CASNET: INVESTIGATING CHANNEL ROBUSTNESS FOR SPEECH SEPARATION

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ABSTRACT

Recording channel mismatch between training and testing conditions has been shown to be a serious problem for speech separation. This situation greatly reduces the separation performance, and cannot meet the requirement of daily use. In this study, inheriting the use of our previously constructed TAT-2mix corpus, we address the channel mismatch problem by proposing a channel-aware audio separation network (CasNet), a deep learning framework for end-to-end time-domain speech separation. CasNet is implemented on top of TasNet. Channel embedding (characterizing channel information in a mixture of multiple utterances) generated by Channel Encoder is introduced into the separation module by the FiLM technique. Through two training strategies, we explore two roles that channel embedding may play: 1) a real-life noise disturbance, making the model more robust, or 2) a guide, instructing the separation model to retain the desired channel information. Experimental results on TAT-2mix show that CasNet trained with both training strategies outperforms the TasNet baseline, which does not use channel embeddings.

Index Terms— Speech separation, channel embeddings

1. INTRODUCTION

Speech separation \(^1\) originates from the cocktail party problem \(^2\), which refers to the perception of each speech source in a noisy social environment. To understand each speaker’s speech, we first need to separate overlapping speech, which is the goal of speech separation. As a necessary pre-processing for downstream tasks, such as speaker diarization \(^3\) and automatic speech recognition \(^4\), many efforts have been made in speech separation.

Nowadays, the main dataset used in speech separation research is the WSJ0-2mix dataset \(^5\). In WSJ0-2mix, an artificially synthesized dataset, all mixed utterances are full overlaps of clean speech from two speakers. In recent research, a popular architecture is the time-domain audio separation network (TasNet) \(^6\). Many TasNet-based models have achieved extraordinary performance \(^7\) \(^8\) \(^9\) \(^10\) \(^11\) on WSJ0-2mix. However, WSJ0-2mix sets many restrictions on the experiments, which may lead to domain mismatches.

Domain mismatch can be attributed to four factors: speaker, content, channel, and environment. Regarding speaker mismatch, the speakers in the test sets of all datasets are designed to be unseen in the training sets. However, there is no noticeable drop in performance, demonstrating the speaker generalization of these models. Environment mismatch refers to reverberation and noise that may be encountered in reality and are not seen in the training set. To address this issue, two new datasets have been presented: WHAM! \(^12\) and WHAMR! \(^13\), which are the noisy and reverberant extensions of WSJ0-2mix, respectively.

Content mismatch focuses on what the speaker said, such as vocabulary or even different languages that contain various phonemes. In \(^14\) \(^15\), the authors argue that the larger the vocabulary presented in the training set, the better the generalization of the model. In \(^16\), using the GlobalPhoneMS2 dataset consisting of 22 spoken languages, the authors show that when trained on a multilingual dataset, the model can improve its performance on unseen languages. Regarding channel mismatch, it focuses on the type of microphone used in the recording. The authors of \(^17\) argue that near-field data are easier to separate than far-field data, even though both were recorded in the same environment.

In the COVID-19 pandemic era, virtual meetings have become prevalent and recorded with a wider variety of microphones. Furthermore, smartphones are frequently used tools in the daily recording. If all training sets are recorded with condenser microphones, the speech separation performance will drop significantly in daily use. Therefore, channel mismatch should be investigated in more depth to meet demand. In our previous work \(^18\), we found that the impacts of different languages are small enough to be ignored compared to the impacts of different channels. Also, although the content is the same, the separation performance varies due to the different microphones. To address the channel mismatch, it is necessary to create a channel-robust speech separation model. Here, we define “channel robustness” in two directions according to the channel of the target. The first is classic speech separation: no matter which channel the mixture is recorded through, the separated utterances must remain on the same channel as the mixture. The other definition is that separated utterances should be enhanced as if they were recorded by a
clean channel, i.e., a condenser microphone. The benefit of this definition is that the downstream model does not need to be channel-robust when receiving the output of the separation model. In both definitions, the separation model should perform well on channels unseen in the training set.

In this paper, we focus on the first definition of channel robustness. We propose a channel-aware audio separation network, CasNet, which can separate mixtures guided by channel embeddings. A channel encoder inspired by speaker verification models is designed to generate channel embeddings, which are introduced into the separation module via the FiLM technique. Our model can be applied to any TasNet-based model to enhance channel robustness. We conducted experiments on the TAT-2mix dataset designed in our previous work and explored the role of channel embeddings as guiding or disturbing by inputting different auxiliary mixtures during model training. The results show that CasNet trained in both ways outperform the TasNet baseline. We open-sourced the code for training on GitHub\footnote{https://github.com/Sinica-SLAM/CasNet}.

The contribution of this paper spans the following aspects: 1) To the best of our knowledge, we are the first to study solutions for channel mismatch; 2) we create a module that can generate channel embeddings to enhance robustness; 3) we investigate the different roles of channel embeddings; 4) our proposed model, CasNet, outperforms the TasNet baseline.

2. PROPOSED: CASNET

As shown in Fig. 1 our model is based on TasNet but with a channel encoder. The input of TasNet is a mixture of overlapping speech $\hat{x}^m_{c,i}$, and the outputs of TasNet are separated utterances $\hat{x}^c_{n,i}$. Using an auxiliary mixture $x^m_c$, the channel encoder generates a channel embedding to support or interfere with separation. The separation model integrates the channel embedding after the separation blocks and before the Post-Net. During training, we considered different schemes whether $m = n$ or not and whether $c = c'$ or not. In the inference stage, we examined different $x^m_{c'}$ to feed in the Channel Encoder, as shown in Fig. 2. The details of each module are described as follows. Training objectives will be discussed at the end of this section.

2.1. TasNet

The main concept of TasNet is speech separation in the time domain. The waveform input is not transformed into a spectrogram for processing, and the output is also a waveform. TasNet is mainly composed of three parts: waveform encoder, separator, and waveform decoder. First, the waveform encoder (Conv1D) takes the mixture as input and transforms it into the corresponding representation. This representation is then fed into the separator, which estimates individual speaker masks. Finally, the waveform decoder (TransposeConv1D) is used to reconstruct each source waveform from the masked encoder features.

2.2. Channel Encoder

Inspired by previous speaker verification research\cite{20,21,22}, the structure of Channel Encoder is mainly composed of a Residual Net and a pooling layer. We argue that the input should be a mixture instead of a single-speaker utterance to ensure that the channel embedding mainly captures channel information rather than speaker information. Suppose a training batch $\{x^m_c\}_{m=1}^M$ contains $M$ input utterances. First, the batch is transformed into a representation $X_0$ in the embedding space by the same waveform encoder as TasNet. Then, $X_0$ is sent to the Residual Net.

The Residual Net is composed of one ConvBlock and $B$ SE-ResBlocks. $X_0$ is processed by the ConvBlock, which consists of a 1D convolution (Conv1D), a nonlinear activation function ($ReLU$), and a normalization operation ($BatchNorm$)\cite{23}, as expressed by

$$X_1 = BatchNorm(ReLU(Conv1D(X_0))).$$ (1)

For $i = 1, \ldots, B$, $X_i$ is fed into SE-ResBlocks. In a SE-ResBlock, there are two ConvBlocks and a squeeze-and-excitation (SE) layer. The SE layer utilizes a two-layer fully connected network (FC) with average pooling (AvgPool) and the sigmoid function ($Sigmoid$) to calculate the weights of the original feature maps and scales each dimension of the channel according to its importance. The SE process involves two steps: 1) generating global information (squeeze step);
and 2) re-weighting each feature map (excitation step), as recursively expressed by
\[
X_{i+1} = \text{Sigmoid}(FC(AvgPool(X_i))) \times X_i + X_i, \quad (2)
\]
where \( i \) ranges from 1 to \( B - 1 \). Note that after each SE-ResBlock, a residual path is added to the end of the block.

Then, the output \( X_B \) goes through a pooling layer to get the channel embedding. An attentive pooling layer is used to compute the weighted mean of the last dimension (i.e., time frames) of \( X_B \):
\[
A = \text{Sigmoid}(FC(X_B)), \quad A = [a_1, \ldots, a_M], \quad (3)
\]
\[
Z = A^T \times X_B. \quad (4)
\]
where \( A \in \mathbb{R}^{T \times M} \), and \( T \) is the temporal length. Finally, a linear operation \((\text{Linear})\) is applied to produce the channel embedding \( C = [c_1, \ldots, c_M] \in \mathbb{R}^{D \times M} \), where \( D \) is the dimension of channel embedding:
\[
C = \text{Linear}(Z). \quad (5)
\]

### 2.3. FiLM

We adopt FiLM \cite{Perez2019FiLM} to integrate channel embedding into TasNet. We first transform the channel embedding \( C \) to weight \( W \) and bias \( b \) by two different linear operations:
\[
W = \text{Linear}(C), \quad b = \text{Linear}(C). \quad (6)
\]
The separation feature maps \( S \) estimated by TasNet (waveform encoder + \( N \) separation blocks) is normalized by instance normalization \((\text{Norm})\) \cite{Ulyanov2016InstanceNormal} and multiplied by the weight \( W \) and biased by \( b \), and then goes through a non-linear activation function \((\text{PReLU})\):
\[
S' = \text{PReLU}(W \times \text{Norm}(S) + b). \quad (7)
\]
Finally, the separation feature maps \( S' \) are turned into the estimated masks by the Post-Net.

### 2.4. Training Objectives

The main training objective for speech separation is to minimize the reconstruction loss \( L_{re} \) according to the scale-invariant signal-to-distortion ratio (SI-SNR). SI-SNR can be calculated with the output of the network and the target source through the definition in Eqs. 13-15 of [6].

Our goal is to maximize SI-SNR or minimize the negative SI-SNR. Since there are multiple speakers in a mixture, permutation-invariant training (PIT) is performed, which computes the combination that yields the highest SI-SNR for backward propagation. Additionally, to ensure that the channel embedding contains channel information, we include the channel identification loss \( L_{ci} \), which is a cross-entropy loss. We feed the channel embedding into a channel classifier to distinguish through which channel \( x_{ci}' \) is recorded. Therefore, the total loss used in this paper is
\[
L_{total} = L_{re} + \gamma \times L_{ci}, \quad (8)
\]
where \( \gamma \) is the weight of the channel identification loss.

### 3. EXPERIMENTS

#### 3.1. Dataset

The dataset used in this paper is TAT-2mix, a dataset created in our previous work \cite{Wu2020TAT}. TAT-2mix is based on the Taiwanese across Taiwan (TAT) corpus \cite{Tu2017Taiwanese}. Taiwanese, also known as Southern Min, is a common dialect in Taiwan and belongs to the same language family as Mandarin. The corpus was recorded on six channels simultaneously, including one close-talk (Audio-Technica AT2020), one distant X-Y stereo microphone (ZOOM XYH-6 stereo microphone, containing left and right channels), one lavalier (Superlux WO518+PS418D), iOS devices (including iPhones, iPads, and iPods), and Android phones (produced by ASUS and Samsung). From these six channels, we created six corresponding datasets. All datasets are comprised of the same mixtures of utterances but from different channels. TAT-2mix is designed to have the same number of mixed utterances and similar statistics as WSJ0-2mix. Details can be referred to in our previous work \cite{Wu2020TAT}.

#### 3.2. Experimental Setup

All our experiments were performed using the SpeechBrain toolkit \cite{Battenberg2019SpeechBrain}. DPRNN-TasNet was used as the TasNet baseline. CasNet was implemented on the TasNet baseline by adding the proposed channel embedding mechanism. We used the Adam optimizer with default parameters. The learning rate starts at 1.5e-4 and is halved when there is no improvement for 2 epochs. There are 4 SE-ResBlocks (\( B = 4 \)) in the Residual Net of CasNet, and the dimension of channel embedding is 128 (\( D = 128 \)). CasNet was trained for 100 epochs on 3-second-long segments with a batch size of 8.

There are six types of channels in TAT-2mix. We trained with five of them and tested the models with the sixth channel to test the channel robustness. In our previous work \cite{Wu2020TAT}, we found that training with TAT-2mixAndroid can achieve a certain level of channel robustness, since there are multiple brands in

![Diagram](image-url)
the Android system, including ASUS and Samsung. Therefore, we chose the Android channel as the test channel to avoid gaining robustness from a single kind of channel. In each minibatch, we randomly selected a channel as “c” for training to save training time.

### 3.3. Results

According to the selection of $x_{n}^{c'}$ during model training, our experiments are divided into two parts. In the first experiment, the channel of $x_{m}^{c'}$ is the same as that of $x_{n}^{c}$ (i.e., $c' = c$) to investigate the guiding ability of channel embedding. Inspired by target speaker extraction [28], where models use a speaker vector to extract a target speaker in a mixture, channel embeddings can be considered a guide in speech separation to extract the signal of the target channel. In the second experiment, training $x_{m}^{c}$ and $x_{n}^{c'}$ have different content and are from different channels (i.e., $m \neq n$ and $c \neq c'$). We believe that CasNet can become more robust when different interfering mixtures are used in training, similar to how data augmentation adds interference to the training data to make speaker verification models robust.

The results of the first experiment are shown in Table 1. The number of parameters is recorded in the **param.** column. Whether $m = n$ or not during training is noted in the **utter.** column. The number of parameters is recorded in the **param.** column. Whether $x_{m}^{c}$ or $x_{n}^{c'}$ are from the same channel ($c = c'$). Whether the content of $x_{m}^{c'}$ is the same as that of $x_{n}^{c}$ during training ($m = n$) is noted in the **utter.** column. The number of parameters is recorded in the **param.** column. $\gamma$ is the weight of the channel identification loss.

### 4. CONCLUSION AND FUTURE WORK

To alleviate the channel mismatch problem, we have proposed a channel-aware audio separation network CasNet, which is based on TasNet with an additional Channel Encoder that generates channel embeddings. The embedding is integrated with TasNet via the FiLM technique. In the experiments, we explored different roles of channel embeddings and found that both training methods, either guiding or disturbing, outperformed the TasNet baseline. In the future, we will investigate the second definition of channel robustness, i.e., enhancing speech with reduced channel effects during separation.
5. REFERENCES

[1] Deliang Wang and Jitong Chen, “Supervised speech separation based on deep learning: An overview,” IEEE Trans. Audio, Speech, Lang. Process., vol. 26, no. 10, pp. 1702–1726, 2018.

[2] Simon Haykin and Zhe Chen, “The cocktail party problem,” Neural Comput., vol. 17, no. 9, pp. 1875–1902, 2005.

[3] Thilo Von Neumann, Keisuke Kinoshita, Marc Delcroix, Shoko Araki, Tomohiro Nakatani, and Reinhold Haeb-Umbach, “All-neural online source separation, counting, and diarization for meeting analysis,” in Proc. ICASSP, 2019.

[4] Desh Raj, Pavel Denisov, Zhuo Chen, Hakan Erdogan, Zili Huang, Maokui He, Shinji Watanabe, Jun Du, Takuya Yoshioka, Yi Luo, Naoyuki Kanda, Jinyu Li, Scott Wisdom, and John R. Hershey, “Integration of speech separation, diarization, and recognition for multi-speaker meetings: System description, comparison, and analysis,” in Proc. IEEE SLT, 2021.

[5] John R. Hershey, Zhuo Chen, Jonathan Le Roux, and Shinji Watanabe, “Deep clustering: Discriminative embeddings for segmentation and separation,” in Proc. ICASSP, 2016.

[6] Yi Luo and Nima Mesgarani, “TasNet: Time-domain audio separation network for real-time, single-channel speech separation,” in Proc. ICASSP, 2018.

[7] Yi Luo, Zhuo Chen, and Takuya Yoshioka, “Dual-path RNN: Efficient long sequence modeling for time-domain single-channel speech separation,” in Proc. ICASSP, 2020.

[8] Jingjing Chen, Qirong Mao, and Dong Liu, “Dual-path transformer network: Direct context-aware modeling for end-to-end monaural speech separation,” in Proc. Interspeech, 2020.

[9] Neil Zeghidour and David Grangier, “Wavesplit: End-to-end speech separation by speaker clustering,” arXiv preprint arXiv:2002.08933v1, 2020.

[10] Xiaolin Hu, Kai Li, Weiyi Zhang, Yi Luo, Jean-Marie Lemercier, and Timo Gerkmann, “Speech separation using an asynchronously fully recurrent convolutional neural network,” in Proc. NeurIPS, 2021.

[11] Cem Subakan, Mirco Ravanelli, Samuele Cornell, Mirko Bronzi, and Jianyuan Zhong, “Attention is all you need in speech separation,” in Proc. ICASSP, 2021.

[12] Gordon Wichern, Joe Antognini, Michael Flynn, Licheng Richard Zhu, Emmett McQuinn, Dwight Crow, Ethan Manilow, and Jonathan Le Roux, “Wham!: Extending speech separation to noisy environments,” in Proc. Interspeech, 2019.

[13] Matthew Maciejewski, Gordon Wichern, Emmett McQuinn, and Jonathan Le Roux, “WHAMR!: Noisy and reverberant single-channel speech separation,” in Proc. ICASSP, 2020.

[14] Berkant Kadioğlu, Michael Horgan, Xiaoyu Liu, Jordi Pons, Dan Darcy, and Vivek Kumar, “An empirical study of Conv-TasNet,” in Proc. ICASSP, 2020.

[15] Joris Cosentino, Manuel Pariente, Samuele Cornell, Antoine Deleforge, and Emmanuel Vincent, “LibriMix: An open-source dataset for generalizable speech separation,” arXiv preprint arXiv:2005.11262, 2020.

[16] Marvin Borsdorf, Haizhou Li, and Tanja Schultz, “Target language extraction at multilingual cocktail parties,” in Proc. IEEE ASRU, 2021.

[17] Matthew Maciejewski, Gregory Sell, Yusuke Fujita, Leibny Paola Garcia-Perera, Shinji Watanabe, and Sanjee Khudanpur, “Analysis of robustness of deep single-channel speech separation using corpora constructed from multiple domains,” in Proc. WASPAA, 2019.

[18] Fan-Lin Wang, Hung-Shin Lee, Yu Tsao, and Hsin-Min Wang, “Disentangling the impacts of language and channel variability on speech separation networks,” in Proc. Interspeech, 2022.

[19] Yi Luo and Nima Mesgarani, “Conv-TasNet: Surpassing ideal time-frequency magnitude masking for speech separation,” IEEE Trans. Audio, Speech, Lang. Process, vol. 27, no. 8, pp. 1256–1266, 2019.

[20] Brecht Desplanques, Jentence Thiennon, and Kris Demuynck, “ECAPA-TDNN: Emphasized channel attention, propagation and aggregation in TDNN based speaker verification,” in Proc. Interspeech, 2020.

[21] Joon Son Chung, Jaesung Huh, Seongkyu Mun, Minjae Lee, Hee-Soo Heo, Soyeon Choe, Chiheon Ham, Sunghwan Jung, Bong-Jin Lee, and Icksang Han, “In defence of metric learning for speaker recognition,” in Proc. Interspeech, 2020.

[22] Mickael Rouvier and Pierre-Michel Bousquet, “Studying squeeze-and-excitation used in CNN for speaker verification,” arXiv preprint arXiv:2109.05977, 2021.

[23] Sergey Ioffe and Christian Szegedy, “Batch normalization: Accelerating deep network training by reducing internal covariate shift,” in Proc. ICML, 2015.

[24] Ethan Perez, Florian Strub, Harm De Vries, Vincent Dumoulin, and Aaron Courville, “FiLM: Visual reasoning with a general conditioning layer,” in Proc. AAAI, 2018.

[25] Dmitriy Ulyanov, Andrea Vedaldi, and Victor Lempitsky, “Instance Normalization: The missing ingredient for fast stylization,” arXiv preprint arXiv:1607.08022, 2016.

[26] Yuan-Fu Liao, Chia-Yu Chang, Hak-Khiam Tiun, Huang-Lan Su, Hui-Lu Khoo, Jane S. Tsay, Le-Kun Tan, Peter Kang, Tsun-Guan Thiami, Un-Gian Iunn, Jyh-Her Yang, and Chih-Neng Liang, “Formosa speech recognition challenge 2020 and Taiwanese across Taiwan corpus,” in Proc. O-COCOSDA, 2020.

[27] Mirco Ravanelli, Titouan Parcollet, Peter Plantinga, Aku Rouhe, Samuele Cornell, Loren Lugosch, Cem Subakan, Naman Dawalatabad, Abdelwahab Heba, Jianyuan Zhong, Ju-Chieh Chou, Sung-Lin Yeh, Szu-Wei Fu, Chien-Feng Liao, Elena Rastorgueva, François Grondin, William Aris, Hwidong Na, Yan Gao, Renato De Mori, and Yoshua Bengio, “SpeechBrain: A general-purpose speech toolkit,” arXiv preprint arXiv:2106.04624, 2021.

[28] Kateřina Žmolíková, Marc Delcroix, Keisuke Kinoshita, Tsubasa Ochiai, Tomohiro Nakatani, Lukáš Burget, and Jan Černocký, “SpeakerBeam: Speaker aware neural network for target speaker extraction in speech mixtures,” IEEE J. Sel. Top. Sig. Proc., vol. 13, no. 4, pp. 800–814, 8 2019.