ICASSP 2021 ACOUSTIC ECHO CANCELLATION CHALLENGE: DATASETS AND TESTING FRAMEWORK

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\section*{ABSTRACT}

The ICASSP 2021 Acoustic Echo Cancellation Challenge is intended to stimulate research in the area of acoustic echo cancellation (AEC), which is an important part of speech enhancement and still a top issue in audio communication and conferencing systems. Many recent AEC studies report good performance on synthetic datasets where the train and test samples come from the same underlying distribution. However, the AEC performance often degrades significantly on real recordings. Also, most of the conventional objective metrics such as echo return loss enhancement (ERLE) and perceptual evaluation of speech quality (PESQ) do not correlate well with subjective speech quality tests in the presence of background noise and reverberation found in realistic environments. In this challenge, we open source two large datasets to train AEC models under both single talk and double talk scenarios. These datasets consist of recordings from more than 2,500 real audio devices and human speakers in real environments, as well as a synthetic dataset. We open source an online subjective test framework based on ITU-T P.808 for researchers to quickly test their results. The winners of this challenge will be selected based on the average P.808 Mean Opinion Score (MOS) achieved across all different single talk and double talk scenarios.

Index Terms— Acoustic Echo Cancellation, deep learning, single talk, double talk, subjective test

\section{1. INTRODUCTION}

With the growing popularity and need for working remotely, the use of teleconferencing systems such as Microsoft Teams, Skype, WebEx, Zoom, etc., has increased significantly. It is imperative to have good quality calls to make the users’ experience pleasant and productive. The degradation of call quality due to acoustic echoes is one of the major sources of poor speech quality ratings in voice and video calls. While digital signal processing (DSP) based acoustic echo cancellation (AEC) models have been used to remove these echoes during calls, their performance can degrade given devices with poor physical acoustics design or environments outside their design targets and lab-based tests. This problem becomes more challenging during full-duplex modes of communication where echoes from double talk scenarios are difficult to suppress without significant distortion or attenuation [1].

With the advent of deep learning techniques, several supervised learning algorithms for AEC have shown better performance compared to their classical counterparts [2, 3, 4]. Some studies have also shown good performance using a combination of classical and deep learning methods such as using adaptive filters and recurrent neural networks (RNNs) [4, 5] but only on synthetic datasets. While these approaches provide a good heuristic on the performance of AEC models, there has been no evidence of their performance on real-world datasets with speech recorded in diverse noise and reverberant environments. This makes it difficult for researchers in the industry to choose a good model that can perform well on a representative real-world dataset.

Most AEC publications with evaluations use objective measures such as echo return loss enhancement (ERLE) [6] and perceptual evaluation of speech quality (PESQ) [7]. ERLE is defined as:

\[ ERLE = 10 \log_{10} \frac{\mathbb{E}[y^2(n)]}{\mathbb{E}[\hat{y}^2(n)]} \]

where \( y(n) \) is the microphone signal, and \( \hat{y}(n) \) is the enhanced speech. ERLE is only appropriate when measured in a quiet room with no background noise and only for single talk scenarios (not double talk). PESQ has also been shown to not have a high correlation to subjective speech quality in the presence of background noise [8].

Using the datasets provided in this challenge we show the ERLE and PESQ have a low correlation to subjective tests (Table 1). In order to use a dataset with recordings in real environments, we can not use ERLE and PESQ. A more reliable and robust evaluation framework is needed that everyone in the research community can use.

This AEC challenge is designed to stimulate the research work in the AEC domain by open sourcing a large training dataset, test set, and subjective evaluation framework. We provide two new open source datasets for training AEC models. The first is a real dataset captured using a large-scale crowdsourcing effort. This dataset consists of real recordings that have been collected from over 2,500 diverse audio devices and environments. The second is a synthetic dataset with added room impulse responses and background noise derived from [9]. An initial test set will be released for the researchers to use during development and a blind test near the end which will be used to decide the final competition winners. We believe these datasets are not only the first open source datasets for AECs, but ones that are large enough to facilitate deep learning and representative enough for practical usage in shipping telecommunication products.

In the Deep Noise Suppression Challenge [9] we showed that a crowdsourced subjective quality evaluation was effective for a speech enhancement challenge. Therefore, we will again use the

\begin{table}[h]
\centering
\begin{tabular}{|c|c|c|}
\hline
Metric & PCC & SRCC \\
\hline
ERLE & 0.31 & 0.23 \\
PESQ & 0.67 & 0.57 \\
\hline
\end{tabular}
\caption{Pearson and Spearman rank correlation between ERLE, PESQ and P.808 ACR results on single talk with delayed echo scenarios (see Section 5).}
\end{table}
ITU-T P.808 [10] crowdsource subjective quality evaluation to compare the submitted AEC methods. For reference during evaluation we include a DNN-based AEC method (Section 4). The online subjective evaluation framework is discussed in Section 5. The rules of the challenge and other logistics are described in Section 6.

2. TRAINING DATASETS

The challenge will include two new open source datasets, one real and one synthetic. The datasets are available at https://github.com/microsoft/AEC-Challenge.

2.1. Real dataset

The first dataset was captured using a large-scale crowdsourcing effort. This dataset consists of more than 2,500 different real environments, audio devices, and human speakers in the following scenarios:

1. Far end single talk, no echo path change
2. Far end single talk, echo path change
3. Near end single talk, no echo path change
4. Double talk, no echo path change
5. Double talk, echo path change
6. Sweep signal for RT60 estimation

For the far end single talk case, there is only the loudspeaker signal (far end) played back to the users and users remain silent (no near end signal). For the near end single talk case, there is no far end signal and users are prompted to speak, capturing the near end signal. For double talk, both the far end and near end signals are active, where a loudspeaker signal is played and users talk at the same time. Echo path change was incorporated by instructing the users to move their device around or bring themselves to move around the device. Each scenario includes the loudspeaker, microphone, and loopback signal. The near end single talk speech quality is given in Figure 1. The RT60 distribution for the dataset is estimated using a method by Karjalainen et al. [11] and shown in Figure 2. The RT60 estimates can be used to sample the dataset for training.

We use Amazon Mechanical Turk as the crowdsourcing platform and wrote a custom HIT application which includes a custom tool that raters download and execute to record the six scenarios described above. The dataset includes only Microsoft Windows devices.

For clean speech far end signals, we use the speech segments from the Edinburgh dataset [12]. This corpus consists of short single speaker speech segments (1 to 3 seconds). We used a long short term memory (LSTM) based gender detector to select an equal number of male and female speaker segments. Further, we combined 3 to 5 of these short segments to create clips of length between 9 and 15 seconds in duration. Each clip consists of a single gender speaker. We create a gender balanced far end signal source comprising of 500 male and 500 female clips. Recordings are saved at the maximum sampling rate supported by the device and in 32-bit floating point format; in the released dataset we down-sample to 16KHz and 16-bit using automatic gain control to minimize clipping.

For noisy speech far end signals we use data from the DNS Challenge [9] as well as clips from near end single talk scenarios in this dataset.

For near end speech, the users were prompted to read sentences from TIMIT [13] sentence list. Approximately 10 seconds of audio is recorded while the users are reading.

2.2. Synthetic dataset

The second dataset provides 10,000 synthetic examples representing single talk, double talk, near end noise, far end noise, and various nonlinear distortion situations. Each example includes a far end speech, echo signal, near end speech, and near end microphone signal clip. We use 12,000 cases (100 hours of audio) from both the clean and noisy speech datasets derived in [9] from the LibriVox project as source clips to sample far end and near end signals. The LibriVox project is a collection of public domain audiobooks read by volunteers. [9] used the online subjective test framework ITU-T P.808 to select audio recordings of good quality (4.3 ≤ MOS ≤ 5) from the LibriVox project. The noisy speech dataset was created by mixing clean speech with noise clips sampled from Audioset [14], Freesound1 and DEMAND [15] databases at different signal to noise ratio levels.

To simulate a far end signal, we pick a random speaker from a pool of 1,627 speakers, randomly choose one of the clips from the speaker, and sample 10 seconds of audio from the clip. For the near end signal, we randomly choose another speaker and take 3-7 seconds of audio which is then zero-padded to 10 seconds. To generate an echo, we convolve a randomly chosen room impulse response from a large internal database with the far end signal. In 80% of the cases, the far end signal is processed by a nonlinear function to mimic loudspeaker distortion. This signal gets mixed with the near end signal at a signal to echo ratio uniformly sampled from -10 dB to 10 dB. The far end and near end signals are taken from the noisy dataset in 50% of the cases. The first 500 clips can be used for validation as these have a separate list of speakers and room impulse responses. Detailed metadata information can be found in the repository.

3. TEST SET

Two test sets will be included, one at the beginning of the challenge and a blind test set near the end. Both consist of approximately 800 recordings and are partitioned into the following scenarios:

1. clean speech (MOS > 4) for both near and far end
2. noisy speech for both near and far end

1https://librivox.org
2https://freesound.org
4. BASELINE AEC METHOD

We adapt a noise suppression model developed in [16] to the task of echo cancellation. Specifically, a recurrent neural network with gated recurrent units takes concatenated log power spectral features of the microphone signal and far end signal as input, and outputs a spectral suppression mask. The STFT is computed based on 20 ms frames with a hop size of 10 ms, and a 320-point discrete Fourier transform. We use a stack of two GRU layers followed by a fully connected layer with a sigmoid activation function. The estimated mask is point-wise multiplied with the magnitude spectrogram of microphone signal to suppress the far end signal. Finally, to resynthesize the enhanced signal, an inverse short time Fourier transform is used on the phase of the microphone signal and the estimated magnitude spectrogram. We use a mean squared error loss between the clean and enhanced magnitude spectrograms. The Adam optimizer with a learning rate of 0.0003 is used to train the model.

5. ONLINE SUBJECTIVE EVALUATION FRAMEWORK

ITU-T P.808

The primary standards for AEC evaluation are G.168 [6] for objective evaluations (e.g., ERLE), and P.831 [17] for subjective evaluation. As previously discussed, ERLE and PESQ are not viable metrics for AEC performance with real data. The subjective tests given in P.831 Section 7 are viable, though it assumes a quiet test environment. For example, in P.831 to measure the far end single talk echo performance, a recording is done using the setup in Figure 3 and raters are asked to rate the amount of echo at \( S_{\text{out}} \). However, any background noise can confuse raters to what is echo leak or not. Our solution is to implement a subjective rating of a 3-way call with the rater being the listener (see Figure 4). To construct a delayed echo signal that a listener would hear we combine the far end signal (speaker signal) with a 600 ms delayed output signal of the AEC output to simulate a large network delay. This allows the raters to hear the far end speech and a delayed echo leak (if any), which helps raters better discriminate between echo leak and noise. We then use a P.808 framework [10] to get echo MOS scores using the following rating survey from P.831 [17]: How would you judge the degradation from acoustic echo in this conversation?

5 Imperceptible
4 Perceptible but not annoying
3 Slightly annoying
2 Annoying

The audio pipeline used in the challenge is shown in Figure 5. In the first stage (AGC1) a traditional automatic gain control is used to target a speech level of -24 dBFS. The output of AGC1 is saved in the test set. The next stage is an AEC, which participants will process and upload to the challenge CMT site. The next stage is a traditional noise suppressor (DMOS < 0.1 improvement) to reduce stationary noise. Finally, a second AGC is run to ensure the speech level is still -24 dBFS.

For the double talk scenario, we use a standard P.808 ACR rating to estimate the MOS score for AEC microphone output, which is one of the measures P.831 estimates at \( S_{\text{out}} \).

The subjective test framework is available at https://github.com/microsoft/P.808.

6. AEC CHALLENGE RULES AND SCHEDULE

6.1. Rules

This challenge is to benchmark the performance of real-time algorithms with a real (not simulated) test set. Participants will evaluate their AEC on a test set and submit the results (audio clips) for evaluation. The requirements for each AEC used for submission are:

- The AEC must take less than the stride time \( T_s \) (in ms) to process a frame of size \( T \) (in ms) on an Intel Core i5 quad-core machine clocked at 2.4 GHz or equivalent processors. For example, \( T_s = T / 2 \) for 50% overlap between frames. The total algorithmic latency allowed including the frame size \( T \), stride time \( T_s \), and any look ahead must be \( \leq 40 \) ms. For example,
6.2. Timeline

- **September 8, 2020**: Release of the datasets.
- **October 2, 2020**: Blind test set released to participants.
- **October 9, 2020**: Deadline for participants to submit their results for objective and P.808 subjective evaluation on the blind test set.
- **October 16, 2020**: Organizers will notify the participants about the results.
- **October 19, 2020**: Regular paper submission deadline for ICASSP 2021.

7. CONCLUSIONS

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