SPEECH ENHANCEMENT GUIDED BY CONTEXTUAL ARTICULATORY INFORMATION

Yen-Ju Lu\textsuperscript{1}, Chia-Yu Chang\textsuperscript{1}, Yu Tsao\textsuperscript{1}, Jeih-weih Hung\textsuperscript{2},

\textsuperscript{1}Research Center for Information Technology Innovation, Academia Sinica
\textsuperscript{2}Dept of Electrical Engineering, National Chi Nan University

ABSTRACT
Previous studies have confirmed the effectiveness of leveraging articulatory information to attain improved speech enhancement (SE) performance. By augmenting the original acoustic features with the place/manner of articulatory features, the SE process can be guided to consider the articulatory properties of the input speech when performing enhancement. Hence, we believe that the contextual information of articulatory attributes should include useful information and can further benefit SE. In this study, we propose an SE system that incorporates contextual articulatory information; such information is obtained using broad phone class (BPC) end-to-end automatic speech recognition (ASR). Meanwhile, two training strategies are developed to train the SE system based on the BPC-based ASR: multitask-learning and deep-feature training strategies. Experimental results on the TIMIT dataset confirm that the contextual articulatory information facilitates an SE system in achieving better results. Moreover, in contrast to another SE system that is trained with monophonic ASR, the BPC-based ASR (providing contextual articulatory information) can improve the SE performance more effectively under different signal-to-noise ratios (SNR).

Index Terms— speech enhancement, broad phonetic classes, articulatory attribute, robust automatic speech recognition, end-to-end

1. INTRODUCTION
Speech enhancement (SE) systems aim to improve the intelligibility and quality of contaminated speech by searching for the mapping between a distorted speech signal and its clean counterpart. SE has been widely adopted as a front-end processor in many real-world applications, such as assistive listening devices \[1,2\], speech coding \[3,4\], speaker recognition \[5\], and automatic speech recognition (ASR) \[6,8\]. Recently, the application of deep learning (DL) approaches to SE tasks has become popular and has been extensively investigated \[9,17\]. DL-based SE models with nonlinear processing units can learn high-order statistical information of the denoising process; hence, they can significantly outperform traditional SE methods, particularly under extremely low SNR scenarios and/or nonstationary noise environments. In addition, alternative signal processing approaches allow end-to-end neural networks of DL to incorporate speech signals with heterogeneous data. Previous studies have confirmed the effectiveness of leveraging face/lip images \[18\] and symbolic sequences for acoustic signals \[19\] in an SE system.

Owing to the high correlation between the enhancement and recognition for speech, the phoneme information in an acoustic model (AM) has been utilized to improve SE performance \[20,22\]. Moreover, leveraging articulatory features has been proven effective in SE tasks. In our previous study \[23\], acoustic features were augmented with broad phonetic class (BPC) posteriorgrams to achieve a more robust SE system; furthermore, it was demonstrated that the speech signals within the same BPC shared the same noisy-to-clean transformation. Despite the improved SE results, we believe that the contextual information of BPC phonemes, which was disregarded in this method, will benefit SE. Therefore, we herein propose an SE method that incorporates the contextual articulatory information acquired by an end-to-end BPC–ASR system, which is expected to generate more intelligibility enhancement results and improve the SE performance in noisy conditions.

In this study, we conducted experiments on an end-to-end SE–ASR system comprising an SE model and a phoneme-based end-to-end ASR module. ESPNet was selected as the end-to-end ASR model with its phoneme targets replaced by BPCs. Two training methods were used to learn the SE system: multitask learning and deep-feature training. Three types of BPCs were considered, including the manner of articulation “BPC(M),” place of articulation “BPC(P),” and data-driven BPC “BPC(D).” The proposed SE system was evaluated on the TIMIT dataset with two standard SE evaluation metrics: perceptual evaluation of speech quality (PESQ) and short-time objective intelligibility (STOI), both of which were applied to measure the SE results.

This paper is organized as follows: Section 2 introduces the criteria used to define the BPC and the ESPNet, which is an end-to-end ASR system. Section 3 describes the proposed end-to-end BPC SE–ASR system. Section 4 presents the experimental setup and results. Finally, Section 5 concludes this paper.
2. BACKGROUND KNOWLEDGE

2.1. Broad Phonetic Classes

2.1.1. Knowledge-based BPC

Two knowledge-based BPCs were used in this study: the place and manner of articulation. The place of articulation indicates the location at which the air stream is blocked in the vocal tract when uttering a sound. By contrast, the manner of articulation indicates the manner in which the air stream is blocked. Similar characteristics appear in phonemes with the same manner/place of articulation, and the type of articulation manner can be discerned by observing the shape of its waveform [24]. In speech processing, similar spectral characteristics have been discovered in phonemes with the same manner/place of articulation, which caused confusion in speech recognition [25]. Nevertheless, previous studies have shown that ASR can be improved using contextual articulatory information [26–29]. In this study, we separated 60 phonemes into 5 clusters: vowels, stops, fricatives, nasals, and silence by the articulation manner. The vowel class included diphthongs and semi-vowels, as suggested in [25]. For the place of articulation, the phonemes were segregated into nine clusters: bilabial, labiodental, dental, alveolar, post-alveolar, velar, glottal, vowels, and silence, as suggested in [24].

2.1.2. Data-driven BPC

Meanwhile, the similarity between phonemes can be evaluated using the data-driven method, which is derived from the recognition result of a pretrained AM. In a previous study [30], a confusion matrix $M$ for phonemes was created, where its entry $M_{ij}$ was defined by the number of events for phoneme $i$ to be misidentified as phoneme $j$. This matrix was assumed to reflect the similarities between each pair of phonemes. When clustering the phonemes through the similarity metric, a merging process was performed until the cluster number reached 9, as recommended in [30], and this process is referred to as the data-driven BPC.

2.2. ESPnet

ESPnet adopts two major end-to-end ASR implementations, i.e., connectionist temporal classification (CTC) and attention, and provides a single neural network architecture to perform speech recognition in an end-to-end manner [31]. Multitask learning based on CTC and attention endows ESPnet with the advantages of both structures and solves misalignment issues encountered in ordinary attention-based end-to-end ASR. The end-to-end network eliminates the need for linguistic resources and hence enables joint training with additional model placed in advance of the ASR. Furthermore, the complexity of the end-to-end ASR building process is significantly reduced as it does not require GMM/HMM construction, DNN pretraining, lattice generation, and complex searches during decoding.

In ESPnet, a shared BLSTM encoder transforms the input sequence into high-level features and is used with multi-objective learning. That is, a CTC objective function is used as an auxiliary task to train the encoder of the attention model. Compared with the sole attention model, combining the forward-backward algorithm in CTC not only accelerates the process of finding a desired alignment in a monotonic manner, but also mitigates the prediction from a letter-wise attention objective to a sequence-level CTC objective. During decoding, attention- and CTC-based scores are combined in a one-pass beam search algorithm to obtain the ASR results and further eliminate irregular alignments.

3. PROPOSED MODEL

3.1. End-to-end model architecture

The proposed end-to-end model connects the SE model and the BPC-based pre-trained ASR model with a feature extractor using the overall loss of both models for backpropagation. Figure 1 shows the architecture of the model.
was set to since the ASR model has been pretrained, the parameter $\alpha$ loss is typically much larger than the SE loss. Furthermore, a simple SE model without considering the ASR loss. Such an $\alpha$ where the SE model was trained for 70 epochs without considering the ASR loss. Such an arrangement has been shown to yield better SE performances in our experiments.

3.2.2. Deep feature loss

In addition to the recognition error as the ASR loss, we herein present another objective function associated with the ASR model that focuses on the SE performance. The respective model architecture is shown on the right side of Figure 1. In ESPnet, we extracted the features at the last layer (of size 320) of the encoder from both clean and noisy speech; those features are known as deep features. Subsequently, the difference between the clean and enhanced deep features was set as another form of ASR loss, which was then used together with the SE loss for the joint training, as shown in Eq. (2).

$$\text{loss}_{\text{total}} = (1 - \alpha) \times \text{loss}_{\text{SE}} + \alpha \times \text{loss}_{DF},$$

(2)

4. EXPERIMENT

4.1. Experimental setup

In this study, experiments were conducted on the TIMIT database [37] with multiple noise sources [38]. A total of 10,000 noisy-clean paired training utterances were used, and they comprised 3696 utterances in the TIMIT training set as well as their noisy counterparts comprising 100 random noise types from [38] at 32 different SNR levels. The core test set of TIMIT (including 192 utterances) was mixed with five unseen noise types at five SNR levels (10, 5, 0, -5, and -10 dB) to build the test set in our experiments. In addition, the training and test sets did not share common speakers.

The speech waveforms were recorded at a 16 kHz sampling rate and converted into 257-dimensional spectograms by the short-time Fourier transform with a Hamming window size of 32 ms and a hop size of 16 ms. The $\log 1p$ function ($\log 1p(x) = \log(1 + x)$) was adopted on the magnitude spectrogram to ensure non-negative outputs, and normalization was performed on the waveform. In the test stage, the enhanced magnitude spectral features and the phases from the noisy signals were used to synthesize the enhanced signals.

A two-stage training was applied to train the SE model. Hence, the SE model was trained for 70 epochs without considering the ASR results (by setting $\alpha = 0$ in Eq. (1)) and then further updated with the combined objective loss (by setting $\alpha = 0.001$ for ASR loss and $\alpha = 0.05$ for deep feature loss in Eq. (1)) for the next 80 epochs. The ASR model was pretrained with the clean dataset, and its parameters were fixed afterward. Early stopping was performed based on the validation performance to prevent overfitting, and the learning rate was set using the Adam optimizer [39]. Based on the model architecture in Fig. 1 we implemented three systems using three types of BCs, namely BPC(M), BPC(P), and BPC(D).

3.1.1. Transformer-based SE network

The transformer was originally proposed for machine translation [32] and has been investigated extensively in the SE studies [33,35]. For sequence-to-sequence learning, the transformer comprises encoder and decoder networks. In our method, because noisy and enhanced sequences share the same length, we only preserved the encoder part for the SE process. The used transformer comprised four convolutional layers for encoding the input spectrum with its location information and eight attention blocks. Each of the attention blocks comprised multihead self-attention and two fully connected layers as the feedforward network. Both sublayers comprised a residual connection and layer normalization [36].

3.1.2. Mel-filters processing

To render our process differentiable, we replaced the Kaldi feature extractor in the original ESPnet with a filter-bank extractor, which was used to create speech features from the enhanced waveforms from the SE module. The filter-bank extractor applied 40 triangular filters on the Mel-scale to the power spectrum to extract frequency bands. Compared with the original Kaldi feature extractor, the filter-bank extractor can connect the SE module with the ASR model and ensure that the end-to-end training process is back-propagatable.

3.1.3. ESPnet-based end-to-end BPC-ASR Network

To obtain the BPC context information, we changed the original output word labels of the end-to-end ASR to the desired BPC labels. Accordingly, the goal of the BPC–ASR model is to predict the BPC label sequence corresponding to the utterances. We pretrained the BPC–ASR model using the filter-bank features of clean utterances as the input before the overall end-to-end model training. In addition, to ensure that the predicted feature of the SE model only contained audio signals, the parameters in the pretrained BPC–ASR model were fixed during the subsequent end-to-end training.

3.2. Joint training methods

3.2.1. SE-ASR joint training

In the joint training stage, the optimization of the ASR objective function was treated as an auxiliary task for training the SE model. The losses of both the SE and ASR models were combined with a tuning parameter $\alpha$, as shown in Eq. (1):

$$\text{loss}_{\text{total}} = (1 - \alpha) \times \text{loss}_{\text{SE}} + \alpha \times \text{loss}_{\text{ASR}},$$

(1)

where $\alpha$ was set in the range [0.001, 0.002] because the ASR loss is typically much larger than the SE loss. Furthermore, since the ASR model has been pretrained, the parameter $\alpha$ was set to 0 in the first few epochs of the joint training to learn a simple SE model without considering the ASR loss. Such an

$$\text{log1p}(x) = \log(1 + x)$$

for deep fea-
Table 1: Average PESQ and STOI scores for end-to-end SE–ASR systems with BPC(M), BPC(P), BPC(D), and Mono. Scores of noisy speech and transformer baseline are listed for comparison. Boldfaced numbers indicate best scores among different methods for each SNR level.

| SNR | Noisy PESQ STOI | Transformer PESQ STOI | Mono PESQ STOI | Broad Phone Class BPC(M) PESQ STOI | BPC(P) PESQ STOI | BPC(D) PESQ STOI | BPC(M) PESQ STOI |
|-----|-----------------|-----------------------|----------------|-----------------------------------|-----------------|-----------------|-----------------|
| -10 | 1.138 0.503     | 1.282 0.534           | 1.274 0.540    | 1.293 0.552                       | 1.285 0.550     | 1.295 0.542     | 1.292 0.539     |
| -5  | 1.380 0.595     | 1.684 0.651           | 1.742 0.675    | 1.743 0.683                       | 1.736 0.677     | 1.709 0.665     | 1.692 0.659     |
| 0   | 1.693 0.701     | 2.119 0.771           | 2.216 0.790    | 2.210 0.796                       | 2.213 0.793     | 2.157 0.780     | 2.139 0.779     |
| 5   | 2.039 0.800     | 2.529 0.862           | 2.612 0.868    | 2.612 0.873                       | 2.616 0.871     | 2.556 0.860     | 2.564 0.867     |
| 10  | 2.389 0.880     | 2.896 0.919           | 2.952 0.915    | 2.965 0.920                       | 2.953 0.919     | 2.902 0.910     | 2.936 0.921     |
| Avg | 1.728 0.696     | 2.102 0.748           | 2.159 0.758    | 2.165 0.765                       | 2.160 0.762     | 2.124 0.751     | 2.125 0.753     |

Fig. 2: The error rates at different SNR levels obtained by the end-to-end ASR for monophone and BPCS for noisy and enhanced speech.

4.2. Results and Discussions

4.2.1. Phonetic/BPC recognition error rates

To corroborate the assumption that the end-to-end ASR model can guide the SE process, we first analyzed the error rates of the end-to-end ASR system in noisy and enhanced conditions, as shown in Figure 2. First, we observed that the error rate for the monophone system increased significantly as the SNR decreased, reaching 84% at 0 dB SNR and exceeding 100% at −10 dB SNR. Next, compared with the results for the monophones, the error rates for the BPCs increased less significantly with the noise level (e.g., the error rates were from 37% to 52% for BPC(M)). Subsequently, we discovered that the BPC(D), which employed the confusion matrix from the AMs, had the lowest error rate; this was likely due to its clustering method. Finally, all of the recognition results improved through SE, indicating that the SE process guided by the contextual phonetic information can benefit the recognition accuracy of end-to-end ASR.

4.2.2. Enhancement results

Table I presents the PESQ and STOI scores of our proposed SE model. As shown in the table, almost all of the end-to-end SE–ASR systems outperformed the transformer baseline in terms of the PESQ and STOI metrics, including those using the ASR loss and deep feature loss. Hence, this confirmed that end-to-end ASR can guide the SE system in improving the speech quality and intelligibility. The only exception was the low PESQ scores achieved by the monophone system at low SNRs, attributable to its poor recognition results. Additionally, all of the BPC systems surpassed the transformer baseline in all of the SNR cases, indicating the superiority even at high noise levels.

Moreover, the knowledge-based BPCs, i.e., BPC(M) and BPC(P), performed better than the monophone system. However, although BPC(D) indicated the lowest error rate, it performed worse than the monophone system in terms of both the PSEQ and STOI scores. This shows that the combination of confusion phonemes did not contribute to a better performing SE system. Finally, it is noteworthy that BPC(M) achieved the optimal STOI scores, implying that the characteristics captured in the same phone group of the BPC(M) guided the SE process effectively.

5. CONCLUSION

In this study, we proposed an end-to-end BPC-based ASR to guide the SE process to achieve better intelligibility for speech signals. We investigated three BPC clustering methods, and the results confirmed that the context information regarding the BPCs improved the SE performance significantly over different SNR conditions. The main contributions of this study are as follows: (1) This is the first study that employed the context information of phonemes for an end-to-end SE–ASR system. (2) We demonstrated that using both knowledge-based and data-driven criteria BPCs as the enhancement target improved the intelligibility of enhanced speech. (3) We validated that knowledge-based BPCs benefitted SE more than data-driven BPCs and monophones.
6. REFERENCES

[1] Y.-H. Lai, F. Chen, S.-S. Wang, X. Lu, Y. Tsao, and C.-H. Lee, “A deep denoising autoencoder approach to improving the intelligibility of vocoded speech in cochlear implant simulation,” IEEE Transactions on Biomedical Engineering, vol. 64, no. 7, pp. 1568–1578, 2016.

[2] D. Wang, “Deep learning reinvents the hearing aid,” IEEE spectrum, vol. 54, no. 3, pp. 32–37, 2017.

[3] A. J. Accardi and R. V. Cox, “A modular approach to speech enhancement with an application to speech coding,” in Proc. ICASSP 1999.

[4] R. Martin and R.V. Cox, “New speech enhancement techniques for low bit rate speech coding,” in Proc. Workshop on Speech Coding Proceedings, Model, Coders, and Error Criteria 1999.

[5] D. Michelsanti and Z.-H. Tan, “Conditional generative adversarial networks for speech enhancement and noise-robust speaker verification,” in Proc. Interspeech 2017.

[6] J. Li, L. Deng, Y. Gong, and Reinhold H.-U., “An overview of noise-robust automatic speech recognition,” IEEE/ACM Transactions on Audio, Speech, and Language Processing, vol. 22, no. 4, pp. 745–777, 2014.

[7] F. Weninger, H. Erdogan, S. Watanabe, E. Vincent, J. Le Roux, J. R. Hershey, and B. Schuller, “Speech enhancement with lstm recurrent neural networks and its application to noise-robust asr,” in Proc. LVA/AIC, 2015.

[8] H. Erdogan, J. R. Hershey, S. Watanabe, and J. Le Roux, “Phase-sensitive and recognition-boosted speech separation using deep recurrent neural networks,” in Proc. ICASSP 2015.

[9] X. Lu, Y. Tsao, S. Matsuda, and C. Hori, “Speech enhancement based on deep denoising autoencoder...” in Proc. Interspeech 2015.

[10] Y. Xu, J. Du, L.-R. Dai, and C.-H. Lee, “A regression approach to speech enhancement based on deep neural networks,” IEEE/ACM Transactions on Audio, Speech, and Language Processing, vol. 23, no. 1, pp. 7–19, 2014.

[11] Y. Wang, A. Narayanan, and D. Wang. “On training targets for supervised speech separation,” IEEE/ACM transactions on audio, speech, and language processing, vol. 22, no. 12, pp. 1849–1858, 2014.

[12] K. Tan, X. Zhang, and D. Wang, “Real-time speech enhancement using an efficient convolutional recurrent network for dual-microphone mobile phones in close-talk scenarios,” in Proc. ICASSP 2019.

[13] M. Kolbék, Z.-H. Tan, and J. Jensen, “Speech intelligibility potential of general and specialized deep neural network based speech enhancement systems,” IEEE/ACM Transactions on Audio, Speech, and Language Processing, vol. 25, no. 1, pp. 153–167, 2016.

[14] J. Qi, J. Du, S. M. Siniscalchi, and C. Lee, “A theory on deep neural network based vector-to-vector regression with an illustration of its expressive power in speech enhancement,” IEEE/ACM Transactions on Audio, Speech, and Language Processing, vol. 27, 2019.

[15] B. Xia and C. Bao, “Wiener filtering based speech enhancement with weighted denoising auto-encoder and noise classification,” Speech Communication, vol. 60, pp. 13–29, 2014.

[16] D. Liu, P. Smaragdis, and M. Kim, “Experiments on deep learning for speech denoising,” in Fifteenth Annual Conference of the International Speech Communication Association, 2014.

[17] P. G. Shivakumar and P. G. Georgiou, “Perception optimized deep denoising autoencoders for speech enhancement,” in INTERSPEECH, 2016, pp. 3743–3747.

[18] J. Hou, S. Wang, Y. Lai, Y. Tsao, H. Chang, and H. Wang, “Audio-visual speech enhancement using multimodal deep convolutional neural networks,” IEEE Transactions on Emerging Topics in Computational Intelligence, vol. 2, no. 2, pp. 117–128, 2018.

[19] C.-F. Liao, Y. Tsao, X. Lu, and H. Kawai, “Incorporating Symbolic Sequential Modeling for Speech Enhancement,” in Proc. Interspeech 2019.

[20] T. Gao, J. Du, L. Dai, and C. Lee, “Joint training of front-end and back-end deep neural networks for robust speech recognition,” in Proc. ICASSP 2015.

[21] Z. Chen, S. Watanabe, H. Erdogan, and J. H. Hershey, “Speech enhancement and recognition using multi-task learning of long short-term memory recurrent neural networks,” in Proc. Interspeech 2015.

[22] Z. Wang and D. Wang, “A joint training framework for robust automatic speech recognition,” IEEE/ACM Transactions on Audio, Speech, and Language Processing, vol. 24, no. 4, pp. 796–806, 2016.

[23] Y.-J. Lu, C.-F. Liao, X. Lu, J.-W. Hung, and Y. Tsao, “Incorporating broad phonetic information for speech enhancement,” arXiv preprint arXiv:2008.07618, 2020.

[24] P. Ladefoged and K. Johnson, A course in phonetics, Nelson Education, 2014.

[25] P. Scanlon, D. P. W. Ellis, and R. B. Reilly, “Using broad phonetic group experts for improved speech recognition,” IEEE transactions on audio, speech, and language processing, vol. 15, no. 3, pp. 803–812, 2007.

[26] S. M. Siniscalchi, T. Svendsen, and C.-H. Lee, “An artificial neural network approach to automatic speech processing,” Neurocomputing, vol. 140, pp. 326 – 338, 2014.

[27] J. Lin, W. Li, Y. Gao, Y. Xie, N. Chen, M. Siniscalchi, J. Zhang, and C.-H. Lee, “Improving mandarin tone recognition based on dnn by combining acoustic and articulatory features using extended recognition networks,” Journal of Signal Processing Systems, 02 2018.

[28] S. M. Siniscalchi, D. Yu, L. Deng, and C.-H. Lee, “Exploiting deep neural networks for detection-based speech recognition,” Neurocomputing, vol. 106, pp. 148 – 157, 2013.

[29] A. S. Shahrebabaki, N. Olaffi, S. M. Siniscalchi, G. Salvi, and T. Svendsen, “Transfer learning of articulatory information through phone information,”.

[30] C. Lopes and F. Perdigão, “Broad phonetic class definition driven by phone confusions,” EURASIP Journal on Advances in Signal Processing, vol. 2012, no. 1, pp. 158, 2012.

[31] S. Watanabe, T. Hori, S. Karita, T. Hayashi, J. Nishitoba, Y. Unno, N. E. Y. Soplin, J. Heymann, M. Wiesner, N. Chen, et al., “Esnet: End-to-end speech processing toolkit,” arXiv preprint arXiv:1804.00015, 2018.

[32] A. Vaswani, N. Shazeer, L. Jones, N. Gomez, L. Kaiser, and I. Polosukhin, “Attention is all you need,” in Proc. NeurIPS, 2017.

[33] X. Hao, C. Shan, Y. Xu, S. Sun, and L. Xie, “An attention-based neural network approach for single channel speech enhancement,” in Proc. ICASSP 2019.

[34] C. Yang, J. Qi, P. Chen, X. Ma, and C. Lee, “Characterizing speech adversarial examples using self-attention u-net enhancement,” in Proc. ICASSP 2020.

[35] Y. Koizumi, K. Yaiabe, M. Delcroix, Y. Maxuxama, and D. Takeuchi, “Speech enhancement using self-adaptation and multi-head self-attention,” in Proc. ICASSP 2020.

[36] J. L. Ba, J. R. Kiros, and G. E. Hinton, “Layer normalization,” arXiv preprint arXiv:1607.06450, 2016.

[37] J. S Garofolo, “Timit acoustic phonetic continuous speech corpus,” Linguistic Data Consortium, 1993.

[38] G. Hu, “100 nonspeech environmental sounds,” The Ohio State University, Department of Computer Science and Engineering, 2004.

[39] D. P. Kingma and J. Ba, “Adam: A method for stochastic optimization,” arXiv preprint arXiv:1412.6980, 2014.