INTERSPEECH 2021 DEEP NOISE SUPPRESSION CHALLENGE

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ABSTRACT

The Deep Noise Suppression (DNS) challenge is designed to foster innovation in the area of noise suppression to achieve superior perceptual speech quality. We recently organized a DNS challenge special session at INTERSPEECH and ICASSP 2020. We open-sourced training and test datasets for the wideband scenario. We also open-sourced a subjective evaluation framework based on ITU-T standard P.808, which was also used to evaluate participants of the challenge. Many researchers from academia and industry made significant contributions to push the field forward, yet even the best noise suppressor was far from achieving superior speech quality in challenging scenarios. In this version of the challenge organized at INTERSPEECH 2021, we are expanding both our training and test datasets to accommodate full band scenarios. The two tracks in this challenge will focus on real-time denoising for (i) wideband, and (ii) full band scenarios. We are also making available a reliable non-intrusive objective speech quality metric for wideband called DNSMOS for the participants to use during their development phase.

Index Terms— Speech Enhancement, Perceptual Speech Quality, P.808, Deep Noise Suppressor, Machine Learning.

1. INTRODUCTION

With the explosion in the number of people working remotely due to the pandemic, there has been a surge in the demand for reliable collaboration and real-time communication tools. Excellent speech quality in our audio calls is a need during these times as we try to stay connected and collaborate with people every day. We are easily exposed to a variety of background noises such as a leaf blower, washing machine, dog barking, a baby crying, kitchen noises, etc. Background noise significantly degrades the quality and intelligibility of the perceived speech leading to fatigue. Background noise poses a challenge in other applications such as hearing aids and smart devices as well.

Real-time Speech Enhancement (SE) for perceptual quality is a decades old classical problem and researchers have proposed numerous solutions [1, 2]. In recent years, learning-based approaches have shown promising results [3, 4, 5]. The Deep Noise Suppression (DNS) Challenge organized at INTERSPEECH 2020 [6] and ICASSP 2020 [7] showed great progress, while also indicating that we are still about 1.6 Differential Mean Opinion Score (DMOS) away from the ideal Mean Opinion Score (MOS) of 5 when tested on the challenge test set, which was reasonable representative of realistic scenarios. The DNS Challenge is the first contest that we are aware of using the subjective evaluation to benchmark SE methods using a realistic noisy test set [6].

We open sourced a large dataset for INTERSPEECH 2020 and ICASSP 2021 DNS challenge1. For ease of reference, we will call the INTERSPEECH 2021 challenge as DNS Challenge 3, ICASSP 2021 challenge as DNS Challenge 2 and the INTERSPEECH 2020 challenge as DNS Challenge 1. The DNS Challenge 3 will be focused on real-time denoising similar to track 1 of both the DNS challenges 1 and 2. We will have two tracks in DNS challenge 3 for wideband (sampling rate = 16000 Hz) and full band (sampling rate = 48000 Hz) scenarios. The datasets include over 760 hours of clean speech including singing voice, emotion data, and non-English languages. Noise data in training set remains the same as DNS Challenge 2. Both clean speech and noise are made available for both wide and full band scenarios. We provide over 118,000 room impulse responses (RIR), which includes real and synthetic RIRs from public datasets for wideband. We provide acoustic parameters: Reverbatarion time (T60) and Clarity (C50) for read clean speech and RIR sample. The test set includes a variety of noisy speech utterances in English and non-English. We also include emotional speech and singing in the presence of background noise.

Unlike ITU-T P.808 that was used for DNS Challenge 1 and 2, we will use the implementation of ITU-T P.835 [8] for the DNS Challenge 3. In addition to the overall speech quality as in P.808, P.835 provides standalone quality scores of speech and noise. The standalone ratings will guide us better to focus on the areas that requires improvement to achieve better overall quality. Many noise suppressors are very good in suppressing the background noise but do not improve the quality of speech, which becomes the bottleneck for improving the overall quality. We will also provide a non-intrusive objective speech quality metric for wideband scenario called DNSMOS3 as an Azure service. We show that DNSMOS is more reliable than other widely used objective metrics such as PESQ, SDR and POLQA [9]. Also, it does not require reference clean speech and hence can work on real recordings. Participants can request for the DNSMOS API by following instructions in the challenge git page.

2. CHALLENGE TRACKS

The challenge will have the following two tracks:

1. Track 1: Real-Time Denoising track for wide band scenario
   - The noise suppressor 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 processor. 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, for a real-time system that receives 20ms audio chunks, if you use a frame length of 20ms with a stride of 10ms

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1https://github.com/microsoft/DNS-Challenge
2https://github.com/microsoft/P.808
3https://github.com/microsoft/DNS-Challenge/tree/master/DNSMOS
resulting in an algorithmic latency of 30ms, then you satisfy the latency requirements. If you use a frame of size 32ms with a stride of 16ms resulting in an algorithmic latency of 48ms, then your method does not satisfy the latency requirements as the total algorithmic latency exceeds 40ms. If your frame size plus stride $T_f = T + T_s$ is less than 40ms, then you can use up to $(40 - T_f)\text{ms}$ future information.

2. Track 2: Real-Time Denoising track for full band scenario
   - Satisfy Track 1 requirements.

3. TRAINING DATASETS

The goal of releasing the clean speech and noise datasets is to provide researchers with an extensive and representative dataset to train their SE models. We initially released MSSNSD [10] with a focus on extensibility, but the dataset lacked the diversity in speakers and noise types. We published a significantly larger and more diverse dataset with configurable scripts for DNS Challenge 1 [6]. Many researchers found this dataset useful to train their noise suppression models and achieved good results. However, the training and the test datasets did not include clean speech with emotions such as crying, yelling, laughter, or singing. Also, the dataset only includes the English language. For DNS Challenge 2, we are adding speech clips with other emotions and included about 10 non-English languages. Clean speech in training set is total 760.53 hours: read speech (562.72 hours), singing voice (8.80 hours), emotion data (3.60 hours), Chinese mandarin data (185.41 hours). We have grown the speech audio files by 400 native speakers (47% male and 53% female) of Mandarin Chinese Shell Technology Co. Ltd. It has clean speech recorded in noise-free conditions by professional singers. This subset is derived from VocalSet corpus [13] with Creative Commons Attribution 4.0 International License (CC BY 4.0). It has 10.1 hours of clean singing voice recorded by 20 professional singers: 9 males, and 11 females. This data was recorded on a range of vowels, a diverse set of voices on several standard and extended vocal techniques, and sung in contexts of scales, arpeggios, long tones, and excerpts. For wideband, we downsampled the mono .WAV files from 44.1kHz to 16kHz and added it to clean speech used by the training data synthesizer.

The third subset consists of emotion speech recorded in noise-free conditions. This is derived from Crowd-sourced Emotional Multimodal Actors Dataset (CREMA-D) [14] made available under the Open Database License. It consists of 7,442 audio clips from 91 actors: 48 male, and 43 female accounting to total 3.5 hours of audio. The age of the actors was in the range of 20 to 74 years with diverse ethnic backgrounds including African America, Asian, Caucasian, Hispanic, and Unspecified. Actors read from a pool of 12 sentences for generating this emotional speech dataset. It accounts for six emotions: Anger, Disgust, Fear, Happy, Neutral, and Sad at four intensity levels: Low, Medium, High, Unspecified. The recorded audio clips were annotated by multiple human raters in three modalities: audio, visual, and audio-visual. Categorical emotion labels and real-value emotion level values of perceived emotion were collected using crowd-sourcing from 2,443 raters. This data was provided as 16 kHz .WAV files so we added it to our wideband clean speech as it is.

The fourth subset has clean speech from non-English languages. It consists of both tonal and non-tonal languages including Chinese (Mandarin), German and Spanish. Mandarin data consists of OpenSLR18 3 THCHS-30 [15] and OpenSLR33 6 AISHELL [16] datasets, both with Apache 2.0 license. THCHS30 was published by Center for Speech and Language Technology (CSLT) at Tsinghua University for speech recognition. It consists of 30+ hours of clean speech recorded at 16-bit 16kHz in noise-free conditions. Native speakers of standard Mandarin read text prompts chosen from a list of 1000 sentences. We added the entire THCHS-30 data in our clean speech for the training set. It consisted of 40 speakers: 9 male, 31 female in the age range of 19-55 years. It has total 13,389 clean speech audio files [15]. The AISHELL dataset was created by Beijing Shell Shell Technology Co. Ltd. It has clean speech recorded by 400 native speakers (47% male and 53% female) of Mandarin with different accents. The audio was recorded in noise-free conditions using high fidelity microphones. It is provided as 16-bit 16kHz .wav files. It is one of the largest open-source Mandarin speech datasets. We added the entire AISHELL corpus with 141,600 utterances spanning 170+ hours of clean Mandarin speech to our training set.

Spanish data is 46 hours of clean speech derived from OpenSLR39, OpenSLR61, OpenSLR71, OpenSLR73, OpenSLR74 and OpenSLR75 where re-sampled all .WAV files from 48 kHz to 16 kHz to use them in wideband setting. German data is derived from four corpora namely (i) The Spoken Wikipedia Corpora [17], (ii) Telecooperation German Corpus for Kinect [18], (iii) M-AILABS data [19], (iv) zambia-speech forschergest corpora. Complete German data constitute 636 hours. Italian (128 hours), French (190 hours), Russian (47 hours) are taken from M-AILABS data [19]. M-AILABS Speech Dataset is a publicly available multi-lingual corpora for training speech recognition and speech synthesis systems.

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3http://www.openslr.org/18/
6http://www.openslr.org/33/
3.2. Noise

The noise clips were selected from Audioset\textsuperscript{7} [20] and Freesound\textsuperscript{8}. Audioset is a collection of about 2 million human labeled 10s sound clips drawn from YouTube videos and belong to about 600 audio events. Like the Librivox data, certain audio event classes are over-represented. For example, there are over a million clips with audio classes music and speech and less than 200 clips for classes such as toothbrush, creak, etc. Approximately 42\% of the clips have a single class, but the rest may have 2 to 15 labels. Hence, we developed a sampling approach to balance the dataset in such a way that each class has at least 500 clips. We also used a speech activity detector to remove the clips with any kind of speech activity, to strictly separate speech and noise data. The resulting dataset has about 150 audio classes and 60,000 clips. We also augmented an additional 10,000 noise clips downloaded from Freesound and DEMAND databases\textsuperscript{9}. The chosen noise types are more relevant to VOIP applications. In total, there is 181 hours of noise data. The noise files were originally of full band, which were resampled for wide band use case.

3.3. Room Impulse Responses

We provide 3076 real and approximately 115,000 synthetic rooms impulse responses (RIRs) where we can choose either one or both types of RIRs for convolving with clean speech. Noise is then added to reverberant clean speech while DNS models are expected to take noisy reverberant speech and produce clean reverberant speech. Challenge participants can do both de-reverb and denoising with their models if they prefer. These RIRs are chosen from openSLR26\textsuperscript{10} and openSLR28\textsuperscript{11} datasets, both released with Apache 2.0 License.

3.4. Acoustic parameters

We provide two acoustic parameters: (i) Reverberation time, T60 [23] and (ii) Clarity, C50 [24] for all audio clips in clean speech of training set. We provide T60, C50 and isReal Boolean flag for all RIRs where isReal is 1 for real RIRs and 0 for synthetic ones. The two parameters are correlated. A RIR with low C50 can be described as highly reverberant and vice versa [23, 24]. These parameters are supposed to provide flexibility to researchers for choosing a sub-set of provided data for controlled studies.

4. TEST SET

For DNS challenge 3, the test set includes utterances in English and non-English languages recording in the presence of a variety of background noises at different SNR and target levels. The utterances were collected at a distance of 1-5 meters from the microphone when they were not using the headphone. These clips are more reverberant. The development test set also includes utterances with emotions such as laughter, crying, yelling and surprise in the presence of background noise. This is to ensure that the human emotions are not suppressed by the noise suppressors. A small segment of the clips include speech in the presence of musical instruments such as guitar, piano, violin playing in the background. We will provide the T60 and C50 estimates to all the clips, which can help researchers to tune their models to perform well in highly reverberant conditions.

5. CHALLENGE RULES AND SCHEDULE

5.1. Rules

- The participants must adhere to the requirements specified in Section 2 for each track.
- Participants may participate only in one track or both the tracks.
- Participants must report the number of parameters and the number of operations per second. Number of operations per second = Number of operations per frame / Frame shift in seconds.
- Participants can use any data of their choice to train their models and are not limited to challenge data sets.
- Participants can use a signal processing based or a learning-based deep model or a combination of both. There are no restrictions on the algorithm used.
- Submission must follow the instructions on https://dns-challenge.azurewebsites.net/. Use Shift+F5 (Windows) or Cmd+R(Mac) to get the latest updates on that site.
- Winners will be picked based on the subjective evaluation using ITU-T P.835 overall scores.
- Participants must send the results (audio clips) achieved by their developed models to the organizers.
- For track 2, the participants must send the audio clips enhanced with and without using speaker information and must show that quality is better with using speaker information.
- We will use the submitted clips with no alteration to conduct ITU-T P.808 subjective evaluation and pick the winners based on the results. Participants are forbidden from using the blind test set to retrain or tune their models.
- Participants must submit results only if they intend to submit a paper to INTERSPEECH 2021.
- Participants should report the computational complexity of their model in terms of the number of parameters and the time it takes to infer a frame on a particular CPU (preferably Intel Core i5 quad core machine clocked at 2.4 GHz).
- Among the submitted proposals, if the difference between the proposals is not statistically significant, the submission with the least number of operations per second will be ranked higher.

\textsuperscript{7}https://research.google.com/audioset/
\textsuperscript{8}https://freesound.org/
\textsuperscript{9}http://www.openslr.org/26/
\textsuperscript{10}http://www.openslr.org/28/
5.2. Timeline

- January 8, 2021: Release of the datasets and scripts for training and testing.
- March 8, 2021: Blind test set released to participants.
- March 15, 2021: Deadline for participants to submit their results for P.835 subjective evaluation on the blind test set.
- March 22, 2021: Organizers will notify the participants about the results.
- March 26, 2021: Regular paper submission deadline for INTERSPEECH 2021.
- June 2, 2021: Paper acceptance/rejection notification.
- June 4, 2021: Notification of the winners.

5.3. Support

Participants may email organizers at dns.challenge@microsoft.com with any questions related to the challenge or in need of any clarification about any aspect of the challenge.

6. SUMMARY & CONCLUSIONS

The INTERSPEECH 2021 DNS Challenge was designed to advance the field of real-time noise suppression optimized for human perception in challenging noisy conditions. Large inclusive and diverse training and test datasets with supporting scripts were open sourced. Many participants from both industry and academia found the datasets very useful and submitted their enhanced clips for final evaluation. Only two teams participated in the personalized DNS track, which also shows that the field is in its nascent phase.

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