MULTI-CHANNEL AND MULTI-MICROPHONE ACOUSTIC ECHO CANCELLATION USING A DEEP LEARNING BASED APPROACH

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ABSTRACT

Building on the deep learning based acoustic echo cancellation (AEC) in the single-loudspeaker (single-channel) and single-microphone setup, this paper investigates multi-channel AEC (MCAEC) and multi-microphone AEC (MMAEC). We train a deep neural network (DNN) to predict the near-end speech from microphone signals with far-end signals used as additional information. We find that the deep learning approach avoids the non-uniqueness problem in traditional MCAEC algorithms. For the AEC setup with multiple microphones, rather than employing AEC for each microphone, a single DNN is trained to achieve echo removal for all microphones. Also, combining deep learning based AEC with deep learning based beamforming further improves the system performance. Experimental results show the effectiveness of both bidirectional long short-term memory (BLSTM) and convolutional recurrent network (CRN) based methods for MCAEC and MMAEC. Furthermore, deep learning based methods are capable of removing echo and noise simultaneously and work well in the presence of nonlinear distortions.

Index Terms— Acoustic echo cancellation, deep learning, multi-channel AEC, multi-microphone AEC, nonlinearity

1. INTRODUCTION

Acoustic echo cancellation (AEC) is the task of removing undesired echoes that result from the coupling between a loudspeaker and a microphone in a communication system \cite{1}. Modern hands-free communication devices are usually equipped with multiple microphones and loudspeakers. The availability of additional devices also elevates the need for enhanced sound quality and realism, which can hardly be satisfied with single-channel AEC. Therefore, it is necessary to design AEC for multiple loudspeakers and/or microphones, which leads to the study of MCAEC and MMAEC. MCAEC and MMAEC present additional challenges and opportunities compared to single-channel AEC and have received considerable attention recently.

Multi-channel AEC refers to the setup with at least two loudspeakers or channels (stereophonic sound). Although conceptually similar, MCAEC is fundamentally different from single-channel AEC and a straightforward generalization of single-channel AEC does not result in satisfactory performance because of the non-uniqueness problem \cite{2}. This problem is due to the correlation between loudspeaker signals. As a result, the convergence of adaptive technique could be degraded and the echo paths cannot be determined uniquely \cite{3}. Many methods have been proposed to circumvent this problem \cite{3,4,5,6,7}, among which coherence reduction methods are most commonly used. Such methods, however, inevitably degrade sound quality, and a compromise must be made between enhanced convergence and sound quality corruption \cite{2,7}.

MMAEC is required for situations in which multiple microphones are present and beamforming techniques are usually combined with AEC for efficient reduction of noise and acoustic echoes. The most straightforward ways of combining these two processing modules are applying AEC separately for each microphone signal before beamforming or applying a single-microphone AEC to the output of a beamformer \cite{8}. In general, the former scheme outperforms the latter one \cite{9}. Other algorithms employ relative echo transfer functions \cite{10,11} or joint optimization strategies \cite{12,13} to improve the MMAEC performance. However, efficient combinations of AEC and beamforming are still challenging and many of the strategies exhibit convergence deficiencies \cite{2}.

Recently, deep learning based methods have been proposed for solving AEC problems and have shown to be effective for echo and noise removal, especially in situations with nonlinear distortions \cite{4,5,6,7,8,14,15,16,17}. On the basis of the deep learning based single-channel AEC approach, we investigate AEC setups with multiple loudspeakers and microphones. The BLSTM based and CRN \cite{18} based methods are introduced to address MCAEC and MMAEC problems. Evaluation results show that the proposed methods effectively remove acoustic echo and background noise in the presence of nonlinear distortions.

The proposed work has four major advantages over traditional methods. First, although there are multiple acoustic paths in the MCAEC and MMAEC setups, the deep learning based approach can naturally address the problem with model training, rather than employing a separate AEC module for each echo path. Second, instead of estimating echo paths, deep learning based MCAEC works by directly estimating near-end speech, which intrinsically avoids the non-uniqueness problem. Third, combining deep learning based AEC and deep learning based beamforming elevates AEC performance remarkably. Fourth, deep learning based methods can remove echo and noise simultaneously in the presence of nonlinear distortions.

The remainder of this paper is organized as follows. Section 2 presents the deep learning based approach for MCAEC and MMAEC. Experiments and evaluation results are given in Section 3. Section 4 concludes the paper.

2. METHOD DESCRIPTION

2.1. Deep learning based AEC

As is shown in Fig. 1(a), the microphone signal \( y(n) \) in the single-channel AEC setup is a mixture of echo \( d(n) \), near-end speech \( s(n) \), and background noise \( v(n) \):

\[ y(n) = d(n) + s(n) + v(n) \] 

(1)
supervised speech separation problem and the overall approach is to estimate the near-end speech from microphone signal with far-end signal used as additional information. The diagrams of deep learning based methods are shown in Fig. 2. The input signals, sampled at 16 kHz, are windowed into 20 ms frames with a 10-ms overlap between consecutive frames. Then a 320-point short time Fourier transform (STFT) is applied to each frame to extract the real, imaginary, and magnitude spectra of signals, which are denoted as $s_r$, $s_i$, and $s_m$, respectively.

### 2.1. BLSTM based AEC

A BLSTM is trained to predict the spectral magnitude mask (SMM) of near-end speech from the magnitude spectrograms of input signals ($Y_m$ and $X_m$), as is shown in Fig. 2(a). The SMM is defined as:

$$ SMM(t, f) = \min \{1, |S_m(t, f)|/|Y_m(t, f)| \} \quad (2) $$

where $|S_m(t, f)|$ and $|Y_m(t, f)|$ denote the spectral magnitudes of near-end speech and microphone signal within a T-F unit at frame $t$ and frequency $f$, respectively. Once the model is trained, the estimated spectral magnitude of near-end speech $\hat{S}_m$ is obtained from point-wise multiplication of $Y_m$ and estimated SMM. Then $\hat{S}_m$, along with the phase of microphone signal, is sent to the inverse short time Fourier transform to derive an estimated near-end signal $\hat{s}(n)$. A detailed description of the BLSTM based method is given in [14].

### 2.1.2. CRN based AEC

The CRN based method trains the CRN, which is a causal system, for complex spectral mapping [18]. As is shown in Fig. 2(b), it estimates the real and imaginary spectrograms of near-end speech ($\hat{S}_r$ and $\hat{S}_i$) from the real and imaginary spectrograms of microphone signal and far-end signal ($Y_r$, $Y_i$, $X_r$, and $X_i$). Hence, it is capable of enhancing both magnitude and phase responses simultaneously and $\hat{s}(n)$ resynthesized achieves better speech quality. A detailed description the CRN architecture is provided in [15].

### 2.2. Deep learning for MCAEC

Without loss of generality, let us take stereophonic AEC as an example to study deep learning based MCAEC. The signal model is given in Fig. 1(b) where the stereophonic signals, $x_1(n)$ and $x_2(n)$, are transmitted to loudspeakers and then coupled to one of the microphones. The signal picked up by microphone $j$ is composed of two echo signals $d_{ij}(n)$, $d_{2j}(n)$, near-end speech $s_j(n)$, and background noise $v_j(n)$:

$$ y_j(n) = \sum_{i=1}^{2} d_{ij}(n) + s_j(n) + v_j(n), \quad j = 1, 2. \quad \text{(3)} $$

where $d_{ij}(n) = x_i(n) * h_{ij}(n)$, $i = 1, 2$, $h_{ij}(n)$ denotes the echo path from loudspeaker $i$ to microphone $j$, and * denotes linear convolution.

Deep learning based MCAEC works by estimating the target $s_j(n)$ given $y_j(n)$, $x_1(n)$, and $x_2(n)$ as inputs. Specifically, for BLSTM based MCAEC, we use $[Y_m, X_1m, X_2m]$ as inputs and train the BLSTM to estimate the SMM of $s_j(n)$. For CRN based AEC, we use $[Y_{jr}, Y_ji, X_1r, X_1i, X_2r, X_2i]$ as inputs and train the network to estimate $[S_{jr}, S_{ji}]$. The training signals are generated by randomly selecting $j$ from $[1, 2]$, i.e. the model is exposed to signals picked up by the two microphones in MCAEC during training. A model trained this way is able to achieve echo removal for both microphones in the system.
2.3. Deep learning for MMAEC

Considering an MMAEC setup with one loudspeaker and $M$ microphones, as is shown in Fig. 1(b). The signal picked up by microphone $j$ is

$$y_j(n) = d_j(n) + s_j(n) + v_j(n), \quad j = 1, 2, \cdots, M$$

where $d_j(n) = x(n) * h_j(n)$ is the echo received at microphone $j$.

Different from traditional MMAEC methods that may need to employ a separate AEC module for each microphone in the array, deep learning based MMAEC can be trained to achieve echo removal for all the microphones in the array with a single DNN. During training, we use $y_j(n)$ and $x(n)$ as inputs and set the training target to the corresponding near-end speech $s_j(n)$. The training signals are generated by randomly choosing $j$ from $\{1, 2, \cdots, M\}$.

Once the model is trained, the outputs of deep learning based MMAEC could be used for deep learning based minimum variance distortion-less response (MVDR) beamforming [19]. Choosing the first microphone in the array as reference microphone, the MVDR beamformer can be constructed as:

$$\hat{\mathbf{w}}(f) = \frac{\hat{\Phi}_N^{-1}(f)\hat{\mathbf{e}}(f)}{\hat{\mathbf{e}}(f)\hat{\Phi}_N^{-1}(f)\hat{\mathbf{e}}(f)}$$

where $(\cdot)^H$ denotes conjugate transpose, $\hat{\Phi}_N(f)$ is the estimated covariance matrix of overall interference (acoustic echo and background noise), $\hat{\mathbf{e}}(f)$ is the estimated steering vector, which is estimated as the principal eigenvector of the estimated speech covariance matrix $\hat{\Phi}_S(f)$ [19][20]. The covariance matrices of speech and overall interference are estimated from the output of deep learning based MMAEC as

$$\hat{\Phi}_S(f) = \frac{1}{T} \sum_t \hat{\mathbf{S}}(t,f)\hat{\mathbf{S}}^H(t,f)$$

$$\hat{\Phi}_N(f) = \frac{1}{T} \sum_t \hat{\mathbf{N}}(t,f)\hat{\mathbf{N}}^H(t,f)$$

where $\hat{\mathbf{S}}(t,f)$ is the STFT representation of estimated speech signals and $\hat{\mathbf{N}}(t,f)$ is the estimated overall interference obtained as $\mathbf{Y}(t,f) - \hat{\mathbf{S}}(t,f)$, $T$ is the total number of frames used in the summation.

The beamformer is usually applied on microphone signal $\mathbf{Y}(t,f)$ and the enhancement results are calculated from

$$\hat{\mathbf{Y}}_H = \hat{\mathbf{w}}^H(f)\mathbf{Y}(t,f)$$

Considering that MVDR beamformer performs spatial filtering to maintain signals from the desired direction while suppressing interferences from other directions. A trick we used is to employ the MVDR beamformer as a post-filter for further enhancement. It can be implemented by feeding the output of DNN based MMAEC forward to the deep learning based beamformer with the latter calculated using the same DNN. The overall structure is shown in Fig. 3.

The further enhanced output is obtained using

$$\hat{\mathbf{Y}}_H = \hat{\mathbf{w}}^H(f)\hat{\mathbf{S}}(t,f)$$

3. EXPERIMENTS

3.1. Experiment setting

The simulation setups for evaluation are designed as follows. The near-end and far-end speech signals are generated using the TIMIT dataset [21] by following the same way provided in [13].

![Fig. 3. Diagram of combining deep learning based AEC with deep learning based beamforming for further enhancement.](image-url)
SNR = 10 \log_{10} \left[ \frac{\sum_n s^2(n)}{\sum_n v^2(n)} \right] \quad (12)

Test mixtures are created similarly but using different utterances, noises, RIRs, SERs and SNRs.

The AMSGrad optimizer [27] and the mean squared error (MSE) cost function are used to train both BLSTM based and CRN based methods. The networks are trained for 30 epochs with a learning rate of 0.001. The performance of MCAEC and MMAEC is evaluated in terms of utterance-level echo return loss enhancement (ERLE) [11] for single-talk periods and perceptual evaluation of speech quality (PESQ) [28] for double-talk periods.

### 3.2. Performance of MCAEC methods

We first evaluate the performance of deep learning based MCAEC. The proposed methods are compared with the stereophonic version of joint-optimized normalized least mean square algorithm [29] equipped with a coherence reduction technique proposed in [30] (SJONLMS). And post-filtering (PF) [31] is employed to further suppress noises and residual echo (SJONLMS-PF). The parameters for these methods are set accordingly to the values given in [29] [30] [31]. The comparison results are given in Table 1. In general, the proposed BLSTM based and CRN based MCAEC methods outperform conventional methods and the performance generalizes well to untrained RIRs.BLSTM based method achieves better ERLE results while the CRN based method outperforms all other methods in terms of PESQ.

### 3.3. Performance of MMAEC methods

This part studies the performance of deep learning based MMAEC. We employ single-channel JONLMS [29] for each microphone in the array as a baseline and then combine the outputs with the ideal MVDR beamformer (JONLMS-IBF). The ideal MVDR beamformer (IBF) is calculated by substituting the true speech and interference components of the microphone signal \(s(t, f)\) and \(n(t, f)\) into (6), (7), and (5). Therefore, it can be regarded as a stronger baseline compared to other MVDR beamformers. Three results are provided for each deep learning based method, in which \(\hat{s}\) is the output of the reference microphone, \(\hat{y}\) and \(\hat{\delta}\) are, respectively, the time-domain beamformed microphone signal and beamformed enhanced signal introduced in Section 2.2. The comparison results are given in Table 2. As can be seen from the table, deep learning based methods outperform traditional MMAEC methods in terms of ERLE and PESQ. Single-channel outputs of deep learning based methods (\(\hat{s}\)) are good enough for echo and noise removal while combining deep learning based beamformer as a post-filter (\(\hat{\delta}\)) further improves the overall performance in most of the cases.

### 3.4. Performance in situations with nonlinear distortions

This part tests the performance of BLSTM based and CRN based MCAEC and MMAEC in situations with nonlinear distortions introduced by loudspeaker. The results are shown in Table 3. Comparing the results with those without nonlinear distortions shows that the deep learning based methods can be trained to handle cases with and without nonlinear distortions and the performance generalizes well to untrained nonlinearity (\(\eta^2 = 0.5\)).

### 4. CONCLUSION

We have proposed a deep learning approach to MCAEC and MMAEC. Our approach overcomes the limitations of traditional methods and produces remarkable performance in terms of ERLE and PESQ. Evaluation results show the effectiveness of both BLSTM and CRN based methods for removing echo and noise in cases with and without nonlinear distortions, and the performance generalizes well to untrained RIRs. Moreover, the proposed methods can be extended to handle a general AEC setup with an arbitrary number of microphones and an arbitrary number of loudspeakers, which will be demonstrated in future research.

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