SPEECH DENOISING USING ONLY SINGLE NOISY AUDIO SAMPLES

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ABSTRACT

In this paper, we propose a novel Single Noisy Audio Denoising Framework (SNA-DF) for speech denoising using only single noisy audio samples, which overcomes the limitation of constructing either noisy-clean training pairs or multiple independent noisy audio samples. The proposed SNA-DF contains two modules: training audio pairs generated module and audio denoising module. The first module adopts a random audio sub-sampler on single noisy audio samples for the generation of training audio pairs. The sub-sampled training audio pairs are then fed into the audio denoising module, which employs a deep complex U-Net incorporating a complex two-stage transformer (cTSTM) to extract both magnitude and phase information for taking full advantage of the complex features of single noisy audios. Experimental results show that the proposed SNA-DF not only eliminates the high dependence on clean targets of traditional audio denoising methods, but also outperforms the methods using multiple noisy audio samples.

Index Terms—Speech denoising, single noisy audio samples, audio sub-sampler, two-stage transformer, deep complex network

1. INTRODUCTION

In our daily conversation, the intelligibility of speech communication, especially through telecommunication devices, is inevitably disturbed by various noises. Methods dedicated to speech denoising were then continuously developed. Recently, algorithms based on deep learning were proposed to address this issue. Generally speaking, speech denoising algorithms can be classified into two kinds: speech denoising using noisy-clean training pairs [1]-[9] and speech denoising using multiple independent noisy audios [10].

The former means that we use the noisy audio samples as the input and the perfectly clean audio samples as the output while training. For example, Wang et al. [7] proposed a context-aware U-Net (CAUNet), which stacked a real two-stage transformer module (rTSTM) between the deep real U-Net [8]. The rTSTM, consisting of multiple two-stage transformer blocks (TSTBs), are used to extract local and global context information. Additionally, by using both amplitude and phase information effectively, Choi et al. [9] present a deep complex U-net (DCUnet) to deal with complex-valued spectrograms. The common problem encountered by this type of method is that we generally only obtain noisy audio samples without pure perfectly clean audio samples.

The latter indicates that we only use noisy audio pairs to train denoising models, such as the Noise2Noise speech denoising method [10], which is still very time-consuming to collect pairwise noisy-noisy audios. This is still a long way from actual application scenarios, because in real life we may only get single noisy audio samples.

Then, two question raised: Can we solve the speech denoising problem with only single noisy audio samples? Is the performance of speech denoising using only single noisy audio samples better than other speech denoising methods?

Recently, a new Neighbor2Neighbor method [11] was proposed for image denoising from single noisy images. Inspired by this work, we propose a novel Single Noisy Audio Denoising Framework (SNA-DF) for solving the speech denoising from single noisy audio samples. Compared to image denoising from single noisy images [11], there are some additional challenges for solving:

- In the training image pairs generated module, the sub-sampled images can be directly obtained from original images. However, in audio space, we should consider whether to sub-sample directly from the raw audio signals or from spectrograms.
- In the image denoising module, images are directly input into deep real networks since they are real-valued and static. However, in audio space, we should design a complex network that can extract contextual information since the raw audio signals are time series and the corresponding spectrograms are complex-valued.

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In order to meet the above challenges, in this paper, we propose a new SNA-DF based on Neighbor2Neighbor method. Our contributions can be summarized as follows:

- We develop a novel framework for speech denoising using single noisy audio samples, putting an end to the need for noisy-clean pairs and multiple noisy audio samples.
- We design an effective complex-valued speech denoising network, which integrates the proposed complex TSTM (cTSTM) into the DCUnet by modeling the correlation between magnitude and phase.
- Our method performs very favorably against compared denoising methods not only on synthetic datasets, but also on real world datasets, demonstrating the superiority and potential of our denoising method.

2. THEORETICAL BACKGROUND

Similar to Neighbor2Neighbor for the single noisy image denoising work [11], we provide the following two key conditions for the single noisy audio denoising task:

**Condition 2.1** Once two paired audios are sub-sampled from adjacent but different time domain locations from a single noisy audio sample, the pair having similar but different characteristics with each other can be used to train a denoising network.

**Condition 2.2** To avoid over-smoothing while training, it is necessary to consider a regularization loss by addressing the essential difference of the ground-truth time domain values between the sub-sampled pairs on the original audio.

Based on the assumption in Condition 2.1, the sub-sampled audio pairs should satisfy the following requirements: (1) given the ground-truth \( \mathcal{X} \) of a single noisy audio sample \( x \), the sub-sampled audio pair \( (s_1(x), s_2(x)) \) has conditional independence; (2) the underlying ground-truth gap between \( s_1(x) \) and \( s_2(x) \) is small.

Considering the regularization loss discussed in Condition 2.2, with the sub-sampled audio pairs used to train the denoising network, the following optimization problem with a constraint is considered to solve the audio denoising task:

\[
\begin{align*}
\min_{f_a} & \text{E}_{y,x} \| f_a(s_1(x)) - s_2(x) \|_2^2 \\
+ & \gamma \text{E}_{y,x} \| f_a(s_1(x)) - s_1(f_a(x)) + s_2(f_a(x)) \|^2_2
\end{align*}
\]

where \( x \) and \( y \) denote a single noisy audio sample and a clean audio sample respectively, \( f_a \) represents the audio denoising network, \( s_1 \) and \( s_2 \) represent the audio sub-samplers, \( \gamma \) is a tunable parameter.

The proof of Eq. (1) can be deduced in a similar way to the Neighbor2Neighbor image denoising [11], thus there is no further elaboration in this paper due to space limitations.

3. PROPOSED METHOD

As shown in Fig. 1, the proposed SNA-DF includes two modules: training audio pairs generated module and audio denoising module.

### 3.1. Generation of training audio pairs

The generation process from a single noisy sample to a noisy audio pair is shown in Fig. 2(a), which is mainly implemented using an audio sub-sampler. Denote a single noisy audio sample as \( x \) with hyper-parameters \( k \) to control the sampling interval, where \( k \geq 2 \). From the \( i \)-th to the \((i + k - 1)\)-th time domain audio value in \( x \), two adjacent random values are selected, which are used as the \( i/k \)-th value of the paired audios \( s_1(x) \) and \( s_2(x) \). Then, we shift the sampling area to the right by \( k \), which then spread from the \((i + k)\)-th to the \((i + 2k - 1)\)-th value, and so on. Since \( s_1(x) \) and \( s_2(x) \) are selected from adjacent squares in \( x \), the ground-truths of audio pairs are similar, satisfying the requirements stated in Section 2 and can be used to train an audio denoising network.

Note that, we sub-sample from the raw audios but not from the spectrograms of the audios. The reason is that it is unreasonable to implement sub-sampling from spectrograms as the highlighted information on spectrograms vary with the properties of the selected window, its size and the overlapping rate of consecutive windows when applying the short-time-Fourier-transform (STFT). Furthermore, a great benefit of sub-sampling from the raw audios is that any network that performs well in supervised audio denoising tasks can be used on our sub-sampling method.
where $\mathcal{L}_{basic}$ is the basic loss, $\mathcal{L}_{reg}$ is the regularization loss, and $\gamma$ is a tunable parameter.

As shown in Fig. 1, we combine the frequency domain loss $\mathcal{L}_f$, the time domain loss $\mathcal{L}_p$ and weighted SDR loss function ($\mathcal{L}_{wSDR}$) [9] to construct $\mathcal{L}_{basic}$ determined by the characteristics of denoising network. Specifically, $\mathcal{L}_f$ is computed based on the mean square error (MSE) between the enhanced waveforms and the clean waveforms, while $\mathcal{L}_p$ [13] can monitor the model to learn more information, resulting in higher speech intelligibility and perceived quality. $\mathcal{L}_{wSDR}$ [9] is used as another term to directly optimize the well-known evaluation measures defined in the time-domain.

Based on Condition 2.2, $\mathcal{L}_{reg}$ shown in Fig.1 is adopted as an additional constraint. In order to stabilize learning, the gradient update of $s_1(f_o(x))$ and $s_2(f_o(x))$ is stopped during the training, and the hyperparameter $\gamma$ in Eq. (8) is gradually increased to reach the best training effect.

4. EXPERIMENTS AND RESULTS

4.1. Experimental setup

Datasets. The dataset is generated by overlapping two noise categories over clean audios. The clean audios are selected from Voice Bank + DEMAND dataset [14]. While the first noise dataset uses white gaussian to generate synthetic noisy audio dataset, the second is UrbanSound8K (US8K) dataset [15], which is used to generate real world noisy audio dataset.

Evaluation metrics. To evaluate the quality of denoising effect, the following metrics are used: signal-to-noise ratio (SNR), segmental signal-to-noise ratio (SSNR), wide-band perceptual evaluation of speech quality (PESQ-WB) [16], narrow-band perceptual evaluation of speech quality (PESQ-NB) [16], short term objective intelligibility [17] (STOI).

Training details. The original raw audio waveforms are first sampled at 48kHz and then transformed by the STFT with a 64ms Hamming window and 16ms hop length to obtain complex-valued spectrograms. The number of channels for the deep complex U-Net is $\{45, 90, 90, 90, 90, 90, 90, 45, 1\}$. The convolution kernels are set to (3, 3), and the step sizes are set
to (2, 1) except for the middle two layers which are set to (2, 2). The number of TSTBs is 6. In the loss function, we set $\alpha = 0.8, \beta = 1/200, \gamma = 2$ in the synthetic experiments and $\gamma = 1$ in the real world experiments empirically. We use Adam optimizer with a learning rate of 0.001. All experiments are implemented in Pytorch on a NVIDIA GTX1080 Ti GPU.

### 4.2 Results

Our proposed model is evaluated based on white noise and four kinds of US8K noise. The results are shown in Table 1, the mean and standard deviation of metrics are calculated separately. For comparison, all encoder and decoder layers of SNA-cTSTM and SNA-rTSTM have the same configuration as SNA. The dark-colored tables represent our proposed methods and values shown in bold denote the best performer among five methods. According to the comparative experiments in Table 1, the following conclusions can be drawn:

**Comparison with other methods.** All the proposed methods (i.e., SNA, SNA-rTSTM, SNA-cTSTM) showed superior results compared with N2C [10] and N2N [10]. Even in white noise where N2N does not exceed N2C, our framework also demonstrates the superiority in denoising performance, with each indicator exceeding two benchmark methods.

**Evaluation of cTSTM.** (1) In US8K category 2 (Children Playing), SNA outperforms SNA-cTSTM and SNA-rTSTM, but the difference is negligible. It can be considered that for noisy samples overlaying noises of children playing in the real world, speech features extracted by TSTM has little influence on the denoising network. (2) In US8K category 0 (Air Conditioning), all metrics except STOI in SNA-cTSTM show best results. STOI is calculated based on the time envelope correlation coefficient of clean speech and noisy speech, which offers a high correlation with speech intelligibility. Therefore, the cTSTM has little effect on improving the speech intelligibility of denoising results in US8K category 0, but improvements on other metrics still work. (3) For white noise and US8K category 1 and 3, the adoption of cTSTM is very effective to reconstruct speech features output from the encoder. It makes the denoising network not only process the magnitude and phase information from spectrograms more accurately, but also ensure that the context information is not ignored. In general, our SNA-cTSTM produces superior denoising performance on synthetic and real world noises.

### 5. Conclusion

In this paper, we propose a novel speech denoising method, which overcomes the limitation of clean speech acquisition and puts an end to the need for multiple independent noisy speech samples. Our approach successfully solves the single speech sample denoising problem by generating sub-sampled paired audios with audio sub-samplers, and employs a cTSTM in a DCUNet. The proposed SNA-DF has shown the superiority over other compared methods, benefiting from the denoising network which models complex-valued spectral characteristics effectively by extracting local and global context information. In the future, we would like to extend the proposed method to scenes of multimodal denoising, in order to highlight the advantages of single sample speech denoising method in scenarios where noisy audios are limited and rare.
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