A DEEP LEARNING LOSS FUNCTION BASED ON AUDITORY POWER COMPRESSION FOR SPEECH ENHANCEMENT

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ABSTRACT

Deep learning technology has been widely applied to speech enhancement. While testing the effectiveness of various network structures, researchers are also exploring the improvement of the loss function used in network training. Although the existing methods have considered the auditory characteristics of speech or the reasonable expression of signal-to-noise ratio, the correlation with the auditory evaluation score and the applicability of the calculation for gradient optimization still need to be improved. In this paper, a signal-to-noise ratio loss function based on auditory power compression is proposed. The experimental results show that the overall correlation between the proposed function and the indexes of objective speech intelligibility, which is better than other loss functions. For the same speech enhancement model, the training effect of this method is also better than other comparison methods.

Index Terms— Deep Learning, Loss function, Speech Enhancement, Objective Intelligibility

1. INTRODUCTION

Speech enhancement technology aims to improve the quality and the comfort of hearing while improving speech intelligibility [1]. In recent years, deep learning has been widely used in speech enhancement. In addition to exploring various deep network structures to build effective enhancement models, related research also involves the construction and optimization of loss functions used to guide model training. In general, the loss function is constructed based on a certain distance measure between the predicted speech and the reference one. Common methods are mean square error (MSE) [2] and mean absolute error (MAE) [3] as distance measures, which are very convenient to calculate. [4] proposed the scale-invariant signal-to-noise ratio (SI-SNR), and [5] proposed the scale-dependent signal distortion ratio (SD-SDR). This kind of loss function directly uses the distance between the enhanced speech signal waveform and the reference one to evaluate the enhanced speech quality, and there are many successful applications [6][7]. However, this kind of objective distance is different from subjective auditory one, so it is necessary to introduce auditory effect into the composition of distance measure. The basic idea is to simulate the perceptual characteristics of human ear to frequency and loudness [8], and to implement nonlinear warp of frequency and compression of intensity [9]. Jesper proposed extended short-time objective intelligibility (ESTOI) [10] based on STOI [11][12], and it’s obtained by calculating subband spectral envelope correlation coefficient. [13] introduced the perceptual evaluation of speech quality (PESQ) [14], and combined with the MSE in the logarithmic power spectra to form perceptual metric for speech quality evaluation (PMSQE) loss function (To distinguish the MSE in [13] from the ordinary MSE, we abbreviate it as LogMSE). [15][16] use the power exponent to compress the value of each component in their loss functions. In addition, [17][18] trained an exclusive network for speech quality evaluation, and in [19], the evaluation network is connected to the tail of the speech enhancement model to guide the training of the model.

Due to the need to test large amounts of data, subjective evaluation consumes too much resources. Several objective indexes, such as PESQ provided by ITU-T P.862 [14], STOI and SI-SNR become the main scheme to measure the quality of speech. By analyzing the loss functions such as MSE, PMSQE, SI-SNR, and STOI, we find that the correlation coefficients [20] between these loss functions and PESQ are generally lower than 0.9. During training, PMSQE and STOI can’t pay attention to the phase information because they are measured on the magnitude spectra, and too much empirical auditory processing will make the model be inclined to the corresponding indexes (PESQ or STOI). Since SI-SNR is measured by waveform in the time-domain, the magnitude and phase can be investigated indirectly and it introduces a reasonable expression of signal-to-noise ratio (SNR) to make its effect better and more stable. However, when the performance of the model is improved, the guiding effect of SI-SNR loss function will deteriorate. Therefore, a signal-to-noise ratio loss function based on auditory power compression (APC-SNR) is proposed. Firstly, the auditory power exponents used in PESQ are referenced and mapped back to the power spectrum. Secondly, the exponent operation in the power spectrum is converted into the proportional factor in the time-frequency spectrum, and the proportional factor is controlled by hyper-parameters before it is applied to the signal. Finally, we refer
to the SNR representation method of time-domain SI-SNR to calculate the loss function in the compressed time-frequency domain (tf-domain). The experimental results show that this method has a good correlation with most speech quality evaluation indexes. And it can make the comprehensive performance of the model better.

The rest of this paper is arranged as follows: Section 2 introduces the related algorithms. The third section is the description of the auditory power compression loss function. Section 4 is experiment and result analysis. The fifth section is the work summary.

Fig. 1 SI-SNR in the different domains. $S_x$ and $S_n$ represent noisy and noise waveform respectively. $r$ and $i$ represent real and imaginary axis of tf-domain respectively.

2. RELATED WORK

2.1. Scale-invariant signal-to-noise ratio

The scale-invariant signal-to-noise ratio (SI-SNR) $\text{HI}$ is a reasonable expression of SNR. Measurement in time-domain can take into account both magnitude and phase as shown in the Fig 1(a). So SI-SNR is a commonly used loss function and is defined as,

$$
\begin{align*}
    & S_{\text{target}} := (\hat{s}, s) / \|s\|^2 \\
    & e_{\text{noise}} := s - S_{\text{target}} \\
    & \text{SI-SNR} := 10 \log_{10} \left( \|S_{\text{target}}\|^2 / \|e_{\text{noise}}\|^2 \right)
\end{align*}
$$

(1)

where $s \in \mathbb{R}^{1 \times T}$ and $\hat{s} \in \mathbb{R}^{1 \times T}$ represent the referenced and the enhanced signal respectively. $\|s\|^2 = < s, s >$ represents the energy of the signal.

2.2. Perceptual metric for speech quality evaluation

When calculating PMSQE $[13]$ or PESQ $[14]$, the first step is level alignment. PESQ aligns the enhanced to label. But since we can’t artificially introduce the influence of label during training, PMSQE aligns label to the enhanced:

$$
\hat{x}_t = x_t \cdot \frac{P_c}{\sum_i (g^T \cdot x_t)}
$$

(2)

where $x_t$ is the $t$-th frame of the power spectrum. $g$ is a spectral weighting mask which replicates the band-pass filtering and $P_c$ is a power correction factor which accounts for the frame length, overlapping and windowing applied during the spectral computation (via STFT). Then the power spectrum is mapped to the Bark spectrum by transformation matrix $H$,

$$
b_t = \hat{x}_t \cdot H
$$

(3)

where $b_t = [B_{t,1}, \ldots, B_{t,q}]^T$, $\hat{x}_t \in \mathbb{R}^{1 \times F}$, $H \in \mathbb{R}^{F \times Q}$, $Q$ and $F$ are the dimensions of the Bark spectrum and power spectrum. Then signals are transferred to loudness spectra as,

$$
S_{t,q} = s_t \cdot \left( \frac{P_{0}(q)}{0.5} \right)^{\gamma_q} \cdot \left( 0.5 + 0.5 \frac{B_{t,q}}{P_{0}(q)} \right)^{\gamma_q} - 1
$$

(4)

where $s_t$ is the scaling factor, and $P_0(q)$ is the absolute auditory threshold for the $q$-th Bark band. Each Bark band has a corresponding variable $\gamma_q$ [21]. Then, PESQ and PMSQE simplify the computation of the symmetrical disturbance vector proposed in PESQ by applying a center-clipping operator over the absolute difference between the loudness spectra as,

$$
d_t^{(s)} = \max(|s_t - \hat{s}_t| - 0.25 \cdot \min(s_t, \hat{s}_t), 0)
$$

(5)

where $s_t = [S_{t,1}, \ldots, S_{t,q}]^T$ and $\hat{s}_t = [\hat{S}_{t,1}, \ldots, \hat{S}_{t,q}]^T$ represent the referenced and enhanced loudness spectra respectively. $\cdot$, $\min(\cdot)$, and $\max(\cdot)$ are element-wise operation. Then the asymmetric disturbance vector can be obtained as,

$$
d_t^{(a)} = d_t^{(s)} \odot r_t
$$

(6)

where $\odot$ represents element-wise multiplication, elements of $r_t = [R_{t,1}, \ldots, R_{t,q}]^T$ are computed from the Bark spectra of referenced $B_{t,q}$ and enhanced $\hat{B}_{t,q}$ as follows,

$$
R_{t,q} = \left( \frac{B_{t,q} + \epsilon}{\hat{B}_{t,q} + \epsilon} \right) ^ \lambda
$$

(7)

$\epsilon$ and $\lambda$ are 50 and 1.2. Symmetric disturbance and asymmetric disturbance measurement are calculated as follows,

$$
D_t^{(s)} = ||w||_F^2 \cdot ||w \odot d_t^{(s)}||_2
$$

(8)

$$
D_t^{(a)} = ||w \odot d_t^{(a)}||_1 = w^T \cdot d_t^{(a)}
$$

(9)

where $w$ is a vector filled with weights proportional to the width of the Bark band, obtained from [13].

Finally, PMSQE introduces LogMSE, because the resulting PESQ includes highly nonlinear and non-fully differentiable operators which can lead to gradient misguidance if applied alone [13]. The loss is defined as,
\[ L = \frac{1}{T} \sum_{t} \left( \frac{1}{F} \sum_{f} \frac{1}{\delta_f^2} \left( \log \frac{|X_{t,f}|^2}{|\hat{X}_{t,f}|^2} \right)^2 + \alpha D_t^{(s)} + \beta D_t^{(s)} \right) \]

where \(|X_{t,f}|^2\) and \(|\hat{X}_{t,f}|^2\) are the reference and enhanced power spectra respectively. \(\delta_f\) is the standard deviation of \(L\). \(T\) is the number of frames.

3. PROPOSED METHOD

3.1. Scale-invariant signal-to-noise ratio in time-frequency spectrum

The idea of signal-to-noise ratio expression of SI-SNR in time-domain is migrated to the time-frequency spectrum:

\[
\begin{align*}
{x}_{\text{target}} & := \frac{\langle \hat{x}, x \rangle}{\|x\|^2} \\
{e}_{\text{noise}} & := x - {x}_{\text{target}} \\
\text{SI-SNR}_{\text{TF}} & := 10 \log_{10} \left( \|{x}_{\text{target}}\|^2 / \|{e}_{\text{noise}}\|^2 \right)
\end{align*}
\]

where \(\hat{x}\) and \(x\) represent the time-frequency spectra of enhanced and referenced signal respectively. As shown in Fig.[1]b, different from the time-domain, the SI-SNR_{TF} can only focus on the phase, so the effect will be far worse than the SI-SNR in time-domain. We will introduce the scaling calculated based on the magnitude to compensate for the magnitude insensitivity. In the time-frequency spectrum, we can make the loss function focus on magnitude and phase more controllable. It is also more conducive to gradient transfer for tf-domain model.

3.2. Auditory power compression

Auditory loudness spectrum \((4)\) is the core of PMSQE and PESQ, so we conducted a in-depth analysis of it.

\[
\begin{align*}
S_{t,q} & = s_t \cdot \left( \frac{P_0(q)}{0.5} \right)^{\gamma_q} \left[ \left( 0.5 + 0.5 \frac{B_{t,q}}{P_0(q)} \right)^{\gamma_q} - 1 \right] \\
& = s_t \cdot \left[ \left( \frac{P_0(q)}{0.5} \right)^{\gamma_q} \left( 0.5 + 0.5 \frac{B_{t,q}}{P_0(q)} \right)^{\gamma_q} - \left( \frac{P_0(q)}{0.5} \right)^{\gamma_q} \right] \\
& = s_t \cdot \left[ \left( P_0(q) + B_{t,q} \right)^{\gamma_q} - (2 \cdot P_0(q))^{\gamma_q} \right]
\end{align*}
\]

With the expansion of the formula \((11)\). The abstract formula becomes easier to explain. The loudness conversion mainly calculates the distance between the power of each band and the absolute auditory threshold under the action of \(\gamma_q\) in the Bark spectra.

Since we need to use it in the loss function, we need to consider its gradient,

\[
\frac{\partial S_{t,q}}{\partial B_{t,q}} = s_t \cdot \gamma_q \cdot \left( P_0(q) + B_{t,q} \right)^{\gamma_q - 1}
\]

where \(\gamma_q\) is a constant in \([0.23, 0.27]\), \(P_0(q)\) is the a constant in \([0.251189, 51286152]\). It can be observed that the maximum multiple between different \(P_0(q)\) can reach 200 million. It is easy to make a large deviation of gradients between different subbands with an exponential about \(-0.77\). We speculate that the difference of gradient and masking effect \((5)\) can easily make the model unbalanced in training. It will make the optimizer only focus on the parts beneficial to the PESQ score. Using the Zwicker exponentials without the absolute auditory thresholds could also endow different subbands with auditory difference characteristics. So we simplify the loudness expression \((12)\) to,

\[
\hat{S}_{t,q} = \left( B_{t,q} + \epsilon \right)^{\gamma_q}
\]

where \(\epsilon\) is set to prevent the base number from zero.

The second problem is the gradient blur. Let’s return to the formula \((3)\), where the \(H\) matrix is a sparse zero-one matrix. It aims to calculate the sum of the specified subbands and obtain the corresponding subband values of the Bark spectrum. It will cause the gradient of some (up to 25) subbands to become the same when the gradient is propagated back, resulting in gradient blur.

So we map the Zwicker auditory effect exponentials \(\gamma = [\gamma_1, \cdots, \gamma_q]\) to the power spectrum \(\tilde{S} = [\gamma_1, \cdots, \gamma_f]\) according to the correspondence between the Bark bands and power bands \([21]\). Then we change the Bark spectrum \(\tilde{S} \in \mathbb{R}^{T \times Q}\) in formula \((14)\) to the power spectrum \(\tilde{S} \in \mathbb{R}^{T \times F}\), and the auditory expression is changed to,

\[
\tilde{S} = [\left( x_r^2 + x_i^2 \right) + \epsilon]^{\tilde{\gamma}}
\]

where \(x_r\) and \(x_i\) represent the real and imaginary part of the time-frequency spectrum respectively.

In order to avoid the absence of phase in the power spectrum, we convert the exponential operation of the power spectrum into the proportional scaling relationship \(\lambda\) of the real and imaginary part in time-frequency spectrum. And the auditory expression \(\tilde{S} \in \mathbb{R}^{T \times F}\) is changed to \(\tilde{S} \in \mathbb{R}^{2T \times 2F}\),

\[
\begin{align*}
\tilde{S}_r & = x_r \odot \lambda \\
\tilde{S}_i & = x_i \odot \lambda
\end{align*}
\]

where \(\tilde{S}_r \in \mathbb{R}^{T \times F}\) and \(\tilde{S}_i \in \mathbb{R}^{T \times F}\) represent the real and imaginary part of auditory expression \(\tilde{S}\). \(\lambda \in \mathbb{R}^{T \times F}\) is a scaling factor computed by,

\[
\lambda = \left( x_r^2 + x_i^2 + \epsilon \right)^{\frac{2-\gamma}{\gamma}}
\]

In order to prevent the difference of scaling between different bins become too large. A limiting threshold \(\theta\) is set to
change the value less than $\theta$ to $\theta$,

$$\lambda_{t,f} = \begin{cases} 
\lambda_{t,f}, & \theta \leq \lambda_{t,f} \leq 1 \\
\theta, & \lambda_{t,f} < \theta 
\end{cases} \quad s.t. \ \theta \in [0, 1] \quad (18)$$

Finally, we measure the loss by formula (11) in compressed spectra $\tilde{S}$. A signal-to-noise ratio loss function based on auditory power compression (APC-SNR) is obtained,

$$\begin{align*}
\tilde{S}_{\text{target}} & := \left( \frac{\tilde{S} \cdot \tilde{S}_{\text{ref}} - \tilde{S}_{\text{ref}}}{||\tilde{S}_{\text{ref}}||^2} \right) \\
\tilde{S}_{\text{noise}} & := \tilde{S} - \tilde{S}_{\text{target}} \\
\text{APC-SNR} & := 10 \log_{10} \left( \frac{||\tilde{S}_{\text{target}}||^2}{||\tilde{S}_{\text{noise}}||^2} \right)
\end{align*} \quad (19)$$

where $\tilde{S}$ and $\tilde{S}_{\text{ref}}$ represent enhanced and referenced spectrum, and their $\lambda$ is calculated from their energy spectra respectively.

4. EXPERIMENTS

4.1. Model design and training setup

The model used in our experiment is similar to that in these papers [15, 22]. The overall framework is shown in the Fig 2.

We used the short-time Fourier transform (STFT) and its inversion (iSTFT) with 512 window length, 256 frame shift, and hanning window. The magnitude spectrum was taken as the input. The model is mainly composed of fully-connected layer (FC) and gated recurrent units (GRUs) [23]. Rectified linear unit (ReLU) [24] is used as activations except for the last layer. Sigmoid activation [25] is used to predict the gain mask. The result is obtained by the noisy time-frequency spectrum multiplied by the gain mask.

![Fig. 2. The framework of model and loss function.](image)

The calculation of the loss function was divided into cases A or B. If the loss function is calculated in the time-frequency spectrum, operation A will be performed. If the loss function is calculated in the time-domain, operation B will be performed. And parameters of model are optimized by Adam method [26]. And the learning rate was initialized to $10^{-3}$, which was decayed to 50% when the loss on the verification set plateaued for 5 epochs. The training was stopped if the loss plateaued for 20 epochs.

4.2. Data

We used the speech and noise data in DNS-Challenge [27] to generate a total of 200 hours noisy speech. The SNR was between $-5$dB and 20dB. We shifted pitch of speech by pysisox [28], and the shifted value was between $-2$ and 2 semitones. Data was then divided into training and validation set at 4:1.

The SNR of the test data was between $-10$dB and 30dB, and the pitch shift was also between $-2$ and 2 semitones. The speech data in the test set did not participate in the training or validation set, and the noises were from the ESC-50 [29] dataset. A total of 14,000 10-seconds audio were generated for testing.

4.3. Correlation analysis

Pearson correlation coefficient is often used to measure the correlation between indexes [30]. We calculated the PESQ, STOI, LogMSE ($\alpha = \beta = 0$ in formula (10)), PMSQE1 (formula (10) without LogMSE), MSE, SI-SNR, and APC-SNR on test data. The reason why we decomposed PMSQE into PMSQE1 and LogMSE is that the value ranges of them are quite different. If combined, the correlation will be dominated by LogMSE. Table I shows the absolute values of the correlation coefficient between indexes. It can be observed that the overall correlation between our proposed method and other indexes is better than other methods. We also additionally tested the MSE after compression (APC-MSE). From the perspective of correlation, APC-MSE is better than MSE, which also proves the effectiveness of auditory perception compression.

We also drew the distribution of each loss and PESQ in Fig 3. The larger value of loss function, the smaller value of the PESQ. It can be seen that STOI, PMSQE1, and LogMSE become insensitive with the decrease of PESQ. MSE and APC-MSE are insensitive on both sides. We speculate that insensitivitiy will mislead the model in the case of correspond- ing speech quality. For SI-SNR, although the variance is large, it have a more stable downward trend with the increase of PESQ, and the tail of the insensitive area is smaller. This also explains why SI-SNR can achieve good results although it converges slowly. For the APC-SNR we proposed, its overall variance is smaller, and the insensitivity of the head and tail is also weakened. It can be seen that the proposed loss function is more sensitive to the speech quality, and the small variance can make the model converge faster. It is more suitable for model training.

4.4. Evaluation scores for experiments

Although many indexes are listed in the table I only PESQ, STOI, and SI-SNR are widely used in model performance evaluation [31], [32], [33]. PESQ introduces non-differentiable auditory effects and considers numerical differences in loudness spectra, which can accurately measure the energy value
Table 1. The correlation coefficient between evaluation indexes.

|          | PESQ | STOI | PMSQE1 | LogMSE | MSE | SI-SNR |
|----------|------|------|--------|--------|-----|--------|
| PESQ     |      | 0.71 | 0.87   | 0.65   | 0.40| 0.88   |
| STOI     | 0.71 |      | 0.86   | 0.71   | 0.47| 0.80   |
| PMSQE1   | 0.87 | 0.86 |       | 0.79   | 0.49| 0.87   |
| LogMSE   | 0.65 | 0.71 | 0.79   |       | 0.43| 0.68   |
| MSE      | 0.40 | 0.47 | 0.49   | 0.43   |     | 0.51   |
| APC-MSE  | 0.50 | 0.60 | 0.61   | 0.60   | 0.94| 0.59   |
| SI-SNR   | 0.88 | 0.80 | 0.87   | 0.68   | 0.51|       |
| APC-SNR  | 0.91 | 0.91 | 0.91   | 0.74   | 0.52| 0.99   |

in the range of human ear hearing. PMSQE is only a differentiable suboptimal mixture for PESQ and LogMSE. STOI measures correlation on octave spectra, it’s more sensitive to the delay between the spectra. SI-SNR is a reasonable measure of SNR and it can measure both magnitude and phase. MSE and LogMSE are the most traditional distance metrics, they neither accord with human hearing, nor have a reasonable expression of SNR. So MSE and LogMSE can’t reasonably measure the performance of the model, but comprehensive consideration of PESQ, STOI and SI-SNR can.

4.5. Hyper-parameters analysis

Based on the model and data in 4.1, we analyzed the hyper-parameters $\epsilon$ and $\theta$ in formula (17) and formula (18).

Shown as Fig. 4, firstly we set $\epsilon$ to 1 and $\theta$ was set to 0.0001, 0.0005, 0.001, 0.005, 0.01, 0.05, 0.1 and 0.5 respectively to test. It can be seen from the graph that PESQ and STOI with $\theta$ value of 0.01 are the best, and SI-SNR is slightly lower than 0.001. On the whole, the three indexes were concave distribution. The reason is that $\theta$ controls the lower bound of compression $\lambda$ in formula (17), and 0.01 is equivalent to 100 times the maximum compression difference when $\epsilon$ is set to 1. The maximum difference of compression ratio will increase with the decrease of $\theta$. If the difference is too large, it is easy to lead to over-fitting of the model. If it is too small, it will weaken the compression effect, so 0.01 is a suitable value. Similarly, we set $\theta$ to 0.01 and conducted experiments on $\epsilon$. The experiment found that $\epsilon$ setting 1 was appropriate. The reason is that the exponent of formula (17) is about 0.38. If $\epsilon$ is set as a small number, the $\lambda$ in the region with energy less than $(1-\epsilon)$ will be very large, which will lead to the distraction for the model. So set $\epsilon$ to 1 can control scaling $\lambda$ below 1 and reserve exponential scaling effect.

It can be seen from the above experiments that $\epsilon$ and $\theta$ are used to control the upper and lower bounds of $\lambda$ respectively. The two can be regulated according to different situations.

4.6. Experimental results and discussion

We trained models by STOI, PMSQE1 (without LogMSE), PMSQE, MSE, SI-SNR, and APC-SNR respectively. The results are shown in the table 2. Due to the different value ranges of PESQ, STOI and SI-SNR, we take the average of the standardized values of each index as the comprehensive index (CI), which is defined as,

$$ CI = \left\{ \sum_{i \in \text{indexes}} \left[ \left( I_i - \mu_i \right) / \sigma_i \right] \right\} / 3 $$

(20)
where indexes $= [\text{PESQ, STOI, SI-SNR}]$. $\mu_i$ and $\sigma_i$ represent the mean and standard deviation of corresponding index respectively (computed by column elements in Table 2). $I_i$ represent the value of corresponding index of each method.

As shown in the table [2], PMSQE1 can greatly improve the performance on PESQ, but the performance on STOI and SI-SNR will be weakened. We speculate that the gradient inhomogeneity and blur problems mentioned in section [5] will make the model tend to optimize the favorable parts for PESQ, and ignores the structural characteristics of the signal itself. STOI converges very slowly and results show that the model only inclines to STOI. Because PMSQE1 and STOI only focus on magnitude, they perform poorly in SI-SNR. After adding LogMSE to PMSQE1, the effect on the PESQ score will be weakened, and the other scores are improved. MSE and SI-SNR methods perform well. This proves that the conversion of auditory domain and the introduction of a large number of auditory constants are not conducive to model training. Our method shows better comprehensive performance (CI=0.570) than other referenced loss functions. The proposed loss function can properly introduce the auditory compression effect without auditory spectral mapping, and endow the measurement method that only focuses on the phase with magnitude difference. It can improve the auditory quality (PESQ and STOI) under the premise of ensuring the original signal structure (SI-SNR), so that the comprehensive performance is improved.

Besides, we also combined APC-SNR with PMSQE1 and achieved better results. We speculate that APC-SNR is a linear loss function similar to LogMSE, and PMSQE1 is a nonlinear loss function. And our method is much better than LogMSE, it just makes up for the shortcomings of PMSQE1, so the combination can get very good results (CI=0.838).

### Table 2. Test results of models trained by each loss function

|          | PESQ  | STOI  | SI-SNR | CI   |
|----------|-------|-------|--------|------|
| PMSQE1   | 2.819 | 0.915 | 6.793  | -1.067 |
| STOI     | 2.422 | 0.942 | 14.932 | -0.337 |
| PMSQE    | 2.609 | 0.928 | 15.538 | -0.310 |
| MSE      | 2.593 | 0.934 | 17.098 | 0.010  |
| SI-SNR   | 2.638 | 0.937 | 17.482 | 0.295  |
| APC-SNR  | 2.718 | 0.939 | 17.532 | 0.570  |
| PMSQE1+APC-SNR | 2.794 | 0.940 | 17.638 | 0.838  |

### 5. CONCLUSIONS

In this paper, we proposed a signal-to-noise ratio loss function based on auditory power compression (APC-SNR) for model training, which can improve the overall performance of the model under various indexes. The experimental results show that the comprehensive quality score of the model trained based on our method is better than other referenced ones. This method also maintains a good correlation with evaluation indexes. Not only can it be used to train models, but it can also be used to evaluate speech quality. But this method still needs improvement, such as the adaptation of auditory power index under different frequency resolutions and the adaptation with different mask apply methods of model. More effort is needed to delve into the solutions.

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