Cleanformer: A microphone array configuration-invariant, streaming, multichannel neural enhancement frontend for ASR

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Abstract

This work introduces the Cleanformer, a streaming multichannel neural based enhancement frontend for automatic speech recognition (ASR). This model has a conformer-based architecture which takes as inputs a single channel each of raw and enhanced signals, and uses self-attention to derive a time-frequency mask. The enhanced input is generated by a multichannel adaptive noise cancellation algorithm known as Speech Cleaner, which makes use of noise context to derive its filter taps. The time-frequency mask is applied to the noisy input to produce enhanced output features for ASR. Detailed evaluations are presented with simulated and re-recorded datasets in speech-based and non-speech-based noise that show significant reduction in word error rate (WER) when using a large-scale state-of-the-art ASR model. It also will be shown to significantly outperform enhancement using a beamformer with ideal steering. The enhancement model is agnostic of the number of microphones and array configuration and, therefore, can be used with different microphone arrays without the need for retraining. It is demonstrated that performance improves with more microphones, up to 4, with each additional microphone providing a smaller marginal benefit. Specifically, for an SNR of 6dB, relative WER improvements of about 80% are shown in both noise conditions.

Index Terms: automatic speech recognition, noise robust ASR, adaptive noise cancellation, noise context, speech enhancement, ideal ratio mask

1. Introduction

Robustness of automatic speech recognition in the presence of noise has made significant gains in recent years. This can be largely attributed to the adoption of neural network based acoustic models [1, 2, 3, 4] and large scale training [5, 6, 7] coupled with improved data augmentation strategies [8, 9, 10]. However, conditions like reverberation, significant background noise, and competing speech still pose a formidable challenge for ASR models [11, 12]. Consequently, speech enhancement frontends for ASR that specifically address background noise have been widely studied [13].

A particular challenge is the multi-talker scenario, where more than one person is speaking. This is especially true for smart speakers where it is desired to respond to one of the speech sources and not the others whether they are from television, radio, or other people. In such a scenario, the desired speaker needs to be determined and isolated from the other sources. There have been several proposed solutions aimed at separating the multiple speakers using a single microphone [14, 15, 16] or taking advantage of the spatial information provided by a microphone array [17, 18]. However, these are often designed for separating multiple voices rather than identifying one target. Techniques that target a particular speaker often make use of speaker-id [19] or the noise context [20].

Proposed enhancement solutions sometimes combine neural modeling with signal processing algorithms. A commonly used technique in such situations is a beamformer [21]. Beamformers have long seen success in suppressing noise while allowing the desired signal to pass through while minimizing distortion [22, 23]. A time-frequency mask can be used to estimate statistics of a desired source to steer a beamformer[24, 25]. This can be very effective when the desired speaker is in the presence of non-speech noise but challenges may be encountered when deciding between one or more voices. Recent work has shown promising results with signals enhanced by signal processing techniques used as input to enhancement models. For example, [26] and [27] use multiple beamformed signals as input to a neural network while [28] iterates between a beamformer and network. In the smart speaker environment, latency is a paramount issue. The desired speaker needs to be identified quickly so that appropriate filtering can be configured enabling ASR to be performed in a streaming manner. Some of these techniques have been shown to have difficulties operating under such constraints [29, 30].

A signal processing technique that has had some enhancement success is an adaptive noise cancellation algorithm called Hotword Cleaner [31, 32] which has shown significant improvement in hotword recognition in noisy environments. In this work, the underlying algorithm will be re-purposed to processing query speech, and will be referred to as Speech Cleaner.

In this paper, we introduce a conformer-based enhancement frontend, called Cleanformer. This input to this model is a single channel of raw audio input and a signal channel of enhanced...
output that has been processed by Speech Cleaner. Together these input signals are used to estimate a time-frequency mask to help isolate the desired source. Although it is designed to operate with a multi-channel array, Cleanformer itself is agnostic to the number of microphones in the array or their configuration. As the array size changes, the only difference is in the number of microphone channels that Speech Cleaner receives as input; the output of Cleanformer, which is what Cleanformer receives as input, is always a single enhanced channel. We will show Cleanformer significantly improving word error rate (WER), often by greater than 50% relative WER improvement in the presence of speech-based or non-speech based noise. Also shown is that increasing the number of microphones improves performance with each additional microphone provided diminished gains.

The rest of the paper is organized as follows. In Section 2 the conformer-based Cleanformer enhancement model is presented. The experimental setup is described in Section 3 while Section 4 details the results. Conclusions are listed in Section 5.

2. Cleanformer

Cleanformer is a multichannel neural frontend enhancement model for speech recognition whose overall architecture is shown in Figure 1. This model takes as input a single channel of raw noisy features and a single channel of enhanced features. It estimates a time-frequency mask designed to filter out unwanted signals. The mask is applied to the noisy input features to produce estimates of the clean input features. These features serve as the input to an ASR model.

2.1. Speech Cleaner

The enhanced input features used in this model are generated using an adaptive noise cancellation algorithm known as Speech Cleaner. It is briefly described below; for additional details, readers are referred to [31, 32]. In those previous works, this algorithm had been applied to hotword detection; here, it is applied directly to the target query in addition to the hotword. Because Speech Cleaner functions on device, it can make use of the signal that occurs directly before the hotword which serves as the noise context. As the desired speaker is expected to be the one speaking the hotword, we can assume with high confidence that the desired speaker is present during this time segment. In the period of time directly before the hotword, it is assumed that the desired speaker is not speaking. Therefore, statistics of the noise can be estimated during this time.

Speech Cleaner operates on STFT-processed input signals and functions independently for each frequency. A finite impulse response (FIR) filter with a tapped delay line of length \( L \) is applied to the signals from all microphones except one, which is arbitrarily selected here to be the zeroth microphone. The summed output of these is subtracted from the received signal at the first microphone:

\[
Z(k, n) = Y_0(k, n) - \sum_{m=1}^{M-1} U_m(k)^H Y_m(k, n), \tag{1}
\]

where,

\[
Y_m(k, n) = [Y_m(k, n), \ldots Y_m(k, n-(L-1))]^T, \tag{2}
\]

is a vector of time delayed STFT-processed input corresponding to frames \( n \) through \( n-(L-1) \) for microphone \( m \) and frequency \( k \),

\[
U_m(k, n) = [U_{m,0}(k, n), U_{m,1}(k, n), \ldots U_{m,L-1}(k, n)]^T \tag{3}
\]

is a vector of the filter coefficients to be applied to microphone input \( m \) at frequency \( k \). The filter coefficients are specified as those that minimize the expectation of the power of the output over all frames:

\[
\hat{U}_m(k) = \arg \min_{U_m(k)} E_n [|Z(k, n)|^2]. \tag{4}
\]

The minimization is accomplished through adaptation during the noise context, when it is assumed there is no desired speech present. When the hotword is detected, the filter coefficients are frozen and those coefficients, \( \hat{U}_m^f(k) \), are then applied to the query to produce the enhanced output:

\[
\hat{Z}(k, n) = Y_0(k, n) - \sum_{m=1}^{M-1} \hat{U}_m^f(k)^H Y_m(k, n). \tag{5}
\]

This enables to the filter to cancel the noise but not the desired signal, which was not present during adaptation. In all of the examples presented here the filter length \( L \) used in the cleaner is 3 and a recursive least squares (RLS) algorithm is used for adaptation.

2.2. Conformer

Cleanformer is based on the conformer architecture. The conformer layer used here is based on [4] which introduced minor changes from the original conformer [33]. Each layer consists of a half-step feed-forward module, a convolution module, a multi-head self-attention module and another half-step feed-forward module. This differs from the original Conformer in that the order of the convolution and the self-attention have been swapped, thereby eliminating the need for relative positional embedding in the self-attention module. This is because the convolution module implicitly provides positional information as it aggregates content from the neighboring context.

The convolutional block is comprised of point-wise convolution, gated linear units, 1-D depth-wise convolution, and layer normalization. Residual connections are present between each block. Layer normalization takes place before each processing block as well as after the final half-step feed-forward module.

2.3. Implementation Details

2.3.1. Features

The enhancement frontend takes as input one channel of raw audio and the single channel output of the Speech Cleaner. Each of these inputs is converted to the 128-dimensional log-mel domain using a window size of 32ms with a step size of 10ms. Four of these frames from each of the two sources are stacked at the input with a 30ms step.

2.3.2. Target

The ideal ratio mask (IRM) [34] is used as the training target. It is computed in the mel-spectral space using reverberant speech and reverberant noise, with the assumption that speech and noise are uncorrelated: \( M(n, f) = X(n, f) / N(n, f) \). \( X \) and \( N \) represent, respectively, mel filterbank magnitudes of the reverberant speech and reverberant noise. \( n \) and \( f \) correspond to the indices of the frame and mel frequency bin. Using the IRM as the target enables enhancement to be performed directly in the feature space eliminating the need to reconstruct the waveform.
2.3.3. Loss
A combination of two losses is used during training. The first loss is a spectral loss that is a combination of $\ell_1$ and $\ell_2$ losses between the IRM and the estimated IRM:

$$
L = \sum_{n,f} (|M(n, f) - \hat{M}(n, f)| + (M(n, f) - \hat{M}(n, f))^2). 
$$

The second loss is an ASR-based loss. It is computed by passing log filterbank energies (LFBE) of the target utterance and those produced by the enhancement frontend to a pre-trained end-to-end ASR model. As in [35], the loss is computed using only the ASR model encoder. The $\ell_2$ distance between the encoder output of the target features and that of the enhanced features are calculated. The ASR model encoder is kept fixed during training in order to decouple it from the enhancement model.

2.3.4. Inference
During inference, the estimated IRM is scaled and floored. This will reduce the amount of speech distortion in the masked output at the expense of diminished noise suppression. Because the ASR model is sensitive to speech distortion and non-linear processing, this can have an impact on performance [36].

The enhanced estimate of the clean mel spectrogram $\hat{X}$ is obtained by applying the scaled and floored estimated mask to the noisy mel spectrogram $Y$ via pointwise multiplication:

$$
\hat{X}(t, f) = Y(t, f) \odot \max(\hat{M}(t, f), \beta)\alpha. 
$$

where $\alpha$ and $\beta$ are the exponential mask scalar and mask floor, respectively. In all experiments, $\alpha$ is set to 0.5 and $\beta$ to 0.01. The output is log compressed, $\log \hat{X}$, and passed to the ASR model.

2.3.5. Model Architecture
The enhancement frontend consists of 4 conformer layers each having 256 units. The feed-forward module has 1024 dimensions and the kernel size in the convolution module is 15. The self-attention modules apply masked attention with 8 heads. Each frame attends to 31 frames in the past. Only past frames are used so as to enable a streaming model. After the final conformer layer, a single fully-connected layer with sigmoid activation is utilized. The model has approximately 6.5M parameters.

2.3.6. ASR Model
A recurrent neural transducer model with LSTM-based encoder layers [37] is used for ASR evaluations. This model was pretrained independently of the Cleanformer using approximately 400K hours of anonymized and hand-transcribed English utterances from domains like VoiceSearch, Telephony and YouTube. Data augmentation has been applied during training to simulate SNR values between 0 and 30 dB and reverberation such that $\tau_{60}$, the time for the signal to decay by 60 dB, ranges from 0 to 900ms. This model takes as input log-mel features of the same characteristics as those produced by the Cleanformer.

3. Experimental Settings

3.1. Datasets

3.1.1. Training
The datasets used for training are based on LibriSpeech [38] and internal vendor-collected utterances. LibriSpeech is comprised of 281K utterances while the vendor-collected set contains 1916K utterances. A room simulator [8] is used to add reverberation and noise to these utterances and to model reception by a 3-microphone triangular array. Room configurations with $\tau_{60}$ reverberation times ranging from 0ms to 900ms are used. Noise is taken from internally collected sets in conditions like cafes, kitchens and cars as well as from the freely available noise sources Getty1 and YouTube Audio Library2. Also, to simulate multi-talker conditions, randomly selected speech from the training sets is used as noise. The signal-to-noise (SNR) ratio ranges from $-10$ dB to 30 dB. Each query is prefaced with six seconds of noise to serve as the noise context. Each of the original utterances is used to generate multiple noisy utterances with different noise and room configurations to increase the diversity of the training set.

3.1.2. Evaluation
Two groups of noisy sets are used for evaluation. The first is obtained by processing the test-clean subset of LibriSpeech with our room simulator. The output mimics the same three microphone triangular array configuration used during training. Separate sets are generated corresponding to speech-based and non-speech based noise. The noise comes from hold-out noise segments from the training set. These sets are mixed at three SNR levels, -5, 0, and 5 dB, with 2500 utterances each.

The second group used in this study was re-recorded in a living-room lab with no sound treatment. Desired speech and noise were recorded separately using a four microphone array. The first two microphones were spaced 7.1cm apart on the top of the device while the third and fourth were on the front and side, respectively. The queries were played through a speaker from 7 different positions at a height of approximately 1.5m at a distance of 4m from the microphone array. From each location 100 different queries were played at a volume such that they were approximately 40 dB over ambient room noise. Noise was separately played through a loudspeaker from the same 7 locations. Two types of noise were recorded: speech-based from a movie and non-speech based environmental noise. They were mixed at five different SNR values, $-12$, $-6$, 0, 6, and 12 dB, such that there was 6 sec of noise before the start of the query.

4. Results

Table 1 presents results using the simulated three microphone LibriSpeech sets with added non-speech environmental noise. Three SNR levels are explored as well as a clean case with no noise added to the reverberant signal. Cleanformer results are shown along with other techniques for comparison. The baseline uses just our ASR model with no enhancement frontend. For non-speech noise, the relative error rate improvements are 61% at $-5$ dB, 51% at 0 dB and 34% at 5 dB while performance is maintained for the clean case. Also listed are results where the single channel output of the Speech Cleaner is fed directly into the ASR model. This has comparable gains to the Cleanformer at low SNRs; however, for the clean case, it produces a degradation. The Speech Cleaner incorporates no constraint to control speech distortion which is limited only by having the noise.

Table 1: WER comparisons with proposed Cleanformer on the LibriSpeech set with added reverberation and non-speech noise.

| WER (%) | Non-Speech | 0 dB | 5 dB |
|---------|------------|------|------|
| Baseline | 36.5       | 22.5 | 14.0 |
| Beamformer | 31.8       | 19.1 | 12.3 |
| Speech Cleaner | 14.3       | 12.4 | 11.4 |
| Cleanformer | 14.2       | 11.0 | 9.3  |

1https://www.gettyimages.com/about-music
2https://youtube.com/audiolibrary
Table 2: WER comparisons with proposed Cleanformer on the LibriSpeech set with reverberation and speech-based noise.

| LibriSpeech | Speech -5 dB | Speech 0 dB | Speech 5 dB |
|-------------|--------------|-------------|-------------|
| Baseline    | 65.3         | 44.8        | 28.0        |
| Beamformer  | 50.4         | 39.4        | 25.0        |
| Speech Cleaner | 24.0        | 20.3        | 18.4        |
| Cleanformer | 20.4         | 16.4        | 14.1        |

adaptation occur during the noise context. At higher SNRs, the degradation caused by the speech distortion outweighs the benefit of noise reduction. Cleanformer is able to avoid this degradation because the self-attention mechanism serves to determine the relevance of the raw audio and the noise-reduced but possibly distorted Speech Cleaner output.

The final comparison is the output of a beamformer fed directly into the ASR model. A common technique is to use a neural network to produce time-frequency masks [24, 25, 29] which are used to estimate the statistics of the desired speech and noise. These, in turn, are used to produce beamformer coefficients. Here, as an upper bound on performance, the desired speech and noise statistics are used directly to specify beamformer coefficients via a principal eigenvector steering mechanism[30]. At lower SNRs, the beamformer shows improvement over the baseline but lags behind Speech Cleaner and Cleanformer. The single coefficient per microphone of the beamformer cannot match the noise cancellation ability of the FIR filter of the Speech Cleaner. However, in the clean case, beamformer maintains the WER of the baseline as speech distortion is limited by the specification of the steering vector.

Results for the simulated LibriSpeech sets with added speech-based noise are in Table 2. Both noise types are challenging at these low SNRs; however, the speech-based noise is more so. The Cleanformer model again shows significant improvement over the baseline across the range with relative error rate improvements of 69% at -5dB, 63% at 0dB and 50% at 5dB. Speech Cleaner provided significant benefit with a relative error rate improvement of 55% at 0dB, but failed to match the Cleanformer. The ideal beamformer again showed gains but lagged considerably behind both Cleanformer and Speech Cleaner.

Experiments were conducted using a single channel beamformed output as an input instead of, or in addition to the Speech Cleaner input. However, it was found that neither case a significant impact.

In Table 3, results are shown for the internal re-recorded dataset with environmental noise. WERs are presented for seven different noise levels. Clean represents the case of no added noise but still incorporates the reverberation incurred during the re-recording process as well as any ambient noise. Along with Cleanformer, performance is tabulated for our baseline ASR model without an enhancement frontend.

Table 3: WER for the proposed Cleanformer with different array sizes with re-recorded data and non-speech noise.

| SNR | Baseline | Cleanformer Number of Mics
|-----|----------|-----------------------------|
|     |          | 2  | 3  | 4  |
| Clean| 3.5      | 3.5 | 3.3 | 3.4 |
| 12   | 6.3      | 4.9 | 4.5 | 4.4 |
| 6    | 11.6     | 5.3 | 4.6 | 4.7 |
| 0    | 24.1     | 8.7 | 5.4 | 4.9 |
| -6   | 40.3     | 18.6| 9.9 | 8.5 |
| -12  | 52.7     | 34.9| 20.5| 17.0|

For the Cleanformer, results are shown using different numbers of microphones in the array ranging from 2 to 4. It is important to note that the underlying Cleanformer model does not need to be aware of the number of microphones used or of the configurations of the microphone in the array. It still receives one channel of raw input and one channel of enhanced input from the Cleaner. The model was only trained using the three channel triangular array data described previously and was not retrained for these cases. The only adjustment is the number of channels of input that the Speech Cleaner receives.

The Cleanformer provides significant benefit across the range of SNRs considered with the benefit being more significant at the lower values considered. Each additional microphone provides a performance boost but the relative amount diminishes as the number increases. Consider the case for -6 dB SNR. The two channel Cleaner provides a 54% relative WER improvement over the baseline. Increasing to three microphones provided a 47% relative improvement over the two microphone case and going from three to four microphones resulted in a 14% relative WER gain. Also note that in the clean case, the Cleanformer does not adversely impact performance.

Table 4 lists results for the internal re-recorded dataset with speech-based noise. Again, the Cleanformer provides significant improvements across the considered SNR range with each additional microphone providing increased but diminishing returns. Considering again the -6dB case, a 64% relative WER improvement is provided by the Cleanformer with two channels versus the baseline. The relative improvement from 2 to 3 microphones is 44% and while 3 to 4 microphones yields 19%.

5. Conclusion

This work introduced the Cleanformer, a streaming, array configuration-invariant neural frontend enhancement model for ASR. Cleanformer, which takes a single channel of raw input and a single channel of enhanced input, showed relative WER improvements often greater than 50% across SNR levels for simulated and re-recorded data sets in both speech-based and non-speech based noise. Improvement increased with the number of microphones used in the array with diminishing returns for each additional microphone. There was no adverse impact in the absence of added noise. The model can be used without regard to the array size or configuration and does not need to be retrained for different arrays. The Cleanformer represents a promising alternative architectural direction for combining signal processing and machine learning, demonstrating better applicability to streaming applications than the commonly used mask-steered beamformer.

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