END-TO-END MULTI-TASK DENOISING FOR THE JOINT OPTIMIZATION OF
PERCEPTUAL SPEECH METRICS

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ABSTRACT
Although supervised learning based on a deep neural network has recently achieved substantial improvement on speech enhancement, the existing schemes have either of two critical issues: spectrum or metric mismatches. The spectrum mismatch is a well known issue that any spectrum modification after short-time Fourier transform (STFT), in general, cannot be fully recovered after inverse short-time Fourier transform (ISTFT). The metric mismatch is that a conventional mean square error (MSE) loss function is typically sub-optimal to maximize perceptual speech measure such as signal-to-distortion ratio (SDR), perceptual evaluation of speech quality (PESQ) and short-time objective intelligibility (STOI). This paper presents a new end-to-end denoising framework. First, the network optimization is performed on the time-domain signals after ISTFT to avoid the spectrum mismatch. Second, three loss functions based on SDR, PESQ and STOI are proposed to minimize the metric mismatch. The experimental result showed the proposed denoising scheme significantly improved SDR, PESQ and STOI performance over the existing methods.

Index Terms— Speech Denoising, SDR, PESQ, STOI

1. INTRODUCTION
In recent years, deep neural networks have shown great success in speech enhancement compared with traditional statistical approaches. Neural networks directly learn nonlinear complicated mapping from noisy speech to clean one only by referencing data without any prior assumption.

Spectral mask estimation is a popular supervised denoising method that predicts a time-frequency mask to obtain an estimate of clean speech by scaling the noisy spectrum. There are numerous types of spectral mask estimation techniques depending on how to define mask labels. For example, authors in [1] proposed the ideal binary mask (IBM) as a training label, where it is set to be zero or one depending on the signal to noise ratio (SNR) of the noisy spectrum. The ideal ratio mask (IRM) [2] and the ideal amplitude mask (IAM) [3] provided non-binary soft mask labels to overcome the coarse label mapping of IBM. The phase sensitive mask (PSM) [3] considers the phase spectrum difference between clean and noisy signals, in order to correctly maximize the signal to noise ratio (SNR).

Generative models, such as generative adversarial networks (GANs) suggested an alternative to supervised learning. In speech enhancement GAN (SEGAN) [4], a generator network is trained to output a time-domain denoised signal that can fool a discriminator from a true clean signal. TF-SEGAN [5] extended SEGAN to use a time-frequency mask.

However, all the schemes described above suffer from at least one of two critical issues: metric mismatch or spectrum mismatch. Signal-to-distortion ratio (SDR), perceptual evaluation of speech quality (PESQ) and short-time objective intelligibility (STOI) are the most well-known perceptual speech metrics. The typical mean square error (MSE) criterion popularly used for spectral mask estimation is not optimal to maximize them. For example, decreasing the mean square error of noisy speech signals often degrades SDR, PESQ or STOI due to different weighting of the frequency components or non-linear transforms involved in those metrics. The spectrum mismatch is a well known issue. Any modification of the spectrum after the short-time Fourier transform (STFT), in general, cannot be fully recovered after inverse short-time Fourier transform (ISTFT). Therefore, spectral mask estimation and other alternatives optimized in the spectrum domain always have a potential risk of performance loss.

This paper presents a new end-to-end multi-task denoising scheme with the following contributions. First, the proposed framework presents three loss functions:

- **SDR loss function**: The SDR metric is used as a loss function. The scale-invariant term in the SDR metric is incorporated as a part of training, which provided a significant SDR boost.
- **PESQ loss function**: The PESQ metric is redesigned to be usable as a loss function.
- **STOI loss function**: The proposed STOI loss function modified the original STOI metric by allowing 16 kHz sampled acoustic signal to be used without resampling.

The proposed multi-task denoising scheme combines loss functions mentioned above for the joint optimization of SDR,
2. THE PROPOSED FRAMEWORK

![Diagram of End-to-End Multi-Task Denoising based on CNN-BLSTM](image)

**Fig. 1.** Illustration of End-to-End Multi-Task Denoising based on CNN-BLSTM

Figure 1 describes the proposed end-to-end multi-task denoising framework. The underlying model architecture is composed of convolutional layers and bidirectional LSTMs. The spectrogram formed by 11 frames of the noisy amplitude spectrum $|X_{m,k}|$ is the input to the convolutional layers with the kernel size of 5x5. $u$ is an utterance index, $m$ is a frame index and $k$ is a frequency index. The dilated convolution with rate of 2 and 4 is applied to the second and third layers, respectively, in order to increase kernel’s coverage on frequency bins. Dilation is only applied to the frequency dimension because time correlation will be learned by bi-directional LSTMs. Griffin-Lim ISTFT is applied to the synthesized complex spectrum $\hat{X}_{m,k}$ to obtain time-domain denoised output $\hat{x}^u(n)$. Three proposed loss functions are evaluated based on $\hat{x}^u(n)$ and therefore, they are free from the spectrum mismatch.

### 2.1. SDR Loss Function

Unlike SNR, the definition of SDR is not unique. There are at least two popularly used SDR definitions. The most well-known Vincent’s definition [6] is given by

$$\text{SDR}^u = 10 \log_{10} \frac{||x^u_{\text{target}}||^2}{||e^u_{\text{noise}} + e^u_{\text{artif}}||^2} \quad (1)$$

$x^u_{\text{target}}$ and $e^u_{\text{noise}}$ can be found by projecting the denoised signal $\hat{x}^u(n)$ into the clean and noise signal domains, respectively. $e^u_{\text{artif}}$ is a residual term. They can be formulated as follows:

$$x^u_{\text{target}} = \frac{(x^u)^T \hat{x}^u}{||x^u||^2} x^u \quad (2)$$

$$e^u_{\text{noise}} = \frac{(n^u)^T \hat{x}^u}{||n^u||^2} n^u \quad (3)$$

$$e^u_{\text{artif}} = \hat{x}^u - \left( \frac{(x^u)^T \hat{x}^u}{||x^u||^2} x^u + \frac{(n^u)^T \hat{x}^u}{||n^u||^2} n^u \right) \quad (4)$$

Substituting Eq. (2), (3) and (4) into Eq. (1), the rearranged SDR is given by

$$\text{SDR}^u = 10 \log_{10} \frac{|| (x^u)^T \hat{x}^u ||^2}{|| (x^u)^T x^u - \hat{x}^u ||^2} = 10 \log_{10} \frac{|| \alpha^u x^u - \hat{x}^u ||^2}{|| \alpha^u x^u - \hat{x}^u ||^2} \quad (5)$$

where $\alpha^u = \arg \min_{\alpha} || \alpha x^u - \hat{x}^u || = \frac{(x^u)^T \hat{x}^u}{||x^u||^2} x^u$. Eq. (5) coincides with SI-SDR, which is another popularly used SDR definition [7]. In the general multiple source denoising problems, SDR and SI-SDR do not match each other. However, for the single source denoising problem, we can use them interchangeably. SDR loss function is defined as mini-batch average of Eq. (5):

$$L_{\text{SDR}} = \frac{1}{B} \sum_{u=0}^{B-1} 10 \log_{10} \frac{|| \alpha^u x^u ||^2}{|| \alpha^u x^u - \hat{x}^u ||^2} \quad (6)$$

### 2.2. PESQ Loss Function

![Diagram of Block Diagram for the PESQ loss function](image)

**Fig. 2.** Block Diagram for the PESQ loss function: $x^u(n)$ and $\hat{x}^u(n)$ are clean and denoised time-domain signals.

PESQ [8] is defined by ITU-T Recommendation P.862 for the objective speech quality evaluation. Its value ranges from -0.5 to 4.5 and the higher PESQ means better perceptual quality. Although SDR and PESQ have high correlation, it is frequently observed that signals with smaller SDR have higher PESQ than the ones with the higher SDR.
2.3. STOI Loss Function

\[ L_{\text{STOI}} = \frac{1}{B M J} \sum_{u=0}^{B-1} \sum_{m=0}^{M-1} \sum_{j=0}^{J-1} d_{mj}^u \]  

where \( B \) is the number of mini-batch utterances, \( M \) is the number of frames, \( J \) is the number of 1/3 octave bands and \( d_{mj}^u \) is intelligibility measure at utterance \( u \), frame \( m \) and 1/3-octave band \( j \) which is described in detail at Eq. (5) in [11].

2.4. Joint optimization of perceptual speech metrics

In this section, several new loss functions are defined by combining SDR, PESQ and STOI loss functions. The first one is to jointly maximize SDR and PESQ by combining \( L_{\text{SDR}} \) and \( L_{\text{PESQ}} \):

\[ L_{\text{SDR-PESQ}} = L_{\text{SDR}} + \alpha L_{\text{PESQ}} \]  

where \( \alpha \) is a hyper-parameter to adjust relative weighting between SDR and PESQ loss functions.

Similarly, SDR and STOI can be jointly maximized by combining \( L_{\text{SDR}} \) and \( L_{\text{STOI}} \) as follows:

\[ L_{\text{SDR-STOI}} = L_{\text{SDR}} + \beta L_{\text{STOI}} \]  

where \( \beta \) is a hyper-parameter to adjust relative weighting between SDR and STOI loss functions.

Finally, we can combine all three loss functions to jointly optimize SDR, PESQ and STOI metrics as follows:

\[ L_{\text{SDR-PESQ-STOI}} = L_{\text{SDR}} + \alpha L_{\text{STOI}} + \beta L_{\text{STOI}} \]  

3. EXPERIMENTAL RESULTS

3.1. Experimental Settings

Two datasets were used for the evaluation of the proposed denoising framework. QUT-NOISE-TIMIT [13] is synthesized by mixing 5 different background noise sources with the TIMIT [14]. For the training set, -5 and 5 dB SNR data were used but the evaluation set contains all SNR ranges. The total length of train and test data corresponds to 25 hours and 12 hours, respectively. For VoiceBank-DEMAND [15], 30 speakers selected from Voice Bank corpus [16] were mixed with 10 noise types: 8 from Demand dataset [17] and 2 artificially generated one. Test set is generated with 5 noise types from Demand.

3.2. Main Result

Table 1 compared SDR and PESQ performance between different denoising methods on QUT-NOISE-TIMIT corpus. All the schemes were based on the same CNN-BLSTM...
Table 1. SDR and PESQ results on QUT-NOISE-TIMIT: Test set consists of 6 SNR ranges: -10, -5, 0, 5, 10, 15 dB. The highest SDR or PESQ scores for each SNR test data were highlighted with bold fonts.

| Loss Type  | SDR       | PESQ     |
|------------|-----------|----------|
|            | -10dB     | -5dB     | 0dB  | 5dB  | 10dB | 15dB | -10dB | -5dB | 0dB  | 5dB  | 10dB | 15dB |
| Noisy Input| -11.82    | -7.33    | -3.27 | 0.21 | 2.55 | 5.03 | 1.07  | 1.08 | 1.13 | 1.26 | 1.44 | 1.72 |
| IAM        | -3.23     | 0.49     | 2.79  | 4.63 | 5.74 | 7.52 | 1.29  | 1.47 | 1.66 | 1.88 | 2.07 | 2.30 |
| PSM        | -2.95     | 0.92     | 3.37  | 5.40 | 6.64 | 8.50 | 1.30  | 1.49 | 1.71 | 1.94 | 2.15 | 2.37 |
| SDR        | -2.66     | 1.55     | 4.13  | 6.25 | 7.53 | 9.39 | 1.26  | 1.42 | 1.65 | 1.92 | 2.16 | 2.41 |
| SDR-STOI   | -2.45     | 1.67     | 4.22  | 6.38 | 7.62 | 9.56 | 1.30  | 1.49 | 1.72 | 1.99 | 2.21 | 2.49 |
| SDR-PESQ   | -2.31     | 1.80     | 4.36  | 6.51 | 7.79 | 9.65 | 1.43  | 1.65 | 1.89 | 2.16 | 2.35 | 2.54 |
| SDR-PESQ-STOI | -2.34  | 1.78    | 4.22  | 6.37 | 7.54 | 9.36 | 1.37  | 1.59 | 1.83 | 2.13 | 2.37 | 2.61 |

Table 2. STOI results on QUT-NOISE-TIMIT

| Loss Type  | STOI     |
|------------|----------|
|            | -10dB     | -5dB     | 0dB  | 5dB  | 10dB | 15dB |
| Noisy Input| 51.9      | 60.4     | 68.6  | 76.9 | 82.4 | 86.9 |
| SDR        | 58.5      | 70.8     | 79.0  | 84.6 | 87.3 | 89.6 |
| SDR-PESQ   | 60.6      | 72.6     | 80.4  | 85.6 | 88.2 | 90.3 |
| SDR-STOI   | 60.6      | 72.5     | 80.2  | 85.5 | 88.1 | 90.3 |
| SDR-PESQ-STOI | 60.8  | 73.0    | 80.6  | 85.7 | 88.3 | 90.3 |

Table 3. Evaluation on VoiceBank-DEMAND corpus

| Models       | CSIG | CBK | COV | PESQ | SSNR | SDR      |
|--------------|-----|-----|-----|------|------|----------|
| Noisy Input  | 3.37| 2.49| 2.66| 1.99 | 2.17 | 8.68     |
| SEGAN        | 3.48| 2.94| 2.80| 2.16 | 7.73 | -        |
| W A V ENET   | 3.62| 3.23| 2.98| -    | -    | -        |
| TF-GAN       | 3.80| 3.12| 3.14| 2.53 | -    | -        |
| SDR-PESQ (ours) | 4.09| 3.54| 3.55| 3.01 | 10.44| 19.14    |

3.3. Comparison with Generative Models

Table 3 showed comparison with other generative models. All the results except our end-to-end model came from the original papers: SEGAN [4], W A V ENET [18] and TF-GAN [5]. CSIG, CBK and COV are objective measures, where high value means better quality of speech [19]. CSIG is mean opinion score (MOS) of signal distortion, CBK is MOS of background noise intrusiveness and COV is MOS of the overall effect. SSNR is Segmental SNR defined in [20].

The proposed SDR and PESQ joint optimization scheme outperformed all the generative models in all the perceptual speech metrics listed above. One thing to note is that any of the metrics at Table 3 was not used as a loss function but the proposed SDR and PESQ combined loss function is highly effective to those metrics, which suggested its good generalization performance.

4. CONCLUSION

In this paper, a new end-to-end multi-task denoising scheme was proposed. The proposed scheme resolved two issues addressed before: spectrum and metric mismatches. The experimental result presented that the proposed joint optimization scheme significantly improved SDR, PESQ and STOI performances over both spectral mask estimation schemes and generative models. Moreover, the proposed scheme provided good generalization performance by showing substantial improvement on the unseen perceptual speech metrics.
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