A MODULATION-DOMAIN LOSS FOR NEURAL-NETWORK-BASED REAL-TIME SPEECH ENHANCEMENT

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ABSTRACT

We describe a modulation-domain loss function for deep-learning-based speech enhancement systems. Learnable spectro-temporal receptive fields (STRFs) were adapted to optimize for a speaker identification task. The learned STRFs were then used to calculate a weighted mean-squared error (MSE) in the modulation domain for training a speech enhancement system. Experiments showed that adding the modulation-domain MSE to the MSE in the spectro-temporal domain substantially improved the objective prediction of speech quality and intelligibility for real-time speech enhancement systems without incurring additional computation during inference.

Index Terms— Real-time speech enhancement, spectro-temporal receptive field, loss functions

1. INTRODUCTION

Supervised speech enhancement (SE) using deep neural networks (DNNs) has received tremendous attention in recent years. The availability of abundant amounts of training data and advancements in DNN architectures have resulted in systems that provide better performance than the ideal binary mask [1] – a target that highly correlates with speech intelligibility [2, 3]. The core design of a DNN-based SE system involves decisions that perform compensation in one feature domain and calculate the loss function in another. Despite the emerging time-domain compensation methods (e.g., [1]), predicting a time-varying gain function, or a time-frequency (TF) mask [4], has been the most popular and reliable approach.

Loss functions for supervised SE in the TF domain have historically been calculated in the time or frequency domain. However, most existing loss functions [5] were motivated by statistically-optimal solutions [6, 7, 8] and do not necessarily correlate with perceptual quality or intelligibility of speech [9]. More recently, perceptually-motivated loss functions have been proposed to optimize modified predictors of speech quality [10] and intelligibility [11]. Interestingly, these methods did not show improvement over objective metrics for which the loss functions did not directly optimize, suggesting that there is room for improving their generalization ability.

Modulation is closely related to speech intelligibility. The speech transmission index (STI) measures the extent to which amplitude modulation of speech is preserved in degraded environments and is highly correlated with speech intelligibility [12, 13]. The spectro-temporal modulation index (STMI) was subsequently proposed to account for joint spectro-temporal modulation [14]. SE in the modulation domain has also been explored [15,16]. However, these methods assume that speech and noise are separable in the modulation domain. Moreover, they typically require a complete set of spectro-temporal receptive fields (STRFs) in order to invert the processed modulation spectra back to the TF domain. This may be computationally infeasible for real-time applications.

In this paper, we propose a simple mean-squared error (MSE)-based loss function in the spectro-temporal modulation domain for supervised SE. We call the loss spectro-temporal modulation error (STME) because of its close relation to template-based STMI [14], which correlates well with speech intelligibility. The calculation of the STME is based on a set of pre-selected modulation kernels, which had been shown to be critical for the accuracy of predicted speech intelligibility using speech stimuli [13]. Following our recent success in discriminating live speech from synthetic or broadcast speech using learnable spectro-temporal receptive field (STRF) kernels [17], we develop an automatic way to determine these kernels through an auxiliary speaker identification (SID) task. STME is applicable to any deep neural network (DNN) system as long as the short-time Fourier transform magnitude (STFTM) of the target and degraded speech are accessible when training the DNN. Our proposed system’s loss is easy to compute, does not incur additional computation during inference, and avoids lossy inversion, which is a problem with conventional modulation-domain SE approaches [15].

Organization of this paper. In the next section, we introduce related work in supervised SE and the background of STMI. We then describe our selection procedure for the STRFs and the loss function. Finally, we describe the evalu-
tion procedure and discuss the experimental results.

2. BACKGROUND

In this section we briefly review supervised speech enhancement and the spectro-temporal modulation index.

Supervised DNN-based speech enhancement. We assume that the observed noisy speech contains clean speech corrupted by additive noise. This relationship in the short-time Fourier transform (STFT) domain is described by

\[ X[t, k] = S[t, k] + N[t, k] \]  \hspace{1cm} (1)

where \( X[t, k], S[t, k], \) and \( N[t, k] \) represent the STFT at time frame \( t \) and frequency bin \( k \) of the observed noisy speech, clean speech and noise, respectively. Without loss of generality, we assume that a DNN is trained to predict a magnitude gain, \( G[t, k] \), from past and current information of degraded speech. The enhanced STFTM is obtained by element-wise multiplication of the predicted gain by the noisy STFTM,

\[ \hat{S}[t, k] = G[t, k] |X[t, k]|. \]  \hspace{1cm} (2)

A popular loss function that drives the learning for this DNN is the MSE between the enhanced STFTM and the clean STFTM, or the time-frequency error (TFE),

\[ \text{TFE} = ||(\hat{S} - \hat{S})||^2 \]  \hspace{1cm} (3)

where \( \hat{S} \) and \( \hat{S} \) denote the vector representations of the clean STFTM and enhanced STFTM, respectively.

Spectro-temporal modulation index. The spectro-temporal modulation index (STMI) is a measure of speech integrity in the modulation domain as viewed by a model of the auditory system [14]. At the core of this model is a bank of STRFs that are believed to exist in the central auditory system and respond to a range of patterns of temporal and spectral modulation [18]. Each STRF is a TF template in a spectrographic representation of speech to a STRF is typically integrated over time before being converted to the vector form. In previous implementations of modulation-domain SE, compensation was performed directly on STRM \( X[t, k] \) [15] [14]. In our method, we perform enhancement in the TF domain and use a loss function in the modulation domain that is closely related to STMI \( T \) for training the DNN.

It should be noted that the selection of meaningful modulation frequency becomes an issue when speech signals (instead of modulated noise) are used to calculate an estimate of speech intelligibility [13]. Previous work using STRFs typically performed dimensionality reduction on features extracted from densely-sampled STRFs [19] [20] [21]. We learn the parameters of the STRFs through an auxiliary SID task. We describe our own method next.

3. METHOD

In this section, we present the DNN system we used for speech enhancement and the calculation of our spectral-temporal modulation error loss.

Speech enhancement system. We used the normalized log power spectra (LPS) as the input feature. The STFT is first obtained using a 20-millisecond Hamming window with 50% overlap and a 512-point discrete Fourier transform. Then we take the natural logarithm of the power of the STFT and normalize the LPS with frequency-dependent online normalization following [22].

To estimate the magnitude gain for each frame, we used a similar real-time network architecture to the one described in [5]. The network consists of a single fully connected (FC) layer followed by two stacked unidirectional Gated Recurrent Units (GRUs) and three more FC layers. Rectified linear unit (ReLU) activation is used after each of the FC layers except the very last one where a sigmoid activation is used to bound the output magnitude gain to be between zero and one. We obtain the enhanced waveform by multiplying the magnitude gain element-wise with the noisy STFTM and using the original noisy phase for reconstruction. In total, the network contained roughly 2.8 million learnable parameters.

Tuning learnable STRFs on speaker identification. One central problem involving the construction of the loss function is the selection of modulation parameters that are relevant to speech intelligibility [13]. Previous work has shown that the STMR is redundant [19] and the possible values for those modulation parameters span a wide range [20] [21]. Following the success of our previous work on discriminating live speech from synthetic speech using learnable STRFs [17], we trained the STRFNet system on SID using the Librispeech [23] dataset with artificially-added noise from Sound Bible [1] to learn the parameters of each Gabor-based STRF [20] automatically. The SID system was able to achieve an average of 95% accuracy with 2484 speakers and signal-to-noise ratios (SNRs) ranging from 0 to 30 dB. We

\[ \text{TFE} = ||(\hat{S} - \hat{S})||^2 \]  \hspace{1cm} (3)

where \( \hat{S} \) and \( \hat{S} \) denote the vector representations of the clean STFTM and enhanced STFTM, respectively.
then keep the learned STRFs fixed and utilize them for our loss. We use 60 STRF kernels, each with a time support of 300 milliseconds and a span of 20 channels on the Mel scale. This pipeline is depicted in the upper panel of Figure. 

### 4. EXPERIMENTAL SETUP

#### Datasets

We used a small-scale and a large-scale dataset for evaluating the SE system. The small-scale dataset by Valentin et al. [24] (VBD henceforth) contains 9.4 hours and 35 minutes of noisy speech in the training and test set, respectively. We downsampled the entire dataset to 16 kHz. For the large-scale dataset, we used the Interspeech 2020 Deep Noise Suppression (DNS) dataset [25] with RIR responses provided by [26]. The DNS training set contains a total of 500 hours of noisy speech. For evaluation, the DNS dataset has two test sets named no_reverb and with_reverb, which both contain 25 minutes of noisy speech. In both datasets, we are also provided with the original clean speech that was used to artificially generate the noisy speech.

We evaluated our system’s capabilities to improve speaker verification performance in noisy conditions by using a modified version of the VoxCeleb1 test set [27]. The original test set contained 4784 speech pairs spoken by 40 unseen speakers. We modified the VoxCeleb1 test set by randomly adding noise from the DNS test set at SNRs ranging from -6 to 6 dB.

#### Training and evaluation procedure

To train our SE systems on the VBD dataset and DNS dataset, we randomly sampled 1-second noisy speech segments from the training data and 5-second noisy speech segments from the training data, respectively. All the SE systems were trained using the Adam optimizer with a learning rate of $5 \cdot 10^{-4}$ and a batch size of 64 in PyTorch. For evaluation, we used the perceptual evaluation of speech quality (PESQ) [28], scale-invariant signal-to-distortion ratio [29], and short-time objective intelligibility (STOI) [30] metrics.

To evaluate our SE systems on speaker verification, we used a DNN-based speaker verification system [31] pretrained on VoxCeleb2 [32], a dataset that contains over 1 million utterances and 6112 speakers. The verification system obtained an equal error rate (EER) of 2.2% on the VoxCeleb1 test set, which is one of the lowest reported EER compared to any other method with a similar number of parameters [31]. Although the system was not trained with artificial degradation, all the audio clips were extracted from YouTube which will naturally contain different acoustic conditions. To test if our SE system improves the performance of this strong speaker verification system in noisy conditions, we added noise from the DNS test set to the original VoxCeleb1 test set at SNRs ranging from -6 to 6 dB. We evaluated the EER of the speaker verification system on clips enhanced by the SE system.

#### Baseline systems

We evaluated three different baseline systems to illustrate the benefits of the additional STME loss. Each of the baseline systems have the exact same network architecture, but they were each trained with different loss functions. Our first baseline system, GRU(TFE), was trained only with the TFE loss. To evaluate the benefits of the STME loss by itself, we trained a second baseline system, GRU(STME), using only the STME loss. Our third baseline system, GRU(TFE+STME$^R$), was trained with both loss terms, although the parameters of the Gabor-based STRF kernels that were used to calculate the STME were randomly selected. Specifically, the temporal and spectral modulation fre-
Table 1. Table summarizing the objective speech quality evaluation on the VBD test set

| Methods       | PESQ  | SI-SDR | STOI |
|---------------|-------|--------|------|
| Noisy         | 1.97  | 8.5    | 92.1 |
| ERNN [33]     | 2.54  | —      | —    |
| GRU(TFE)      | 2.68  | 17.0   | 93.3 |
| GRU(STME)     | 2.78  | 14.4   | 93.1 |
| GRU(TFE+STME) | 2.76  | 16.9   | 93.2 |
| GRU(TFE+STME) | 2.82  | 17.0   | 93.8 |

Table 2. Table summarizing the objective speech quality evaluation on the DNS no_reverb (with_reverb) test set

| Method               | PESQ (MOS) | SI-SDR (dB) | STOI (%) |
|----------------------|------------|-------------|----------|
| Noisy                | 1.58 (1.82)| 9.1 (9.0)  | 91.5 (86.6) |
| GRU(TFE)             | 1.83 (1.52)| 12.5 (9.2) | 90.6 (82.1) |
| GRU(STME)            | 2.27 (2.36)| 14.9 (13.2)| 94.2 (89.4) |
| GRU(TFE+STME)        | 2.59 (2.64)| 12.4 (12.0)| 94.2 (90.1) |
| GRU(TFE+STME)        | 2.57 (2.63)| 15.9 (14.5)| 95.2 (90.6) |
| GRU(TFE+STME)        | 2.71 (2.75)| 15.9 (14.5)| 95.5 (91.2) |

Table summarizing the objective speech quality evaluation on the DNS no_reverb (with_reverb) test set

| Method           | PESQ (MOS) | SI-SDR (dB) | STOI (%) |
|------------------|------------|-------------|----------|
| Noisy            | 1.58 (1.82)| 9.1 (9.0)  | 91.5 (86.6) |
| ERNN [33]        | 1.83 (1.52)| 12.5 (9.2) | 90.6 (82.1) |
| GRU(TFE)         | 2.27 (2.36)| 14.9 (13.2)| 94.2 (89.4) |
| GRU(STME)        | 2.59 (2.64)| 12.4 (12.0)| 94.2 (90.1) |
| GRU(TFE+STME)    | 2.57 (2.63)| 15.9 (14.5)| 95.2 (90.6) |
| GRU(TFE+STME)    | 2.71 (2.75)| 15.9 (14.5)| 95.5 (91.2) |

5. EXPERIMENTAL RESULTS AND DISCUSSION

In this section, we present and discuss results of our STME loss on speech enhancement and speaker verification.

VBD results. In Table 1 we show the objective evaluation of each SE system trained with different losses using the VBD dataset. On a small dataset, our GRU(TFE+STME) outperformed the GRU(TFE) baseline in all the objective metrics. Interestingly, different initialization of the STRF kernels in GRU(TFE+STME) resulted in similar improvements over the baseline TFE loss, but roughly 20% of the time the random parameter selection resulted in a much worse performance. This highlights the benefits of using automatically-learned Gabor-based STRF kernels over randomly-selected Gabor-based STRF kernels.

DNS results. The objective evaluation of our SE systems trained with different losses using the DNS no_reverb and with_reverb test set is summarized in Table 2. Even with a large amount of training data, our GRU(TFE+STME) loss function outperformed both the GRU(TFE) baseline and the provided challenge baseline [22] in all the objective metrics. Most notably, there is a significant improvement in PESQ which results in our system having a similar PESQ to the top system in the official DNS challenge [34]. We also evaluated the benefits of the STME loss by itself, GRU(STME). Curiously, training with only our the STME loss provides a higher PESQ but much lower SI-SDR compared to training with only the TFE loss. Nevertheless, optimizing the combination of both losses during training caused both the PESQ and SI-SDR scores to increase compared to training on each loss individually. This confirms our belief that the medium-time STME loss is complemented by the short-time TFE loss. As in the VBD experiments, the use of automatically-learned Gabor-based STRF kernels provides a greater increase of PESQ scores compared to the use of randomly-selected Gabor-based STRF kernels.

Speaker verification results. The performance of the speaker verification system with noise added at low SNRs is shown in Figure 2. At low SNRs, the speaker verification system’s performance starts to substantially degrade. Our system GRU(TFE+STME) improved the EER by an average of 15.4% relative and outperformed our baseline GRU(TFE) by an average of 5.5% relative. At higher SNRs, the verification system’s performance quickly approached the state-of-the-art performance of 2.2% and our enhancement systems did not provide any additional benefits.

6. CONCLUSIONS

In this paper, we introduced a novel modulation-domain loss function for training neural-network-based speech enhancement systems. We showed that by adding spectro-temporal modulation loss to the standard time-frequency error during training, all three common objective speech quality metrics substantially improved on two different datasets. Additionally, we demonstrated the value of utilizing automatically-learned Gabor-based STRF kernels over randomly-selected kernels. We also showed that our speech enhancement system can improve a strong speaker verification system at low SNRs. In the future, we plan on exploring deep-learning-based techniques to perform SE directly in the modulation domain. We will also explore ways of directly optimizing the STRF parameters for speech enhancement.

Fig. 2. Equal error rates on the VoxCeleb1 Test Set.
7. REFERENCES

[1] Y. Luo and N. Mesgarani, “Conv-TasNet: Surpassing ideal time-frequency magnitude masking for speech separation,” IEEE/ACM Transactions on Audio, Speech, and Language Processing, vol. 27, no. 8, pp. 1256–1266, Aug. 2019.

[2] P. C. Loizou and G. Kim, “Reasons why current speech-enhancement algorithms do not improve speech intelligibility and suggested solutions,” IEEE/ACM Transactions on Audio, Speech, and Language Processing, vol. 19, no. 1, pp. 47–56, Jan. 2011.

[3] K. D. Kryter, “Validation of the articulation index,” The Journal of the Acoustical Society of America, vol. 34, no. 11, pp. 1698–1702, Nov. 1962.

[4] Y. Wang, A. Narayanan, and DeLiang Wang, “On training targets for supervised speech separation,” IEEE/ACM Transactions on Audio, Speech, and Language Processing, vol. 22, no. 12, pp. 1849–1858, Dec. 2014.

[5] S. Braun and I. Tashev, “A consolidated view of loss functions for supervised deep learning-based speech enhancement,” Sep. 2020.

[6] Y. Ephraim and D. Malah, “Speech enhancement using a minimum-mean square error short-time spectral amplitude estimator,” IEEE Transactions on Acoustics, Speech, and Signal Processing, vol. 32, no. 6, pp. 1109–1121, Dec. 1984.

[7] ——, “Speech enhancement using a minimum mean-square error log-spectral amplitude estimator,” IEEE Transactions on Acoustics, Speech, and Signal Processing, vol. 33, no. 2, pp. 443–445, Apr. 1985.

[8] J. S. Lim and A. V. Oppenheim, “Enhancement and bandwidth compression of noisy speech,” Proceedings of the IEEE, vol. 67, no. 12, pp. 1586–1604, Dec. 1979.

[9] P. C. Loizou, Speech Enhancement : Theory and Practice, Second Edition. CRC Press, Feb. 2013.

[10] J. M. Martin-Donas, A. M. Gomez, J. A. Gonzalez, and A. M. Peinado, “A deep learning loss function based on the perceptual evaluation of the speech quality,” IEEE Signal Processing Letters, vol. 25, no. 11, pp. 1680–1684, Nov. 2018.

[11] Y. Zhao, B. Xu, R. Giri, and T. Zhang, “Perceptually guided speech enhancement using deep neural networks,” in 2018 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP). Calgary, AB: IEEE, Apr. 2018, pp. 5074–5078.

[12] H. J. Steeneken and T. Houtgast, “A physical method for measuring speech-transmission quality,” The Journal of the Acoustical Society of America, vol. 67, no. 1, pp. 318–326, 1980.

[13] K. L. Payton and L. D. Braida, “A method to determine the speech transmission index from speech waveforms,” The Journal of the Acoustical Society of America, vol. 106, no. 6, pp. 3637–3648, Nov. 1999.

[14] M. Ehilitalo, T. Chi, and S. A. Shamma, “A spectro-temporal modulation index (STMI) for assessment of speech intelligibility,” Speech Communication, vol. 41, no. 2-3, pp. 331–348, Oct. 2003.

[15] N. Mesgarani and S. Shamma, “Denoising in the domain of spectro-temporal modulations,” EURASIP Journal on Audio, Speech, and Music Processing, vol. 2007, pp. 1–8, 2007.

[16] M. Mirbagheri, N. Mesgarani, and S. Shamma, “Nonlinear filtering of spectrotemporal modulations in speech enhancement,” in 2010 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP). Dallas, TX, USA: IEEE, Mar. 2010, pp. 5478–5481.

[17] T. Vuong, Y. Xia, and R. M. Stern, “Learnable spectro-temporal receptive fields for robust voice type discrimination,” in Interspeech 2020. ISCA, Oct. 2020, pp. 1957–1961.

[18] T. Chi, P. Ru, and S. A. Shamma, “Multiresolution spectrotemporal analysis of complex sounds,” The Journal of the Acoustical Society of America, vol. 118, no. 2, pp. 887–906, Aug. 2005.

[19] N. Mesgarani, M. Slaney, and S. Shamma, “Discrimination of speech from nonspeech based on multiscale spectro-temporal modulations,” IEEE/ACM Transactions on Audio, Speech and Language Processing, vol. 14, no. 3, pp. 920–930, May 2006.

[20] B. T. Meyer and B. Kollmeier, “Robustness of spectro-temporal features against intrinsic and extrinsic variations in automatic speech recognition,” Speech Communication, vol. 53, no. 5, pp. 753–767, May 2011.

[21] S. V. Ravuri and N. Morgan, “Easy does it: Robust spectro-temporal many-stream ASR without fine tuning streams,” in 2012 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP). Kyoto, Japan: IEEE, Mar. 2012, pp. 4309–4312.

[22] Y. Xia, S. Braun, C. K. A. Reddy, H. Dubey, R. Cutler, and I. Tashev, “Weighted speech distortion losses for neural-network-based real-time speech enhancement,” in 2020 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP). IEEE, May 2020, pp. 871–875.

[23] V. Panayotov, G. Chen, D. Povey, and S. Khudanpur, “Librispeech: An ASR corpus based on public domain audio books,” in 2015 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP). IEEE, Apr. 2015, pp. 5206–5210.

[24] C. Valentini-Botinhao, X. Wang, S. Takaki, and J. Yamagishi, “Investigating RNN-based speech enhancement methods for noise-robust text-to-speech.” in ISWC, 2016, pp. 146–152.

[25] C. K. A. Reddy, E. Beyrami, H. Dubey, V. Gopal, R. Cheng, R. Cutler, S. Matuszewych, R. Aichner, A. Aazami, S. Braun, P. Rana, S. Srinivasan, and J. Gehrke, “The INTERSPEECH 2020 deep noise suppression challenge: Datasets, subjective speech quality and testing framework,” arXiv:2001.08662 [cs, eess], Apr. 2020.

[26] C. K. A. Reddy, H. Dubey, V. Gopal, R. Cutler, S. Braun, H. Gamper, R. Aichner, and S. Srinivasan, “ICASSP 2021 deep noise suppression challenge,” 2020.

[27] A. Nagran, J. S. Chung, and A. Zisserman, “VoxCeleb: A large-scale speaker identification dataset,” in Interspeech 2017. ISCA, Aug. 2017, pp. 2616–2620.

[28] A. Rix, J. Beerends, M. Hollier, and A. Hekstra, “Perceptual evaluation of speech quality (PESQ)-a new method for speech quality assessment of telephone networks and codecs,” in 2001 IEEE International Conference on Acoustics, Speech, and Signal Processing (ICASSP), vol. 2, Salt Lake City, UT, USA: IEEE, 2001, pp. 749–752.

[29] J. Le Roux, S. Wisdom, H. Erdogan, and J. R. Hershey, “SDR–half-baked or well done?” in 2019 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP). IEEE, 2019, pp. 626–630.

[30] C. H. Taal, R. C. Hendriks, R. Heusdens, and J. Jensen, “A short-time objective intelligibility measure for time-frequency weighted noisy speech,” in 2010 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP). Dallas, TX, USA: IEEE, 2010, pp. 4214–4217.

[31] J. S. Chung, J. Huh, S. Mun, M. Lee, H. S. Heo, S. Choe, C. Ham, S. Jung, B.-J. Lee, and I. Han, “In defence of metric learning for speaker recognition,” arXiv:2003.11982 [cs, eess], Apr. 2020.

[32] J. S. Chung, A. Nagran, and A. Zisserman, “VoxCeleb2: Deep speaker recognition,” in Interspeech 2018. ISCA, Sep. 2018, pp. 1086–1090.

[33] D. Takeuchi, K. Yatabe, Y. Koizumi, Y. Oikawa, and N. Harada, “Real-time speech enhancement using equilibrated RNN,” in 2020 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP). IEEE, 2020, pp. 851–855.

[34] U. Isik, R. Giri, N. Phansalkar, J.-M. Valin, K. Helwani, and A. Krishnaswamy, “Poconet: Better speech enhancement with frequency-positioned embeddings, semi-supervised conversational data, and biased loss,” arXiv preprint arXiv:2008.04470, 2020.