A deep complex network with multi-frame filtering for stereophonic acoustic echo cancellation

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Abstract

In hands-free communication system, the coupling between the loudspeaker and the microphone will generate echo signal, which can severely impair the quality of communication. Meanwhile, various types of noise in the communication environment further destroy the speech quality and intelligibility. It is hard to extract the near-end signal from the microphone input signal within one step, especially in low signal-to-noise ratios. In this paper, we propose a multi-stage approach to address this issue. On the one hand, we decompose the echo cancellation into two stages, including linear echo cancellation module and residual echo suppression module. A multi-frame filtering strategy is introduced to benefit estimating linear echo by utilizing more inter-frame information. On the other hand, we decouple the complex spectral mapping into magnitude estimation and complex spectra refine. Experimental results demonstrate that our proposed approach achieves stage-of-the-art performance over previous advanced algorithms under various conditions.

Index Terms: deep learning, stereophonic acoustic echo cancellation, multi-stage

1. Introduction

In hands-free audio and video communication system, the acoustic coupling between the loudspeaker and the microphone will generate echo signal, which will severely impair the quality of communication. Stereophonic systems are becoming more and more widely used as they can provide the listener with spatial information compared with single-channel system \cite{11}. Traditional stereophonic acoustic echo cancellation (SAEC) algorithms use adaptive filter to identify the echo path to cancel acoustic echo \cite{2}. However, these algorithms are affected by the correlation between stereo far-end signals, resulting in a non-unique problem \cite{3,4}. Thus, the echo cancellation performance degrades rapidly when the echo paths between the loudspeakers and the microphones change.

To solve the non-unique problem, a series of decorrelation methods have been proposed to reduce the correlation between far-end signals as a preprocessor before SAEC algorithm \cite{5}. Benesty et al. \cite{6} proposed to add a small nonlinearity into each channel. Romoli et al. \cite{7} utilized the missing fundamental phenomenon to decorrelate the stereophonic channels by suppressing the fundamental frequency component of one far-end signal frame by frame. In order to achieve better performance, a hybrid decorrelation methods have been proposed in \cite{8}, where an improved sinusoidal phase modulation was applied in the high-frequency band and a pitch-driven sinusoidal injection scheme with a simplified binaural masking model was adopted in the low-frequency band. Although these decorrelation methods can mitigate the nonuniqueness to a certain extent, almost all of them will degrade the audio quality and stereophonic spatial perception to some degree. And these SAEC algorithms can usually only remove some linear echo, thus some post-processing methods are often combined with these SAEC algorithms to suppress residual echo \cite{9,10}. Yang et al. \cite{11} proposed a stereophonic acoustic echo suppression (SAES) approach without preprocessing, which employed the Wiener filter in the short-time Fourier transform (STFT) to suppress the echo signal directly instead of identifying echo path. A modified SAES algorithm has been proposed by Lee et al. \cite{12} by incorporating the spectral and temporal correlations in the STFT domain, which utilized the adjacent time-frequency (TF) bins of far-end signals. These traditional algorithms usually perform well in white noise environment while susceptible to non-stationary noise. And their performance is also limited in the presence of double talk and the rapid change of the echo path.

Recently, with the rapid development of deep learning, deep neural network (DNN)-based monophonic acoustic echo cancellation (MAEC) algorithms have become a research hotspot. They can be roughly classified into two categories. One is to combine DNN with traditional adaptive filter for echo cancelation and DNN is used as a residual echo suppressor \cite{13,14}. The other is to directly suppress the acoustic echo end-to-end using DNN \cite{15,16}. Deep learning-based MAEC methods are robust to double-talk situation and can better suppress acoustic echo in non-stationary noise environments. The performance of deep learning-based MAEC methods in real-world environment is verified in AEC challenge \cite{17,18}, which open large real recording datasets for researchers to test their proposed algorithm in practical situation.

Deep learning has not received much attention in SAEC research. A convolutional recurrent network (CRN)-based SAES algorithm has been first proposed in \cite{19}, which use deep neural network to directly suppress stereophonic acoustic echo from microphone input signal without decorrelation. And a CRN-based complex SAES with a two-stage approach was proposed in \cite{20}. The echo signal is estimated in the first stage and the near-end speech is achieved in the second stage by using estimated signal and microphone input signal as the inputs for network. Meanwhile, the input features and training targets used in the network are the complex spectral of signals, which can recover the phase information of the near-end speech. The two-stage complex CRN method performs much better than a single CRN model in both single-talk and double situations and the deep learning-based SAES methods can avoid the nonunique problem, thus it is not necessary to decorrelate the far-end signals.

However, we found that the two-stage complex CRN algo-
A DNN-based multi-frame filtering structure is used to preprocess the linear echo and a stacked network is used to suppress residual echo and noise. Secondly, we estimate the complex spectrum of near-end speech by decomposing amplitude and phase in two networks, respectively. A network is used to estimate the magnitude spectrum of near-end speech firstly and then, the other network is used to complement the missing phase information.

The remainder of this paper is organized as follows. Section 2 introduces the signal model and formulates the problem. The overall framework of the proposed algorithm is described in Section 3. The experimental setup is presented in Section 4. In Section 5, the results and analysis are given to validate the performance of the proposed framework. Finally, some conclusions are drawn in Section 6.

2. Signal Model

The diagram of a typical SAEC system is illustrated in Fig. 1. The receiving room is on the left while the transmission room is on the right. Without loss of generality, we choose only one microphone in the receiving room to form one of the microphone input signal is then given by:

\[ y_1(n) = x_1(n) * h_{11}(n) + x_2(n) * h_{12}(n) + s_1(n) + v_1(n) \]

\[ = d_1(n) + s_1(n) + v_1(n) \]

where * denotes linear convolution, \( n \) denotes the discrete time index, \( d_1(n) \) is the generated echo signal, \( s_1(n) \) is the near-end speech signal, and \( v_1(n) \) represents the additive noise signal. The goal of SAEC is to estimate the near-end signal \( \hat{s}_1(n) \) from \( y_1(n) \).

3. Algorithm description

3.1. Network Structure

The overall scheme of the proposed system is shown in Fig. 2(a). In this paper, we denote the \{Y_{1R}, Y_{1L}\}, \{X_{1R}, X_{1L}\}, and \{Y_{2R}, Y_{2L}\} as the real and imaginary parts of \( y(n), x_1(n) \) and \( x_2(n) \), respectively. \( Y_{1k}, \{X_{1k}, \{X_{2k}\} \) are the magnitude spectra of \( y(n), x_1(n) \) and \( x_2(n) \), respectively. \( \tilde{Y}_{1k} \) is the output of SLE-Net with residual echo and noise. \( \{\hat{S}_{SRN_{1L}}, \hat{S}_{SRN_{1R}}\} \) are the real and imaginary parts of estimated near-end speech processed by SRN-Net and \( \hat{S}_{SRN_{1k}} \) is its magnitude spectrum. The real and imaginary parts of the final estimated near-end speech processed by CSR-Net and \( \hat{S}_{CR_{1k}} \), respectively. These variables are all omitted \((k,l)\) for convenience, where \( l \) and \( k \) are the frame index and frequency index, respectively.

The proposed architecture consists of three modules, namely suppressing linear echo network (SLE-Net), suppressing residual echo and noise network (SRN-Net), and complex spectrum refining network (CSR-Net). Each module is a CRN structure, which includes encoder, decoder, and two gated recurrent unit (GRU) layers. The motivation of the proposed algorithm is based on two points. One is that we divide stereophonic echo suppression into two steps. The SLE-Net is used to estimate the linear echo part while the SRN-Net is responsible for suppressing residual echo and background noise. The other is that we decompose the complex spectrum mapping into magnitude spectrum estimation and complex spectrum refine. The output of SRN-Net is the magnitude spectrum of the near-end speech. Then a coarse complex spectrum is obtained by coupling the estimated magnitude spectrum and the phase of microphone input signal. In CSR-Net, both the coarse complex spectrum and original microphone input signal are used as inputs to generate the residual complex spectrum, which is added to the coarse spectrum to obtain a refined counterpart. On the one hand, the estimated magnitude spectrum reduces the solution space of the complex spectrum optimization network. On the other hand, the step-by-step approach can improve the performance in complex acoustic scenarios.

The details of SLE-Net is presented in Fig. 2(b). We draw on the principle of traditional adaptive filtering-based SAEC methods. The SLE-Net uses the complex spectra of \( y(n), x_1(n), \) and \( x_2(n) \) as input features with a dimension of \([6, T, F]\), where \( T \) and \( F \) denote the size in the time and frequency axes, respectively. The outputs are the cross spectra of estimated RIR. In Fig. 2(b), \{\( H_{11R}, H_{11L}\) and \( H_{12R}, H_{12L}\)\} denote the real and imaginary parts of \( h_{11} \) and \( h_{12} \), respectively. And \( \{H_{1R}, H_{1L}, H_{2R}, H_{2L}\} \) are the corresponding estimations of \{\( H_{11R}, H_{11L}, H_{12R}, H_{12L}\)\}. The estimated RIRs are combined with far-end signals in complex spectrum domain to estimate the linear echo \( \{\hat{D}_{1R}, \hat{D}_{1L}\} \) as follows:

\[ \hat{D}_{1R} = f_{MF}(\hat{H}_{11R}, X_{1R}) - f_{MF}(\hat{H}_{11L}, X_{1L}) + f_{MF}(\hat{H}_{12R}, X_{2R}) - f_{MF}(\hat{H}_{12L}, X_{2L}), \]

\[ \hat{D}_{1L} = f_{MF}(\hat{H}_{11R}, X_{1L}) + f_{MF}(\hat{H}_{11L}, X_{1R}) + f_{MF}(\hat{H}_{12R}, X_{2L}) + f_{MF}(\hat{H}_{12L}, X_{2R}), \]
where \( f_{MF} \) denotes the multi-frame filter. There is a strong temporal correlation between adjacent frames of echo signal. So we propose to use a multi-frame structure \([21]\) to estimate linear echo signal. The dimensions of \( \{ L, T, F \} \) are all \([ L, T, F ] \), where \( L \) is the number of channels and it also represents the filter length. Take \( f_{MF}(\tilde{H}_{11R}, X_{1R}) \) as an example, the calculation of \( f_{MF} \) is given as:

\[
f_{MF}(\tilde{H}_{11R}, X_{1R})(l, k) = \sum_{q=0}^{L-1} \tilde{H}_{11R}(q, l, k) \cdot X_{1R}(l - q, k).
\]

\[ (4) \]

Then subtract the estimated echo from the microphone input signal \( \{ Y_{1R}, Y_{11} \} \) to obtain the outputs \( \{ Y_{1R}, Y_{11} \} \) with residual echo and noise.

As shown in Fig. (c), the inputs of SRN-Net are the magnitude spectra of original microphone input signal, far-end signals, and the output of SLE-Net with a dimension of \([4, T, F] \). The output is the estimated magnitude spectrum of near-end speech \( |\hat{S}_{1k}| \).

Fig. (d) illustrates the detailed stream of CSR-Net. First, \( |\hat{S}_{1k}| \) is combined with the phase of \( y_1(n) \) to obtain a coarse estimated complex spectrum of near-end speech \( \hat{S}_{1k}^{CSR} \). Second, \( \hat{S}_{1k}^{CSR} \) and \( |\hat{S}_{1k}| \) are concatenated with \( \{ Y_{1R}, Y_{11} \} \) as the inputs of CSR-Net. Two decoders in CSR-Net output the real and imaginary parts of the residual complex spectrum of near-end speech, respectively, denoted by \( \hat{S}_{1k}^{CSR} \) and \( \hat{S}_{11}^{CSR} \). The estimated near-end speech is obtained by adding \( \hat{S}_{1k}^{CSR} \) and \( \hat{S}_{11}^{CSR} \):

\[
\hat{S}_{1k} = \hat{S}_{1k}^{CSR} + \hat{S}_{1k}^{SRN}, \quad \hat{S}_{11} = \hat{S}_{11}^{CSR} + \hat{S}_{11}^{SRN}. \tag{5}
\]

\[ 3.2. \text{Loss function} \]

The output of SLE-Net is a finite-length estimated RIR, which is regraded as a hidden mapping in this paper. The training of network includes two stages. In the first stage, the parameters of SRN-Net and SLE-Net are updated by using a same cost function, which is the mean square error (MSE) of the magnitude spectrum of near-end speech:

\[
\mathcal{L}_{SLE-SRN} = \left( |\hat{S}_{1k}^{SRN}| - |S_{1k}| \right)^2 = \left( M_1^{SRN} |\hat{S}_{1k}^{SRN}| - |S_{1k}| \right)^2. \tag{7}
\]

where \( M_1^{SRN} \) is the output of last layer in the decoder of SRN-Net and \( |S_{1k}| \) is the magnitude spectrum of near-end speech \( s_1(n) \). Here we use a signal approximation (SA) method to estimate the magnitude spectrum of near-end speech.

After the training of SLE-Net and SRN-Net, in the second stage, the complex spectrum of near-end speech is used to train...
Table 1: Evaluation results of different methods in terms of PESQ, ESTOI, and ERLE at different SNRs. BOLD denotes the best result in each case.

| Noise  | Model      | PESQ 10dB | PESQ 15dB | PESQ 20dB | PESQ 25dB | PESQ 30dB | ESTOI 10dB | ESTOI 15dB | ESTOI 20dB | ESTOI 25dB | ESTOI 30dB | ERLE   |
|--------|------------|-----------|-----------|-----------|-----------|-----------|-----------|-----------|-----------|-----------|-----------|--------|
|        |            | 2.21      | 2.89      | 3.02      | 3.11      | 3.28      | 0.58      | 0.79      | 0.82      | 0.82      | 0.82      | 0.82   |
| Home   | None       | 2.35      | 3.16      | 3.23      | 3.35      | 3.44      | 0.67      | 0.89      | 0.92      | 0.93      | 0.93      | 0.93   |
|        | TS-CRN     | 2.40      | 3.17      | 3.25      | 3.36      | 3.44      | 0.74      | 0.92      | 0.94      | 0.94      | 0.94      | 0.94   |
|        | TS-CCRN    | 2.45      | 3.21      | 3.31      | 3.41      | 3.48      | 0.79      | 0.93      | 0.94      | 0.94      | 0.94      | 0.94   |
|        | SLE-SRN    | 2.50      | 3.27      | 3.33      | 3.43      | 3.49      | 0.82      | 0.93      | 0.94      | 0.94      | 0.94      | 0.94   |
|        | Proposed   | 2.55      | 3.35      | 3.42      | 3.50      | 3.56      | 0.88      | 0.95      | 0.96      | 0.96      | 0.96      | 0.96   |
| Babble | None       | 2.63      | 3.27      | 3.33      | 3.43      | 3.50      | 0.84      | 0.96      | 0.97      | 0.97      | 0.97      | 0.97   |
|        | TS-CRN     | 2.72      | 3.31      | 3.37      | 3.46      | 3.52      | 0.90      | 0.99      | 0.99      | 0.99      | 0.99      | 0.99   |
|        | TS-CCRN    | 2.76      | 3.35      | 3.41      | 3.50      | 3.56      | 0.92      | 1.00      | 1.00      | 1.00      | 1.00      | 1.00   |
|        | SLE-SRN    | 2.79      | 3.39      | 3.45      | 3.54      | 3.60      | 0.94      | 1.01      | 1.01      | 1.01      | 1.01      | 1.01   |
|        | Proposed   | 2.85      | 3.40      | 3.46      | 3.54      | 3.60      | 0.96      | 1.02      | 1.02      | 1.02      | 1.02      | 1.02   |

The CSR-Net, while the parameters of SLE-Net and SRN-Net are refined to get better optimization. The loss function in second stage can be given as:

$$\mathcal{L}_{CSR} = \mathcal{L}_{CSR} + 0.1 \mathcal{L}_{SLE-SRN},$$

$$\mathcal{L}_{CSR} = 0.5 \left( \hat{S}_1 - S_1 \right)^2 + 0.5 \left( \hat{S}_2 - S_2 \right)^2.$$ (9)

4. Experimental Results

4.1. Experimental setup

The widely used TIMIT dataset [22] is chosen to evaluate the performance of proposed approach. 120 pairs of speakers are randomly selected as far-end and near-end speakers. Each speaker has ten sentences. For each far-end speaker, three utterances are randomly selected and concatenated to form a far-end signal. An utterance from a near-end speaker is randomly chosen and extended to the same length as that of the far-end signal by zero-padding both in front and in rear. The RIRs are generated using the image method [23]. Three sizes of near-end and far-end rooms are selected, which are 4, 3, 3 m, [6, 4, 3] m, and [8, 7, 3] m. The Reverberation time is set to be 0.3 s, 0.6 s, and 0.9 s. The distance between loudspeakers microphones are set to be 2.0 m and 0.4 m, respectively. The distance between each speaker position and the center of microphones is set to be [0.3, 0.7, 1.0] m. The near-end speech is mixed with the echo signals at a signal-to-echo ratio (SER) randomly chosen from [0, 0.5, 1.0, 1.5] dB. 881 non-stationary noises are used as background noise to be mixed with near-end speech and generated echo signal at SNR=[10, 15, 20, 25, 30]. The total amount of training dataset is about 100 hours. We randomly choose 80% of these mixtures for training and the remaining 20% are chosen for validation.

All of these signals are sampled at 16 kHz. Take the microphone signal $y(n)$ as an example, we use a 320-point (20 ms) hamming window to segment the microphone signal $y(n)$ into a set of time frames with 50% overlap in consecutive frames. Then the 320-point STFT is applied, leading to a 161-dimensional spectral feature in each frame. The encoders of three modules have five layers with the number of channels are [8, 16, 32, 64, 128] for each layer in turn. Accordingly, the number of channels of decoders are [64, 32, 16, 8, 1]. The kernel size and stride of encoders and decoders are (1, 3) and (1, 2) in the time and frequency axes except that the kernel size is set to (3, 3) in SLE-Net to utilize the inter-frame information to benefit the estimation of linear echo. The networks are optimized by Adam algorithm. The learning rate is set to $3 \times 10^{-4}$ and the mini-batch size is 16 at the utterance level.

We compare the proposed algorithm with the advanced deep learning-based SAEC methods, which are the two-stage CRN model with magnitude spectrum (TS-CRN) and complex spectrum (TS-CCRN) [20]. In the proposed approach, the filter length $L$ is set to 10. And to evaluate the performance of decomposing amplitude and phase strategy, we let the SLE-Net and SRN-Net to directly estimate the complex spectrum of near-end speech and set to be a comparison approach, namely SLE-SRN. In single-talk periods, ERLE is used as performance metric to evaluate the echo attenuation, while PESQ [24] and ESTOI [25] are used to evaluate the speech quality and intelligibility in double-talk periods.

4.2. Results and Analysis

The performance of different methods in terms of PESQ, ESTOI, and ERLE are shown in Table 1. The background noises are Home noise from QUT-NOISE dataset and Babble noise from Noise-92 dataset. One can see that the proposed algorithm has achieved best performance in all conditions, especially in lower SNR situation. The ERLE scores of TS-CCRN method are lower than TS-CRN, which means that the mapping complex spectrum directly does not benefit the echo suppression. Introducing multi-frame structure improves the ERLE score by about 3 dB, and the proposed algorithm has further improved
the ERLE score by approximately 7 dB. The ESTOI results of TS-CRN and TS-CCRN are almost the same. However, the ESTOI score difference between the proposed algorithm and TS-CCRN is about 0.03 in Home noise situation and 0.05 in Babble noise situation.

The spectrograms of the microphone input signal, near-end signal, and enhanced signals are plotted in Fig. It is shown that there are still some residual echo in the enhanced signal processed by TS-CRN. Compared with TS-CCRN and SLE-SRN, the proposed method can better suppress the residual echo while ensuring speech quality and intelligibility, especially in lower frequency band.

5. Conclusions

In this paper, we proposed a multi-frame filtered SAES algorithm with decoupling amplitude and phase. The linear echo is first estimated using SLE-Net with a multi-frame structure and the residual echo and signal is processed by SRN-Net. In order to better extract the phase information of the near-end speech, the complex spectrum of near-end speech is estimated by decoupling its amplitude and phase recovery. The experimental results show that the proposed algorithm significantly improves the speech quality and intelligibility in double-talk situation and the amount of echo reduction in single-talk situation.

6. References

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