JOINT NOISE REDUCTION AND LISTENING ENHANCEMENT FOR FULL-END SPEECH ENHANCEMENT

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ABSTRACT
Speech enhancement (SE) methods mainly focus on recovering clean speech from noisy input. In real-world speech communication, however, noises often exist in not only speaker but also listener environments. Although SE methods can suppress the noise contained in the speaker’s voice, they cannot deal with the noise that is physically present in the listener side. To address such a complicated but common scenario, we investigate a deep learning-based joint framework integrating noise reduction (NR) with listening enhancement (LE), in which the NR module first suppresses noise and the LE module then modifies the denoised speech, i.e., the output of the NR module, to further improve speech intelligibility. The enhanced speech can thus be less noisy and more intelligible for listeners. Experimental results show that our proposed method achieves promising results and significantly outperforms the disjoint processing methods in terms of various speech evaluation metrics.

Index Terms: noise reduction, listening enhancement, intelligibility, full-end speech enhancement

1. INTRODUCTION
Speech communication systems, such as mobile telephony and hearing aids, are supposed to work under adverse conditions of environmental noise. In real-world application scenarios, as depicted in Fig. 1, noises may exist in not only far-end speaker but also near-end listener environments, resulting in severe degradation of speech quality and intelligibility. To improve the listener’s listening experience, speech processing should be accordingly carried out as two sub-tasks: (1) noise reduction (NR): to suppress noise and recover clean speech in the far-end speaker side; and (2) listening enhancement (LE): to pre-process speech signals (the output of the NR module) before playback to improve its intelligibility in the near-end listener side. In this paper, we refer to this two-stage task as full-end speech enhancement.

Many previous works have been proposed to address the above-mentioned sub-tasks separately. For the far-end NR scenario, deep neural network (DNN)-based speech enhancement (SE) methods \cite{1, 2, 3, 4} have gradually become mainstream and shown notable improvement over traditional methods \cite{5, 6}. For the near-end LE scenario, the common idea is to redistribute speech energy in the time-frequency domain in such a way as to boost the perceptually important acoustic cues. A redistribution strategy can be artificially designed on the basis of expert knowledge (e.g., spectral tilt flattening and dynamic range compression \cite{7, 8}) or automatically derived from an optimization solution for an intelligibility metric (e.g., speech intelligibility index (SII) \cite{9}). In our previous work, we introduced generative adversarial network (GAN) model into LE task and achieved impressive results \cite{10}. However, these methods assume that the input speech is clean, which is incompatible with the scenario of a full-end SE task where the input speech is often noisy.

Recently, researchers have explored joint processing of noise reduction and listening enhancement \cite{11, 12, 13, 14}. To achieve it, most existing works jointly control the NR filter along with near-end filter gain to optimize a certain target intelligibility metric, e.g., SII in \cite{11} and mutual information in \cite{12}. However, to make the optimization problem mathematically tractable, the NR filter is considered to be relatively simple (e.g., Niermann et al. \cite{11} used Wiener filter). Besides, most of them introduce additional assumptions and approximations to some extent, including target metric approximation \cite{11, 13} and Gaussian signal model \cite{12}, therefore limiting performance.

In this paper, we propose a novel joint model for full-end SE. We intuitively extend our previous GAN-based LE method \cite{10} by integrating it with a mainstream DNN-based NR method, leading to a fully DNN-based solution. This model can fully benefit from the powerful modeling capabilities of neural networks. Moreover, it can be jointly optimized using a unified loss function and without being dependent on unnecessary assumptions and approximations. Our experiments indicate that the proposed model significantly improves speech quality and intelligibility and clearly outperforms the disjoint pipeline methods.

2. PROBLEM FORMULATION
Consider the application scenario of full-end SE that is depicted in Fig. 1. The signal model follows\footnote{We disregard all related room transfer functions for simplicity.}:

\[ x = s + u, \quad \hat{s} = NR(x), \quad y = LE(\hat{s}|v), \quad o = y + v, \quad (1) \]
where $s$ is the clean speech, $u$ is the far-end environmental noise, $v$ is the near-end environmental noise, and $x$ is the signal received by the far-end microphone. The NR module receives $x$ and outputs the estimated clean speech $\hat{s}$, i.e., the denoised speech. By conditioning on the near-end noise estimation, the LE module further modifies $\hat{s}$ before it is played by loudspeaker. The output enhanced speech is denoted as $g$. Finally, the signal $o$ is observed by the near-end listener. Our goal is to improve the listening experience for listeners, i.e., the quality of $g$ (without the near-end noise $v$) and intelligibility of $o$ under $v$, by designing effective NR and LE modules. Also, to limit loudspeaker overload and unpleasant playback volume, we follow the equal-power constraint that requires that signal power before and after LE modification (i.e., $s$ and $g$) to be the same.

### 3. PROPOSED METHOD

In this section, we introduce the proposed joint model. Figure 2 shows its overall diagram. It consists of three main modules: (1) a far-end NR module that suppresses noise; (2) a near-end LE module that increases the intelligibility of denoised speech by redistributing its energy over time and frequency; and (3) the noise token module that extracts noise embedding and informs other modules of far-end environmental information. We use causal configurations for these three modules, which enables the model to perform real-time speech processing. Next, we will describe details of each module.

#### 3.1. Far-end Noise Reduction

Far-end NR aims to suppress noise. The input is the noisy speech recorded by the far-end microphone, and the ideal output is a clean speech signal without noise disturbance.

To achieve this, we use a convolutional recurrent network (CRN) [15] as the main neural architecture. As shown in Fig. 3(a), the noisy speech is first converted into real and imaginary spectrograms by using short-time Fourier transformation (STFT). We use a Hanning window with window size of 32 ms and hop size of 8 ms. The encoder consists of five 2D convolutional layers each with 1 (along the time axis)×3 (along the frequency axis) kernel, 1×2 stride, layer normalization [16], and parametric ReLU (PReLU). The output channels are set to 16, 32, 48, 64, 96, and 128, respectively. Between the encoder and the decoder, we insert a two-layer unidirectional long short-term memory (LSTM) with 512 nodes to model the temporal dependencies. The decoder comprises five transposed 2D convolutional layers with the same kernel and stride size as the encoder. Since skip connections are used to feed the output of each encoder layer as the additional input of the decoder layer, the output channels of the decoder are accordingly set to 256, 192, 128, 96, 64, and 32, respectively. The following two decoders respectively predict the real and imaginary parts of a complex ratio mask [17], which are then multiplied with the original complex spectrogram to obtain the denoised one. The denoised speech is then generated with inverse STFT and passed on to the following LE module.

#### 3.2. Near-end Listening Enhancement

The LE module modifies the denoised speech to make it sound more intelligible under the near-end environmental noise. Unlike the far-end process in which the clean speech is ground-truth labels, in the near-end case, there is no definition of what the perfectly intelligible speech is. To address this, in our previous work [10], we modified speech in such a way as to maximize the selected speech intelligibility metrics. Moreover, we also incorporated multiple speech quality metrics as optimization targets to compensate for the quality loss caused by intelligibility-enhancing modifications. The target metrics are SIIB [18], HASPI [19], ESTOI [20], PESQ [21], ViSQOL [22], and HASQI [19]. The former three are intelligibility metrics and the latter three are quality metrics.

However, these metrics are quite complex and even non-differentiable, resulting in difficulty in optimization. Therefore, we introduced GAN model into the LE task, in which the generator ($G$) enhances the intelligibility of speech and the discriminator ($D$) mimics the behavior of objective metrics by learning to predict the correct intelligibility scores of modified speech. Specifically, the discriminator has to closely approximate the intelligibility metrics as a learned surrogate, and then the generator can be trained with the guidance of this surrogate. As shown in Fig. 2, the input features for the LE module ($G$) includes: (1) spectrogram magnitude of denoised speech, (2) the near-end noise estimation (i.e., noise power spectral density estimated by reference microphone), and (3) neural noise embedding extracted from noisy input speech (we will explain this in Section 3.3). The architecture of $G$ is shown in Fig. 3(b). It consists of six 1D convolutional layers each with cumulative layer normalization [23] and PReLU activation, followed by an FC layer. The detailed parameters are same as those used in [10]. The element-wise exponential activation is given as follow:

$$
\alpha = \exp(4 \cdot \tanh(u)),
$$

where $u$ is the result of the last FC layer. Amplification factor $\alpha$, which ranges from 0.02 to 55, is predicted for each time-frequency bin. The $\alpha$ is then applied to the spectrogram of denoised speech to redistribute its energy across time and frequency bins: the bin is boosted when $\alpha > 1$ and otherwise suppressed. Finally, we apply an energy normalization layer to satisfy the equal-power constraint.

For discriminator ($D$), we prepare $D_{qua}$ and $D_{int}$ for predicting the quality and intelligibility scores of enhanced speech, respectively. Each discriminator consists of five 2D convolutional layers with the same parameters used in [10]. The sigmoid activation acts as the final output layer of discriminators, which predicts the scores of modelled target metrics. For example, the output nodes of $D_{int}$ are set to 3, corresponding to three target intelligibility metrics, i.e., SIIB, HASPI, and ESTOI.

#### 3.3. Noise Token

We also insert the noise token module [24] into the joint model. Noise tokens are a set of neural noise templates used to encode the far-end environment information and generate the noise embedding. Such embedding is regarded as additional noise knowledge and fed into both NR and LE modules. We previously demonstrated [24] that noise token embedding can improve the performance of the NR module. We expect that they can also benefit the LE module.
Listening enhancement module

Noise token module

\textbf{metrics:}

\textbf{L} is intelligibility loss comparing the denoised speech with the clean reference speech. Invariant signal-to-noise ratio (SI-SNR) [23], which is calculated by

\textbf{D} is the final enhanced speech output by the LE module, \(D_{\text{int}}(y|v)\) is the predicted scores (under noise \(v\)) output by the intelligibility discriminator, and \(t_{\text{int}}\) is the maximum scores of the selected intelligibility metrics, respectively. By means of this loss, the whole model (including noise token, NR, and LE modules) by

The training objective is composed of three terms:

\[ L = L_{\text{int}} + \alpha * L_{\text{qua}} + \beta * L_{\text{sisnr}}, \]  

where \(L_{\text{int}}\) is intelligibility loss calculated by the intelligibility discriminator, \(L_{\text{qua}}\) is quality loss calculated by the quality discriminator, and \(L_{\text{sisnr}}\) is speech denoising loss. \(\alpha\) and \(\beta\) denote the weight parameters, respectively. To be more specific, \(L_{\text{sisnr}}\) is the scale-invariant signal-to-noise ratio (SI-SNR) [23], which is calculated by comparing the denoised speech with the clean reference speech. Intelligibility loss \(L_{\text{int}}\) is defined as the mean square error between the predicted intelligibility scores and the maximum scores of target metrics:

\[ L_{\text{int}} = \vert \vert D_{\text{int}}(y|v) - t_{\text{int}} \vert \vert ^2 \]  

For test set, the far-end noise type is cafeteria at three SNRs, i.e., 6, 10, and 14 dB; near-end noise type is airport announcement at three SNRs, i.e., -9, -5, and -1 dB. To summarize, the test set contained 1,080 utterances (60 sentences \times 2 genders \times 3 far-end SNRs \times 3 near-end SNRs). Note that all the sentences, SNR levels, and noise types of the test set were unseen during model training.

\subsection{4.2. Implementation Details}

All signals used in the experiments were resampled at 16 kHz. Improved minima controlled recursive averaging algorithm (IMCRA) [29] was used to estimate power spectral density of the near-end noise. During training, we applied parametric logistic function to normalize all metric scores into the range of \([0, 1]\), i.e., the same range with sigmoid activation, and set the corresponding target maximum scores (e.g., \(t_{\text{int}}\) in Eq. (4)) to 1. We used Adam optimizer [30] for training, with initial learning rates of 0.0002 for the three neural module components (noise token, NR, and LE) and 0.0001 for the discriminators \((D_{\text{int}}\) and \(D_{\text{qua}}\)). The batch size was 1, and the hyper-parameters \(\alpha\) and \(\beta\) in Eq. (3) were set to 0.6 and 0.005, respectively.

\subsection{4.3. Objective Evaluations}

We evaluated the proposed method using six objective metrics. As mentioned in Section 3.2, the intelligibility metrics are SIIB, HASPI, and ESTOI; the quality metrics are PESQ, VISSQOL, and HASQI. For the above-mentioned metrics, higher scores indicate better performance. The far-end noisy speech is processed by a certain system and then played under the near-end noise. We evaluated seven systems and notate them as follows.

- \textbf{Noisy}: The far-end input noisy speech is played under the near-end noise without any modification.
- \textbf{Noisy+NR}: The far-end input noisy speech is processed only by the NR module.
- \textbf{Noisy+LE}: Processed only by the LE module.
- \textbf{DPSPipe}: Processed by the signal processing-based disjoint pipeline, which consists of Wiener filter (for NR) and SSDRC algorithm [7] (for LE).
- \textbf{NeuralPipe}: Processed by neural network-based disjoint pipeline, which consists of the pretrained CRN-based NR [15] and GAN-based LE [10] modules.
- \textbf{Joint}: Processed by the partial joint model (without the noise token module), in which the NR and LE models are jointly optimized.
- \textbf{Joint+NT}: Processed by the full proposed joint model (with the noise token module).

\section{4. EXPERIMENTS}

\subsection{4.1. Data Preparation}

We used two public corpora of Harvard sentences [26] (one spoken by male [27] and one by female [28]) in the experiments. We split the whole 720 Harvard sentences into 600, 60, and 60 for training, validation, and test data, respectively.

For training and validation, eight noise types were used in both far-end (speaker) and near-end (listener) environments. Far-end SNR levels were set to 4, 8, and 12 dB; near-end SNR levels were set to -11, -7, and -3 dB. By randomly combining these settings, we generated 28,800 and 2,880 utterances for training and validation, respectively.

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Intelligibility evaluation results are listed in Table 1, where the scores were averaged over the three near-end SNR levels. As we can see, applying only NR (Noisy+NR) or LE (Noisy+LE) does not increase the intelligibility. Noisy+LE has even lower scores than Noisy, since the LE module amplifies the noise contained in the noisy input. To address the full-end SE problem, NeuralPipe, Joint, and Joint+NT integrate both NR and LE modules, resulting in significant intelligibility gains compared with Noisy. In contrast, DSPPipe has extremely low scores. This is because the SSDRC processor wrongly amplifies the residual noise that is produced by the former Wiener filter. Besides, we can clearly see that joint trained models improve upon the disjoint processing methods (DSPPipe and NeuralPipe). Moreover, benefiting from the noise token module that exploits the far-end environment information, Joint+NT consistently outperforms Joint and achieves the overall best performance.

Table 2 lists the objective quality scores of enhanced speech $y$ (without the near-end noise $v$). Since intelligibility-enhancing modifications inevitably degrade the speech quality at the cost of increasing intelligibility, Noisy+NR performs better than the proposed joint models. However, joint models preserve speech quality much better than DSPPipe and NeuralPipe, which indicates the effectiveness of our proposed method.

4.4. Subjective Listening Tests

We conducted subjective preference tests to further evaluate the speech intelligibility and perceptual quality. We conducted pairwise comparisons between Joint+NT and the three systems: (1) DSPPipe, (2) NeuralPipe, and (3) Joint. 300 enhanced samples were randomly selected from the test set for each system, resulting in 900 tested sample pairs (300 samples × 3 system pairs). A total of 20 native English speakers were recruited to participate in intelligibility and quality preference tests, respectively, and all were paid. For intelligibility test, each participant was instructed to listen to 45 randomized sample pairs played back under the near-end noise (i.e., the signal $o$ in Eq. (1)), and for each pair, they had to select the one that sounded clearer or that they could hear with less listening efforts. For quality test, each participant had to listen to 45 sample pairs (without the near-end noise, i.e., the signal $y$ in Eq. (1)) and select the one that sounded better in terms of listening quality. As

![Fig. 4](Image 332x324 to 540x393)

![Fig. 4](Image 332x407 to 540x476)

**Fig. 4**: Preference scores (%) with 95% confidence intervals. We can see from Fig. 4, the proposed Joint+NT achieved significantly higher preference scores than all three compared systems in terms of both speech intelligibility and quality. More interestingly, we found that Joint+NT outperformed Joint by a large margin in listening test results, which further indicates that exploiting far-end noise knowledge is crucial for not only far-end noise reduction but also near-end listening enhancement.

5. CONCLUSION

To address the full-end speech enhancement task where both speaker and listener environments are noisy, we proposed a DNN-based joint framework integrating noise reduction with listening enhancement. These two modules can be jointly optimized under the proposed framework. The NR module suppresses the noise of the input noisy speech, and the LE module further improves its intelligibility. Experimental results using both objective evaluations and subjective listening tests indicate that the joint model can achieve significant intelligibility gain while preserving speech quality well. It also consistently outperforms the disjoint processing pipelines by a large margin.

| Table 1: Objective intelligibility scores averaged over three near-end SNRs for each far-end SNR condition. |
| System | Far-end SNR = 6 dB | Far-end SNR = 10 dB | Far-end SNR = 14 dB |
|--------|---------------------|---------------------|---------------------|
|        | SIIB     HASPI   ESTOI | SIIB     HASPI   ESTOI | SIIB     HASPI   ESTOI |
| Noisy  | 17.98 2.20 0.221 | 19.72 2.31 0.237 | 21.07 2.41 0.249 |
| Noisy+NR | 19.52 2.24 0.250 | 20.73 2.32 0.259 | 21.65 2.39 0.266 |
| Noisy+LE | 15.79 2.09 0.180 | 18.76 2.28 0.206 | 21.91 2.47 0.232 |
| DSPPipe | 15.58 1.96 0.208 | 18.22 2.10 0.229 | 21.06 2.24 0.251 |
| NeuralPipe | 24.47 2.67 0.302 | 27.34 2.85 0.319 | 30.09 3.00 0.333 |
| Joint | 26.16 2.70 0.305 | 28.65 2.84 0.319 | 30.77 2.96 0.330 |
| Joint+NT | 28.48 2.73 0.320 | 31.45 2.87 0.334 | 33.79 2.99 0.344 |

| Table 2: Objective quality scores averaged over three near-end SNRs for each far-end SNR condition. |
| System | Far-end SNR = 6 dB | Far-end SNR = 10 dB | Far-end SNR = 14 dB |
|--------|---------------------|---------------------|---------------------|
|        | PESQ     HASQI   ViSQOL | PESQ     HASQI   ViSQOL | PESQ     HASQI   ViSQOL |
| Noisy  | 1.41 0.15 1.83 | 1.55 0.18 1.94 | 1.69 0.21 2.09 |
| Noisy+NR | 2.33 0.28 2.48 | 2.52 0.32 2.69 | 2.70 0.36 2.91 |
| Noisy+LE | 1.24 0.10 1.66 | 1.32 0.12 1.71 | 1.41 0.14 1.78 |
| DSPPipe | 1.32 0.10 1.68 | 1.43 0.12 1.74 | 1.54 0.14 1.81 |
| NeuralPipe | 2.01 0.23 2.14 | 2.19 0.26 2.25 | 2.35 0.28 2.35 |
| Joint | 2.14 0.28 2.20 | 2.30 0.30 2.32 | 2.43 0.33 2.43 |
| Joint+NT | 2.26 0.30 2.32 | 2.45 0.32 2.43 | 2.58 0.35 2.52 |

(a) Intelligibility preference test
(b) Quality preference test
(c) Joint+NT: 95.3 DSPPipe: 4.7
(d) Joint+NT: 60.7 NeuralPipe: 39.3
(e) Joint+NT: 69.3 Joint: 30.7
(f) Joint+NT: 96.3 DSPPipe: 3.7
(g) Joint+NT: 72.3 NeuralPipe: 27.7
(h) Joint+NT: 87.3 Joint: 12.7

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