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► **To cite this version:**

Yicheng Du, Aditya Arie Nugraha, Kouhei Sekiguchi, Yoshiaki Bando, Mathieu Fontaine, et al.. Direction-Aware Joint Adaptation of Neural Speech Enhancement and Recognition in Real Multiparty Conversational Environments. INTERSPEECH, 2022, Incheon, South Korea. hal-03727181

HAL Id: hal-03727181

<https://telecom-paris.hal.science/hal-03727181v1>

Submitted on 19 Jul 2022

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Direction-Aware Joint Adaptation of Neural Speech Enhancement and Recognition in Real Multiparty Conversational Environments

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Abstract

This paper describes noisy speech recognition for an augmented reality headset that helps verbal communication with in *real* multiparty conversational environments. A major approach that has actively been studied in *simulated* environments is to sequentially perform speech enhancement and automatic speech recognition (ASR) based on deep neural networks (DNNs) trained in a supervised manner. In our task, however, such a pretrained system fails to work due to the mismatch between the training and test conditions and the head movements of the user. To enhance only the utterances of a target speaker, we use beamforming based on a DNN-based speech mask estimator that can adaptively extract the speech components corresponding to a head-relative particular direction. We propose a semi-supervised adaptation method that jointly updates the mask estimator and the ASR model at run-time using clean speech signals with ground-truth transcriptions and noisy speech signals with highly-confident estimated transcriptions. Comparative experiments using the state-of-the-art distant speech recognition system show that the proposed method significantly improves the ASR performance.

Index Terms: speech enhancement, speech recognition, human-computer interaction, run-time adaptation.

1. Introduction

Smart glasses or augmented reality (AR) headsets (*e.g.*, Microsoft HoloLens¹) equipped with multimodal IO devices including cameras, microphones, AR displays, loudspeakers, and inertial measurement unit (IMUs) are expected to become more powerful and compact and totally change a way of daily communication. One of the most important applications of speech processing technology is to help a (hearing-impaired) user make verbal communication by enhancing the speech of a target speaker while showing its transcriptions using an AR technique. Such a system could be extended for helping a user talk with foreign people in a cocktail party with loud noise by translating the speech of a target speaker. The key ingredient of these systems is distant noisy speech recognition capable of working robustly regardless of acoustic conditions and user movements. The typical approach to noisy speech recognition using a microphone array is to sequentially perform multichannel speech enhancement and automatic speech recognition (ASR) [1, 2].

Beamforming has recently been the main choice for speech enhancement and its performance depends on the accuracy of estimating the spatial covariance matrices (SCMs) or steering

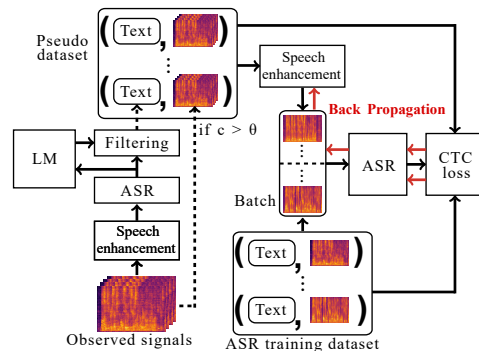


Figure 1: The proposed joint adaptation approach.

vectors of speech and noise. One may select the SCMs corresponding to the source and noise directions from those prepared in advance (*e.g.*, computed from the array geometry or measured in an anechoic room). This strategy often fails due to the mismatch between the prepared and real SCMs. To estimate the speech and noise SCMs at run-time, one can train a deep neural network (DNN) that predicts speech masks in the short-time frequency transform (STFT) domain [1, 2]. To enhance only the utterances of a particular speaker regardless of speech overlaps in multiparty conversation, the mask estimator can be informed of the speaker direction and/or identity [3–10]. The performance of such supervised learning, however, is still severely limited due to the mismatch between the training and test conditions. When an AR headset is used, the head movement of the user adversely affects the performance. Existing methods of separating moving sources [11–13] are vulnerable to fast movements.

The condition mismatch has also been one of the central problems in the state-of-the-art end-to-end approach to ASR that directly maps speech signals to symbols (*e.g.*, characters and words) with the attention mechanism and/or the connectionist temporal classification (CTC) strategy. The most basic way of improving the robustness against noise is multi-condition training of an ASR model [14, 15]. In multichannel speech recognition, some studies concatenate a speech mask estimator and an ASR model in a differentiable manner such that both DNNs can be jointly optimized [6, 16]. Most studies on these topics have been conducted under offline closed conditions where synthesized noisy speech signals with the ground-truth transcriptions are used for training and evaluation. This prohibits the practical application of ASR to an AR headset in the real world.

Under these circumstances, we propose a speech recognition system for an AR headset that works robustly and adaptively in real conversational environments (Fig. 1). As in the standard

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¹<https://www.microsoft.com/en-us/hololens>

architecture, our system consists of speech enhancement and recognition modules, which are implemented with minimum variance distortionless response (MVDR) beamforming with DNN-based mask estimation and an audio-to-word CTC model, respectively. These DNNs are separately trained in a *supervised manner in advance* and jointly updated with backpropagation in a *semi-supervised manner at run-time* using clean speech signals with ground-truth transcriptions taken from the training data and observed noisy speech signals with estimated transcriptions whose confidence scores are larger than a threshold. To focus on a particular speaker in multiparty conversation, the mask estimator is given as directional clues the premeasured steering vectors corresponding to the head-relative speaker direction, which is assumed to be estimated by multimodal sensors.

The major contribution of this work is to enable both the speech enhancement and recognition modules to be jointly updated for run-time adaptation in real online environments unlike existing studies restricting the joint optimization to the training phase in simulated offline environments [16]. We experimentally prove the importance of the run-time adaptation on the recently-released Easy Communications (EasyCom) dataset [17] consisting of real multiparty conversation recordings.

2. Related Work

This section briefly reviews how to reflect the characteristics of observed data for adapting beamforming-based speech enhancement and end-to-end speech recognition.

2.1. Adaptive Speech Enhancement

We review speech enhancement in the short-time Fourier transform (STFT) domain spanned by F frequency bins and T time frames. Our goal is to estimate the STFT coefficients of clean speech $\mathbf{S} \triangleq \{s_{ft}\}_{f,t=1}^{F,T} \in \mathbb{C}^{FT}$ from those of an observed multichannel noisy speech $\mathbf{X} \triangleq \{\mathbf{x}_{ft}\}_{f,t=1}^{F,T} \in \mathbb{C}^{FTM}$ obtained from M sensors. In general, $\mathbf{x}_{ft} \in \mathbb{C}^M$ is assumed to be the output of a time-frequency linear system given by

$$\mathbf{x}_{ft} = \mathbf{a}_f s_{ft} + \mathbf{e}_{ft}, \quad (1)$$

where $\mathbf{e}_{ft} \in \mathbb{C}^M$ is additive noise and $\mathbf{a}_f \in \mathbb{C}^M$ is the steering vector of frequency f corresponding to the speaker direction. The classic beamforming technique estimates the clean speech as

$$\hat{s}_{ft} = \mathbf{w}_f^H \mathbf{x}_{ft} = \mathbf{w}_f^H \mathbf{a}_f s_{ft} + \mathbf{w}_f^H \mathbf{e}_{ft}, \quad (2)$$

where $\mathbf{w}_f \in \mathbb{C}^M$ is a demixing filter of frequency f and H is the conjugate transpose. The minimum variance distortionless response (MVDR) beamforming [18] computes \mathbf{w}_f as

$$\mathbf{w}_f = \mathbf{R}_f^{-1} \mathbf{V}_f [\text{Tr}(\mathbf{R}_f^{-1} \mathbf{V}_f)]^{-1} \mathbf{u}, \quad (3)$$

where $\mathbf{V}_f = \mathbb{E}[s_{ft} \mathbf{s}_{ft}^H]$ and $\mathbf{R}_f = \mathbb{E}[\mathbf{e}_{ft} \mathbf{e}_{ft}^H]$ are the SCMs of the speech and noise, respectively, and $\mathbf{u} \in \{0, 1\}^M$ is a one-hot vector indicating the reference microphone.

2.1.1. Mask-Informed Beamforming

Given soft masks $\mathbf{Z} \triangleq \{z_{ft}\}_{f,t=1}^{F,T} \in [0, 1]^{FT}$, where z_{ft} represents the ratio of the speech component at frequency f and time t , the speech and noise SCMs are typically computed as $\mathbf{V}_f = \mathbb{E}[z_{ft} \mathbf{x}_{ft} \mathbf{x}_{ft}^H]$ and $\mathbf{R}_f = \mathbb{E}[(1 - z_{ft}) \mathbf{x}_{ft} \mathbf{x}_{ft}^H]$, respectively. In general, the speech masks \mathbf{Z} can be estimated with a DNN that takes the noisy speech spectrogram \mathbf{X} as input [1, 2]. Such a DNN is trained in advance such that the binary cross entropy between the estimated masks \mathbf{Z} and the ground-truth binary masks is minimized. This technique has been shown to achieve good performance in simulated environments because \mathbf{V}_f and \mathbf{R}_f can be *adaptively* estimated from \mathbf{X} . However, the

DNN used for estimating \mathbf{Z} is still *fixed* and thus suffers from the condition mismatch problem in real environments.

2.1.2. Direction-Aware Mask Estimation

Several attempts have been made for informing the mask estimator of directional information. Li *et al.* [7] proposed an attention network that estimate the speech spectra as the weighted sum of multiple fixed beamformers. The enhanced spectra and an utterance of the target speaker are then fed to the Speaker-Beam network [4] that estimates the speech masks corresponding to the speaker direction and identity. Chen *et al.* [3] and Subramanian *et al.* [19] computed directional features from the observed noisy speech spectra and the steering vectors of the target direction premeasured in an ideal environment. These features are fed to a mask estimator together with the other common features including inter-microphone phase differences and the output of a fixed beamformer. The performances of these methods in real environments with unseen speakers would also be drastically degraded by the condition mismatch problem.

2.2. Adaptive Speech Recognition

The end-to-end approach to ASR has recently become popular due to the easy implementation, good performance, and fast inference. Among various end-to-end models implemented with the attention mechanism [20], the connectionist temporal classification (CTC) architecture [21], the recurrent neural network (RNN) transducer [22], and the transformer [23], those based on the CTC and RNN transducer have been experimentally shown to work relatively well in real noisy reverberant environments of the CHiME-6 Challenge [24], but still have large room for improvement [25]. In fact, even the state-of-the-art models that achieve the best performance in standard ASR benchmarks fail to work for noisy distant ASR when the speaker characteristics or acoustic environments significantly differ between the training and test conditions. Such overfitting to a particular dataset is one of the most serious problems in the ASR field.

The condition mismatch problem can be mitigated by semi-supervised adaptation methods that use annotated training data (clean speech) with ground-truth transcriptions and non-annotated test data (noisy speech) with the estimated transcriptions (pseudo-labels) for further updating ASR models [26–29]. To avoid using test data with erroneous transcriptions for effective model adaptation, one may use a dropout-based uncertainty measure [30]. In momentum pseudo labeling (MPL), the pseudo-labels are iteratively updated based on an ensemble of ASR models at different time steps [31].

3. Proposed Method

This section describes the proposed method integrating a direction-aware mask estimator to solve the speech overlap problem, a head-movement-aware speech enhancement to deal with the user's head movements, and a semi-supervised environment adaptation algorithm to adjust the enhancement and recognition model parameters to the test environment.

3.1. Problem Specification

We aim to estimate the clean speech \mathbf{S} given the observed multichannel noisy speech \mathbf{X} . Instead of using the time-invariant steering vector as in Eq. (1), we let the steering vector to be time-varying to deal with the user's head movements as follows:

$$\mathbf{x}_{ft} = \mathbf{a}_{ft} s_{ft} + \mathbf{e}_{ft}, \quad (4)$$

where $\mathbf{a}_{ft} \in \mathbb{C}^M$ is the time-varying steering vector corresponding to the speaker direction at time t . A time-varying filter $\mathbf{w}_{ft} \in \mathbb{C}^M$ is thus required to perform speech enhancement.

3.2. Direction-Aware DNN-Based Mask Estimator

Let $\mathcal{M} \triangleq \{1, \dots, M\}$ be the set of microphone indices, and r be the index of a reference microphone. The mask estimator takes as input spectral features, inter-channel phase difference (IPD) features, and directional features. The spectral features are the logarithmic power spectra of \mathbf{X} at the reference microphone, denoted by $\{x_{ftr}\}_{f,t=1}^{F,T}$. The IPD features are the sines and cosines of $\{\{P_{ftr}\}_{f,t=1}^{F,T}\}_{m \in \mathcal{M} - \{r\}}$, where $P_{ftr} \triangleq \angle(x_{ftr}/x_{ftr})$ is the IPD between the m -th microphone and the reference microphone at frequency f and time t . Similarly, the directional features are the sines and cosines of $\{\{D_{ftr}\}_{f,t=1}^{F,T}\}_{m \in \mathcal{M} - \{r\}}$, where $D_{ftr} \triangleq \angle(a_{ftr}/a_{ftr})$ is computed from the premeasured steering vectors of the target direction determined by leveraging the multimodal sensors, *e.g.*, by applying a face detection algorithm on the camera images. The mask estimator thus has $(F, T, 4 \times (M-1) + 1)$ -dimensional input and outputs time-frequency masks \mathbf{Z} for the target speaker for calculating the demixing filters.

3.3. Head-Movement-Aware Speech Enhancement

To deal with the head movements of the user, we compute demixing filters for the time-varying target direction. Let D be the number of directions with $d \in \{1, \dots, D\}$ is the index. The MVDR demixing filter for direction d is given by

$$\mathbf{w}_{fd} = (\mathbf{R}_{fd})^{-1} \mathbf{V}_{fd} [\text{Tr}((\mathbf{R}_{fd})^{-1} \mathbf{V}_{fd})]^{-1} \mathbf{u}, \quad (5)$$

where the speech and noise SCMs of the direction d are respectively given by $\mathbf{V}_{fd} \triangleq \sum_{t=1}^T \phi_{d,t} z_{ft} \mathbf{x}_{ft} \mathbf{x}_{ft}^H$ and $\mathbf{R}_{fd} \triangleq \sum_{t=1}^T \phi_{d,t} (1 - z_{ft}) \mathbf{x}_{ft} \mathbf{x}_{ft}^H$ with $\phi_{d,t} = 1$ if the target speaker is in direction d at time t and $\phi_{d,t} = 0$ otherwise, assumed to be known by utilizing multimodal sensors. The separated signal \hat{s}_{ft} is then obtained by

$$\hat{s}_{ft} = \sum_{d=1}^D 1_{d,t} \mathbf{w}_{fd}^H \mathbf{x}_{ft}. \quad (6)$$

3.4. Adaptation of Speech Enhancement and Recognition

The performances of the mask estimator trained on simulated noisy speech signals and the ASR system trained on clean speech signals are degraded in real noisy environments. To address this environment mismatch issue, we propose to update the mask estimator and parts of the ASR system using transcription estimates that are deemed to be reliable (Fig. 1). The reliability is determined by a confidence score c computed as

$$c = \alpha \log p_{\text{ASR}}(\mathbf{y}|\mathbf{x}) + \beta \log p_{\text{LM}}(\mathbf{y}) + \gamma |\mathbf{x}|, \quad (7)$$

where $p_{\text{ASR}}(\mathbf{y}|\mathbf{x})$ is the probability for the ASR system to output sequence \mathbf{y} given the enhanced signal \mathbf{x} , $p_{\text{LM}}(\mathbf{y})$ is the probability for the language model to output sequence \mathbf{y} , $|\mathbf{x}|$ is the length of \mathbf{x} , and $\alpha, \beta, \gamma \in \mathbb{R}$ are weight coefficients. The pairs of observed signal and transcription estimate whose confidence score exceeds a threshold θ are included in a pseudo dataset that is used together with the original ASR training dataset to perform the adaptation. It updates the parameters of the mask estimator and parts of the ASR system by minimizing a loss function:

$$\mathcal{L}^{\text{AD}} = \text{CTCLoss}(\mathbf{y}, \mathbf{t}) + \lambda \|\boldsymbol{\omega} - \boldsymbol{\omega}^{\text{init}}\|^2, \quad (8)$$

where \mathbf{y} is the ASR output sequence and \mathbf{t} is the ground-truth transcription for the batch sample from the original ASR training dataset or the transcription estimate for that from the pseudo dataset. The second term of Eq. (8) regularizes the mask estimator updates, where $\boldsymbol{\omega}$ is the current parameters, $\boldsymbol{\omega}^{\text{init}}$ is the initial parameters before the adaptation, and $\lambda \in \mathbb{R}$ is a weight. Conversely, the regularization for the ASR system updates is achieved by the use of the original ASR training dataset.

4. Evaluation

This section reports our experiments to validate the effectiveness of the proposed joint adaptation of speech enhancement and recognition for an AR headset used in real environments.

4.1. Experimental Settings

We used the Easy Communications (EasyCom) dataset [17] for evaluation. There are 12 sessions of conversational recordings (5 h 18 min) with the ground-truth transcriptions. We used Session 2 to 12 for adaptation and Session 1 for evaluation. Although the dataset contains 6-channel audio data, we used only the first 4 microphones fixed on the AR headset. All audio signals were resampled from 48 kHz to 16 kHz. For dereverberation, we applied weighted linear prediction (WPE) [32] with a tap length of 16 and a delay of 2 in the STFT domain with a window length of 512 pts and a shifting interval of 128 pts. Using the provided impulse responses recorded in an anechoic chamber, we computed steering vectors for $D = 1020$ directions. At run-time, assuming the target direction to be accurately estimated from multimodal data, we exploited the user and target poses tracked with an OptiTrack system for giving the steering vectors of the target direction to the mask estimator.

Dividing the test data (Session 1) into non-overlapped and overlapped speech regions based on the voice activity annotation, we evaluated the impacts of the proposed head-movement-aware enhancement and environment adaptation in each region in terms of the word error rate (WER) and the source-to-distortion ratio (SDR) [33], where the close microphone signal was regarded as the reference. We obtained the baseline performance by feeding the observed signals of the first microphone to the ASR system without enhancement. Similarly, we also obtained the oracle performance by feeding the signals of the close microphone. The rest of this subsection details the settings for the mask estimator, the ASR system, including the language model, and the environment adaptation.

4.1.1. Mask Estimator Settings

The mask estimator was trained on simulated data generated using the room simulation in Pyroomacoustics [34]. The simulated data mimics the scenario in the EasyCom dataset, where several people make conversation while sitting around a table. Nonetheless, we varied the rooms by randomly sampling the width from [5.0 m, 7.0 m], the depth from [6.0 m, 8.0 m], and the height from [2.5 m, 3.5 m] with a reverberation time sampled from [150 ms, 300 ms]. The device user positions w.r.t. the room dimensions were sampled from $[0.4 \times \text{width}, 0.6 \times \text{width}]$, $[0.15 \times \text{depth}, 0.35 \times \text{depth}]$, and $[1.0 \text{ m}, 1.5 \text{ m}]$, respectively. We assumed the device had a 4-microphone array whose geometry followed the one in the EasyCom dataset. Let the azimuth and elevation of the positive depth direction be 0.0° . For each utterance, the azimuth and elevation of the device were initially sampled from $[-72^\circ, 72^\circ]$ and $[-45^\circ, 45^\circ]$, respectively, and resampled once more from the same ranges to simulate a head movement. The target speaker and interferer positions w.r.t. the room dimensions were sampled from $[0.1 \times \text{width}, 0.9 \times \text{width}]$, $[0.4 \times \text{depth}, 0.85 \times \text{depth}]$, and $[1.0 \text{ m}, 1.5 \text{ m}]$, respectively.

The utterances of the target speaker and interferer were taken from the train-clean-100 subset of the LibriSpeech corpus [35]. For each target speaker's utterance, the interferer was randomly active with a probability of 50%. A background noise taken from the CHiME-3 dataset [36] was then added to the simulated multichannel signals such that the signal-to-noise ratio (SNR) was in $[-2 \text{ dB}, 8 \text{ dB}]$. In total, the training dataset contained 28,540 pairs of multichannel mixture signal and its corresponding ground-truth target speech signal.

The mask estimator consisted of three bi-directional LSTM layers with 256 hidden units, a dropout layer with a dropout rate of 0.2, and a fully connected layer with 201 units. It was trained by minimizing the phase-sensitive magnitude spectral approximation loss [37] given by

$$\mathcal{L}^{\text{MA}} = \sum_{f=1}^F \sum_{t=1}^T \| |z_{ft}| |x_{ft}| - |s_{ft}| \max(0, \cos \Delta_{ft}) \|^2, \quad (9)$$

where $|\cdot|$ computes the magnitude and $\Delta_{ft} \triangleq \angle x_{ft} - \angle s_{ft}$ with \angle computes the phase. It was trained for 200 epochs using the AdamW optimizer [38] with $\beta_1 = 0.9$, $\beta_2 = 0.999$, and a weight decay of 0.01. The learning rate was initially set to 0.001 and then decayed for 0.96 every epoch.

4.1.2. ASR System Settings

We used a CTC-based [21] end-to-end ASR model consisting of 2 VGG-like convolutional layers, 6 bi-directional LSTM layers with 512 hidden units, and 1 fully connected layer. The input features were 80-dimensional log-mel spectrograms computed with a window length of 400 samples (25 ms) and a shift interval of 160 samples (10 ms). The outputs were 8191 sub-words tokenized by byte pair encoding (BPE) [39].

The ASR model was pretrained on the LibriSpeech corpus [35]. It was then trained on the CHiME-6 dataset [24], the CommonVoice corpus [40], and a noisy reverberant dataset we derived from the CommonVoice corpus by convolving the clean utterances with simulated room impulse responses and adding background noise taken from the CHiME-3 dataset [36] such that the SNR is in [5 dB, 10 dB]. The pretraining and training were performed for 100 epochs using the AdamW optimizer [38] as for the mask estimator. The learning rate was first linearly increased from 0 to 1.5×10^{-4} over the minibatches in the first epoch, and then decayed for 0.97 every epoch. The minibatch size was 32 and the dropout rate was 0.2.

The language model used for computing $\log p_{\text{LM}}(\mathbf{y})$ was a Transformer-based model [41] composed of 4 encoder layers with 8-head attention and 1 fully connected sublayers, whose output dimensions are 512. It was trained on the CommonVoice and the CHiME-6 datasets for 10 epochs using the Adam optimizer with varying learning rate as in [41, Sec. 5.3].

4.1.3. Environment Adaptation Settings

Based on preliminary experiments, the coefficients in Eqs. (7) and (8) are set to $\alpha = 1$, $\beta = 50$, $\gamma = 1000$, and $\lambda = 5 \times 10^{-4}$. The whole mask estimator and the convolutional layers of the ASR system were updated for 20 epochs using the Adam optimizer [42] with $\beta_1 = 0.9$, $\beta_2 = 0.999$, and a learning rate of 5×10^{-4} . One minibatch was composed of 32 samples from the original ASR training dataset and 32 random samples from the pseudo dataset. To investigate the impacts of adaptation data amount, we varied the threshold θ such that the top 250, 500, 1000, 1500, or 2363 (of 2363) utterances with the highest confidence scores are used as the pseudo dataset. The pseudo dataset was reconstructed every 5 epochs. For comparison, we also investigate an oracle setting, where the ground-truth transcriptions are used for the adaptation.

4.2. Experimental Results and Discussion

Table 1 shows the effectiveness of the proposed environment adaptation for both non-overlapped speech and overlapped speech. It indicates that the proposed joint adaptation of neural speech enhancement and recognition alleviates the mismatch between the acoustic properties of real environments and those of simulated environments. However, the threshold θ for the pseudo dataset construction must be adjusted appropriately to

Table 1: *The average performances obtained with/without the proposed head-movement awareness (denoted by ‘HMA’) and environment adaptation using different numbers of transcription estimates. * indicates the use of ground-truth transcriptions.*

(a) Non-overlapped Speech				
MVDR	HMA	Adaptation	SDR [dB]	WER [%]
-	-	-	-1.28	55.53
✓	-	-	0.64	47.45
✓	✓	-	1.99	41.99
✓	✓	250	2.12	39.25
✓	✓	500	2.10	38.39
✓	✓	1000	2.18	38.38
✓	✓	1500	2.10	39.38
✓	✓	2363	2.13	44.10
✓	✓	2363*	2.11	38.39
Oracle (close mic.)			∞	24.72
(b) Overlapped Speech				
MVDR	HMA	Adaptation	SDR [dB]	WER [%]
-	-	-	-6.30	81.70
✓	-	-	-9.46	78.06
✓	✓	-	-5.30	71.29
✓	✓	250	-4.97	64.87
✓	✓	500	-4.93	63.23
✓	✓	1000	-4.76	62.36
✓	✓	1500	-5.44	63.75
✓	✓	2363	-5.24	74.85
✓	✓	2363*	-3.14	57.94
Oracle (close mic.)			∞	33.39

avoid a detrimental effect on the performance. In our experiments, we found that using the top 1000 (of 2363) utterances with the highest confidence scores was optimal.

There was still a huge gap between the performance of our proposed system and the performance of the oracle setting. For the overlapped speech case, the WERs of the proposed system were 71.29% before adaptation and 62.36% after adaptation, while the WER of the oracle setting using the close microphone was 33.39%. We observed that the device user’s speech was not suppressed well due to inaccurate mask estimates. It can be attributed to the fact that the user’s speech was captured much louder than the target’s because the user’s mouth was closer to the microphones and that the spatial characteristics of the user’s speech were significantly different from those of training data.

5. Conclusion

This paper presented a joint adaptation method for a neural speech enhancement and recognition system to handle the data mismatch problem related to unseen environments or speakers. The method exploits a number of transcription estimates with higher confidence scores for run-time model updates, in which the original training data are also used for regularization. For the evaluation, we considered its application to the ASR system for an AR headset operated in real conversational environments. Our experiments showed that the proposed joint adaptation improved the WERs by 3.61 points for the non-overlapped speech case and by 8.93 points for the overlapped speech case. Future work includes better treatment of the user’s own speech.

6. Acknowledgments

This work was supported in part by JSPS KAKENHI Nos. 19H04137, 20K19833, and 20K21813.

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