ANCHORED SPEECH RECOGNITION WITH NEURAL TRANSDUCERS

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ABSTRACT

Neural transducers have achieved human level performance on standard speech recognition benchmarks. However, their performance significantly degrades in the presence of cross-talk, especially when the primary speaker has a low signal-to-noise ratio. Anchored speech recognition refers to a class of methods that use information from an anchor segment (e.g., wake-words) to recognize device-directed speech while ignoring interfering background speech. In this paper, we investigate anchored speech recognition to make neural transducers robust to background speech. We extract context information from the anchor segment with a tiny auxiliary network, and use encoder biasing and joiner gating to guide the transducer towards the target speech. Moreover, to improve the robustness of context embedding extraction, we propose auxiliary training objectives to disentangle lexical content from speaking style. We evaluate our methods on synthetic LibriSpeech-based mixtures comprising several SNR and overlap conditions; they improve relative word error rates by 19.6% over a strong baseline, when averaged over all conditions.

Index Terms— RNN-T, background speech suppression, anchored speech recognition

1. INTRODUCTION

Neural transducers (using RNNs or transformers) [1] have become the dominant modeling technique in end-to-end on-device speech recognition [2, 3, 4, 5], since they allow streaming transcription similar to CTC models [6, 7, 8], while still retaining conditional dependence, like attention-based encoder-decoders (AEDs) [9, 10]. Although they have shown state-of-the-art performance on several benchmarks [11], they still suffer from degradation caused by interference due to background speech and noise [12, 13]. Recent studies have used context audio for implicit speaker and environment adaptation of transducer models [14].

In this paper, we focus on the problem of suppressing background speech using explicit auxiliary information (often referred to as target speech extraction/recognition in literature [15]). Such auxiliary information is usually provided in the form of speaker embeddings (e.g., d-vectors in VoiceFilter-Lite [16, 17]) or enrollment utterances (e.g., SpeakerBeam [18, 19]). However, these strategies require the target speaker to be enrolled with the device, which may not always be feasible or desirable from a privacy perspective. In contrast, anchored speech recognition refers to a class of methods that use information from an anchor segment (such as a wake-word) to recognize device-directed speech. By relying only on the anchor segment and extracting the auxiliary information on-the-fly, these models bypass the need for a speaker enrollment stage. The idea was first proposed in the context of hybrid ASR systems [20] and later extended to AED models using a speaker encoder network to extract auxiliary information from the anchor segment [21].

We investigate anchored speech recognition to improve the performance of transducers in the presence of background speech. In particular, we add a tiny auxiliary network to extract context information from the anchor segment, and use it to bias the transducer towards the primary speaker. In order to disentangle speaking style from lexical content in the context embedding, we explore several auxiliary training objectives. We conduct controlled evaluations on LibriSpeech mixtures, where our models show relative word error rate (WER) improvements of 19.6%, on average, compared to an Emformer baseline trained with background augmentation.

2. ANCHORED SPEECH RECOGNITION

2.1. Preliminary: ASR with neural transducers

Given an utterance \( x = (x_1, \ldots, x_T) \), where \( x_t \in \mathbb{R}^d \) denotes audio features, transducers model the conditional probability of the output sequence \( y = (y_1, \ldots, y_U) \), where \( y_u \in \mathcal{Y} \) denotes output units such as graphemes or word-pieces. This is achieved by marginalizing over the set of all alignments \( a \in \mathcal{A} \), where \( \mathcal{Y} = \mathcal{Y} \cup \{\phi\} \) and \( \phi \) is called the blank label. Formally,

\[
P(y|x) = \sum_{a \in \mathcal{A}^{-1}(y)} P(a|x),
\]

Fig. 1: Overview of transducer-based anchored speech recognition.
where $B$ is a deterministic mapping from an alignment $a$ to an output sequence $y$. As shown in the box in Fig. 1, transducers parametrize $P(a|x)$ with an encoder, a prediction network, and a joiner. The encoder maps $x$ into hidden representations $f_{1:T}$, while the prediction network maps $y$ into $g_{1:T}$. The joiner combines the outputs from the encoder and the prediction network to compute logits $z_{t,u}$ which are fed to a softmax function to produce a posterior distribution over $y$.

2.2. Biasing with the anchor segment

Under the anchored speech recognition framework, we assume that the model is deployed on a device where each utterance is preceded by an anchor segment (e.g., “Hey Assistant”) that is relatively clean. We extract context information from this anchor segment and use it to guide the transcription of the main utterance. Assuming that the anchor segment is the first $T_w$ frames of the utterance $x$, we modify equation (1) as

$$P(y|x) = \sum_{a \in B^{T_w}} P(a|x,T_w).$$

(2)

Next, we describe our proposed methods for biasing the transducer using a jointly trained auxiliary network to provide context information from the anchor segment.

3. HOW TO BIAS THE TRANSDUCER?

Interference due to the presence of background speech may result in two categories of errors: (i) substitution/deletion errors caused by overlapping speech, and (ii) insertion errors from transcribing the undesired background speech. We propose two complementary methods for tackling these issues.

3.1. Encoder biasing

We extract a context embedding $c = \text{Aux}(x_{1:T_w}) \in \mathbb{R}^D$ from the anchor segment and use it to bias the encoder of the transducer, i.e., $f_{1:T} = \text{Enc}(x,c)$. By adding the anchor segment extra information to extract primary speech (or suppress overlapping background speech) in the hidden representations $f_t$. This context information encourages the model to focus on speech with acoustics similar to the anchor segment, potentially reducing both type (i) and (ii) errors.

In our experiments, we use encoders which consist of time-stacked log Mel filterbanks (with 4x subsampling) fed into an Enformer [22]. By slight abuse of notation, let $x_{1:T}$ refer to this down-sampled feature sequence (instead of the original input sequence). We found that a strategy of concatenating $c$ to the time-stacked features followed by a non-linear projection works well\(^1\). Formally, this means that the input to the Enformer (originally $x_t$) is now given as $x'_t = \text{ReLU}(x_t^T e^T W_{\text{proj}})$, where $W_{\text{proj}} \in \mathbb{R}^{(d+D) \times d}$ is a projection matrix.

3.2. Joiner gating

In principle, encoder biasing should be sufficient for suppressing background speech in regions where the main speaker is inactive.

\(^1\)We tried other biasing techniques such as dynamic layer normalization [23] and context-aware query in the Enformer, but they did not perform well.

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\(2\)The term “gating” here is not used in the standard sense of multiplicative gating, although that can be considered potential future work.

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Fig 2: (a) Feature reconstruction and (b) VIC regularization as auxiliary objectives. FR uses frame-aligned chenone labels obtained from an HMM-based aligner, whereas VIC does not require such labels.

However, we found that it still allows some cross-talk to leak, particularly in low SNR conditions. To alleviate the potential insertion error, we propose joiner gating which explicitly boosts the prediction of silence in non-target regions\(^2\). Let $x_{1:t}$ denote a small sub-segment of the input $x$ at time $t$ with some left and right context. We obtain $b_t = \text{Aux}(x_{1:t})$ and compute a per-frame similarity bias $b_t = \varphi(c, h_t)$, where $\varphi : \mathbb{R}^D \times \mathbb{R}^D \rightarrow (0,1)$ is a function that increases monotonically with increasingly similar inputs. This bias is added to the non-blank label logits of the joiner output, and its complement is added to the blank logit. Formally, the logits after gating are given as

$$z_{t,u} = \begin{cases} z_{t,u} + (1 - b_t) & \text{if } \bar{y}_u = \phi, \\ z_{t,u} + b_t & \text{otherwise}. \end{cases}$$

(3)

Here, we used $\varphi(c, h_t) = \sigma\left(\frac{c - h_t}{\|c\| + \|h_t\|}\right)$, where $\sigma(\cdot)$ is the sigmoid function. Since we use function merging [8] to compute RNN-T loss directly from the logits, and since layer-norm is applied on the encoder and predictor outputs, it is both tractable and reasonable to add the bias to the logits instead of to the softmax output.

4. DISENTANGLING STYLE FROM CONTENT

Training the model to recognize only the anchored speech should incentivize the auxiliary network to extract only speaking style characteristics from the anchor segment. Nevertheless, we employ auxiliary objective functions (shown in Fig. 2) to further suppress lexical content information in the context embedding $c$.

4.1. Feature reconstruction

Let $s \in \mathbb{Z}^{T_w}$ denote the frame-level estimated chenone (or senone) sequence corresponding to the anchor segment $x_{1:T_w}$. The context embedding $c$ and the chenone labels $s$ are used to reconstruct the anchor segment using a feature reconstruction network similar to [24] (shown in the yellow box in Fig. 2(a)), and the network is jointly trained using mean squared error:

$$L_{\text{FR}} = \text{MSE}(x,\bar{x}), \quad \bar{x} = g_{\text{FR}}(s,c;\Theta_{\text{FR}}),$$

(4)

where $g_{\text{FR}}$ is the feature reconstruction (FR) network.

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4.2. VIC regularization

Alternatively, we can penalize the auxiliary network for encoding lexical content by ensuring that the context embeddings generated from different parts of the anchor segment are similar. This penalty is enforced through a non-contrastive self-supervised learning technique called VIC (variance-invariance-covariance) regularization, originally proposed in [25] and shown in Fig. 2(b).

Given a batch of anchor segments, we split it into two parts \((X, X')\) by length and obtain the corresponding context embeddings \((C, C') \in \mathbb{R}^{N \times D}\). An expander network projects them into higher dimensional representations \((Z, Z')\). The VIC regularization objective is then given as

\[
\mathcal{L}_{\text{VIC}} = \gamma (v(Z) + v(Z')) + \mu s(Z, Z') + \nu (c(Z) + c(Z'))
\]

where the terms are defined as

\[
v(Z) = \frac{1}{D} \sum_{j=1}^{D} \max(0, 1 - \sqrt{\text{var}(Z_j)}),
\]

\[
s(Z, Z') = \text{MSE}(Z, Z'), \quad \text{and} \quad c(Z) = \frac{1}{D} \sum_{i \neq j} |C(Z)|_{i,j}^2,
\]

and \(C(Z)\) is the covariance matrix for \(Z\). The invariance term pulls the representations for the two halves closer, while the variance term prevents them from collapsing to a constant. The covariance term ensures that the dimensions are decorrelated so as to increase information content. The overall training objective is then given as

\[
\mathcal{L} = \mathcal{L}_{\text{RNNT}} + \mathcal{L}_{\text{VIC}}.
\]

Unlike the feature reconstruction loss, this method does not require frame-level chenone labels during training.

5. EXPERIMENTAL SETUP

5.1. Data

To enable a granular evaluation, we created synthetic mixtures (dev and test) using LibriSpeech [26] utterances (clean + other) as follows. For each (main) utterance, we randomly sampled another (background) utterance and cropped/tiled it to the length of the main utterance. The two were then mixed with a specific SNR (chosen from \{1, 5, 10, 20, 50\} dB) and shifts (chosen from \{0, 50, 100\}%), as shown in Fig. 3.

This simulation resulted in 15 evaluation sets (5 SNR conditions \(\times 3\) shift conditions), each containing 5564 and 5556 utterances for the dev and test sets, respectively. Although we are unable to show results using real device-directed speech due to internal privacy regulations, the synthetic mixtures are still meaningfully similar. For training, we randomly mixed utterances from the 960h train set on-the-fly with 50% probability, a fixed SNR of 10 dB, and a randomly sampled shift between 0% and 100%. Since LibriSpeech does not contain an explicit anchor segment, we fixed the first 2 seconds of the utterance as the anchor. The 0% shift condition illustrates the scenario when the anchor segment is also noisy. During training, the wake-word segment was extracted from the clean or mixed utterances with 80% and 20% probability, respectively.

5.2. Baselines

We compared our models against 20-layer (base) and 24-layer (large) Emformer-transducer [22] trained with background speech augmentation as described above. Additionally, since our model uses the anchor segment to suppress background speech, we implemented simple anchor mean baselines: (i) subtraction (AMS), based on [20], where the feature-level mean of the anchor segment is subtracted from the utterance, and (ii) concatenation (AMC), where the mean is appended to the input features, followed by an affine transformation\(^3\).

5.3. Implementation details

All implementations used an in-house extension of the PyTorch-based [27] fairseq toolkit. We used 80-dimensional log Mel filterbank features that are first projected to 128, then spliced and stacked to 512 dimensions, reducing the sequence length by 4x. The encoder consists of Emformer blocks with 8 attention heads and a 2048-dimensional feed-forward layer. The prediction network contains three 512-dimensional LSTM layers with layer-norm and dropout. Both the encoder and predictor outputs are projected to 1024 dimensions before passing to an additive joiner, which contains a linear layer with \(|\mathcal{Y}| = 4097\) output BPE units. We fixed context embedding dimensionality \(D = 256\) for all our experiments. For joiner gating, we used 4-frame subsegments with left and right contexts of 32 and 4 frames, respectively. We trained with an alignment-restricted transducer loss where the alignments were obtained using an HMM-based aligner [28]. The auxiliary loss weights were set as: \(\lambda_{\text{FR}} = 0.1, \gamma = 1.0, \mu = 1.0, \text{ and } \nu = 0.05\) (see § 6.3 for a discussion). For feature reconstruction, the chenone labels were obtained using a bootstrapped hybrid ASR system [29].

The output dimensionality of the expander network in VIC regularization was set to \(D = 1024\). All hyperparameters were tuned on the dev set. The models were trained on 32 GPUs for 120 epochs with a warm-up of 10k steps, using the Adam optimizer [30].

6. RESULTS & DISCUSSION

6.1. Performance of baseline models

Table 1 compares our proposed method against the baselines on the synthetic test set. The Emformer models trained with background augmentation achieved reasonable WERs for high SNR conditions, but failed miserably on low SNR. For example, Emformer-base (A) obtained 65.7% on the 100% shift with SNR of 1 dB. Insertion errors caused by trailing background were the biggest contributors in this case, e.g., contributing 77.5% of the overall WER.

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\(^3\)AMS can be considered a special case of AMC when the transformation matrix is \([I_d]_d - I_d\)^T, where \(I_d\) is the identity matrix.

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Fig. 3: Illustration of mixture simulation for all shift conditions (and arbitrary SNR conditions).
AMS improved WERs for low SNR conditions; for example, 65.7% → 11.2% on 1 dB, 100% shift. However, it led to significant regressions for 0% shift and high SNR cases (shown in red), indicating that it is not robust to noisy anchor segments. This is undesirable since such conditions may constitute a major fraction of use cases in device-directed speech. Using concatenation (AMC) instead of subtraction alleviated this issue, improving the relative WER reduction (WERR) from 10.1% to 14.5%, on average.

6.2. Effect of biasing methods

Both encoder biasing and joiner gating provided WER improvements over λ, resulting in average WERR of 15.8% and 18.7%, respectively. Unlike AMS, they did not degrade performance on 0% shift condition, indicating that they are robust to noisy anchor segments. Joiner gating helped most on low SNR, high shift conditions by reducing insertion errors. To analyze the effect of joiner gating, we computed the per-frame similarity scores, b_t, for the dev set for 1 dB SNR and 100% shift condition, as shown in Fig. 4. Since the shift is 100%, the first half of all utterances contains target speech, and the second half contains background speech (see Fig. 3). As such, we should observe higher values of b_t for the first half (shown in blue) than the second half (shown in orange). As expected, we see a clear separation between the distribution of similarity scores assigned to the target speech vs. the background speech, which validates our conjecture. Training with VIC regularization further added a degree of robustness to the model — the resulting system obtained average WERR of 19.6%, outperforming all other systems. Averaged across all SNRs, this model provides WERR of 19.3% and 36.1% on the 50% and 100% shift cases, respectively, compared to λ.

Table 1: Comparison of proposed models with baselines on LibriSpeech-based test set, for different SNR and shift conditions, in terms of WER (%). Our main baseline is the Emformer-base model trained with background speech augmentation, denoted by (A). The last column shows relative WER reduction (WERR) compared to λ, averaged across all conditions. WERs in green are 5% better, and those in red are 5% worse, than λ, in relative terms. 1Extra parameters are only required during training.

| Model                     | Size(M) | Shift = 0% | Shift = 50% | Shift = 100% | WERR |
|---------------------------|---------|------------|-------------|--------------|------|
|                           |         | 1 5 10 20 50 | 1 5 10 20 50 | 1 5 10 20 50 |      |
| Emformer-base (20L) (A)   | 76.7    | 50.28 18.42 10.12 7.82 7.27 | 28.40 11.46 7.88 7.13 7.02 | 65.71 38.74 14.85 7.32 7.03 | 0.0% |
| Emformer-large (24L)      | 89.4    | 49.36 17.03 9.65 7.56 7.02 | 22.14 9.99 7.46 6.98 6.80 | 55.09 29.35 11.24 7.00 7.05 | 9.3% |
| Anchor mean sub.(AMS) [20]| 76.7    | 59.16 27.48 15.00 8.21 7.93 | 10.02 8.30 7.46 7.15 7.71 | 11.24 8.92 7.90 7.69 7.69 | 10.1% |
| Anchor mean concat. (AMC) | 76.8    | 50.45 16.95 9.55 7.64 7.21 | 17.09 9.06 7.51 7.06 7.00 | 42.74 19.83 8.03 6.99 6.99 | 14.5% |
| Encoder biasing           |         |            |             |              |      |
| + joiner gating           | 77.2    | 52.65 19.23 9.82 7.59 7.12 | 13.20 8.67 7.57 7.12 6.92 | 37.46 16.84 7.59 6.93 6.92 | 15.8% |
| ++ VIC-Regularization†     | 78.9    | 52.26 17.38 9.49 7.43 7.04 | 11.46 8.40 7.43 6.97 6.86 | 29.15 13.30 7.26 6.88 6.88 | 19.6% |

6.3. Effect of auxiliary objectives

Table 2 shows ablation studies investigating the impact of auxiliary objectives, as evaluated on the dev set. We see that although VIC regularization is an unsupervised technique, it outperforms feature reconstruction, particularly on very low SNR cases (1 dB). This may be because it encourages the context embedding to be more robust to changes in lexical content, pauses, etc. since we force the two halves of the anchor to have similar representations regardless of their chenone labels. Regarding VIC coefficients, we found that (i) ν was largely inconsequential; and (ii) high values of γ and μ improved WERs for high shift cases, but degraded 0% shift (noisy anchor), indicating that the model was learning to rely too much on the context embedding. Despite their effectiveness, combining the two objectives, FR and VIC, did not provide any additional gains. As a result, we used the model trained with VIC regularization to evaluate the test set (shown in Table 1).

7. CONCLUSION

We investigated anchored speech recognition for improving neural transducers in the presence of background speech. A context embedding extracted from the anchor segment was used to bias the model using two complementary biasing methods at the encoder and joiner modules. We also proposed auxiliary training objectives to disentangle style from content in the context embedding. Our methods significantly improved the performance over a strong Emformer-transducer trained with background augmentation, providing average WER reduction of 19.6% on LibriSpeech mixtures, while being robust to noisy anchor segments.

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