DYNAMIC ACOUSTIC COMPENSATION AND ADAPTIVE FOCAL TRAINING FOR PERSONALIZED SPEECH ENHANCEMENT

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ABSTRACT

Recently, more and more personalized speech enhancement systems (PSE) with excellent performance have been proposed. However, two critical issues still limit the performance and generalization ability of the model: 1) Acoustic environment mismatch between the test noisy speech and target speaker enrollment speech; 2) Hard sample mining and learning. In this paper, dynamic acoustic compensation (DAC) is proposed to alleviate the environment mismatch, by intercepting the noise or environmental acoustic segments from noisy speech and mixing it with the clean enrollment speech. To well exploit the hard samples in training data, we propose an adaptive focal training (AFT) strategy by assigning adaptive loss weights to hard and non-hard samples during training. A time-frequency multi-loss training is further introduced to improve and generalize our previous work sDPCCN for PSE. The effectiveness of proposed methods are examined on the DNS4 Challenge dataset. Results show that, the DAC brings large improvements in terms of multiple evaluation metrics, and AFT reduces the hard sample rate significantly and produces obvious MOS score improvement.

Index Terms— personalized speech enhancement, acoustic environment mismatch, hard sample, dynamic acoustic compensation, adaptive focal training

1. INTRODUCTION

Personalized speech enhancement (PSE) aims to extract and enhance the target speaker’s speech in a complicated multi-talker noisy or reverberant acoustic environment. Recently, there has been increasing attention to PSE, and some competitions such as the 4th Deep Noise Suppression (DNS4) Challenge [9] has set up a specialized track for this task. According to DNS4 Challenge, we can conclude that an excellent PSE system is generally required to enhance the target speech with the help of target speaker’s enrollment speech in three different situations: 1) Noisy with no interfering speaker; 2) Clean but with interfering speakers. 3) Noisy and with interfering speakers.

In recent years, deep learning based personalized speech enhancement has achieved promising performance [4, 15, 16]. However, there are still two problems need to be solved. The first one is the acoustic environment mismatch between the enrollment speech and the noisy speech to be enhanced. Generally, the provided enrollment speech is clean and the speech to be enhanced may contain serious noise, such mismatch makes the reference voiceprint information misleading to some extent. The second problem we found is the hard sample mining and learning. According to objective evaluation metrics, samples with low scores can be regarded as hard and the others as non-hard. Although hard samples tend to have greater losses during training, the model is still biased towards non-hard samples because hard samples are often sparse in training set. That’s why many models can achieve excellent average evaluation scores on the whole test set, but have very poor performance on a few hard samples. In fact, such hard samples will seriously affect the user experience of PSE system in real scenarios, which makes it is meaningful and important to improve the system enhancement ability on hard samples contrapuntally.

Although there are many previous works focused on acoustic mismatch between training and test datasets [23], or even cross-domain speech extraction tasks [1], the works on dealing with acoustic environment mismatch between test noisy and speaker enrollment speech is limited. Authors in [7] have proposed an iterative refined adaptation method, it uses the original speaker embedding to extract target speech first and re-encodes the extracted speech to obtain a refined text-dependent speaker embedding. Then, the refined embedding is combined with original one using weights to form a new embedding to extract the target speech again. This method can lead to good results, but it heavily increased the computational complexity and inference time. The hard sample issue has attracted much attention in computer vision, such as the re-weighting or novel loss function [5, 8, 19], etc. However, it is very difficult to find works on hard sample problem in personalized speech enhancement in the literature. Therefore, we think that it will be interesting to explore methods for hard sample mining in PSE tasks.

In [12], our previous proposed sDPCCN was specially designed for pure target speech extraction and achieved excellent performance and robustness. In this study, we first generalize sDPCCN to the personalized speech enhancement task, then three new improvements are proposed to further enhance the sDPCCN for PSE: 1) TF-loss. The original sDPCCN only uses the time-domain negative scale invariant signal-to-noise ratio (SISNR) [18] loss, here we combine the SISNR with a frequency-domain mean square error (MSE) loss to leverage the information from different domains during model training; 2) Dynamic acoustic compensation (DAC). The DAC is designed to dynamically update the background acoustic characteristics of target speaker enrollment speech with each input test noisy speech, by simply intercepting the noise or environmental acoustic segments from noisy test speech and mixing it with the clean enrollment utterance; 3) Adaptive focal training (AFT). The AFT is proposed to emphasize the importance of hard samples in training data by using an adaptive focal loss during model training, where a $\sin(\cdot)$ transformation is used to weight each batch normalized TF-loss. All our experiments are performed on the DNS4 dataset, results show...
that all the proposed methods are effective, especially the DAC and APT. They make the model outperform sDPCCN baseline significantly in both signal distortion and perceptually evaluation metrics.

2. SDPCCN

Our previous work DPCCN [12], a densely-connected pyramid complex convolutional network, is a U-Net [26] style network that proposed for speech separation. And we extended it to sDPCCN for target speech extraction (TSE), by simply integrating a small block of enrollment speaker encoder to supervise the network towards extracting target speech. Extensive experiments in [12] showed that both DPCCN and sDPCCN achieved good performance and robustness, surpassing some well-known systems such as Conv-TasNet [20] and TD-SpeakerBeam [6] on speech separation and TSE task respectively. In these two networks, DenseNet [14] is used in encoder/decoder to alleviate the vanishing-gradient problem and encourage the feature reuse. Temporal convolutional network (TCN) [2] is used as the bottleneck layer between encoder and decoder to capture long-range time information. A novel pyramid pooling layer [31] introduced after the decoder is used to leverage the global information. Due to the promising performance of SDPCN in TSE task, we generalize it to the personalized speech enhancement. More details of DPCCN and sDPCCN can be found in [12].

3. PROPOSED METHODS

3.1. Architecture

The whole architecture of our proposed methods is shown in Fig.1 We generalize the sDPCCN [12] to personalized speech enhancement with several innovations, including the TF-loss, the dynamic acoustic compensation, and the adaptive focal training. For performance comparison, the traditional pre-processing methods: spectral subtraction [3] and MMSE-LSA [10] are also investigated to deal with the acoustic environment mismatch issue. Details of the new methods are presented as follows.

3.2. TF-loss

The loss function used in original sDPCCN is the negative SISNR [18], which is commonly used in speech separation and target speech extraction tasks. Since we generalize sDPCCN to personalized speech enhancement, it is reasonable to combine the loss which is commonly used in speech enhancement with the negative SISNR. In addition, many previous works [21, 28, 32] have proved that it is beneficial to leverage information from multiple domains when computing the system training loss. Based on these two points, we choose the most commonly used mean square error (MSE) loss

$$L_{\text{MSE}}$$ to provide complementary information for speech enhancement. The combined training loss $L_{TF}$ is defined as:

$$L_{TF} = L_{\text{SISNR}} + L_{\text{MSE}}.$$  

(1)

where the negative SISNR $L_{\text{SISNR}}$ is computed in time domain while $L_{\text{MSE}}$ is computed in frequency domain (the output before iSTFT block in sDPCCN).

3.3. Dynamic Acoustic Compensation

As shown in Fig.1 and Fig.2, given a random test noisy speech $Y$, the acoustic environment mismatch between $Y$ and enrollment speech $S$ varies with $Y$ dynamically during speech enhancement. This is because it is almost impossible for two non-simultaneous recorded speech to be in the same acoustic environment. The acoustic mismatch between noisy $Y$ and enrollment speech $S$ is unfavorable but inevitable, which will lead to a poor PSE performance.

To alleviate this problem, the dynamic acoustic compensation (DAC) is proposed and illustrated in Fig.2. Given $S$ and a random noisy input speech waveform $Y$, we first simply intercept the first $J$ and the last $K$ frames signal of $Y$ as the background noise. Then we concatenate and repeat them to form a signal with the same length as enrollment speech $S$. The final noisy enrollment speech $S_n$ is obtained as,

$$S_n = \text{repeat}(Y_1, \ldots, Y_J, Y_{T-K+1}, \ldots, Y_T) + S$$  

(2)

where $T$ is the total frame length of $Y$. Actually, our DAC is motivated by the traditional spectral subtraction (SS) algorithm [3]. Although it is very simple, it effectively compensates for the acoustic background characteristics of clean enrollment speech in a dynamic manner, which makes the result $S_n$ contains similar noise to $Y$ to avoid the heavy acoustic environment mismatch. As different input noisy speech may be recorded under different background environments, the advantage of DAC makes it very flexible for real PSE scenarios. According to our experiments, we have found that our proposed DAC works well in most cases and there will not be any negative effect during the whole speech enhancement process.

In addition, from the opposite perspective, we can remove the background noise in $Y$ to eliminate the environment mismatch with $S$. Such as, using the traditional spectral addition and MMSE-LSA [10] as pre-processing to remove noise before passing $Y$ to sDPCCN. However, these methods may lead to unrecoverable speech distortion and lower the performance.

3.4. Adaptive Focal Training

In general, the number of hard samples in training set is sparse compared with the non-hard samples, so the model biases towards the non-hard samples in order to reduce the overall loss during training. Hard samples are often ignored because their less contribution...
to the average performance of the whole test set. However, when a PSE system encounters such a hard sample, its bad performance will heavily affect the human auditory perception. Therefore, to improve hard sample enhancement quality, we propose a novel two-stage training strategy, termed adaptive focal training (AFT), by introducing an adaptive focal loss $\mathcal{L}_{AFT}$ for each batch as:

$$
\mathcal{L}_{AFT} = \frac{B}{\sum_{i=1}^{B} (\mathcal{L}_{TF} + \sin \left( \frac{\pi}{2} + \frac{\mathcal{L}_{TF} - \mu}{\sigma} \right))}
$$

where $B$ is the batch size of training data, $\mathcal{L}_{TF}$ is the TF-loss defined in Eq. (2) of $i$-th sample in current batch, $\mu$ and $\sigma$ are the mean and standard deviation of $\mathcal{L}_{TF}$ in each batch.

Two-stage training: Using $\sin(\cdot)$ transformation in Eq. (3) can assign a larger weight to $\mathcal{L}_{TF}$ of hard samples than to non-hard samples during training, because hard samples often tend to have larger $\mathcal{L}_{TF}$ than non-hard ones. However, if we use $\mathcal{L}_{AFT}$ directly during the whole training, it will make the model pay too much attention to hard samples and neglect the major non-hard samples. Therefore, the two-stage training is proposed in AFT to obtain a more balanced model: 1) Stage1: performing $\mathcal{L}_{TF}$ for training to make model focus on major non-hard samples, the early-stop training [24] is used to control the epochs in this stage; 2) Stage2: continue to train the stopped model using $\mathcal{L}_{AFT}$ for more epochs (<20) until model converge. We think that the model in Stage1 is good enough to learn the major non-hard samples, and in Stage2 $\mathcal{L}_{AFT}$ can alleviate the model bias towards non-hard samples that generated in the first stage and result in a more balanced PSE model.

4. EXPERIMENTAL SETUP

4.1. Datasets

The clean speech, noise, and room impulse response (RIR) we used for creating training data are all from DNS4 Challenge dataset [9]. Specifically, the clean speech includes six languages (English, French, German, Italian, Russian, and Spanish) from 3,230 speakers in total. Noise data mainly comes from Audioset [11], Freesound [4] and DEMAND [27]. Since our purpose is to verify the effectiveness of the proposed methods, instead of using the entire DNS4 Challenge dataset, we only create a 160 hours training set, covering three PSE conditions: 1) noise: 100 hours with only target speaker and background noise; 2) mix: 40 hours with target speaker and one interfering speaker, and 3) mmix: 20 hours with target, one interfering speaker and background noise. The noisy speech segments are all simulated by dynamically mixing speech and noise (or interfering speech) with a random SNR ranges from -5 to 20 dB, the RT60 of RIRs ranges from 0.3s to 1.3s.

We also use part of DNS4 Challenge dataset to simulate a test set, termed DNS-test, without any overlap with the 160 hours training data. DNS-test consists of 800 samples, and can also be divided into the same three PSE conditions in the same order as mentioned above: t-noise (500 samples), t-mix (200 samples) and t-mmix (100 samples). The duration of each sample is 10 seconds. The data proportion of the three conditions contained in our both training set and DNS-test is similar as it of official DNS4-Challenge test set.

4.2. Configuration

All training and test data are sampled at 8kHz. For STFT, we use the square root of Hanning window with FFT size of 512 and hop size of 128. Global mean-variance normalization is applied to all input features. Batch size is set to 32. We train all of our models with Adam optimizer [17] and the initial learning rate is set to 0.001. When the loss of the validation set does not decreases for 3 epochs, the learning rate will be decayed by a ratio of 0.5. To make experimental results comparable, all the other configurations are the same as the original SDPPCN in [12].

4.3. Evaluation Metrics

SISNR, PESQ [14] and DNSMOS [25] are used to measure the audio quality comprehensively. DNSMOS is estimated by a trained deep learning model provided by DNS4 Challenge to approximately represent the traditional MOS [22] score, and it consists of three scores that measure speech quality (SIG), background noise quality (BAK), and overall audio quality (OVR) respectively. In addition to these widely used objective metrics, inspired by [29], we also use hard sample rate (HSR) to check the effectiveness of adaptive focal training. For example, HSR0 (%) means the proportion of enhanced samples with SNR lower than 0dB in the whole test set. HSR5 (%) and HSR10 (%) are also used for SNR less than 5dB and 10dB.

5. RESULTS AND DISCUSSION

5.1. Overall performance of TF-loss and DAC

Table 1 shows the performance comparison of SDPPCN with different improvements on the whole DNS-test set, including the proposed TF-loss and dynamic acoustic compensation, SS and MMSE-LSA. We see that the TF-loss improves the original SDPPCN slightly due to the introduced frequency-domain training loss. For the DAC, we investigate several setups to see its performance behavior. DAC(J/K) means DAC with first J and last K frames of input noisy speech as in Eq. (2). DAC(UB) means the upper bound performance of DAC, in which the ground-truth background noise of input noisy speech is directly added into the enrollment speech to eliminate the environment mismatch. It is obvious that the optimal configuration of DAC is DAC(4/2), the SISNR is significantly improved from 15.12 dB to 15.96 dB, and the PESQ and DNSMOS are also greatly improved. Moreover, when compared with DAC(UB), the proposed simple DAC algorithm achieves very close performance to its upper bound, which fully proves the effectiveness of our proposed DAC.

| Methods       | SISNR  | PESQ   | DNSMOS (SIG/BAK/OVR) |
|---------------|--------|--------|----------------------|
| Noisy         | 5.95   | 2.16   | 3.80 / 3.27 / 3.20   |
| sDPPCN        | 15.11  | 3.21   | 3.79 / 3.85 / 3.32   |
| +TF-loss      | 15.12  | 3.28   | 3.79 / 3.88 / 3.34   |
| +DAC(2/0)     | 15.75  | 3.33   | 3.79 / 3.89 / 3.35   |
| +DAC(2/2)     | 15.88  | 3.36   | 3.79 / 3.91 / 3.36   |
| +DAC(8/4)     | 15.81  | 3.35   | 3.77 / 3.91 / 3.35   |
| +DAC(4/2)     | 15.96  | 3.38   | 3.80 / 3.92 / 3.37   |
| +DAC(UB)      | 16.15  | 3.41   | 3.81 / 3.94 / 3.39   |
| +SS(4/0)      | 15.77  | 3.35   | 3.76 / 3.92 / 3.35   |
| +MMSE-LSA     | 15.01  | 3.23   | 3.76 / 3.92 / 3.36   |

In addition, we also tried the spectral subtraction SS(4/0) (the best setup) and MMSE-LSA as a pre-processing to remove the noise for comparison. From the last two lines of Table 1, we observe that MMSE-LSA brings serious performance degradation due to the un-recoverable speech distortion. And such distortion also makes the spectral subtraction slightly worse than DAC(4/2). Therefore, in
Table 2. sDPCCN / (sDPCCN with TF-loss and DAC(4/2)) performance on three DNS-test subsets: t-noise, t-mix and t-nmix.

| Metrics       | t-noise | t-mix | t-nmix |
|---------------|---------|-------|--------|
| SISNR         | 16.43 / 17.36 | 14.74 / 15.32 | 9.26 / 10.08 |
| PESQ          | 3.31 / 3.49 | 3.32 / 3.41 | 2.51 / 2.69 |
| DNSMOS(OVR)   | 3.34 / 3.38 | 3.33 / 3.35 | 3.22 / 3.30 |

The following experiments, we will directly use DAC to represent DAC(4/2) for more concise representation.

5.2. Condition-wise performance of TF-loss and DAC

Table 2 presents the condition-wise performance comparison between sDPCCN and the proposed sDPCCN with TF-loss and DAC on three subsets of DNS-test. Results show that both the sDPCCN baseline and proposed methods perform well on t-noise and t-mix, and relatively poor on t-nmix. This is due to the fact that t-nmix condition is more complicated than other two conditions because the target speech is deteriorated by both interfering speaker and noise. And another reason is that only a small part of nmix condition data is included in our simulation training set. However, when comparing the results of baseline with proposed methods, the performance gains on t-nmix is much larger than other conditions, such as, the relative (%) SISNR/PESQ/DNSMOS improvements are 8.9/7.2/2.5, 5.6/5.4/1.2, 3.9/2.7/0.6 on t-nmix, t-noise and t-mix, respectively. It indicates that the introduced TF-loss plus DAC is more effective to improve PSE performance under complicated condition.

5.3. Examination of adaptive focal training

Table 3 presents the overall performance of three proposed methods for improving sDPCCN. It is clear that the AFT does not provide any average performance gain, although it has led the model to pay more attention to hard samples since we see a large hard sample rate decrease as shown in Table 4 (absolute 0.5, 1.25 and 4.62 are achieved for HSR0, HSR5 and HSR10, respectively). This may be because the number of hard samples in the entire DNS-set is relatively small. In Table 4, it is worth noting that TF-loss and DAC have also reduced the hard sample rate, but it results from the overall performance improvement of DNS-test, rather than especially improving hard samples.

Table 3. Performance of the proposed adaptive focal training on the whole DNS-test.

| Methods | SISNR | PESQ | DNSMOS (SIG/BAK/OVR) |
|---------|-------|------|----------------------|
| sDPCCN  | 15.11 | 3.21 | 3.79/3.85/3.32       |
| +TF-loss | 15.12 | 3.28 | 3.79/3.88/3.34       |
| +DAC    | 15.96 | 3.38 | 3.80/3.92/3.37       |
| +AFT    | 15.89 | 3.36 | 3.79/3.91/3.37       |

Table 4. The hard sample rate HSR0(%), HSR5(%) and HSR10(%) of DNS-test enhanced by different models.

| Methods | HSR0(%) | HSR5(%) | HSR10(%) |
|---------|---------|---------|----------|
| sDPCCN  | 1.38    | 5.75    | 18.13    |
| +TF-loss | 1.50    | 5.38    | 16.63    |
| +DAC    | 1.13    | 4.00    | 13.25    |
| +AFT    | 0.63    | 2.75    | 8.63     |

In this study, we propose three new techniques to improve our previous sDPCCN for personalized speech enhancement. Firstly, TF-loss is used to combine both time domain and frequency domain information during model training. Then, to alleviate the acoustic environment mismatch between input noise speech and clean enrollment utterance, a simple but effective dynamic acoustic compensation is proposed. All the overall and condition-wise results on the DNS-test set show that, this compensation brings significant improvements in terms of multiple evaluation metrics over original sDPCCN. Moreover, the proposed adaptive focal training is proved effective in different aspects for improving the hard sample performance. Some noisy and enhanced samples, including the DNS-test set can be found from https://github.com/orcan369/DNS-test.

Fig. 3. SNR distribution of enhanced samples in DNS-test.

Fig. 4. Performance of different models on hard sample subset.

6. CONCLUSION

In this study, we propose three new techniques to improve our previous sDPCCN for personalized speech enhancement. Firstly, TF-loss is used to combine both time domain and frequency domain information during model training. Then, to alleviate the acoustic environment mismatch between input noise speech and clean enrollment utterance, a simple but effective dynamic acoustic compensation is proposed. All the overall and condition-wise results on the DNS-test set show that, this compensation brings significant improvements in terms of multiple evaluation metrics over original sDPCCN. Moreover, the proposed adaptive focal training is proved effective in different aspects for improving the hard sample performance. Some noisy and enhanced samples, including the DNS-test set can be found from https://github.com/orcan369/DNS-test.
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