MINIMUM BAYES RISK TRAINING FOR END-TO-END SPEAKER-ATTRIBUTED ASR

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ABSTRACT

Recently, an end-to-end speaker-attributed automatic speech recognition (E2E SA-ASR) model was proposed as a joint model of speaker counting, speech recognition and speaker identification for monaural overlapped speech. In the previous study, the model parameters were trained based on the speaker-attributed maximum mutual information (SA-MMI) criterion, with which the joint posterior probability for multi-talker transcription and speaker identification are maximized over training data. Although SA-MMI training showed promising results for overlapped speech consisting of various numbers of speakers, the training criterion was not directly linked to the final evaluation metric, i.e., speaker-attributed word error rate (SA-WER). In this paper, we propose a speaker-attributed minimum Bayes risk (SA-MBR) training method where the parameters are trained to directly minimize the expected SA-WER over the training data. Experiments using the LibriSpeech corpus show that the proposed SA-MBR training reduces the SA-WER by 9.0% relative compared with the SA-MMI-trained model.

Index Terms— Speech recognition, speaker identification, speech separation, speaker counting, minimum Bayes risk training

1. INTRODUCTION

Speaker-attributed automatic speech recognition (SA-ASR) from overlapped speech has been an active research area for meeting transcription [1] [2] [3]. It requires to count the number of speakers, transcribe utterances that are sometimes overlapped, and also diarize or identify the speaker of each utterance. While significant progress has been made especially for multi-microphone settings (e.g., [4]), SA-ASR remains very challenging when we can only access monaural audio.

A substantial amount of research has been conducted to achieve the goal of SA-ASR. One approach is applying speech separation (e.g., [5] [6]) before ASR and speaker diarization/identification. However, a speech separation module is often designed with a signal-level criterion, which is not necessarily optimal for succeeding modules. To overcome this suboptimality, researchers have investigated approaches for jointly modeling multiple modules. For example, there are a number of studies concerning joint modeling of speech separation and ASR (e.g., [7] [8] [9] [10]). Several methods were also proposed for integrating speaker identification and speech recognition [11] [12]. However, these studies focused on the combination of only a subset of the modules needed for SA-ASR.

Only a limited studies have tackled the joint modeling of all the necessary modules for SA-ASR. [13] proposed to generate transcriptions for different speakers interleaved by speaker role tags to recognize doctor-patient conversations. In [14], the authors applied a similar technique where multiple utterances are interleaved with speaker identity tags instead of speaker role tags. However, these methods are difficult to extend to an arbitrary number of speakers because the speaker roles or speaker identity tags are determined and fixed in the training. [15] proposed a joint decoding framework for overlapped speech recognition and speaker diarization, where speaker embedding estimation and target-speaker ASR were performed alternately. While their formulation is applicable to any number of speakers, the method was actually implemented and evaluated in a way that could be used only for the two-speaker case, as target-speaker ASR was performed by using an auxiliary output branch representing a single interference speaker [16].

Recently, an end-to-end (E2E) SA-ASR model was proposed as a joint model of speaker counting, speech recognition, and speaker identification for monaural (possibly) overlapped speech [17] [18]. The E2E SA-ASR model has the advantage that it can recognize overlapped speech of any number of speakers while identifying the speaker of each utterance from an arbitrary number of registered speakers. It was trained based on the speaker-attributed maximum mutual information (SA-MMI) criterion, by which the joint probability for multi-talker speech recognition and speaker identification is maximized over training data. Based on the SA-MMI training, the E2E SA-ASR model achieved a significantly lower speaker-attributed word error rate (SA-WER) than a system that separately performs overlapped speech recognition and speaker identification. However, the training criterion was still not directly linked to the final evaluation metric, i.e., SA-WER. As a result, considerable degradation of SA-WER was still observed for overlapped speech compared with non-overlapped speech, especially when the number of overlapped speakers were large.

In this paper, to further improve the E2E SA-ASR model, we propose a new training method, called speaker-attributed minimum Bayes risk (SA-MBR) training. In SA-MBR training, the entire network parameters are trained to minimize the expected SA-WER over the training data. Note that there has been a lot of studies on MBR training for the conventional (i.e. single-speaker, speaker-agnostic) ASR, such as the one for hybrid ASR [19] [20], connectionist temporal classification [21] [22], recurrent neural network transducers [23] [24], and the attention encoder decoder-based ASR [25] [26]. However, to the best of our knowledge, this is the first work that directly minimizes the SA-WER in the joint framework. We show that the proposed SA-MBR training achieves significantly better SA-WER over the model based on SA-MMI training.

2. REVIEW: E2E SA-ASR

2.1. Overview

In this section, we review the E2E SA-ASR model proposed in [17]. The goal is to estimate a multi-speaker transcription $Y = \{y_1, ..., y_N\}$ and the speaker identity of each token $S = \{s_1, ..., s_N\}$ given acoustic input $X = \{x_1, ..., x_T\}$ and a speaker
inventory $D = \{d_1, ..., d_K\}$. Here, $N$ is the number of the output tokens, $T$ is the number of the input frames, and $K$ is the number of the speaker profiles (e.g., d-vectors [27]) in the inventory $D$. Following the idea of serialized output training (SOT) [28], the multi-speaker transcription $Y$ is represented by concatenating each speaker’s transcription interleaved by a special symbol (sc) representing the speaker change.

In the E2E SA-ASR modeling, it is assumed that the profiles of all the speakers involved in the input speech are included in $D$. Note that, as long as this assumption holds, the speaker inventory may include irrelevant speakers’ profiles.

### 2.2. Model architecture

The E2E SA-ASR model can be decomposed into the ASR block and speaker identification block, which are interdependent. Here, we will briefly review the model architecture. Interested readers can refer to [16] for more details.

The ASR block is similar to the conventional attention encoder-decoder-based ASR and represented as follows.

$$H^{enc} = \{h_1^{enc}, ..., h_T^{enc}\} = \text{AsrEncoder}(X),$$

$$u_n = \text{DecoderRNN}(y_{n-1}, c_{n-1}, u_{n-1}).$$

$$c_n, \alpha_n = \text{Attention}(u_n, \alpha_{n-1}, H^{enc}),$$

$$o_n = \text{DecoderOut}(c_n, u_n, d_n).$$

Given the acoustic input $X$, an AsrEncoder module firstly converts $X$ into a sequence, $H^{enc}$, of embeddings for ASR (Eq. (1)). At each decoder step $n$, DecoderRNN module updates the decoder state $u_n$ given the previous token $y_{n-1}$, previous context vector $c_{n-1}$, and previous decoder state $u_{n-1}$ (Eq. (2)). Then, Attention module generates attention weight $\alpha_n = (\alpha_{n,1}, ..., \alpha_{n,T})$ and the context vector $c_n$ as a weighted sum of $H^{enc}$ (Eq. (3)). Finally, DecoderOut module calculates the output distribution $o_n$ given $c_n, u_n$, and the weighted speaker profile $d_n$ (Eq. (4)). Note that $d_n$ is computed from the speaker inventory $D$ in the speaker identification block, and will be explained in the next paragraph. The posterior probability of token $i$ (i.e. $i$-th token in the dictionary) at the $n$-th decoder step is represented as

$$P(y_n = i | y_{1:n-1}, s_{1:n}, X, D) \sim o_{n,i}.$$

where $o_{n,i}$ represents the $i$-th element of $o_n$.

On the other hand, the speaker identification block is represented as follows.

$$H^{spk} = \{h_1^{spk}, ..., h_T^{spk}\} = \text{SpeakerEncoder}(X).$$

$$p_n = \sum_{t=1}^T \alpha_{n,t} h_t^{spk},$$

$$q_n = \text{SpeakerQueryRNN}(p_n, y_{n-1}, q_{n-1}),$$

$$\beta_n = \text{InventoryAttention}(q_n, D),$$

$$d_n = \sum_{k=1}^K \beta_{n,k} d_k.$$

Firstly, the SpeakerEncoder module converts $X$ into a sequence, $H^{spk}$, of embeddings representing the speaker features of the input $X$ (Eq. (5)). At every decoder step $n$, we reuse the attention weight $\alpha_n$ from the ASR block and apply them over $H^{spk}$ to extract an attention-weighted average, $p_n$, of the speaker embeddings (Eq. (7)). The SpeakerQueryRNN module then generates a speaker query $q_n$ given $p_n$, the previous output $y_{n-1}$, and the previous speaker query $q_{n-1}$ (Eq. (8)). Next, InventoryAttention module estimates attention weight $\beta_n = \{\beta_{n,1}, ..., \beta_{n,K}\}$ over profiles in $D$ given the speaker query $q_n$ (Eq. (9)). The attention weight $\beta_{n,k}$ can be seen as a posterior probability of person $k$ speaking the $n$-th token given all the previous tokens and speakers as well as $X$ and $D$, i.e.,

$$P(s_n = k | y_{1:n-1}, s_{1:n-1}, X, D) \sim \beta_{n,k}. \quad (11)$$

Finally, the weighted speaker profile $\bar{d}_n$ is calculated as the weighted average of the profiles in $D$ (Eq. (10)). As explained earlier, $\bar{d}_n$ is inputted to the ASR block to achieve speaker-biased token estimation (Eq. (4)).

By using Eqs. (5) and (11), we can represent the joint posterior probability of token $Y$ and speaker $S$ given input $X$ and $D$ as follows.

$$P(Y, S | X, D) = \prod_{n=1}^{N} \left\{ P(y_n | y_{1:n-1}, s_{1:n}, X, D) \times P(s_n | y_{1:n-1}, s_{1:n-1}, X, D)^\gamma \right\}. \quad (12)$$

Here, $\gamma$ is a scaling parameter for the speaker estimation probability introduced in [16].

### 2.3. SA-MMI Training

In [16], all network parameters are optimized with SA-MMI training, where the joint posterior probability $P(Y, S | X, D)$ is maximized over training data. In the form of the loss function to be minimized, SA-MMI training is represented as follows.

$$L_{SA-MMi} = \sum_r - \log P(Y_r, S_r | X_r, D_r). \quad (13)$$

Here, $r$ is a training sample index. Terms $X_r, D_r, Y_r$, and $S_r$ represent the input speech, speaker inventory, reference token sequence and reference speaker identity sequence of the $r$-th training sample, respectively. In the SA-MMI training, we set a scaling parameter $\gamma$ to 0.1 per [16].

### 2.4. Decoding

An extended beam search algorithm is used for decoding with the E2E SA-ASR. In the conventional beam search, each hypothesis contains estimated tokens accompanied by the posterior probability of the hypothesis. In addition to these, a hypothesis for the proposed method contains speaker estimation $\bar{\beta}_{n,k}$. Each hypothesis expands until $\langleeos\rangle$ is detected, and the estimated tokens in each hypothesis are segmented by $\langle sc \rangle$ to form multiple utterances. For each utterance, the average of $\bar{\beta}_{n,k}$ values, including the last token corresponding to $\langle sc \rangle$ or $\langle eos \rangle$, is calculated for each speaker. The speaker with the highest average $\bar{\beta}_{n,k}$ score is selected as the predicted speaker of that utterance. Finally, when the same speaker is predicted for multiple utterances, those utterances are concatenated to form a single utterance. Note that, in our experiment, we applied length normalization [29] when comparing the posterior probability of the hypotheses in the beam. Namely, we used the normalized score $P(Y, S | X, D)^{1/L}$ for beam search, where $|Y|$ is the length of sequence $Y$. 
3. SA-MBR TRAINING

In this paper, we propose to train the E2E SA-ASR model parameters by minimizing the expected SA-WER over training data. The proposed loss function to be minimized is represented as follows.

\[
\mathcal{L}^{\text{SA-MBR}} = \sum_{r} \tilde{\mathcal{E}}_r,
\]

where \(\tilde{\mathcal{E}}_r\) is the expected number of errors based on SA-WER calculation for \(r\)-th training sample:

\[
\tilde{\mathcal{E}}_r = \sum_{B(Y,S) \in \mathcal{B}(X_r,D_r)} \hat{P}(Y,S|X_r,D_r) \mathcal{E}(Y,S;Y_r,S_r).
\]

Here, \(\mathcal{B}(X,D)\) represents the \(N\)-best hypotheses obtained by the extended beam search (described in Section 2.4) given input audio \(X\) and speaker inventory \(D\). The function \(\mathcal{E}\) computes the number of errors in hypotheses \(\{Y,S\}\) given reference \(\{Y_r,S_r\}\) according to the error counting of SA-WER calculation. Specifically, we calculate the edit distance between the hypothesis and the reference of each speaker and sum them up over all speakers appearing in \(S\) and \(S_r\).

\[
P(Y,S|X,D) \text{ is a normalized posterior over the } N\text{-best hypotheses as,}
\]

\[
\hat{P}(Y,S|X_r,D_r) = \frac{P(Y,S|X_r,D_r)}{\sum_{Y',S' \in \mathcal{B}(X_r,D_r)} P(Y',S'|X_r,D_r)^{1/|Y'|}^{1/|Y'|}}.
\]

where \(P(Y,S|X_r,D_r)\) is computed by Eq. (12) with \(\gamma = 1.0\). Note that, as we do in the beam search, we apply the length normalization for each raw posterior to compute the normalized posterior.

For each \(N\)-best hypotheses \(\{Y,S\} \in \mathcal{B}(X_r,D_r)\), the error w.r.t. \(o_{n,i}\) is calculated as follows if and only if the estimated token at the \(n\)-th position of \(\hat{Y}\) is token \(i\).

\[
\frac{\delta \mathcal{L}^{\text{SA-MBR}}}{\delta \log(o_{n,i})} = \frac{1}{|Y|} \hat{P}(\hat{Y}, \hat{S}|X_r,D_r) \{ \mathcal{E}(\hat{Y}, \hat{S}; Y_r, S_r) - \tilde{\mathcal{E}}_r \}.
\]

Otherwise, the error w.r.t. \(o_{n,i}\) is zero. The error w.r.t. \(\beta_{n,k}\) is calculated by using exactly the same expression. Namely, if and only if the estimated speaker at the \(n\)-th position of \(\hat{S}\) is speaker \(k\),

\[
\frac{\delta \mathcal{L}^{\text{SA-MBR}}}{\delta \log(\beta_{n,k})} = \frac{1}{|Y|} \hat{P}(\hat{Y}, \hat{S}|X_r,D_r) \{ \mathcal{E}(\hat{Y}, \hat{S}; Y_r, S_r) - \tilde{\mathcal{E}}_r \}.
\]

Otherwise, the error w.r.t. \(\beta_{n,k}\) is zero.

In the training, the model parameters are first trained with the SA-MMI training until they are fully converged. Then, the well-trained model parameters are further trained updated by SA-MBR training. Note that, in past literature of MBR training, it was often reported that combining other training criterion such as cross entropy criterion during MBR-training improved the accuracy [19, 25]. However, we didn’t observe any improvement by combining SA-MMI training with SA-MBR training in our preliminary experiments.

4. EXPERIMENTS

4.1. Evaluation settings

4.1.1. Evaluation data

We evaluated the effectiveness of the proposed method by using simulated multi-speaker signals originally from the LibriSpeech corpus [30]. Following the Kaldi [31] recipe, we used the 960 hours of LibriSpeech training data (“train\_960”) for model learning, the “dev\_clean” set for hyper-parameter tuning, and the “test\_clean” set for testing.

Our training data were generated as follows. For each utterance in train\_960, randomly chosen \((S-1)\) train\_960 utterances were added after being shifted by random delays, where \(S\) was varied from 1 to 3. When mixing the audio signals, the original volume of each utterance was kept unchanged, resulting in an average signal-to-interference ratio of about 0 dB. As for the delay applied to each utterance, the values were randomly chosen under the constraints that (1) the start times of the individual utterances differed by 0.5 sec or longer and that (2) every utterance in each mixed audio sample had at least one speaker-overlapped region with other utterances. For each training sample, speaker profiles were generated as follows. First, the number of profiles was randomly selected from 5 to 8. Among those profiles, \(S\) profiles were for the speakers involved in the overlapped speech. The utterances for creating the profiles of these speakers were different from those constituting the input overlapped speech. The rest of the profiles were randomly extracted from the other speakers in train\_960. Each profile was extracted by using 10 utterances.

The development and evaluation sets were generated from dev\_clean or test\_clean, respectively, in the same way as the training set except that constraint (1) was not imposed. Therefore, multiple utterances were allowed to start at the same time in our evaluation. Also, each profile was extracted from 2 utterances (15 sec on average) instead of 10. We tuned hyper parameters by using the development set, and report the result on the evaluation set.

4.1.2. Evaluation metrics

We evaluated the model with respect to speaker error rate (SER), WER, and SA-WER. SER is defined as the total number of speaker-misattributed utterances generated by the model divided by the number of reference utterances. All possible permutations of the hypothesized utterances were examined by ignoring the ASR results, and the one that yielded the smallest number of errors (including the speaker insertion and deletion errors) was picked for the SER calculation. Similarly, WER was calculated by picking the best permutation in terms of the number of word errors (i.e., speaker labels were ignored). Finally, SA-WER was calculated by comparing the ASR hypothesis and the reference transcription of each speaker. We used SA-WER as the primary evaluation metric.

4.1.3. Model settings

In our experiments, we used a 80-dim log mel filterbank, extracted every 10 msec, for the input feature. We stacked 3 frames of features and applied the model to the stacked features. For the speaker profile, we used a 128-dim d-vector [27], whose extractor was separately trained on VoxCeleb Corpus [32, 33]. The d-vector extractor consisted of 17 convolution layers followed by an average pooling layer, which was a modified version of the one presented in [24].

The AsrEncoder consisted of 5 layers of 1024-dim bidirectional long short-term memory (BLSTM), interleaved with layer normalization [55]. The DecoderRNN consisted of 2 layers of 1024-dim unidirectional LSTM, and the DecoderOut consisted of 1 layer of 1024-dim unidirectional LSTM. We used a conventional location-aware content-based attention [56] with a single attention head. The SpeakerEncoder had the same architecture as the d-vector extractor except for not having the final average pooling layer. The SpeakerQueryRNN consisted of 1 layer of 512-dim unidirectional LSTM.
Table 1. SER (%), WER (%), and SA-WER (%) for E2E SA-ASR trained with SA-MMI and SA-MBR. The number of profiles per test audio was 8. Each profile was extracted by using 2 utterances (15 sec on average). No LM was used in the evaluation.

| Training   | Data type | 1-speaker     | 2-speaker-mixed | 3-speaker-mixed | Total    |
|------------|-----------|---------------|-----------------|-----------------|----------|
|            | SER WER   | SA-WER        | SER WER         | SA-WER          | SER WER  |
| SA-MMI     | 0.2       | 4.2           | 4.5             | 2.5             | 8.6      |
| SA-MMI →SA-MBR | 0.3     | 4.1           | 4.5             | 2.4             | 8.3      |
| 9.9        | 10.2      | 20.1          | 23.1            | 6.0             | 13.6     |
| 9.5        | 9.0       | 18.5          | 20.7            | 5.3             | 12.7     |
| 15.6       | 14.2      | 23.1          | 26.7            | 12.7            | 23.1     |

Table 2. Speaker counting accuracy (%) before and after SA-MBR training.

| Actual # of Speakers | Estimated # of Speakers (%) | in Test Data | 1 | 2 | 3 | ≥4 |
|----------------------|-----------------------------|--------------|---|---|---|----|
| SA-MMI               |                            |              | 1 | 99.96 | 0.04 | 0.00 | 0.00 |
| → SA-MBR            |                            |              | 2 | 97.44 | 0.00 | 0.00 | 0.00 |
|                      |                            |              | 3 | 74.73 | 0.00 | 0.00 | 0.00 |
|                      |                            |              | 1 | 99.96 | 0.04 | 0.00 | 0.00 |
|                      |                            |              | 2 | 97.71 | 0.00 | 0.00 | 0.00 |
|                      |                            |              | 3 | 78.32 | 0.04 | 0.00 | 0.00 |

Table 3. SA-WER (%) without or with the length normalization.

| Length normalization | SA-MMI → SA-MBR |
|----------------------|-----------------|
|                      |                 |
|                      | 16.1            |
|                      | 15.6            |
|                      | 14.2            |

We used 16k subwords based on a unigram language model [37] as a recognition unit. We applied volume perturbation to the mixed audio to increase the training data variability. Note that we applied neither an additional language model (LM) nor any other forms of data augmentation for simplicity.

As explained in Section 3, we firstly optimized the model parameters based on the SA-MMI training until the model was fully converged. The SA-MMI training was performed by using exactly the same settings reported in [16]. All parameters were updated by using an Adam optimizer with a learning rate of $2 \times 10^{-5}$. We used 8 GPUs, each of which worked on 6k frames of minibatch. We report the results of the dev-clean-based best models found after 160k of training iterations. As with [17], we initialized the parameters of AsrEncoder, Attention, DecoderRNN, and DecoderOut by using pre-trained SOT-ASR parameters [28] while initializing the SpeakerEncoder parameters by using those of the d-vector extractor.

After the SA-MMI training, we further updated the model parameters based on the SA-MBR training. The entire network was updated based on $L^{(SA-MBR)}$ by using an Adam optimizer with a learning rate of $4 \times 10^{-7}$. N-best hypotheses were generated on the fly, and we used the N-best size of 4 unless otherwise stated. Each minibatch consisted of 8 samples, and we report the results of the best model for the development set within 20k of training iterations.

4.2. Evaluation results

4.2.1. SA-MMI v.s. SA-MBR

Table 1 shows the SER, WER, and SA-WER of the E2E SA-ASR model based on the SA-MMI training and SA-MBR training. In this experiment, we used the extended beam search with a beam size of 16. As shown in the table, we observed a 9.0% relative SA-WER reduction (15.6% to 14.2%) in total. We observed that the SA-MBR training was especially effective for the most difficult test case, i.e. 3-speaker mixed test case. Because SA-MBR training optimizes the model parameters to reduce total SA-WER, it would be reasonable that the accuracy of the most error-prone case was mainly improved. It is also important that 1- and 2-speaker test cases were also improved or at least on par with the SA-MMI training.

We also evaluated the impact of SA-MBR training on the speaker counting accuracy. The result is shown in Table 2. We observed a significant improvement in the speaker counting accuracy for the 3-speaker-mixed case from 74.73% to 78.32%. Note that we didn’t apply any heuristics to improve the speaker counting accuracy of the model. In SA-MMI training, the mis-recognition of the speaker change symbol in the transcription is counted as only one error. However, in SA-MBR training, the mis-recognition of the speaker change symbol could be more severely penalized since it usually causes a large SA-WER degradation. We think this is the reason of significant improvement of speaker counting by the SA-MBR training.

We also examined the effect of the length normalization, the results of which are shown in Table 3. In case of not using the length normalization, we excluded it both in training (N-best generation and the normalized posterior calculation) and decoding. As shown in the table, the length normalization had a critical role to achieve the good improvement by SA-MBR training. It would be because our training data had very large variance of sequence length due to the variety of number of speakers.

4.2.2. Effect of beam size in training and decoding

To further analyze the SA-MBR training, we investigated the effect of the beam size of SA-MBR training and decoding. Firstly, we evaluated the SA-MBR training with different N-best sizes. For decoding, we fixed the beam size to 16. The results are shown in Table 4. As can be seen in the table, a larger N-best size did not necessarily lead to better result, and the best result was obtained with $N = 4$.

We also evaluated the effect of the beam size in decoding. The result is shown in Table 5. We used the model trained by SA-MBR with the 4-best hypotheses. As shown in the table, the improvement of SA-MBR training became more prominent when we used a larger beam size for decoding.

5. CONCLUSIONS

In this paper, we proposed SA-MBR training where the parameters of the E2E SA-ASR model are trained to minimize the expected SA-WER over the training data. The proposed SA-MBR training achieved 9.0% of relative SA-WER reduction compared with the SA-MMI model in LibriSpeech-based experiments.
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