Abstract—Frame-online speech enhancement systems in the short-time Fourier transform (STFT) domain usually have an algorithmic latency equal to the window size due to the use of overlap-add in the inverse STFT (iSTFT). This algorithmic latency allows the enhancement models to leverage future contextual information up to a length equal to the window size. However, this information is only partially leveraged by current frame-online systems. To fully exploit it, we propose an overlapped-frame prediction technique for deep learning based frame-online speech enhancement, where at each frame our deep neural network (DNN) predicts the current and several past frames that are necessary for overlap-add, instead of only predicting the current frame. In addition, we propose a loss function to account for the scale difference between predicted and oracle target signals. Experiments on a noisy-reverberant speech enhancement task show the effectiveness of the proposed algorithms.

Index Terms—Deep learning, online speech enhancement.

I. INTRODUCTION

Deep learning has elevated the performance of speech enhancement in the past decade [1]. Since the very first success of deep learning in offline enhancement [2], there have been growing interests in using DNNs for low-latency enhancement, as many applications require online real-time processing. For example, the recent deep noise suppression challenges [3] target at enhancement in a monaural teleconferencing setup, requiring a processing latency less than 40 ms on a specified processor. Similar latency requirements exist in other related challenges [4], [5]. The recent Clarity challenge [6] aims at multi-microphone enhancement in a hearing aid setup, requiring an algorithmic latency of at maximum 5 ms.

Numerous deep learning based approaches [7]–[31] have been proposed for frame-online speech enhancement by using frame-online (or causal) DNN modules such as uni-directional recurrent networks, causal normalization layers, causal convolutions and causal attention layers. To the best of our knowledge, almost all the current DNN models adopt a single-frame prediction strategy for online enhancement. That is, the DNN models predict a frame of target speech at the current frame based on the current and past frames, and the prediction at the current frame is overlap-added with the predictions at nearby frames for signal re-synthesis. This leads to an algorithmic latency equal to the window length. However, this strategy cannot fully leverage the future context afforded by the algorithmic latency. To explain this problem, we use an example STFT-based system shown in Fig. 1 for illustration, where the window size is 32 ms and hop size 8 ms. The frame-online DNN model operates in an online streaming fashion, processing one frame at a time when a new frame arrives and producing a predicted frame of signal for each input frame. The predicted signals at nearby frames are then overlapped and added together (see the red-frame rectangle) to get the final output signal for the sub-frame at frame \( t \) (marked in the top of the figure). As we can see, to get the prediction at sample index \( n \) (marked in the top), the system has to first fully observe the input signal at frame \( t + 3 \) before the DNN can perform feed-forwarding. The algorithmic latency is hence equal to the 32 ms window length. In this system, to get the predicted signal at frame \( t \), the model only takes in the input signals up to frame \( t \). The insight of this letter is that we can actually use input signals up to frame \( t + 3 \) for the DNN to get the predicted signal at frame \( t \) as well as at frame \( t + 1, t + 2 \) and \( t + 3 \). The resulting predicted signals would very likely be better, because the DNN can leverage up to three frames of future context, and at the same time the algorithmic latency remains the same as the window size. This can be achieved by training our DNN model for overlapped-frame prediction, where the current and past frames necessary for overlap-add are predicted at each frame at once.

Besides overlapped-frame prediction, we also propose a novel mechanism that equalizes the scales of predicted and oracle target signals before loss computation.

II. PROPOSED ALGORITHMS

Let us denote the monaural mixture \( y = s + v \) in the time domain as a summation of the target signal \( s \) and non-target signal

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For the partial sub-frame summation, following [33] we can use a regular synthesis window \( l \in \mathbb{R}^W \) defined as:
\[
l[n] = \frac{g[n]}{\sum_{e=0}^{W/H-1} g[eH + (n \mod H)]^2},
\]
where \( 0 \leq n < W \). By following the overlap-add procedure, we can verify that perfect reconstruction is satisfied, because
\[
\sum_{e=0}^{W/H-1} g[eH + h] \times l[eH + h] = 1,
\]
for any \( 0 \leq h < H \).

For the full sub-frame summation, we design the synthesis window as follows:
\[
l[n] = \frac{g[n]}{\sum_{e=0}^{W/H-1} ((e + 1) \times g[eH + (n \mod H)]^2)},
\]
where the difference from (1) is that we have a weighting term for the \( W/H \) sub-frames in the denominator. An intuitive way to understand this is that among all the sub-frames marked by the black-frame rectangle in Fig. 2, four are the last sub-frame in various predicted frames, three are the second-last sub-frame, and so on. We therefore need the weighting term in the denominator to have a pair of analysis and synthesis windows that can achieve perfect reconstruction, which can be ensured, because, in the proposed overlap-add procedure, the condition below always holds for any \( 0 \leq h < H \):
\[
\sum_{e=0}^{W/H-1} g[eH + h] \times ((e + 1) \times l[eH + h]) = 1.
\]

C. DNN Configurations

Our STFT-domain DNN model is trained for complex spectral mapping [18], [34]–[37], where the real and imaginary (RI) components of the mixture \( Y \) are concatenated as input features for a DNN to predict the RI components of target speech \( S \). The DNN architecture will be described in Section III-B.

When trained for overlapped-frame prediction, the DNN predicts \( K (= C) \) frames at each frame, essentially producing \( C \) estimated target spectrograms; and when trained for single-frame prediction, the DNN produces one estimated target spectrogram (i.e. \( K = 1 \)). Let us denote the DNN-estimated RI components by \( \hat{R}^{(k)} \) and \( \hat{I}^{(k)} \), where \( k \in \{1, 2, \ldots, K\} \) indexes the \( K \) spectrograms, and the enhanced speech by \( \hat{S}^{(k)} = \hat{R}^{(k)} + j \hat{I}^{(k)} \), where \( j \) is the imaginary unit. We can define the loss function on the RI components and magnitudes of the estimated spectrograms:
\[
L_{RI\text{-}Mag} = \sum_k \left( \| \hat{R}^{(k)} - \text{Real}(S) \|_1 + \| \hat{I}^{(k)} - \text{Imag}(S) \|_1 \\
+ \| \hat{S}^{(k)} - |S| \|_1 \right),
\]
where \( \text{Real}(\cdot) \) and \( \text{Imag}(\cdot) \) extract RI components, \( \| \cdot \|_1 \) computes magnitude, and \( \| \cdot \|_1 \) calculates the \( L_1 \) norm. Based on the described overlap-add mechanisms, an iSTFT is applied to resynthesize the estimated time-domain signal \( \hat{s} = \text{iSTFT}(\hat{S}^{(c)}) \), where \( \hat{S}^{(c)} \) includes all the \( K \) estimated spectrograms. Following [38], we can train through the iSTFT and define the loss on
the re-synthesized signal and its magnitude:

\[
L_{\text{Wav+Mag}} = \| \hat{s} - s \|_1 + \| \text{STFT}(\hat{s}) - \text{STFT}(s) \|_1,
\]

(6)

where \(\text{STFT}(\cdot)\) extracts a spectrogram from a signal\(^1\). When using this loss function with overlapped-frame prediction, at each frame we essentially use signals up to frame \(t + C - 1\) to predict the sub-frame at frame \(t\) (marked in the top of Fig. 2).

When using mapping based approaches with the loss function in (6), the model needs to predict a signal that has the same gain as the target. Although this may not be a problem for offline processing, as the model can observe the entire input mixture to produce a reasonable gain, for frame-online processing this could be difficult. We propose to first compute a real-valued gain- 

\[
L_{\text{Wav+Mag,geq}} = \| \hat{s} - s \|_1 + \| \text{STFT}(\hat{s}) - \text{STFT}(s) \|_1,
\]

(7)

where \(\hat{s} = \arg\min \| \hat{s} - s \|_2^2 = (\hat{s}^T \hat{s}) / (\hat{s}^T \hat{s})\). Note that GEQ can facilitate model training by not restricting the same gain, but \(\hat{s}\) will not be one at run time. This would be fine, as automatic gain adjustment, a common module in modern speech communication, can adjust the gain to a desired level.

We always include in each loss function a magnitude loss, which can improve metrics that favor estimated signals with a good magnitude [38].

D. Extension to Time-Domain Models

Besides STFT-domain models, the proposed algorithms can also be used with time-domain models such as ConvTasNet [13], by replacing the yellow blocks in Figs. 1 and 2 with time-domain models that use overlap-add for signal re-synthesis.

III. EXPERIMENTAL SETUP

We validate our algorithms on a simulated monaural speech enhancement task. This section describes the simulated dataset, DNN architectures, and miscellaneous configurations.

A. Dataset

The WSJCAM0 corpus [39] contains 7,861, 742, and 1,088 clean speech signals in its training, validation, and test sets, respectively. Using the split of the clean signals in WSJCAMO, we simulate 39,245 (~77.7 h), 2,965 (~5.6 h) and 3,260 (~8.5 h) noisy-reverberant mixtures as our training, validation and test sets, respectively. We sample the clips in the development set of FSD50k [40] to simulate the noises for training and validation, and those in the evaluation set for testing. For each simulated mixture, we sample up to 7 noise clips. We consider clips longer than 10 seconds as background noises and as foreground noises otherwise. Each simulated mixed noise file has one background noise and the rest are foreground noises. The energy level between the dry background noise and each dry foreground noise is sampled from the range \([-3, 9]\) dB. The directions of each noise source and the target speaker to the microphone are independently sampled from the range \([0, 2\pi]\). We treat each sampled clip as a point source, convolve each source

\(^1\)We tried to weight the two terms in the loss function, but did not observe gains, likely because they have similar scales due to the Parseval’s theorem.
in recent studies [17]–[20]. The RI components of different input (and output) signals are concatenated as feature maps in the network input (and output). The number of feature maps is 2 for the input tensor and is $2K$ for the output tensor. Linear activation is used in the output layer to get the predicted RI components. Based on this architecture, overlapped-frame prediction uses only slightly more computation than single-frame prediction, since the increased computation, which only stems from the final 2D deconvolution and overlap-add, is negligible compared to the computation of the DNN.

We choose Conv-TasNet [13] as the time-domain model for overlapped-frame prediction, considering its popularity. Its default hyper-parameters reported in [13] are used.

### C. Miscellaneous Configurations

The direct-path signal of the target speaker is used as the target for model training and as the reference for metric computation. SI-SDR in decibel (dB) [44], PESQ [45], and eSTOI [46] are used as the evaluation metrics. For TCN-DenseUNet, we experiment with 4/2 ms analysis window. For Conv-TasNet, we experiment with 4/2 ms and 20/10 ms window/hop sizes. In each table, we provide the offline results obtained by using the offline versions of the DNN architectures. These offline results can be viewed as the performance upper bound of the frame-online models.

Let us first look at Table I. Comparing 1a and 1b (or 2a and 2b), we observe that overlapped-frame prediction with partial sub-frame summation produces better performance than single-frame prediction. Using full sub-frame summation, 1c obtains worse performance than 1b, while 2c obtains similar or slightly better performance than 2b. This is likely because when we use the RI+Mag loss and do not train through iSTFT, the sub-frames summed by using full sub-frame summation contain sub-frame predictions produced at earlier frames (see the black-frame rectangle in Fig. 2), which are not as good as the ones produced at the current frame. When we train through iSTFT and use the Wav+Mag loss, the model may figure out how to best predict each sub-frame and best summate all the sub-frames (in the black-frame rectangle) to optimize the loss. Overall, our proposed systems in 2c show noticeable improvement over 1a and 2a, by better leveraging the 32 ms future context information.

In Table II, similar trend as in Table I is observed. The relative gains of overlapped-frame prediction over single-frame prediction are smaller than those in Table I. This is as expected as there is less future context (i.e., 20 ms) to exploit. In Table III, the gains are very marginal as the future context (i.e., 4 ms) is even less. This Conv-TasNet experiment suggests that the window size needs to be reasonably large for overlapped-frame prediction to work well.

Although the gains brought by overlapped-frame prediction depend on the allowed future context and are small when the allowed context is limited, we always observe consistent and steady improvements in the considered setups. In all the tables, the proposed gain equalization leads to slightly better results in the online cases (see 2c vs. 2d).

### IV. Evaluation Results

Table I, II and III respectively report the results of using 32/8, 20/10 and 4/2 ms window/hop sizes. In each table, we provide the offline results obtained by using the offline versions of the DNN architectures. These offline results can be viewed as the performance upper bound of the frame-online models.

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We have proposed a novel overlapped-frame prediction technique for frame-online speech enhancement. It better leverages future context, without incurring extra algorithmic latency. The increased amount of computation only stems from the output layer and is negligible compared to that of the DNN backbone. The proposed technique can be easily modified for, or directly adopted by, numerous frame-online systems. It would likely yield better performance due to the better exploitation of the future context afforded by the algorithmic latency, no matter whether they are DNN- or non-DNN-based, whether they operate in the T-F domain or in the time domain, or whether they deal with speech enhancement or other related separation tasks, as long as they use overlap-add for signal re-synthesis.

### V. Conclusion

We have proposed a novel overlapped-frame prediction technique for frame-online speech enhancement. It better leverages future context, without incurring extra algorithmic latency. The increased amount of computation only stems from the output layer and is negligible compared to that of the DNN backbone. The proposed technique can be easily modified for, or directly adopted by, numerous frame-online systems. It would likely yield better performance due to the better exploitation of the future context afforded by the algorithmic latency, no matter whether they are DNN- or non-DNN-based, whether they operate in the T-F domain or in the time domain, or whether they deal with speech enhancement or other related separation tasks, as long as they use overlap-add for signal re-synthesis.
REFERENCES

[1] D. Wang and J. Chen, “Supervised speech separation based on deep learning: An overview,” IEEE/ACM Trans. Audio, Speech, Lang. Process., vol. 26, no. 10, pp. 1702–1726, Oct. 2018.

[2] Y. Wang and D. Wang, “Towards scaling up classification-based speech separation,” IEEE Trans. Audio, Speech, Lang. Process., vol. 21, no. 7, pp. 1381–1390, Jul. 2013.

[3] C. K. Reddy et al., “The INTERSPEECH 2020 deep noise suppression challenge: Dataset, objective speech quality and testing framework,” in Proc. Interspeech, 2020, pp. 2492–2496.

[4] R. Cutler et al., “ICASSP 2022 acoustic echo cancellation challenge,” in Proc. IEEE Int. Conf. Acoust., Speech, Signal Process., 2022, pp. 9107–9111.

[5] W. Rao et al., “INTERSPEECH 2021 conferencing speech challenge: First half of multi-channel speech enhancement for video conferencing,” 2021, arXiv:2104.00996.

[6] “Clarity challenge: Machine learning challenges for hearing devices,” [Online]. Available: http://claritychallenge.org/

[7] J. Chen and D. Wang, “Long short-term memory for speaker generalization in supervised speech separation,” J. Acoust. Soc. Amer., vol. 141, pp. 4705–4714, 2017.

[8] G. Wichern and A. Lukin, “Low-latency approximation of bidirectional recurrent networks for speech denoising,” in Proc. IEEE Workshop Appl. Signal Process. Audio, 2017, pp. 66–70.

[9] Y. Luo and N. Mesgarani, “TaSinT: Time-domain audio separation network for real-time, single-channel speech separation,” in Proc. IEEE Int. Conf. Acoust., Speech Signal Process., 2018, pp. 696–700.

[10] K. Wilson et al., “Exploiting trade-offs in models for low-latency speech enhancement,” in Proc. Int. Workshop Acoust. Signal Enhancement, 2018, pp. 366–370.

[11] S. Wisdom et al., “Differentiable consistency constraints for improved deep speech enhancement,” in Proc. IEEE Int. Conf. Acoust., Speech, Signal Process., 2019, pp. 900–904.

[12] T. Higuchi, K. Kimoshita, N. Ito, S. Karita, and T. Nakatani, “Frame-by-frame closed-form update for mask-based adaptive MVDR beamforming,” in Proc. IEEE Int. Conf. Acoust., Speech, Signal Process., 2018, pp. 531–535.

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

[14] T. Yoshioka, Z. Chen, C. Liu, X. Xiao, H. Erdogan, and D. Dimitriadis, “Low-latency speaker-independent continuous speech separation,” in Proc. IEEE Int. Conf. Acoust., Speech, Signal Process., 2019, pp. 6980–6984.

[15] S. Chakrabarty and E. A. P. Habets, “Time-frequency masking based online multi-channel speech enhancement with convolutional recurrent neural networks,” IEEE J. Sel. Topics Signal Process., vol. 13, no. 4, pp. 787–799, Aug. 2019.

[16] S. Sonning, C. Schuldt, H. Erdogan, and S. Wisdom, “Performance study of objectionable speech quality and testing framework,” in Proc. Interspeech, 2020, pp. 6633–6637.

[17] A. Li, W. Liu, X. Luo, C. Zheng, and X. Li, “ICASSP 2021 deep noise suppression challenge: Decoupling magnitude and phase optimization with a two-stage deep network,” in Proc. IEEE Int. Conf. Acoust., Speech, Signal Process., 2021, pp. 6628–6632.

[18] Z. Tu, J. Zhang, N. Ma, J. Barker, and C. Science, “A two-stage end-to-end system for speech-in-noise hearing aid processing,” in Proc. Clarity, 2021, pp. 3–5.

[19] S. J. Yang, S. Wisdom, C. Gnegy, R. F. Lyon, and S. Savlava, “Listening with Googlears: Low-latency neural multiframe beamforming and equalization for hearing aids,” in Proc. Clarity, 2021.

[20] K. Zmolikova and J. H. Cernocky, “BUT system for the first clarity enhancement challenge,” in Proc. Clarity, 2021, pp. 1–3.

[21] S. Ren et al., “A causal U-Net based neural beamforming network for real-time multi-channel speech enhancement,” in Proc. Interspeech, 2021, pp. 1832–1836.

[22] C. Li, L. Yang, W. Wang, and Y. Qian, “SkiiM: Skipping memory LSTM for low-latency real-time continuous speech separation,” in Proc. IEEE Int. Conf. Acoust., Speech, Signal Process., 2022, pp. 1–5.

[23] J. Chen, Y. Wang, S. E. Yoho, D. Wang, and E. W. Healy, “Large-scale training to increase speech intelligibility for hearing-impaired listeners in novel noises,” J. Acoust. Soc. Amer., vol. 139, no. 5, pp. 2604–2612, 2016.

[24] D. W. Griffin and J. S. Lim, “Signal estimation from modified short-time fourier transform,” IEEE Trans. Audio, Speech, Signal Process., vol. 32, no. 2, pp. 236–243, Apr. 1984.

[25] D. S. Williamson, Y. Wang, and D. Wang, “Complex ratio masking for monaural speech separation,” IEEE/ACM Trans. Audio, Speech, Lang. Process., vol. 24, no. 3, pp. 483–492, Mar. 2016.

[26] S.-W. Fu, T.-Y. Hu, Y. Tsao, and X. Lu, “Complex spectrogram enhancement by convolutional neural network with multi-metrics learning,” in Proc. IEEE 27th Int. Workshop Mach. Learn. Signal Process., 2017, pp. 1–6.

[27] Z.-Q. Wang, P. Wang, and D. Wang, “Complex spectral mapping for single- and multi-channel speech enhancement and robust ASR,” IEEE/ACM Trans. Audio, Speech, Lang. Process., vol. 28, pp. 1778–1787, 2020.

[28] Z.-Q. Wang and D. Wang, “Deep learning based target cancellation for speech dereverberation,” IEEE/ACM Trans. Audio, Speech, Lang. Process., vol. 28, pp. 941–950, 2020.

[29] Z.-Q. Wang, G. Wichern, and J. Le Roux, “On the compensation between magnitude and phase in speech separation,” IEEE Signal Process. Lett., vol. 28, pp. 2018–2022, 2021.

[30] T. Robinson, J. Fransen, D. Pye, J. Foose, and S. Renals, “WSJCAMO: A British English speech corpus for large vocabulary continuous speech recognition,” in Proc. IEEE Int. Conf. Acoust., Speech, Signal Process., 1995, vol. 1, pp. 81–84.

[31] E. Fonseca, X. Favory, J. Pons, F. Font, and X. Serra, “FSD50 K: An open dataset of human-labeled sound events,” IEEE/ACM Trans. Audio, Speech, Lang. Process., vol. 30, pp. 829–852, 2022.

[32] Z.-Q. Wang, G. Wichern, and J. Le Roux, “Leveraging low-distortion target estimates for improved speech enhancement,” 2021, arXiv:2110.00570.

[33] Z.-Q. Wang, G. Wichern, and J. Le Roux, “Convolutional prediction for monaural speech dereverberation and noisy-reverberant speaker separation,” IEEE/ACM Trans. Audio, Speech, Lang. Process., vol. 29, pp. 3476–3490, 2021.

[34] Z.-Q. Wang, P. Wang, and D. Wang, “Multi-microphone complex spectral mapping for attenuation-wise and continuous speech separation,” IEEE/ACM Trans. Audio, Speech, Lang. Process., vol. 29, pp. 2001–2014, 2021.

[35] J. Le Roux, S. Wisdom, H. Erdogan, and J. R. Hershey, “SDR - Half-baked or well done!?” in Proc. IEEE Int. Conf. Acoust., Speech, Signal Process., 2015, pp. 629–630.

[36] A. Rin, B. Beersdts, M. Hollier, and A. Hekstra, “Perceptual evaluation of speech quality (PESQ)-A new method for speech quality assessment of telephone networks and codecs,” in Proc. IEEE Int. Conf. Acoust., Speech, Signal Process., 2001, vol. 2, pp. 749–752.

[37] C. H. Taal, R. C. Hendriks, R. Heusdens, and J. Jensen, “An algorithm for intelligibility prediction of time-frequency weighted noisy speech,” IEEE Trans. Audio, Speech, Lang. Process., vol. 19, no. 7, pp. 2125–2136, Sep. 2011.