SELF-SUPERVISED LEARNING FROM CONTRASTIVE MIXTURES FOR PERSONALIZED SPEECH ENHANCEMENT

Aswin Sivaraman & Minje Kim

Indiana University, Intelligent Systems Engineering, Bloomington, IN 47408, USA
asivara@iu.edu, minje@indiana.edu

ABSTRACT

This work explores how self-supervised learning can be universally used to discover speaker-specific features towards enabling personalized speech enhancement models. We specifically address the few-shot learning scenario where access to cleaning recordings of a test-time speaker is limited to a few seconds, but noisy recordings of the speaker are abundant. We develop a simple contrastive learning procedure which treats the abundant noisy data as makeshift training targets through pairwise noise injection: the model is pretrained to maximize agreement between pairs of differently deformed identical utterances and to minimize agreement between pairs of similarly deformed non-identical utterances. Our experiments compare the proposed pretraining approach with two baseline alternatives: speaker-agnostic fully-supervised pretraining, and speaker-specific self-supervised pretraining without contrastive loss terms. Of all three approaches, the proposed method using contrastive mixtures is found to be most robust to model compression (using 85% fewer parameters) and reduced clean speech (requiring only 3 seconds).

Index Terms—Self-supervised learning, personalized speech enhancement, model compression, few-shot learning

1. INTRODUCTION

Fully-supervised machine learning models are a popular choice for single-channel speech enhancement (SE) problems. They are often trained to predict a clean speech signal out of its noisy observation. Often to this end, a large dataset of clean speech signals is artificially mixed with many non-stationary noises; the SE model then learns a parametric function to map the mixture signals to the reference speech recordings. As the availability of speech datasets grows, deep neural networks (DNNs) have become the standard tools for designing SE systems [1]. These models can be seen as generalists, trained on a large database of speakers and noise types then expected to generalize to unseen test environments.

However, with the widespread use of voice command devices (VCD) with virtual assistants, there is incentive to develop efficient privacy-preserving algorithms for speech enhancement (SE). In this paper, we introduce a simple self-supervised feature learning method to build personalized speech enhancement (PSE) systems. Specialization of single-channel SE models (e.g. based on a particular speaker or noise type) has been shown to yield improvements in signal quality and intelligibility, as the model justifiably benefits from solving a smaller subset of the original problem [2]. Additionally, model specialization allows for reduced model complexity, which is critical for resource-constrained devices [3]. We apply this concept to the broader task of few-shot learning (FSL) wherein a machine learning model has a limited amount of supervised training data available [4]. For example, a VCD user might only allow their device to record a few seconds of clean speech data in order to aid personalization. One way to mitigate the lack of clean speech data would be to employ transfer learning, initializing the PSE model with parameters from a fully-trained generalist. Even if the PSE model is efficient and provides optimal improvement, reliance on private user data is a critical issue.

As an alternative to straightforward transfer learning, we propose a universal self-supervised learning methodology for PSE. We show that the self-supervised learning approach can better initialize the PSE model because it fully utilizes large amounts of noisy speech data of the target user to extract speaker-specific discriminative features. This works by injecting further noise onto the noisy speech data in pairs: the SE model is first pretrained to maximize agreement between pairs which share the same noisy speech source (positive pairs) while minimizing agreement between pairs that stem from different noisy speech sources (negative pairs). The limited clean speech data is then used for fine-tuning the model towards speaker-biased SE. We compare the proposed method with two baseline pretraining approaches: (a) standard fully-supervised multi-speaker SE, and (b) single-speaker SE in which the noisy speech is itself the training target (without contrastive learning). The proposed contrastive mixtures method can be viewed as a regularized version of the latter pseudo SE pretext task. We run experiments with all three approaches to determine how little clean speech data is needed from the test-time user and how robust each approach is to reducing the number of model parameters.

2. RELATED WORK

Test-time adaptation of SE systems has been previously studied. For example, adaptive speech denoising autoencoders [5] and modularization of the SE system [6] showed promising performance increase via test-time adaptation, but at the cost of increased model complexity. Ensemble networks have been shown to compress test-time adapted SE models in a no-shot non-personalized context [3]. There is also prior research on speaker-aware SE systems in the single-channel [7] and multi-channel [8] contexts. All of these works are limited to conditioning generalist SE models using a speaker-identifying feature vector, thereby missing the implications of PSE in model compression.

We see the PSE problem as a unique opportunity to apply self-supervised learning [10] which has gained significant traction in image and video processing research communities [11, 12]. Self-supervised models are pretrained on an auxiliary “pretext task”, learning meaningful features out of the unlabeled data which are then reused for the downstream task. For example, in order to predict the relative position between two random patches of an image, a neural network might first pretrain on fitting pairs of patches in
a $3 \times 3$ grid [13] or by solving a jigsaw puzzle [14]. The pretext task posed in many of these works is specific to the image domain, often requiring complex data augmentation strategies in order to make the self-supervised features as robust as possible.

Most recently, it was shown that a simple framework for contrastive learning of visual representations (SimCLR) can streamline the self-supervised learning process [15]. The unlabeled data is transformed in pairs through two data augmentation pipelines then processed by the model. A contrastive loss is applied to projections of the model outputs, maximizing or minimizing cosine similarity depending on whether the pair originated from the same source image or not. SimCLR-learned features were adopted in the subsequent downstream task, yielding competitive performance with the traditional supervised learning image classification systems while requiring only 1% of the labeled examples for finetuning. Compared to other self-supervised learning techniques, SimCLR’s contrastive learning process circumvents the need for heuristics and domain knowledge. We extend this insight in developing our universal contrastive mixtures scheme for PSE.

Data augmentation is frequently seen in audio signal processing research. While musical instrument source separation, one can generate vast amounts of incoherent unrealistic mixtures from random musical stems to augment training data [16]. Towards speech separation, a model may train in an unsupervised permutation-invariant way by indefinitely mixing mixtures and separating them into an arbitrary number of sources minimizing signal-to-noise ratio (SNR) loss [17]. A recent work applies self-supervised learning directly towards speech enhancement—the authors train an autoencoder on unlabeled noisy data, coupling its parameters with another autoencoder pretrained on clean data [18]. In all prior works, the lower bounds of data augmentation are unexplored; in contrast, for PSE, we limit our fine-tuning procedure to a small fixed amount of clean speech data from the test-time user.

3. PROPOSED METHOD

A conventional, speaker-agnostic speech denoising model can be trained in a fully-supervised way if there is access to a large clean speech corpus $S_0$ and a large noise corpus $N_0$. A set of artificial mixture signals $X_0$ is made by selecting random utterances $s \in S_0$ and noises $n \in N_0$ and summing the signals, i.e. $x = s + n$. The model learns a parametric mapping function $g(\cdot)$ such that $g(x) = y \approx s$, where the estimates $y$ approximate the training target $s$. Without any fine-tuning, the model must generalize to test mixtures which may derive from an unseen speaker’s utterances $S_n$ in unseen noisy environments $N_n$; hence, we refer to these models as generalists.

The generalist model $g(\cdot)$ can be personalized to a specific speaker through fine-tuning. To this end, a set of artificial mixture signals $X_n$ is created by mixing $N_n$ with speaker-specific training utterances $S_n \subseteq S_0$. As discussed in Section 1, the test-user of a VCD might only record a few seconds of clean speech due to privacy concerns, i.e. $S_n$ could be very small. If this clean speaker-specific data is insufficient, the generalist may fail to personalize.

3.1. Pseudo Speech Enhancement

Realistically, a VCD might have access to many noisy recordings of the test-time speaker $S_n$—potentially much more than the clean set i.e. $|S_n| \gg |S_0|$. We postulate that the noisy utterances $s \in S_n$ are contaminated by some premix noise signal $n \in N_n$, which is always unknown to the denoising model, i.e. $\hat{s} = s + n$. If the premix signal-to-noise ratio (SNR) is not too low, it may be possible to first pretrain a denoising model using the large noisy set $S_n$ then fine-tune it using the small clean set $S_0$. We refer to this procedure as pseudo speech enhancement (PseudoSE) because it uses $s$ as the training target. This offers a self-supervised learning alternative to transfer learning (fine-tuning) from the generalist.

PseudoSE treats the premixtures noisy data $\hat{S}_n$ as the target: through noise injection [19] [20], we prepare pseudo mixtures $\bar{x}$ by combining $s$ with additional deformation signals $n \in N_n$, i.e. $\bar{x} = \hat{s} + n$. The model learns a PseudoSE mapping function $f$ such that $\hat{f}(\bar{x}) = \hat{y} \approx \hat{s}$. Note that $f$ can only recover the noisy utterance $\hat{s}$ as if it was a clean source, i.e., $f \neq g$. Ultimately, $f$ is fine-tuned into $g$ by using the limited clean speech data $S_0$.

3.2. Contrastive Mixtures

We posit that the quality of the pretraining procedure greatly impacts how the denoising model will personalize. Even if the premixed noisy speech set $\hat{S}_n$ and the deformation noise set $N_n$ are large, the quality of the features learned through PseudoSE are bounded by how noisy $\hat{S}_n$ really is. We propose a novel contrastive mixtures (CM) pretraining procedure in order to overcome this limitation, where the denoising model $f(\cdot)$ pretrains over pairs of pseudo-mixtures ($\bar{x}_1$, $\bar{x}_2$) and outputs pseudo-cleaned estimates ($\hat{y}_1$, $\hat{y}_2$).

CM extends PseudoSE with a pairwise contrastive mechanism. In the CM framework, we construct two kinds of pseudo-mixture pairs: positive and negative pairs, illustrated in Fig. 1. Example spectrograms are shown in Fig. 2 and 3. In a positive pair, both examples share the same premixture source $s$, but are differently deformed. Therefore, in addition to the ordinary denoising objective that maximizes the agreement between $\hat{y}_1$ with $\hat{s}$ and $\hat{y}_2$ with $\hat{s}$, $f(\cdot)$ must also learn the contrastive objective which utilizes the fact that $\hat{y}_1$ must be the same as $\hat{y}_2$. These objectives are expressed in Eq. 4 as a positive pair loss function.

On the other hand, in a negative pair, each pseudo-mixture is made from a different noisy source ($\bar{s}_1 \neq \bar{s}_2$), but with a shared deformation, i.e., $\bar{x}_1 = \bar{s}_1 + n$ and $\bar{x}_2 = \bar{s}_2 + n$. Accordingly, aside from the source-wise denoising objectives, the dissimilarity between the estimates $\hat{y}_1$ and $\hat{y}_2$ must be enforced. These objectives are expressed in Eq. 5 as a negative pair loss function.

3.3. Loss Functions

Towards speech denoising, we choose the scale-invariant signal-to-distortion ratio (SI-SDR) metric [21] as the objective function which the model maximizes in each training iteration. SI-SDR augments conventional SDR [22] through the inclusion of a scaling factor $\alpha$ which maintains orthogonality of the residual vector between some target signal $v$ and an estimate signal $\hat{v}$. It is defined as:

\[
\text{SI-SDR} = \frac{\sum_v (v - \hat{v})^2}{\sum_v v^2}
\]
In addition, with positive pairs, our goal is to maximize the similar-
mate signals with a margin contingent on the difference between the
batches of paired inputs (\(\tilde{s}_1, \tilde{s}_2\)). This is used for few-shot fine-tuning and multi-speaker generalist
\[\alpha = \frac{v^\top w}{v^\top v}.\]
The denoising model loss function uses negative
SI-SDR in order to maximize the reconstruction quality:
\[\mathcal{L}_{\text{denosing}}(s, y) = -\text{SI-SDR}(s, y).\]
This is used for few-shot fine-tuning and multi-speaker generalist
training, where the models have access to clean speech targets \(S_n\) and \(S_t\). PseudoSE pretraining treats the noisy speech input \(s\) as the
training target, so its loss function is defined using SI-SDR similarly:
\[\mathcal{L}_{\text{PseudoSE}}(\tilde{s}, \tilde{y}) = -\text{SI-SDR}(\tilde{s}, \tilde{y}).\]
In the proposed CM pretraining, the model processes balanced
batches of paired inputs (\(x_1, x_2\)) and outputs denoised estimates
(\(\tilde{y}_1, \tilde{y}_2\)), which can be either a positive or negative pair depending
on the context within the batch. The denoising quality can be
directly measured by using the reconstruction loss, similar to Eq. 3.
In addition, with positive pairs, our goal is to maximize the similarity
of the two estimate signals, as they share a common premixture source \(\tilde{s}\). We calculate a loss \(\mathcal{L}_p\) over the positive pairs as:
\[\mathcal{L}_p = -\lambda_p \text{SI-SDR}(\tilde{y}_1, \tilde{y}_2) - \text{SI-SDR}(\tilde{s}, \tilde{y}_1) - \text{SI-SDR}(\tilde{s}, \tilde{y}_2),\]
As for negative pairs, we minimize the similarity of the two estimate
signals with a margin contingent on the difference between the
two premixture sources (\(\tilde{s}_1, \tilde{s}_2\)) along with the usual denoising loss.
\[\mathcal{L}_n = \lambda_n [\text{SI-SDR}(\tilde{y}_1, \tilde{y}_2) + \text{SI-SDR}(\tilde{s}_1, \tilde{s}_1)] - \text{SI-SDR}(\tilde{s}_1, \tilde{y}_1) - \text{SI-SDR}(\tilde{s}_2, \tilde{y}_2),\]
Both \(\mathcal{L}_p\) and \(\mathcal{L}_n\) consist of two terms: the source-to-estimate
errors and the estimate-to-estimate errors, where the former works
as the main denoising loss while the latter regularizes based on
the proposed contrastive mixtures process. We empirically found
that scaling the estimate-to-estimate errors (with \(\lambda_p = 0.5\) and
\(\lambda_n = 0.0002\)) was necessary to keep the various SI-SDR calculations
within the same order of magnitude. The model ultimately
minimizes the sum of these two losses, i.e. \(\mathcal{L}_{\text{CM}} = \mathcal{L}_p + \mathcal{L}_n\). With
the regularizing contrastive terms omitted, \(\mathcal{L}_{\text{CM}}\) reduces to \(\mathcal{L}_{\text{PseudoSE}}\).

### 4. EXPERIMENTS

#### 4.1. Data Preparation

We utilize data from three public audio corpora listed in Table 1.
Our experiments evaluate the three discussed pretraining procedures
by measuring the model’s SI-SDR improvement on test mixtures
generated using unseen noises \(N_{\text{te}}\) and unseen utterances \(S_{\text{te}}\)
from \(k\)-th speaker’s utterances \(L_{\text{te}}^{(k)}\) out of 40 test speakers (we omit
the speaker index for brevity). Each of these speakers is the designated
personalization target. We split \(L_{\text{te}}^{(k)}\) into three partitions: \(S_{\text{te}}, S_{\text{tr}}\),
and \(S_{\text{val}}\). We vary the size of the fine-tuning clean speech set \(S_{\text{tr}}\) to be
either 0, 3, 5, 10, or 30 seconds in total duration; this controls the
fewness of our posed few-shot learning scenario. With \(S_{\text{te}}\) allocated,
the remaining speech data is assigned to each partition: 80% goes to
\(S_{\text{tr}}, 10\%\) goes towards pretraining and fine-tuning validation,
and the remaining 10% goes towards \(S_{\text{te}}\).

To simulate the noisy test-user recordings (premixtures), we mix
\(N_{\text{te}}\) to the first partition, yielding \(S_{\text{te}}\). As conjectured in Section 3.2,
how degraded \(S_{\text{te}}\) will impact the model’s ability to learn speaker-
discriminative features. We investigate this by trying 5 and 10 dB
premixture SNRs. In all other cases, the per-mixture SNR is randomly
selected to be either \(-5, 0, 5, 10\) dB using \(N_{\text{tr}}\) or \(N_{\text{te}}\).

| Corpus       | Subset         | Size / Duration | Symbol |
|--------------|----------------|-----------------|--------|
| LibriSpeech  | train-clean-100| 231 speakers, \(\approx 25\) min. / spkr | \(L_q\) |
|              | dev-clean      | 40 speakers, \(\approx 8\) min. / spkr | \(L_L\) |
|              | test-clean     | 40 speakers, \(\approx 8\) min. / spkr | \(L_N\) |
| MUSAN        | free-sound     | 708 noises, \(\approx 351\) min. | \(N_{\text{fs}}\) |
|              | sound-bible    | 67 noises, \(\approx 18\) min. | \(N_{\text{sb}}\) |
| DEMANIE      | ch01           | 18 noises, \(\approx 90\) min. | \(N_{\text{ch}}\) |

1. Downloaded at [https://openair.org/12/](https://openair.org/12/)
2. Downloaded at [https://openair.org/17/](https://openair.org/17/)
3. Downloaded at [https://zenodo.org/record/1227121/](https://zenodo.org/record/1227121/)
All signals are monaural with a sampling rate of 16 kHz. A batch contains 100 mixtures (or 50 positive and 50 negative mixture-pairs for CM). For both training and testing, with every batch, the audio and noise files are randomly offset and truncated to 2 seconds.

4.2. Pretraining Procedures

The baseline generalist is pretrained using the multi-speaker corpus \( \mathbb{L}_g \) mixed with \( \mathbb{N}_g \). Early stopping is determined based on mixtures made with \( \mathbb{L}_{dev} \) and \( \mathbb{N}_g \). Then, we personalize the generalist by fine-tuning it using the small clean speech set \( \mathbb{S}_N \) mixed with \( \mathbb{N}_g \). Test performance is assessed using \( \mathbb{L}_{dev} \) and \( \mathbb{N}_g \). The baseline generalist does not involve any data augmentation, pretext task, or self-supervised learning. The baseline specialist uses PseudoSE to pretrain on the premixed speaker-specific subset \( \mathbb{S}_N \). As with the generalist, it is fine-tuned using the few clean speech examples \( \mathbb{S}_N \) and tested using \( \mathbb{S}_N \) respectively. Our proposed specialist uses contrastive mixtures (CM) to pretrain on positive and negative pairs generated out of the same premixed speaker-specific subset \( \mathbb{S}_N \). The pretraining and fine-tuning setup parallels that of the PseudoSE experiment.

4.3. Model Architecture

With all experiments, we use the same no-frills neural network architecture intended for single-channel speech enhancement. First, we apply the short-time Fourier transform (STFT) to mixture signal inputs \( \mathbf{x} \) with a Hann window of 1024 samples and 75% overlap. The input spectrograms are then processed through a two-layer unidirectional gated recurrent unit (GRU) \( \mathbb{R} \) recurrent neural network (RNN). Lastly, the RNN outputs are passed to a fully-connected dense layer with sigmoid activation. The dense layer estimates a time-frequency ratio mask (akin to IRM \( \mathbb{R} \)) which is applied onto the noisy input spectrogram. The inverse STFT converts the masked spectrogram into the time-domain estimate signal \( \mathbf{y} \). We vary the number of hidden units in the RNN (to be either 64, 128, or 256) in order to assess how model capacity impacts the effectiveness of the three pretraining strategies. All parameter updates are done using the Adam optimization algorithm \( \mathbb{R} \) with two learning rates: \( 1 \times 10^{-3} \) and \( 1 \times 10^{-4} \) for pretraining and finetuning respectively.

4.4. Results & Discussion

Our experiment results are compiled in Fig. 4. SI-SDR improvement is measured over test utterances across 40 different speakers. We first observe that all initialization procedures benefit from fine-tuning if provided sufficient clean speech (\( |\mathbb{S}_N| \geq 5 \) seconds). However, if a generalist is fine-tuned with little speaker-specific data (\( |\mathbb{S}_N| = 3 \) seconds), the personalized model performs about the same or potentially worse.

The intermediate self-supervised learning solution (PseudoSE) does improve upon the naïve transfer learning approach (i.e. the fine-tuned generalist) when the clean speech set is limited. It is also noticeable that the quality of the premixture matters. In all cases, PseudoSE-learned features improve downstream performance when the premixture SNR is 10 dB as opposed to 5 dB. With enough data (\( |\mathbb{S}_N| \geq 10 \) seconds), the fine-tuned generalist becomes more effective, suggesting that PseudoSE self-supervised learning saturates.

Our most important claim is that the proposed CM provides a robust pretraining mechanism when we lack the clean speech sources. First, in all comparisons, the CM-pretrained models yield the best personalized performance when the premixture SNR is 10 dB and \( |\mathbb{S}_N| \leq 5 \) seconds. In other words, if the premix dataset is in good quality, CM can derive meaningful speaker-specific features with very little clean data. The performance improvement from CM also saturates when \( |\mathbb{S}_N| \geq 10 \) seconds, where the speaker-agnostic generalist begins to fine-tune well. Still, CM-pretraining maintains comparable performance to the adapted multi-speaker generalist. The gains become marginal with the very small network topology. Our results also indicate that CM is less robust to the premixture SNR compared to PseudoSE.

Lastly, we can also see that the proposed personalization schemes can operate with lower model complexity without sacrificing the performance. For example, where \( |\mathbb{S}_N| = 3 \), if a small model GRU(64, 2) is trained using contrastive mixtures with 10 dB premixture SNR, it outperforms all the other larger networks with up to about 16 times more weights that are pretrained by a generalist.

5. CONCLUSION

We introduce a simple, universally-applicable contrastive learning approach towards self-supervised speech enhancement, highlighting its ability to personalize denoising models with reduced model complexity and minimal test-user clean speech data. Compared with the naïve fully-supervised transfer learning approach, as well with an intermediate self-supervised alternative, the contrastive mixtures process succeeds in the few-shot problem thanks to added regularization. Our results suggest that speaker-discriminative features can be found even in noisy recordings, favoring the need for robust privacy-preserving speech processing. Source code for this project is available online at [https://saige.sice.indiana.edu/research-projects/contrastive-mixtures](https://saige.sice.indiana.edu/research-projects/contrastive-mixtures).
6. REFERENCES

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

[2] M. Kolbæk, 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, Jan 2017.

[3] A. Sivaraman and M. Kim, “Sparse Mixture of Local Experts for Efficient Speech Enhancement,” in Proceedings of the Annual Conference of the International Speech Communication Association (Interspeech), 2020.

[4] Y. Wang, Q. Yao, J. T. Kwok, and L. M. Ni, “Generalizing from a Few Examples: A Survey on Few-shot Learning,” ACM Computing Surveys, vol. 53, no. 3, 2020.

[5] M. Kim and P. Smaragdis, “Adaptive denoising autoencoders: A fine-tuning scheme to learn from test mixtures,” in Proceedings of the International Conference on Latent Variable Analysis and Signal Separation (LVA/ICA), August 2015.

[6] M. Kim, “Collaborative deep learning for speech enhancement: A run-time model selection method using autoencoders,” in Proceedings of the IEEE International Conference on Acoustics, Speech, and Signal Processing (ICASSP), 2017.

[7] Q. Wang, H. Muckenhirn, K. Wilson, P. Sridhar, Z. Wu, J. Hershey, R. A. Saurous, R. J. Weiss, Y. Jia, and I. L. Moreno, “Voicefilter: Targeted voice separation by speaker-conditioned spectrogram masking,” arXiv preprint arXiv:1810.04826, 2018.

[8] K. Žmolíková, M. Delcroix, K. Kinoshita, T. Higuchi, A. Ogawa, and T. Nakatani, “Speaker-aware neural network based beamformer for speaker extraction in speech mixtures,” in Proceedings of the Annual Conference of the International Speech Communication Association (Interspeech), 2017.

[9] M. Delcroix, K. Žmolíková, K. Kinoshita, A. Ogawa, and T. Nakatani, “Single channel target speaker extraction and recognition with speaker beam,” in Proceedings of the IEEE International Conference on Acoustics, Speech, and Signal Processing (ICASSP), 2018.

[10] J. Schmidhuber, “Making the world differentiable: On using self-supervised fully recurrent neural networks for dynamic reinforcement learning and planning in non-stationary environments,” 1990.

[11] X. Wang and A. Gupta, “Unsupervised Learning of Visual Representations using Videos,” in Proceedings of the International Conference on Computer Vision (ICCV), 2015, pp. 2794–2802.

[12] A. Veit, N. Alldrin, G. Chechik, I. Krasin, A. Gupta, and S. Belongie, “Learning From Noisy Large-Scale Datasets With Minimal Supervision,” in Proceedings of the IEEE International Conference on Computer Vision and Pattern Recognition (CVPR), 2017, pp. 839–847.

[13] C. Doersch, A. Gupta, and A. A. Efros, “Unsupervised Visual Representation Learning by Context Prediction,” in Proceedings of the International Conference on Computer Vision (ICCV), 2015.

[14] M. Noroozi and P. Favaro, “Unsupervised Learning of Visual Representations by Solving Jigsaw Puzzles,” in Proceedings of the European Conference on Computer Vision (ECCV), 2016.

[15] T. Chen, S. Kornblith, M. Norouzi, and G. Hinton, “A Simple Framework for Contrastive Learning of Visual Representations,” in Proceedings of the International Conference on Machine Learning (ICML), 2020.

[16] E. Manilow and G. Wichern and P. Seetharaman and J. Le Roux, “Cutting Music Source Separation Some Slakh: A Dataset to Study the Impact of Training Data Quality and Quantity,” in Proceedings of the IEEE Workshop on Applications of Signal Processing to Audio and Acoustics (WASPAA), 2019, pp. 45–49.

[17] S. Wisdom, E. Tzinis, H. Erdogan, R. J. Weiss, K. Wilson, and J. R. Hershey, “Unsupervised Sound Separation Using Mixtures of Mixtures,” arXiv preprint arXiv:2006.12701, 2020.

[18] Y.-C. Wang, S. Venkataraman, and P. Smaragdis, “Self-supervised Learning for Speech Enhancement,” arXiv preprint arXiv:2006.10388, 2020.

[19] S. Yin, C. Liu, Z. Zhang, Y. Lin, D. Wang, J. Tejedor, T. F. Zheng, and Y. Li, “Noisy training for deep neural networks in speech recognition,” EURASIP Journal on Audio, Speech, and Music Processing, vol. 2015, no. 1, pp. 2, 2015.

[20] D. Liang, Z. Huang, and Z. C. Lipton, “Learning noise-invariant representations for robust speech recognition,” in 2018 IEEE Spoken Language Technology Workshop (SLT). IEEE, 2018, pp. 56–63.

[21] J. Le Roux, S. Wisdom, H. Erdogan, and J. R. Hershey, “SDR - half-baked or well done?,” arXiv preprint arXiv:1811.02508, 2018.

[22] E. Vincent, C. Fevotte, and R. Gribonval, “Performance measurement in blind audio source separation,” IEEE Transactions on Audio, Speech, and Language Processing, vol. 14, no. 4, pp. 1462–1469, 2006.

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

[24] D. Snyder, G. Chen, and D. Povey, “MUSAN: A Music, Speech, and Noise Corpus,” arXiv preprint arXiv:1510.08484, 2015.

[25] J. Thiemann, N. Ito, and E. Vincent, “The diverse environments multi-channel acoustic noise database (demand): A database of multichannel environmental noise recordings,” Journal of the Acoustical Society of America, vol. 133, no. 5, pp. 3591–3591, 2013.

[26] K. Cho, B. Van Merriënboer, C. Gulcehre, D. Bahdanau, F. Bougares, H. Schwenk, and Y. Bengio, “Learning phrase representations using RNN encoder-decoder for statistical machine translation,” arXiv preprint arXiv:1406.1078, 2014.

[27] A. Narayanan and D. L. Wang, “Ideal ratio mask estimation in deep learning based speech enhancement systems,” EURASIP Journal on Audio, Speech, and Language Processing, vol. 26, no. 10, pp. 2015, pp. 7092–7096.

[28] D.P. Kingma and J. Ba, “Adam: A method for stochastic optimization,” in Proceedings of the International Conference on Learning Representations (ICLR), 2015.