SLNSpeech: solving extended speech separation problem by the help of sign language

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Abstract—A speech separation task can be roughly divided into audio-only separation and audio-visual separation. In order to make speech separation technology applied in the real scenario of the disabled, this paper presents an extended speech separation problem which refers in particular to sign language assisted speech separation. However, most existing datasets for speech separation are audios and videos which contain audio and/or visual modalities. To address the extended speech separation problem, we introduce a large-scale dataset named Sign Language News Speech (SLNSpeech) dataset in which three modalities of audio, visual, and sign language are coexisted. Then, we design a general deep learning network for the self-supervised learning of three modalities, particularly, using sign language embeddings together with audio or audio-visual information for better solving the speech separation task. Specifically, we use 3D residual convolutional network to extract sign language features and use pretrained VGGNet model to exact visual features. After that, an improved U-Net with skip connections in feature extraction stage is applied for learning the embeddings among the mixed spectrogram transformed from source audios, the sign language features and visual features. Experiments results show that, besides visual modality, sign language modality can also be used alone to supervise speech separation task. Moreover, we also show the effectiveness of sign language assisted speech separation when the visual modality is disturbed. Source code will be released in http://cheertt.top/homepage/

Index Terms— Self-supervised learning, cross-model embeddings, sign language, speech separation
I. Introduction

1.1 The introduction of speech separation

The speech separation problem or cocktail party problem [1] refers to the separation of different categories of sounds from a signal containing multiple voices and noises in order to focus on a specific speech in a noisy environment. Fig. 1 (a) shows a simple example of a classic speech separation process of two speakers. The speech separation task is widely existed in speech recognition [2], speech enhancement [3], speech dereverberation [4], etc. In speech recognition and speech enhancement systems, multi-speaker speech separation [5]-[7] is considered to be the most challenging task because of the high correlation of the time-frequency structure between target and noisy speech, which means the acoustic features of target speech are easily confused with those of noisy speech. Another reason for increasing this challenge is that the high non-stationarity of multi-speaker speech, which leads to variations in noise estimation and complexity of predicted target speech. This task becomes more challenging when there is only one channel for the mixed voice, because the audio signal lacks information about the source location of voice. Therefore, this paper focuses on the multi-speaker monoaural speech separation, in which the interference source is other voice and noise.

1.2 Related work

Researchers have done plentiful researches in speech separation, mainly including two aspects which are speech separation datasets and algorithms.

1.2.1 Speech separation datasets

There are various datasets can be applied to speech separation, e.g., speech recognition [8]-[13], lip recognition [14]-[16], many datasets of computer vision [17]-[19] which include
faces and clean audios corresponding to visuals. The common practice is to mix these audios with noises or the other clean speeches. Garofolo et al. [8] proposed the TIMIT dataset which consists of 630 speakers of eight major American English dialects. Patterson et al. [9] published a speaker-independent corpus CUAVE of 36 speakers saying each digit in connected and isolated manner. The WSJ0 database proposed by Vincent et al. [10] was generated from Wall Street Journal news text. The above corpora only contain audio and text modalities. In recent years, audio-visual representation learning has been popular, Cooke et al. [11] proposed GRID which is an audio-visual dataset contains 34 speakers and each speaker says 1000 sentences. The TCD-TIMIT constructed by Harte and Gillen [12] contains 60 volunteer speakers and are collected using both front-facing and 30-degree cameras. LRS [14]-[16] and VoxCeleb [17] were recorded by the visual geometry group which contains both high-quality faces and clean audios. Ephrat et al. [18] constructed a large-scale audio-visual dataset named AVSpeech which contains thousands of hours of videos spoken by various people, languages and face poses. Roth et al. [19] put forward AVA-ActiveSpeaker which contains about 40K distinct speakers and about 38.5 hours of face tracks. Different from the previous datasets, we carefully collect a large-scale dataset named Sign Language News Speech (SLNSpeech) dataset in which three modalities of audio, visual, and sign language are coexisted. Table I summarizes some publicly relevant speech separation datasets and our proposed SLNSpeech dataset.

1.2.2 Speech separation algorithms

Table II list some existing algorithms that can be applied to speech separation. As we can see from this table, the speech separation algorithm can generally be categorized into two kinds: audio-only speech separation algorithm [20]-[33] and audio-visual speech separation algorithm
The term of audio-only speech separation algorithm means that we only separate the mixed speech according to the differences in audio characteristics. Speech separation is traditionally considered as a signal processing problem. The classical methods such as Spectral Subtraction [20], Computational Auditory Scene Analysis (CASA) [21], Nonnegative Matrix Factorization (NMF) [22]-[24] have been proved to achieve excellent results. These methods assume that the speech follows a certain distribution, however, it is difficult for speech in real environment to satisfy these assumptions because of the changeful noises. More recently, several deep learning methods [25]-[28] have been proposed. Wang et al. treated speech separation as a binary classification problem [25] and separated the mixture of the same genders by using deep neural network (DNN) approaches [26]. Chandna et al. [27] used convolutional neural network (CNN) to predict time-frequency masking for speech separation and Fu et al. [28] proposed a fully convolutional network (FCN) model for raw waveform-based speech enhancement. Wang et al. [29] gave a comprehensive overview of these methods. A difficulty in training by using the DNN model is that we cannot relate separated audios to their corresponding speakers. This is a label permutation problem proposed by Hershey et al. [30] and they proposed a deep clustering method to solve it. Moreover, Yu et al. [31] proposed permutation invariant training for speaker independent multi-speaker speech separation. Kolbæk et al. [32] used recurrent neural networks (RNN) to solve permutation problem and Luo et al. [33] proposed a fully-convolutional time-domain audio separation architecture. However, the audio-only speech separation models face difficulties in separating similar sounds which represents the voice of the same gender or the same person at different times [34].
The term of audio-visual speech separation algorithm means that we separate the mixed audios according to speech features together with visual embeddings which is correspond to the audios. Several recent tasks try to use deep learning to learn the audio-visual information to handle similar sounds based on self-supervised learning [35]-[38], such as, Owens et al. [38] utilized visual to supervise and separate the speech, and achieved a good performance in the speech separation. Gao et al. [39] tried to separate and locate the sound of the vocal object in the video. Zhao et al. [40] and Gao et al. [41] supervised the separation of musical instruments according to the visual representations. Afouras et al. [42] consider speech separation in the absence of visual modality which is similar to a part of our work, but we use the weak supervision of sign language when the visual is disturbed instead of the reference audio.

1.3 The importance of sign language

The protection of vulnerable groups has always been a common concern of all countries in the world. At present, there are about 650 million disabled in the world, accounting for about 10% of the world's population. Among them, there are about 35.7 million disabled persons in China according to the "Main Data of the National Basic Database for the Disabled in China" published by the China Disabled Persons' Federation [43]. Table III lists the statistics of the National basic information Database of Persons with disabilities [43]. From Table III, we can see that: (i) From the perspective of education level, there are about 87.84% of the total disabled population obtain the junior high school education and below; (ii) From the perspective of disability categories, there are about 11.52%, 8.09%, 1.75% disabled persons are persons with visual disability, persons with hearing disability, and persons with speech disability, respectively. The disabled are enormous and generally unable to receive a higher level of
education, so they need the protection of society and the efforts of researchers to ensure the normal learning, work and life.

Audio is a very important information for persons with visual disability, and visual is very important for persons with hearing disability and persons with speech disability. However, sign language is one of the most important ways to communicate with each other for persons with hearing disability and persons with speech disability. Audio, visual and sign language are used by millions of people with visual, hearing and voice impairment, respectively. Therefore, in the real life of people with disabilities, more and more scenes appear three modalities (audio, visual and sign language) or two modalities (audio and visual, audio and sign language), some of which are shown in Fig. 2. Fig. 2 (a) shows some coexisting scenes of three modalities, including the gloves for sign language translation of the deaf-mute, free clinics for the deaf-mute by doctors and court conferences for the deaf-mute and common people, etc. However, audio, visual, and sign language do not always appear at the same time in real life scenarios such as the intermittent visual occlusion in entertainment and the cover of microphone or breathing mask to human face which can be seen in Fig. 2 (b). The virtual signer, only the voice of speaker (or announcer) and the sign language of signer were collected which can be seen in Fig. 2 (c).

Koller et al. [44], [45] proposed the RWTH-PHOENIX-Weather-2014 dataset which provides RGB videos for full frames and cropped hand gestures in German Sign Language. It is a popular benchmark dataset for continuous sign language recognition and many researches [46]-[48] are carried out on this dataset. Camgoz et al. [46] proposed a novel deep learning architecture containing convolutional neural networks (CNNs), bidirectional long short term
memory layers (BLSTM), connectionist temporal classification (CTC) loss layer. Huang et al. [47] proposed a new two-stream 3D CNN for the generation of global local video feature representations and a new framework for continuous sign language recognition without requiring temporal segmentation. Pu et al. [48] used a 3D residual convolutional network to extract visual features and used a dilated convolutional network with iterative optimization for continuous sign language recognition. Li et al. [49] introduced a new large-scale Word-Level American Sign Language (WLASSL) video dataset, containing more than 2000 words performed by over 100 signers. Different from the above aforementioned sign language recognition task, in this paper, we only obtain the feature representation of sign language and do not need to know the specific meaning of sign language, just like we do not need to know the specific content of speech in speech separation.

1.4 What do we do?

Generally, sign language has been widely used and is the most effective way of communication for the deaf-mute. It conveys semantic information through posture, hand movement and facial expression. In this paper, sign language is introduced to supervise the problem of speech separation, which is a new problem and we call it extended speech separation problem or extended cocktail party problem shown in Fig. 1 (c). Why we refer the sign language assisted speech separation problem as the extended speech separation problem? As we can see from audio-visual speech separation problem shown in Fig. 1 (b), the audio and visual are from the same speaker, this means visual can be used as a "strongly” self-supervised information for speech separation. However, as we can see from extended speech separation problem shown in Fig. 1 (c), the audio and visual are from the same speaker while the sign language is from the
other signer, which is generally different from the speaker. Although there are two hosts (speaker and signer) right now, the extended speech separation problem can still be considered as self-supervised learning since the two hosts want to express the same news content. It also should be noted that compared with the “strongly” self-supervised information as visual, sign language is a “weakly” self-supervised information for speech separation problem. Besides, the extended speech separation problem has two tasks: audio-sign speech separation and audio-visual-sign speech separation, where sign denotes sign language. Then, two question raised.

The first question is: Can we use the weakly self-supervised sign language replace strongly self-supervised visual in speech separation? Furthermore, our intuition is that the more information we used for supervision, the better the result of speech separation seems to be. Then, a second question raised: Does the weakly self-supervised sign language always increase the performance in the extended speech separation problem? That is, the performance of audio-sign is always better than audio-only speech separation? The performance of audio-visual-sign is always better than audio-visual speech separation?

In an attempt to solve the aforementioned two questions, in this paper, we propose an effective and innovative self-supervised learning framework for solving the extended speech separation problem. The contributions of the paper are as follows:

(a) A new multi-modalities dataset named Sign Language News Speech (SLNSpeech) was carefully collected and constructed. SLNSpeech contains three modalities: audio, visual, and sign language, and each modality corresponds to each other in time sequence. To the best of the authors’ knowledge, SLNSpeech dataset is the first dataset that coexists three modalities of audio, visual, and sign language, and can be used to explore the characteristics of
these three modalities by using self-supervised learning methods. The SLNSpeech is different from the RWTH-PHOENIX-Weather-2014 [44], [45] and WLASL dataset [49] for more modalities, the scene contains audio, visual and sign language is very few and it is difficult to collect the dataset like SLNSpeech.

(b) Based on SLNSpeech dataset, we also give a benchmark for extended speech separation, which deals with the audio, visual, and sign language by ResUNet (an improved UNet [55]), VGGNet [57] and 3DResNet [59], respectively. The separation of mixed audios uses not only the audio source but also the sign language embeddings and/or the visual embeddings.

(c) We explore the influence of sign language modality in speech separation for the first time and discuss when the sign language could work and when it could not perform very well though this seems to be contrary to our intuition to a certain degree.

The rest of the paper is organized as follows. In Section 2, we construct a new dataset named SLNSpeech dataset which contains audio, visual and sign language. In Section 3, we present our model that leverages sign language and visual information as a supervisory signal, and the visual and sign language can promote speech separation. In Section 4, we present several experiments to analyze our model and provide the benchmark of SLNSpeech. The conclusions are formulated in Section 5.

II. SLNSpeech dataset

In order to explore the role of sign language in extended speech separation problem and answer the aforementioned two questions, in this section, we constructed a new large-scale dataset named SLNSpeech, which is a multi-modalities dataset, including three modalities of audio, visual and sign language. To the best of our knowledge, SLNSpeech is the first dataset
that introduces the sign language modality to the speech separation problem. Why the researches do not introduce the sign language to the speech separation problem before? We think there are at least two reasons: (i) in the traditional speech separation problem, we rarely encounter the coexistence of two modalities of audio and sign language, that is, we only collect the audio and the visual of the same speaker (which can be seen in Fig. 2 (b)), who is difficult to express the sign language at the same time; (ii) Sign language is used for persons with hearing disability and persons with speech disability. Therefore, sign language seems to conflict with audio to some extent. It is precisely because of the fact that it is easier and easier to obtain the modality of sign language and the extended speech separation problem that sign language coexists with other modalities (audio, visual, etc.) makes the creation of the dataset with three modalities of audio, visual, and sign language very important.

We will then introduce SLNSpeech from the following two aspects: the overall process of constructing SLNSpeech and the statistics of our constructed dataset.

2.1 The overall process of constructing SLNSpeech

Compared to other modalities like audio and visual, sign language is much more difficult to collect. Chinese Sign Language News is one of the most accessible resources for sign language. Therefore, we construct SLNSpeech by using Chinese Sign Language News and we select the news that contains sign language modality from six TV programs in mainland China which are shown in Table IV. As can be seen from the Table IV, we crop and obtain about 10 hours TV videos that contains three modalities (audio, visual, sign language) from about 519 hours videos of six TV programs. It is not easy to obtain data of three modalities of audio, visual, and sign language at the same time since the face of speaker (or announcer) does not
always appear in the original video, we need annotate the start and the end of faces of speaker.

Fig. 3 shows the example pictures of six TV programs. As we can see from Fig. 3, audio, visual and sign language can be acquired at the same time, where the yellow boxes indicate the visual of speaker and the red boxes represent the sign language of signer.

In order to save a large number of labor cost and potential problems caused by wrong annotation, we developed an automatic video clipping toolbox to collect pure audio, visual and sign language modalities and constructed the SLNSpeech dataset automatically. The overall process of constructing SLNSpeech is shown in Fig. 4. The input of the developed video clipping toolbox is shown in the left of Fig. 4, which is about 519-hour source videos from six TV programs that may contain three modalities (audio, visual, and sign language) shown in Fig. 3 or two modalities (audio and sign language) shown in Fig. 2 (c). The output is the separated three modalities of audio, visual and sign language which are shown in the right of Fig. 4.

The developed automatic video clipping toolbox is shown in the middle of Fig. 4, which mainly includes two parts:

(i) The construction of user-defined face feature database

This part will build a user-defined face feature database. Firstly, we selected 2500 video frames containing the face of the 25 announcers manually, each of whom had 100 discontinuous frames. Then, we use multi-task convolutional neural networks (MTCNN) [50] for face detection to locate the face region in the frames carefully picked. Finally, we will use a pre-trained FaceNet [51] to compute every face feature and combine them into the user-defined face feature database. The function of the face feature database is to judge whether the cut video clip completely contains the clean data of the face of announcer, which is the cornerstone of
our toolbox.

(ii) Automatic cutting of multi-modality data

This part allows our toolbox automatically clip sign language news videos which contain audio, visual and sign language. The first step we cut the 519-hour source videos to many clips according to the Perceptual Hash Algorithm [52] which can identify adjacent video frames with large pixel changes. Then, we pick the cutting clips that meet our requirements which is the face of speaker (or announcer) can appear throughout the cutting clips since the most of cutting clips acquired from the first step are useless. Different from [53], we just detect the first and the last frames of the cutting clips instead of all the frames since the sign language news videos are regular, that is the faces of speaker is opposite the screen and the angle of the faces does not rotate too much. For the first and last two frames of the cutting clips, we use MTCNN to detect the face and use a pre-trained FaceNet to compute the face feature and compare with the face feature database when the face is detected. If the faces are in the face database and the faces in the first and last frames are of the same person, we will save this cutting clip. Finally, the output is the combination of audio information which the loudness of the sound compressed to the same level, visual and sign language, where the visual and the sign language are cut by OpenCV.

2.2 The statistics of SLNSpeech dataset

The detailed statistical results of SLNSpeech dataset are shown in Fig. 5. The video clips of every TV program in Fig. 5 is a pie chart, which represents the proportion of the number of segments per TV program and you can also see it in Table IV. The majority of videos come from “Focus ON”, since the programs is well organized, we could get the source videos conveniently. The video clips of every duration in Fig. 5 is a histogram, which means the
number of video clips of every duration, the horizontal axis represents the interval of segments in seconds, and the vertical axis represents the number of segments. The majority of duration of video clips is between 10 seconds and 30 seconds. In this process, every clip contains 4 or 5 sentences, when we random mix two clips, the audio is really noisy. The video clips of every speaker (or announcer) in Fig. 5 is a bar graph, which represents the number of clips of every speaker, where the yellow bar is male hosts and the green bar is female hosts. We can find that there are much more female segments than those of male.

In total, SLNSpeech dataset contains 25 distinct speakers and roughly 10 hours of video segments, the language is mandarin Chinese, the number of video clips of each speaker is between 42 and 200. Table I compares SLNSpeech with other speech separation datasets. We will then process the data of the constructed SLNSpeech dataset in the next section.

### III. Method

This section describes the architecture of the proposed audio-visual-sign speech separation network, which is given in Fig. 6. The network receives three inputs, which are the mixed audio, the visual frames and the sign language frames correspond to the audio. Note that when the visual frames or sign language frames are missing, our network can also separate the mixed audio. We will then make a detailed introduction of three components of the proposed speech separation network: the speech separation module, the visual embedding module and the sign language embedding module.

#### 3.1 The speech separation module

As acoustic features, the Short Time Fourier Transform (STFT) with a 25ms window length and a 10ms hop length at a sample rate of 16Khz is used to obtain the magnitude and
phase spectrograms, whose sizes are $W \times H$. We send the magnitude spectrograms to an improved U-Net network which we call ResUNet to learn the audio representation. ResUNet is a combination of ResNet [54] and U-Net [55]. U-Net has the same input and output size, and there is a jump connection between the lower sampling layer and the upper sampling layer, can achieve prefect results in speech separation task [56]. We use the convolution structure with skip connections in the subsampling layer of U-Net and remove the last deconvolution layer of U-Net, because the magnitude spectrograms of distinct speakers are very different in the input of mixed magnitude spectrograms, and the shallow layer can easier to capture the differences of magnitude spectrograms of distinct speakers than deep layer, therefore, we use the skip connections to achieve the purpose of feature reuse and thereby assisting the feature extraction of deep layer. The output of ResUNet is a spectrogram mask of size $K \times W \times H$, which represents $K$ channels of $W \times H$ feature map. Then, we obtain the $1 \times 1 \times K$ output of visual embedding module from Section 3.2 and obtain the $1 \times 1 \times K$ output of sign language embedding module from Section 3.3. The two $1 \times 1 \times K$ outputs are then added to get a new $1 \times 1 \times K$ output, which is then combined with the $K \times W \times H$ spectrogram mask to obtain the $N \times W \times H$ spectrogram mask which describes the time-frequency relationships of clean speech and background interference, where $N$ represents the number of predicted audio that input the speech separation module, or the number of speakers that input the visual embedding module, or the number of signers that input the sign language embedding module. To get the final separated audio, we apply the inverse STFT to the predicted spectrogram and use the phase of the noisy input which can be easily acquired from audio preprocessing.

3.2 The visual embedding module
This module receives the pre-processed visual frames and the interval between each frame is greater than 1s. We use VGGNet [57] pretrained on VGGFace [58] to extract the visual embedding whose size is $1 \times 1 \times 512$, which is then reduced to the size of $1 \times 1 \times K$ by temporal max pooling, where $K$ represents the number of channels and is set to 32 in the paper.

3.3 The sign language embedding module

The input of the sign language embedding module is three continuous sign language frames, where the interval between each frame is greater than 1s. We use 3DResNet [59] which is proved to be able to learn spatiotemporal features to extract hand motion features. The architecture of 3DResNet can be seen as a three-dimensional extended version of ResNet18, the main differences are that 3DResNet uses 3D convolutional filters, 3D batch normalization, 3D max pooling, 3D average pooling instead of 2D convolutional filters, 2D batch normalization, 2D max pooling, 2D average pooling in ResNet18, respectively. The detailed architecture of 3DResNet can be seen in Fig. 7. For every input it will go through a 3D convolutional filter and a 3D max pooling layer first. Then, it will go through many block1 and block2 which are shown in the right of Fig. 7, the difference between block1 and block2 is that there is a downsampling process in block2 which is used for realizing translation invariance and reducing the parameters of network. Finally, we use average pooling layer before fully connected layers. This module outputs sign language embeddings of size $1 \times 1 \times K$, where $K$ represents the number of channels and is set to 32 in the paper.

Right now, we have two supervisors for speech separation, we can choose the single visual modality or the single sign language modality as the supervisor, or we can choose the fusion of visual and sign language modalities as the supervisor. Then, how to fuse the visual embedding
of size $1 \times 1 \times K$ and the sign language embedding of size $1 \times 1 \times K$? We try to fuse them by multiplication, concatenation and addition, the experimental results show that the addition of the visual embedding and the sign language embedding outperform other two fusion methods. Therefore, we use the addition as the fusion method between the visual embedding and the sign language embedding. Moreover, it should be noted that the proposed audio-visual-sign speech separation network could handle three modalities at the same time, and it can still work well when the visual modality or the sign language modality is missed. From this point of view, both the audio-only speech separation network and audio-visual speech separation network are the special cases of the proposed audio-visual-sign speech separation network.

**IV. Experiments and results**

4.1 Datasets

We use the SLNSpeech dataset which is proposed in Section II to conduct detailed experiments of training and validation. We extracted 3 second or so audio segments from each speaker and combined distinct speakers’ segments randomly. Finally, we generated 13200 audio synthetic mixtures (4400 male-male pairs, 4400 female-female pairs, 4400 male-female pairs) for our model. For each experiment, the resulting dataset was split into disjoint sets of 12000 synthetic audio mixtures for training and 1200 synthetic audio mixtures for validation.

4.2 Evaluation metrics

In order to test and verify the effectiveness of the proposed model, we take machine as the target receptor and human ear as the target receptor respectively to evaluate the speech separation performance of our model.

4.2.1 Taking machine as the target receptor
In the case of machine as the target receptor, the accuracy of noisy speech recognition is mainly analyzed. There are three performance indicators for speech separation which are Source to Distortion Ratio (SDR), Source to Interactions Ratio (SIR) and Sources to Artifacts Ratio (SAR) according to the blind source separation criteria described in [60] and [61]. These three metrics are the most commonly used ones for blind source separation which has a good correlation with human perception system. The core ideology of blind source separation evaluation is to decompose the predicted $\hat{y}(t)$ into three parts as follows

$$\hat{y}(t) = s_{target}(t) + s_{interf}(t) + s_{artif}(t)$$

$$SDR = 10 \log_{10} \left( \frac{||s_{target}||^2}{||s_{interf} + s_{artif}||^2} \right)$$

$$SIR = 10 \log_{10} \left( \frac{||s_{target}||^2}{||s_{interf}||^2} \right)$$

$$SAR = 10 \log_{10} \left( \frac{||s_{target} + s_{interf}||^2}{||s_{artif}||^2} \right)$$

where $s_{target}(t)$ and $s_{interf}(t)$ are the target speech and interference speech in the predicted audios, respectively. $s_{artif}(t)$ represents the noise introduced by the audio-visual-sign speech separation network. According to (1), the specific definitions of blind source separation evaluation are from (2) to (4). SIR reflects how well the unwanted signals have been suppressed, SAR measures how well the noise signals have been suppressed and SDR is the overall separation quality. The values of SDR, SIR and SAR are about the same size and the larger of them, the better the separation quality. These three metrics are the most commonly ones used for blind source separation which has a good correlation with human perception system.

4.2.2 Taking human ear as the target receptor

In the case of human ear as the target receptor, the main goal is to improve the intelligibility
and perception quality of human ear to noisy speech, among which Perceptual Evaluation of Speech Quality (PESQ) [62] and Short Time Objective Intelligibility (STOI) [63] are the representatives. PESQ is quantified by the difference between ideal speech model and real speech signal by Mean Opinion Score (MOS) which can represent the result of subjective test partly and the range of PESQ is -0.5-4.5. STOI evaluates the intelligibility of the separated speech and the range of STOI is 0-1. The larger the score of PESQ and STOI, the better the quality of the separated speech.

4.3 Implementation details

The following experiment was implemented using PyTorch1.2 on a PC machine, which sets up Ubuntu 16.04 operating system and has an Intel(R) Core(TM) i7-2600 CPU with speed of 3.40 GHz and 64 GB RAM, and has also 4 NVIDIA GeForce GTX1080-Ti GPUs.

For the sign language embedding module and the visual embedding module, the input of the sign language frames and the visual frames are the size of $3 \times 3 \times 140 \times 140$ and $3 \times 3 \times 224 \times 224$, respectively, where the first 3 denotes three frames and the second 3 denotes three channels. The output of the sign language embedding module and the visual embedding module are all with size of $1 \times 1 \times K$, where $K$ is set to 32 in the experiment.

For the speech separation module, we resampled all audio to 16kHz, and the size of input spectrogram is $1 \times 512 \times 320$. Then, the spectrogram is fed into a ResUNet with 6 convolution layers and 6 deconvolution layers. The ResUNet outputs a binary mask after sigmoid activation and the size of the binary mask is $32 \times 512 \times 320$. To obtain the final separated audio waveforms, we combine the binary mask with the addition of sign language embedding and visual embedding by the PyTorch interface of torch.bmm() and the size of output is $1 \times 512 \times 320$ for
each input of mixed audio stream. Therefore, for $N$ inputs of mixed audio stream, the output size of the proposed audio-visual-sign speech separation network is $N \times 512 \times 320$.

In the optimization process, we use SGD optimizer with momentum 0.9 and weight decay $1e^{-4}$ to train our model and the learning rate is $1e^{-2}$. The loss function of binary cross entropy which is used for predicting ideal binary mask of audio spectrogram and the batch size of our experiment is 24.

4.4 Results and analysis

We summarize the results of our experiments in Table V. The second row and the third row represent the results of grand-truth (GT) and the mixture (Mix) before speech separation, respectively. It is really challenging to separate the speech since the SDR, SIR, SAR, PESQ and STOI of the mixture are significantly decreased when compared to that of grand-truth. The initial SDR and SIR is very small, but the SAR is very big. Because of the mixed audio is very noisy, the $s_{interf}(t)$ of initial mixed speech is very large and the initial SAR is very large while the SDR and SIR is very small. This can be seen from Section 4.2.1.

The speech separation result of audio-only network is used as the comparison benchmark which is shown in the fourth row in Table V. Audio-only network means that we only use the audio as the input of the speech separation module which is shown in the top of Fig. 6. Note that the audio-only network is similar to [56] which uses U-Net to separate only one speech and view the other speeches as noises. The speech separation result of audio-sign network is shown in the fifth row in Table V. As shown in Fig. 6, audio-sign network means that we use audio and sign language as the input of the speech separation module and sign language embedding module, respectively. From the fourth row and the fifth row in Table V, we can see that the
audio-sign network is much better than audio-only network, specifically, SDR, SIR, SAR, PESQ, STOI are relatively increased by 33.01%, 22.97%, 20.63%, 14.43%, and 4.88%, respectively. Note that the increase of STOI is relatively small because it is ranged from 0 to 1 and is very high before separation. Therefore, we can conclude that the weakly self-supervised sign language can be used as the supervisor for speech separation when the strongly self-supervised visual supervisor is missed. We think that during model learning, the movement information of the hand provided by sign language modality is proved to be crucial for that ensure the key alignments of the speakers’ voice, which has a supervised influence on the speech separation.

Then, we take two modalities of audio and visual into consideration. The speech separation result of audio-visual network is shown in the seventh row in Table V. As shown in Fig. 6, audio-visual network means that we use audio and visual as the input of the speech separation module and visual embedding module, respectively. Note that the audio-visual network is similar to [40] which uses U-Net to extract audio features and uses pretrained ImageNet to extract visual features and combine them in the last. From the fourth row and the seventh row in Table V, we can see that the audio-visual network is much better than audio-only network, specifically, SDR, SIR, SAR, PESQ, STOI are relatively increased by 42.02%, 30.85%, 23.03%, 18.87%, and 8.24%, respectively. Compared the fourth row and the seventh row in Table V, we can see that the speech separation results of audio-sign network is slightly worse than that of audio-visual network, it is not surprising because the sign language is a weakly self-supervised modality while visual is a strongly self-supervised modality for speech separation. These results just validate the correctness and rationality of the proposed speech separation network, because
the network has learned the relatively strong correlations between audio and visual, and also
the relatively weak correlations between audio and sign language.

Then, we take three modalities of audio, visual and sign language into consideration. The
speech separation result of audio-visual-sign network is shown in the ninth row in Table V. As
shown in Fig. 6, audio-visual-sign network means that we use audio, visual and sign language
as the input of the speech separation module, visual embedding module, and sign language
embedding module, respectively. From the fifth row and the ninth row, we can see that if we
add the strongly self-supervised visual modality to the audio-sign network, the performance of
speech separation can be significantly improved. That is, the increased strongly self-supervised
visual information always plays a positive role in promoting the performance. However, from
the seventh row and the ninth row, we can see that if we add the weakly self-supervised sign
language modality to the audio-visual network, the performance of speech separation is slight
decreased though the drop is not obvious. This phenomenon is strange and contrary to our
intuition that better speech separation results may be achieved by fusing more modalities, since
the increased weakly self-supervised sign language information actually plays a negative role
in promoting the performance in this case. These results show that the two supervisors of visual
modality and sign language modality for speech separation are somewhat contradictory in some
small places. In order to further verify that this decline is not caused by the fusion method, we
have also done a lot of experiments for verification, and the verification results can be seen in
Table VI and Table VII.

Since the performance of audio-visual-sign network is slightly worse than audio-visual
network, the sign language is useless in the audio-visual speech separation system? With the
introduction and popularity of deep fakes [64] and other related technologies, the visual modality is easy attacked. Can the sign language help to relieve performance degradation of the fake face attacked audio-visual speech separation system whose visual module fails to provide normal service? That is, Can the weakly self-supervised sign language information rectify the incorrect strongly self-supervised visual information to a certain degree? In order to answer this question, we design two sets of experiments of fake face in which the visual modality is disturbed while the sign language modality is normal:

(i) The first set of experiment is assuming the fake face appeared in the training process of the network. The results of audio-visual network and audio-visual-sign network are shown in the eighth row and the tenth row, respectively. The weakly self-supervised sign language information seems still playing negative role in speech separation. From the seven row and the eighth row, and from the ninth row and tenth row, we can see that both audio-visual network and audio-visual-sign network show good robustness on the fake face appeared in the training process since their performances only drop a bit.

(ii) The second set of experiment is assuming the fake face appeared in the testing process of the network. This kind of scene is more common in real life. We control the ratio of visual interference in 50% that there are half of visual data is clean. The result of audio-visual network of 50% fake face appeared in the testing process and no fake face appeared in the testing process is shown in the 12th row. As we can see that the performance decreases sharply. This case is the most common scene in real life since you may do not know someone attacks your audio-visual speech separation system in the testing process. If you use audio-visual network of 50% fake face appeared in the testing process and 50% fake face appeared in the training process, the
performance will increase. If you use audio-visual-sign network of 50% fake face appeared in the testing process and 50% fake face appeared in the training process, the performance will further increase when compared to corresponding audio-visual network. The SDR, SIR, SAR, PESQ, STOI are relatively increased by 34.01%, 23.91%, 19.79%, 14.58%, 8.24%, respectively. It can conclude that when the correct visual modality is missing, sign language will be an important auxiliary supervision in speech separation.

Fig. 8 describes the results of visualization of spectrogram. We find that the basic frequency distribution of the separated spectrogram was consistent with the real spectrogram. Finally, we conclude two questions raised in Introduction:

(i) **Can we use the weakly self-supervised sign language replace strongly self-supervised visual in speech separation?** The answer is YES, since the result of audio-sign network is always better than audio-only network, and therefore sign language could replace visual to supervise speech separation, although the audio-visual network is better than the audio-sign network.

(ii) **Does the performance of audio-sign is always better than audio-only speech separation?**

*The performance of audio-visual-sign is always better than audio-visual speech separation?*

The answer is NOT ALWAYS, since the audio-sign network is always better than audio-only network and the audio-visual-sign network is slightly worse than audio-visual network. Maybe there is a negative effect when fusing the weakly supervised sign language and the strongly supervised visual together, however, sign language will be an important auxiliary supervision in speech separation when the visual modality is missing or the visual modality is attacked.

**V. CONCLUSION**
In this paper, we propose an extended speech separation problem which refers in particular to sign language assisted speech separation and separate the audio with different modalities by extracting visual features and sign language features. To solve our problem, we created a new large-scale dataset named SLNSpeech that containing audio, visual, and sign language modalities, which are collected from sign language news of TV programs. We also design a general audio-visual-sign network to solve the extended speech separation problem. The evaluation results show that the weakly supervised sign language can promote the speech separation and work very well when the visual modality is missing or the visual modality is attacked.

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Fig. 1 The comparison of audio-only, audio-visual and audio-visual-sign speech separation. $A_1, A_2$ represent two source audios which are received by acoustic sensor and send to speech separation network, the outputs of speech separation network are predicted audios denoted by $\hat{A}_1$ and $\hat{A}_2$, $V_1, V_2, VS_1, VS_2$ represent two different visual and visual-sign respectively which are received by speech separation network directly.
Fig. 2 The coexistence of audio, sign language and/or visual in real life scenarios. (a) The scene of audio, visual and sign language modalities; (b) The scene of audio and visual modalities; (c) The scene of audio and sign language modalities. Note that the yellow boxes indicate the visual and the red boxes represent the sign language.

Fig. 3. The overview of the source videos where the yellow boxes indicate the visual and the red boxes represent the sign language. The first row is from CCTV, Beijing TV, and Dalian TV, respectively. The second row is from Hangzhou TV, Hangzhou West Lake TV, and Henan TV, respectively.
Fig. 4. The overall process of constructing SLNSpeech dataset.

Fig. 5. The detailed statistical results of SLNSpeech dataset which includes video clips of every news, duration and speaker.

Fig. 6. The architecture of the audio-visual-sign speech separation network which includes three modules: the sign language
embedding module (S), the visual embedding module (V) and the speech separation module (A). The sign embedding module and the visual embedding module receive the sign language frames and visual frames and then outputs sign language embedding and visual embedding, respectively. The speech separation module separates mixed source audios according to the sign embedding and/or the visual embedding. This architecture could introduce audio-only network (A), audio-visual network (A and V), audio-sign network (A and S), and audio-visual-sign network (A, V and S).

![Diagram of 3DResNet](image)

Fig. 7 The detailed architecture of 3DResNet. There are two different block components where \( c, k, s, p \) represents channels, convolutional filters, stride and padding, respectively.

![Visualization of speech separation](image)

Fig. 8 Visualization of speech separation. (a) is the source mixture audio; (b) and (d) are the source video which includes sign language and visual; (c) and (e) are the spectrograms corresponding to (b) and (d), respectively. The first row of (c) and (e) is source spectrograms and the second row of (c) and (e) is predicted spectrograms.
Table I. The comparisons of some existing datasets that can be applied to speech separation

| Datasets            | Duration (h) | Speakers | Language | Modalities               | Year |
|---------------------|--------------|----------|----------|--------------------------|------|
| TIMIT [8]           | 5.3          | 630      | English  | Audio; Text              | 1993 |
| CUAVE [9]           | 3            | 36       | English  | Audio; Text              | 2002 |
| GRID [10]           | 27.5         | 33       | English  | Audio; Visual; Text      | 2006 |
| CHiME2 WSJ0 [11]   | 78           | 101      | English  | Audio; Text              | 2012 |
| TCD-TIMIT [12]      | 6.3          | 59       | English  | Audio; Visual; Text      | 2015 |
| LRS [14-16]         | 800          | 5000     | English  | Audio; Visual; Text      | 2017 |
| VoxCeleb [17]       | 2000         | 7000     | Diversity| Audio; Visual            | 2017 |
| AVSpeech [18]       | 4700         | 1500000  | Diversity| Audio; Visual            | 2018 |
| AVA-ActiveSpeaker [19]| 38.5        | 40000    | Diversity| Audio; Visual            | 2019 |
| SLNSpeech (Ours)    | 17           | 25       | Chinese  | Audio; Visual; Sign Language | -    |

Table II. The comparisons of speech separation algorithms

| References          | Architectures and Algorithms | Modality | Year |
|---------------------|------------------------------|----------|------|
| Boll [20]           | spectral subtraction         | Audio    | 1979 |
| Brown and Cooke [21]| CASA                         | Audio    | 1994 |
| Pentti and Tapper [22]| NMF                         | Audio    | 1994 |
| Virtanen [23]       | NMF                          | Audio    | 2009 |
| Wang and Wang [25]  | DNN, CASA                    | Audio    | 2013 |
| Hershey et al. [30] | DNN, BLSTM                   | Audio    | 2016 |
| Wang et al. [26]    | DNN                          | Audio    | 2017 |
| Chandra et al. [27] | CNN                          | Audio    | 2017 |
| Fu et al. [28]      | FCN                          | Audio    | 2017 |
| Yu et al. [31]      | CNN                          | Audio    | 2017 |
| Kolbæk et al. [32] | RNN                          | Audio    | 2017 |
| Luo and Mesgarani [33]| FCN                        | Audio    | 2019 |
| Owens and Efros [38]| CNN, U-Net                   | Audio, Visual | 2018 |
| Gao et al. [39]     | ResNet, NMF                  | Audio, Visual | 2018 |
| Zhao et al. [40]    | ResNet, U-Net                | Audio, Visual | 2018 |
| Afouras et al. [42] | ResNet, BLSTM                | Audio, Visual | 2019 |

Table III. Statistics of the Chinese Basic Information Database of Persons with Disabilities (deadline for statistics: 2018-12-31)

| Age                | Aged 0-14 | Aged 15-59 | Aged 60 and above |
|--------------------|-----------|------------|--------------------|
|                    | 1045038   | 19331278   | 15285646           |

| Education          | Illiterate | Primary School | Junior High School | Senior High or Vocational School | Junior College and Above | Others |
|--------------------|------------|----------------|--------------------|---------------------------------|--------------------------|--------|
|                    | 6629794    | 13969188       | 10727366           | 2965721                         | 597332                   | 772561 |

| Disability Category | Persons with Visual Disability | Persons with Hearing Disability | Persons with Speech Disability | Persons with Physical Disability | Persons with Intellectual Disability |
|---------------------|--------------------------------|---------------------------------|-------------------------------|---------------------------------|-----------------------------------|
|                    | 4108353                          | 2883649                         | 623691                        | 19886774                        | 3081281                          |
### Table IV. The TV programs that used to construct SNLSpeech dataset and the names of the hosts of the corresponding TV programs

| Sources               | Hosts                                      | Description                                      | Dataset (hours) |
|-----------------------|--------------------------------------------|--------------------------------------------------|-----------------|
| CCTV                  | Guoning Gu, Yanke He, Feng Huang, Tao Pan, Guangquan Zhu, Xiaofeng Bao, Xia Hai, Jia He, Die Hu, Zimeng Li, Linshan Mu, Xiadan Ouyang, Tianliang Zheng | Daily program, 50 minutes every                  | 5.4             |
| Beijing TV            | Chaohui San, Wancong Hu, Yu Shi            | Daily program, 15 minutes every                  | 1.5             |
| Dalian TV             | - Hui Chao                                 | Weekly program, 10 minutes every                 | 0.4             |
| Henan TV              | Yaguang Ma, Ercha Hu                       | Weekly program, 15 minutes every                 | 1.2             |
| Hangzhou TV           | Xuan Zheng, Yi Jin, Li Ka, Ke Xu           | Daily program, 3 minutes every                   | 0.1             |
| Hangzhou West Lake TV | - Yi Jing, Xian Wei                        | Weekly program, 20 minutes every                 | 1               |

### Table V. The comparison of different modalities in speech separation. The table can be divided into three parts: the common comparison, no fake face during evaluation and 50% fake faces during evaluation. 

| Tr. | T. | SDR  | SIR  | SAR  | PESQ | STOI | Incr1 (%) | Incr2 (%) | Incr3 (%) | Incr4 (%) | Incr5 (%) |
|-----|----|------|------|------|------|------|-----------|-----------|-----------|-----------|-----------|
| GT  | -  | -    | 287.72 | -    | 287.72 | -    | 280.61 | -    | 4.55 | - | 1 | - |
| Mix | -  | -    | 0.11  | -    | 144.82 | -    | 1.33 | -    | 0.62 | - | - |
| AO  | ×  | ×    | 4.87  | 0    | 10.6  | 0    | 7.62  | 0    | 1.72 | 0    | 0.78 | 0 |
| AS  | ×  | ×    | 7.27  | 33.01 | 13.76  | 22.97 | 9.6   | 20.63 | 2.01 | 14.43 | 0.82 | 4.88 |

No fake face during testing

| AV  | ×  | ×    | 8.4   | 42.02 | 15.33  | 30.85 | 9.9   | 23.03 | 2.12 | 18.87 | 0.85 | 8.24 |
| AVS | ×  | ×    | 8.2   | 15.06 | 9.78   | 2.08  | 9.5   | 2.05  | -    | -    | -    |
| AVS | ×  | ×    | 8.07  | 14.88 | 9.75   | 2.05  | -    | -    | -    | -    | -    |

50% fake faces during testing

| AV  | ×  | √    | 2.44  | -    | 7.69  | -    | 8.42  | -    | 1.77 | -    | 0.64 | - |
| AVS | ×  | √    | 6.7   | 0    | 12.87 | 0    | 9.18  | 0    | 1.97 | 0    | 0.81 | 0 |
| AVS | ×  | √    | 8.13  | -    | 14.92 | -    | 9.71  | -    | 2.09 | -    | 0.85 | - |
| AVS | √  | √    | 7.38  | 34.01 | 13.93 | 23.91 | 9.5   | 19.79 | 2.02 | 14.85 | 0.85 | 8.24 |