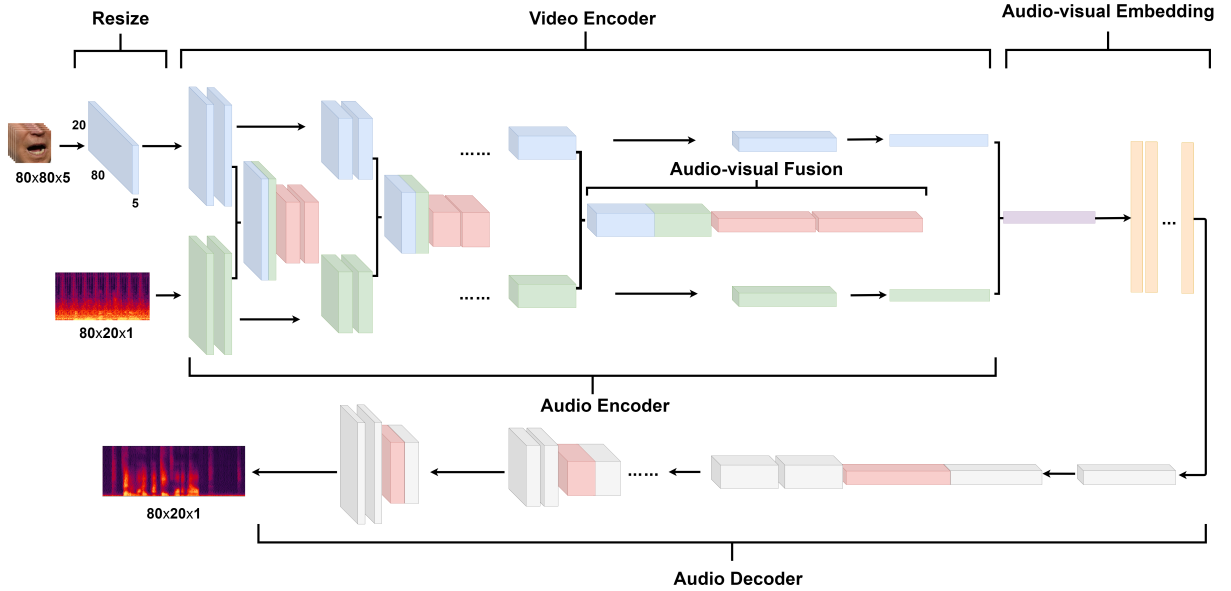


Fig. 2. Illustration of proposed MFFCN model architecture. A sequence of 5 video frames centered on the lip-region is resized by a convolution layer, and fed into video encoding convolution neural network blocks (blue). The corresponding spectrogram of the noisy speech is put into audio encoding convolution neural network blocks (green) in as same fashion as the video encoder. A single audio-visual embedding (purple) is obtained by concatenating the last video and audio encoding layers and is fed into several consecutive fully-connected layers (amber). Finally, a spectrogram of enhanced speech is decoded in audio decoding layers that are obtained by concatenating between audio-visual fusion vector (red), a fusion of audio (green) and visual (blue) modalities generated from encoding layers, and audio decoding vectors (gray), from the last audio decoder layer.

TABLE I  
DETAILED ARCHITECTURE OF THE ENCODERS.

	Conv1	Conv2	Conv3	Conv4	Conv5	Conv6	Conv7	Conv8	Conv9	Conv10
Num Filters	64	64	128	128	256	256	512	512	1024	1024
Filter Size	(5, 5)	(4, 4)	(4, 4)	(4, 4)	(2, 2)	(2, 2)	(2, 2)	(2, 2)	(2, 2)	(2, 2)
Stride(audio)	(2, 2)	(1, 1)	(2, 2)	(1, 1)	(2, 1)	(1, 1)	(2, 1)	(1, 1)	(1, 5)	(1, 1)
MaxPool(video)	(2, 2)	(1, 1)	(2, 2)	(1, 1)	(2, 1)	(1, 1)	(2, 1)	(1, 1)	(1, 5)	(1, 1)

encoder block is followed by batch normalization, Leaky-ReLU for non-linearity, max pooling, and dropout of 0.25.

### C. Audio-visual fusion

The proposed model includes two fusion strategies:

- i) audio-visual fusion which combines the audio and visual streams in each layer directly and feeds the combination into several convolution layers;
- ii) audio-visual embedding which flattens audio and visual streams from 3-D to 1-D, then concatenates both flattened streams together, and finally feed the concatenated feature vector into several fully-connected layers.

Audio-visual fusion process usually designates a consolidated dimension to implement fusion. The principle of concatenation process of audio-visual fusion is shown as

$$Z_{concat} = \{V_i, A_i\} \quad (1)$$

where  $V_i$  and  $A_i$  denotes visual and audio feature in layer  $i$ , in which  $i = 2, 4, 6, 8$  in proposed model. From Fig. 2, each special feature and  $Z_{concat}$  can be regarded as a fusion set

with all the features. For the following convolution layers, the relationship between input and output has been shown as

$$X_i = \text{Conv}_{av}3(\text{Conv}_{av}2(\text{Conv}_{av}1(Z_{concat}))) \quad (2)$$

Then the resulting vectors  $X_i$  are fed into the corresponding audio decoder layer.

Audio-visual embedding process, which requested to flatten feature vector from 3-dimensional to 1-dimensional, to pursue a highly feature fusion. In addition, the concatenation process of audio-visual embedding is shown as

$$Z_{embed} = \{\text{Flatten}(V_j), \text{Flatten}(A_j)\} \quad (3)$$

where  $j$  denotes the index of last encoder layer, and it thus equal to 10 in the proposed model. Then the concatenated feature maps, which named to shared embedding, are subsequently fed into a block of 3 consecutive fully connected layers. The resulting vector is then to build audio decoder.

### D. Audio decoder

The audio decoder consists of 6 transposed convolution layers, mirroring the layers of the audio encoder. Referring to

Fig. 2, each decoder layer input is the concatenation feature vector between the corresponding audio-visual fusion vector and the output from the last decoder layer.

Because of the downsampling blocks, the model can compute several higher-level features on coarser time scales, which are concatenated with the local, high-resolution features computed from the same level upsampling block. This concatenation results in multi-scale features for predictions.

#### IV. DATASET AND PREPROCESSING

This section describes the datasets and the input feature extractions for the audio-visual speech enhancement network.

##### A. Datasets

The model is trained on two datasets: the first is the TCD-TIMIT [15], which consists of 60 volunteer speakers with around 200 videos each, as well as three lip-speakers; the second is GRID audio-visual sentence corpus [16], which is a large dataset of audio and facial recordings of 1,000 sentences spoken by 34 people (18 male and 16 female). The noise dataset includes 12 types of noise recorded in real-world environments.

These videos are divided into a training set which contain 30 speakers (15 male and 15 female) and 900 videos per speakers; a development set which contains 30 speakers and 100 videos per speakers as the training set but not included in the training set; and a test set which contains two speakers that are not in the training set, each with 1,000 videos.

The noise signals are from the dataset which is categorized into 12 types: room, car, instrument, engine, train, human-chatting, air-brake, water, street, mic-noise, ring-bell, and music. For each type, part of noise signals (80%) are conducted into both training data and development data, but the rest are used to mix the test data. Moreover, all of the noise are treated as the *unknown* type and is randomly added to speech data.

##### B. Audio feature extraction

The audio representation is extracted from raw audio waveforms using Short Time Fourier Transform (STFT) with Hanning window function after resampling the audio signal to 16 kHz. Each frame contains a window of 40 milliseconds, which equals 640 samples per frame and corresponds to the duration of a single video frame, and the frame shift is 160 samples (10 milliseconds).

For each speech frame, a log Mel-scale spectrogram is extracted by multiplying the spectrogram via a Mel-scale filter bank. The resulting spectrogram have frequency resolution  $F=321$ , representing 80 Mel frequencies from 0 to 8 kHz. The whole spectrogram sliced into pieces of duration of 200 milliseconds corresponding to the length of 5 video frames, resulting in spectrograms of size  $80 \times 20$ , representing 20 temporal samples, and 80 frequency bins in each sample.

##### C. Video feature extraction

Visual feature is extracted from the input videos that is re-sampled to 25 frames per second. The video is divided into non-overlapping segments of 5 frames each. During the processing stage, each frame that has been cropped a mouth-centered window of size  $128 \times 128$  by using the 20 mouth landmarks from 68 facial landmarks suggested by Kazemi et al. [33]. Then the video segment is processed as input is the size of  $128 \times 128 \times 5$ .

As the mentioned in Part B, Sec. III, the size of video input has to be the same as audio input. By convenience, the processed video segment is zoomed to  $80 \times 80 \times 5$  by bilinear interpolation algorithm [34].

#### V. EXPERIMENT RESULTS

The proposed model is evaluated on several speech enhancement tasks using the dataset provided in Part A, Sec. IV. In all cases, background interference are set by the different types of acoustic environment from the noise dataset. The speech and noise signals are mixed with SNR from 10 dB to -10 dB both from the training and testing dataset.

The model performance is assessed by two objective scores: Short-term Objective Intelligibility (STOI) [35] and Perceptual Evaluation of Speech Quality (PESQ) [36] scores.

##### A. Comparison with audio-only

To examine the effectiveness of the proposed MFCCN model, subjective comparison test were conducted in terms of speech enhancement capability with an audio-only based approach, temporal convolutional neural network (TCNN) [37], which structure is similar with the proposed model. The comparison results is given in Table II.

In each sample, the target speech is mixed with natural interference, and speech interference respectively. Speech interference denotes the background speech produced by unknown talker(s), as the table provided that audio-only based model shows degraded performance on this speech noise, but our approach has a clear improvement with 30% increase of PESQ score if compared with audio-only model. Moreover, for the natural interference, which denotes the noise not produced by the human vocal cord system, the proposed model also outperforms the audio-only approach that the PESQ is improved by 24.2% at -5 dB SNR and 13% at 0 dB SNR.

##### B. Comparison with baseline

To further determine the significance of the results, the performance between the proposed MFCCN model and a baseline speech enhancement algorithm, which proposed by Gabbay et al. [14], is contrasted and the results are shown in Table II.

At the pair-wise comparison, the proposed model has no obvious advantage on 0dB, but a better value at -5 dB SNR, in which results show improvement of STOI score from 77.9% to 80.7% on speech interference set, and improvement of PESQ from 2.35 to up to 2.72 on natural interference set.

TABLE II  
 MODELS COMPARISON IN TERMS OF STOI AND PESQ SCORES, “SPEECH” INTERFERENCE DENOTES THE BACKGROUND SPEECH SIGNAL FROM UNKNOWN TALKER(S); “NATURAL” INTERFERENCE DENOTES THE AMBIENT NON-SPEECH NOISE.

Evaluation metrics	STOI (%)				PESQ			
	-5 dB		0 dB		-5 dB		0 dB	
Test SNR	Speech	Natural	Speech	Natural	Speech	Natural	Speech	Natural
Unprocessed	57.8	51.4	64.7	62.6	1.59	1.03	1.66	1.24
TCNN (Audio-only)	73.2	78.7	80.8	81.3	2.01	2.19	2.47	2.58
Gabbay et al. [2017]	77.9	81.3	<b>88.6</b>	87.9	2.41	2.35	2.77	<b>2.94</b>
MFFCN (proposed)	<b>80.7</b>	<b>82.7</b>	88.4	<b>89.3</b>	<b>2.61</b>	<b>2.72</b>	<b>2.84</b>	2.92

TABLE III  
 MODEL COMPARISON IN TERMS OF STOI AND PESQ SCORES BETWEEN RECENT AV MODEL AND THE PROPOSED MODEL AT -15 DB SNR ON “NATURAL” INTERFERENCE SET

Evaluation metrics	STOI (%)	PESQ
Unprocessed	43.12	0.83
Gabbay et al. [2017]	61.8	1.21
MFFCN (proposed)	<b>69.4</b>	<b>2.06</b>

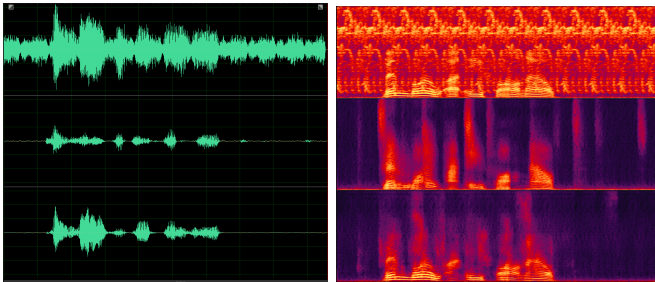


Fig. 3. The waveforms and spectrograms of an example speech utterance under the condition of nature noise at -15 dB. Top: Noisy speech; Middle: Enhancement speech using Gabbay’s approach; Bottom: Enhancement speech using the proposed model.

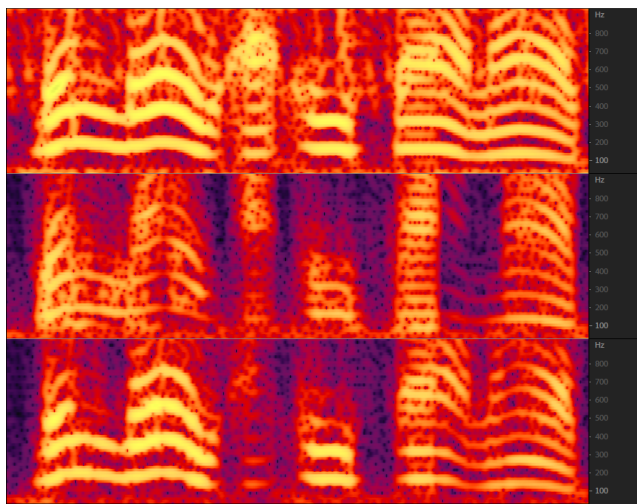


Fig. 4. The details of spectrograms of an example speech utterance under the condition of nature noise at -15 dB in low-frequency band. Top: Noisy speech; Middle: Enhancement speech using Gabbay’s approach; Bottom: Enhancement speech using the proposed model.

In order to verify robustness of the proposed model in stronger noise environment, enhancement capability test on noisy speech of -15 dB, between our approach and Gabbay’s approach, is presented. The test results are shown in Table III, and its waveforms and spectrograms are shown in Fig 3. Moreover, table III strengthens that the proposed approach produces better result than the baseline work on noisy speech at -15 dB SNR, especially the PESQ value is improved from 1.21 to 2.06. What is more, the observation from Fig. 3 supported that the results generated by MFFCN, keeps more speech elements in both time domain and frequency domain.

In addition, Fig. 4 illustrates more details that the proposed model exposes a robust performance on enhancing high noise speech signal, the visualization of spectrogram in low-frequency band (0-1KHz), generated by MFFCN, apparently kept more energy of speech signal.

## VI. DISCUSSION

A multi-layer features fusion based MFFCN model for audio-visual speech enhancement, separating the target speech of visible speaker from background noise, has been presented. A long temporal context is processed by repeated downsampling and convolution of feature maps to combine both high-level and low-level features at different layer steps.

The proposed model consistently improves the quality and intelligibility of noisy speech, and experiment results showed that MFFCN has better performance than recent audio-only based model and also demonstrated a obvious improvement on highly noisy speech enhancement.

The proposed model is compact and operates on short speech segments, and thus potentially suitable for real-time applications. Although the proposed method has shown a robust result on enhancing speech, the proposed method cannot work on enhancing the target speech in high frequency bands well, and also fails when the proposed model cannot capture the target speaker’s lip region clearly, since during training both audio and video are necessary elements.

The future work will be aiming to improve the sound quality of processed speech in high frequency band, and to keep more speech signal when reducing the noise.

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