Self-Supervised Learning for Personalized Speech Enhancement

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Abstract
Speech enhancement systems can show improved performance by adapting the model towards a single test-time speaker. In this personalization context, the test-time user might only provide a small amount of noise-free speech data, likely insufficient for traditional fully-supervised learning. One way to overcome the lack of personal data is to transfer the model parameters from a speaker-agnostic model to initialize the personalized model, and then to finetune the model using the small amount of personal speech data. This baseline marginally adapts over the scarce clean speech data. Alternatively, we propose self-supervised methods that are designed specifically to learn personalized and discriminative features from abundant in-the-wild noisy, but still personal speech recordings. Our experiment shows that the proposed self-supervised learning methods initialize personalized speech enhancement models better than the baseline fully-supervised methods, yielding superior speech enhancement performance. The proposed methods also result in a more robust feature set under the real-world conditions: compressed model sizes and fewness of the labeled data.

1. Introduction
Speech enhancement (SE) algorithms are a vital component of many everyday technologies such as hearing prostheses, mobile telephony, and automatic speech recognition (Maas et al., 2012). In contrast to the more general task of audio source separation, speech enhancement models operate on the assumption that there is only one source of interest—a speech signal—and that the remaining sounds are interfering background noises or unwanted filtering effects which must be suppressed. Although algorithms designed for multiple microphones tend to perform better, some applications limit the number of microphones to one, making a single-channel speech enhancement challenging. In this work we focus on the single-channel algorithms that are designed to suppress additive interference sources.

Single-channel speech denoising methods are typically formulated as a parametric mapping function learned in a fully supervised way; once it is trained it is expected to generalized well to an unseen test speaker’s speech characteristics as well as the test-time acoustic environment. To this end, a large dataset of clean speech signals spoken by many speakers is artificially mixed with many non-stationary noises; an optimization process estimates the model parameters, so that the model maps the mixture signals to the estimated clean speech source. Today, speech enhancement researchers employ deep neural network (DNN) models, which are known to generalize well to unseen data if their architecture is large enough to learn a complex mapping function from the big training dataset (Wang & Chen, 2018). We consider these models as generalists: in order for a generalist model to account for the peculiarities of a specific test-time speaker, one must increase both the diversity of its training speech and noise corpora and the model capacity.

In this work, we target at a popular use case of SE which the generalist models have not addressed efficiently: an SE system specializes in a particular person and his or her acoustic environment as a specialist. Given the widespread use of speech-based interfaces on embedded systems, many use cases fall in the category of personal use. We posit that a personalized speech enhancement (PSE) model can focus on the smaller problem defined by that test-time user and environment, making the learning task easier than a generalist model on the original general-purpose speech enhancement problem. For example, it has been shown that specialization of single-channel SE models (e.g. based on a particular speaker gender or noise type) can yield improvements in signal quality (Kolbæk et al., 2017). The improved enhancement quality also leads to a model compression effect: a smaller model can achieve similar performance as shown in (Sivaraman & Kim, 2020). Given that PSE is for personal devices, efficient inference is critical. While these models have shown merits of specialization in general, they did not discuss the impact of personalization to target at the test-time speaker, which is our goal in this paper.

Another important issue in the PSE tasks is that the solution may require private data from the users. In a straightforward transfer learning scenario, one can achieve personalization first by pretraining a generalist model using the ordinary large speech corpora and sound databases, and then by fine-
tuning it via an additional speaker- and environment-specific dataset. However, this kind of additional data could expose the user’s privacy to the third party, which the user may not want. In this paper, therefore, we employ a few-shot learning (FSL) approach to the PSE task which is to handle the case that there is only a limited amount of labeled training data available (Wang et al., 2020a). For example, the user might only allow their device to record a few seconds of clean speech data in order to aid personalization. Even if the PSE model is efficient and provides optimal improvement, reliance on private user data is a critical issue. Hence, while it is obvious that the transfer learning framework will benefit from more speech signals of the test user, our goal is to achieve the best possible personalization even if the clean utterances are limited to only a few seconds.

In this work, as an alternative to straightforward transfer learning, we propose a universal self-supervised learning (SSL) methodology for PSE. We show that the SSL approach can better initialize the PSE model than a speaker-agnostic SE task, especially when the clean speech for fine-tuning is not enough. Based on the assumption that the noisy speech data of the target user is more available and less private than the clean ones, we propose SSL methods that fully utilize large amounts of noisy speech data which can be seen as unlabeled data in the usual supervised learning setup. To this end, we propose two SSL algorithms, pseudo speech enhancement (PseudoSE) and contrastive mixtures (CM), that are designed to extract speaker-specific discriminative features. Both approaches re-purpose the noisy speech data as the reference speech source and mix additional noise sources to them to simulate an artificial mixture. The fact that the clean test speech is not necessary limits the performance of this model as an SE model, which is why we call it “pseudo” SE and it requires a downstream finetuning step. However, the fact that it learns from the very test speaker’s utterances, although they are still noisy, the features learned via this SSL method can be still more representative than the generic features. The CM method regularizes PseudoSE further via a contrastive learning mechanism that works on the pairs of input signals. For its positive pairs, a pair starts from the same noisy speech utterance as the pseudo-source, but it is contaminated by two different noise sources. Hence, after performing PseudoSE on each of the pair, we regularize the reconstructed reference sources by maximizing their agreement. Conversely, as for the negative pairs, we prepare two different reference sources, whose PseudoSE results should disagree from each other. Our goal is to show that this additional contrastive learning objective can improve the performance of PseudoSE, which is already a better pretraining option than a speaker-agnostic generalist model.

Our main contributions are summarized as follows:

- We formulate the personalized speech enhancement problem as a few-shot learning task to address the privacy-preservation issues.

- We propose a self-supervised pseudo speech enhancement pretraining procedure; it minimizes the amount of speaker-specific clean utterances used during fine-tuning by leveraging speaker-specific noisy utterances, which we posit are relatively more abundant.

- We propose a self-supervised contrastive mixtures pretraining procedure; this method may be viewed as a regularized version of pseudo speech enhancement, as it re-contextualizes the abundant noisy speech through positive and negative pairs. This method expands upon the contrastive learning formulation “SimCLR” which was proposed for self-supervised image classification (Chen et al., 2020).

- We show that PSE can achieve model compression without a loss of enhancement performance.

## 2. Personalized Speech Enhancement
Due to the FSL constraint that the the available clean speech data from the test speaker may be scarce, on the order of seconds, initializing the enhancement model with random weights will make it quickly over-fit to the scarce data. In this section, we overview three potential methods for initializing (i.e. pretraining) a personalized speech enhancement model. Table 1 summarizes the notations and datasets used.

### 2.1. Multi-Speaker SE Initialization

We first train a speaker-agnostic model; this requires a large corpus of many anonymous speakers $\mathcal{G}$ as well as a large corpus of various non-stationary noises $\mathcal{N}_{tr}$. A set of artificial mixture signals $x$ can be made by selecting random utterances $s \in \mathcal{G}$ and noises $n \in \mathcal{N}_{tr}$ and summing the signals, i.e. $x = s + n$ (with a different mixing ratio which we omit for brevity). The universal model learns a parametric mapping function $g(\cdot)$ such that $g(x; W_y) = y \approx s$, where the estimate $y$ approximate the training target $s$ and $W_y$ stands for the model parameters. After this pretraining process initializes the model parameters $W_y$, finetuning updates them further using another kind of input signals $x$ which is the mixture of the small amount of user-specific clean speech data $S_{tr}$ with the training noises $\mathcal{N}_{tr}$. This finetuning process is still a fully-supervised setup—the model has access to the corresponding clean speech sources $s$ which compose each mixture $x$. During both pretraining and finetuning, the model’s objective is to minimize the discrepancy $\mathcal{E}$ between the denoised estimate signals $y$ and the ground-truth clean source signals $s$. The baseline procedure for training a PSE
We postulate that a personal smart device might have access which adapts a generalist model into a specialist model, \( \tilde{s} \). The noisy utterances training target in place of the ground-truth clean speech.

In this regard, we pretrain a denoising model using the large \( N_{\text{pm}} \) signal-to-noise ratio (SNR) is reasonably high, the noisy user's test-time acoustic condition. Hence, if the premixture \( S \) is contaminated by some noise signal \( \tilde{\tilde{s}} \), we conjecture that the features learned in this way can still rely on the speaker-specific clean utterance set being large enough to represent the test speaker. We assume that this is not the case due to the aforementioned goal of maximizing the test speaker's privacy. In an FSL context, the naive adaptation of speaker-agnostic parameters may lead to two failure modes: either under- or over-fitting.

2.2. Single-Speaker PseudoSE Initialization

We postulate that a personal smart device might have access to many noisy recordings of the test-time speaker \( S_{\text{te}} \), likely much more than the clean set—i.e., \( |S_{\text{te}}| \gg |S_{\text{tr}}| \). Similarly to the other applications, where unlabeled data are abundant, exploiting them is our primary goal in doing SSL.

The noisy utterances \( \tilde{s} \in \tilde{S}_{\text{te}} \) must have been already contaminated by some noise signal \( m \in N_{\text{pm}} \) which we call premix noise, i.e. \( \tilde{s} = s + m \). Based on our assumptions, neither \( S_{\text{tr}} \) or \( N_{\text{pm}} \) is known to the denoising system. However, it may be reasonable to assume that this premixture noise source’s loudness varies over time, depending on the user’s test-time acoustic condition. Hence, if the premixture signal-to-noise ratio (SNR) is reasonably high, the noisy speech utterances \( \tilde{S}_{\text{te}} \) can work as a pseudo speech source.

In this regard, we pretrain a denoising model using the large noisy set \( \tilde{S}_{\text{te}} \) the target reference then finetune it using the small clean set \( S_{\text{tr}} \). We refer to the pretraining part as pseudo speech enhancement (PseudoSE) because it uses \( \tilde{s} \) as the training target in place of the ground-truth clean speech.

PseudoSE is to offer a SSL alternative to the ordinary pre-training using the generalist.

Since PseudoSE treats the premixture noisy data \( \tilde{S}_{\text{te}} \) as the target, we prepare mixtures \( \tilde{x} \) through noise injection (Yin et al., 2015; Liang et al., 2018) by combining \( \tilde{s} \) with additional deformation signals \( n \in N_{\text{tr}}, i.e. \tilde{x} = \tilde{s} + n \). The model learns a PseudoSE mapping function \( f \) such that \( f(\tilde{x}) = \tilde{y} \approx \tilde{s} \). Note that \( f \) can only recover the noisy utterance \( \tilde{s} \) as if it was a clean source, hence \( f \neq g \). Ultimately, \( f \) is finetuned into \( g \) by using the limited clean speech data \( S_{\text{tr}} \). The whole transfer learning process is summarized as follows:

\[
\begin{align*}
\text{Premixture:} & \quad \tilde{s} = s + m; \quad s \in S_{\text{tr}}, \ m \in N_{\text{pm}} \quad (4) \\
\text{Noise Injection:} & \quad \tilde{x} = \tilde{s} + n; \quad n \in N_{\text{tr}} \quad (5) \\
\text{Pretraining:} & \quad \arg \min_{\mathcal{W}_f} \mathcal{E}(\tilde{y} = f(\tilde{x}; \mathcal{W}_f) \parallel \tilde{s}) \quad (6) \\
\text{Initialization:} & \quad \mathcal{W}_f(\tilde{x}) = \mathcal{W}_f \quad (7) \\
\text{Finetuning:} & \quad \arg \min_{\mathcal{W}_g} \mathcal{E}(y = g(x; \mathcal{W}_g) \parallel \tilde{s}) \quad (8)
\end{align*}
\]

The PseudoSE method serves as a pretraining mechanism that makes the best use of the potentially abundant noisy speech of the same test speaker. Although the method does not exactly solve the desired speaker-specific SE problem, we conjecture that the features learned in this way can still represent the peculiarity of the test speaker than the baseline multi-speaker initialization scheme. Previous work has shown that mixture signals can work as prediction targets in other source separation context (Wisdom et al., 2020); we extend this insight directly towards the FSL scenario of personalized speech enhancement.

2.3. Single-Speaker Contrastive Mixtures Initialization

We hypothesize that the quality of the pretraining procedure greatly impacts how the denoising model will personalize when the clean speech for finetuning is not enough. Even if

| Corpus         | Subset         | Notation | Description                                                                 |
|----------------|----------------|----------|-----------------------------------------------------------------------------|
| Librispeech    | train-clean-100| \( S_{\text{gr}} \) | Speaker-agnostic noise-free utterances, used for pretraining.            |
|                |                | \( S_{\text{te}} \) | Speaker-specific noise-free utterances, unavailable to models.            |
|                |                | \( S_{\text{tr}} \) | Small subset of \( S_{\text{te}} \) representing clean speech provided by the specific speaker, used for model fine-tuning. |
| MUSAN          | free-sound     | \( N_{\text{tr}} \) | Large set of seen noises, used for pretraining and fine-tuning.            |
|                | sound-bible    | \( N_{\text{pm}} \) | Small set of unseen noises, used for evaluation.                           |
| DEMAND         | ch01           | \( N_{\text{pm}} \) | Noises which contaminate \( S_{\text{te}} \); the self-supervised methods treat the noisy version \( S_{\text{te}} \) as reference signals. |
where \( \tilde{L} \) estimates and source (\( \tilde{y} \)) and positive \( y \) over pairs

In the CM framework, the denoising model \( f(\cdot) \) pretrains over pairs of mixtures (\( \tilde{x}_1, \tilde{x}_2 \)) and outputs pseudo-cleaned estimates (\( \tilde{y}_1, \tilde{y}_2 \)). We create two kinds of mixture pairs, positive and negative, which are illustrated in Figure 3 with example spectrograms shown in Figures 1 and 2.

In a positive pair, both examples (\( \tilde{x}_1, \tilde{x}_2 \)) share the same premixture source \( s^0 \), but are differently deformed; that is, the mixing process makes the input pair slightly dissimilar. Therefore, in addition maximizing the similarities between estimates and source (\( \tilde{y}_1^0 \) to \( s^0 \) and \( \tilde{y}_2^0 \) to \( s^0 \)), the model \( f(\cdot) \) must also satisfy the contrastive objective based on the fact that \( \tilde{y}_1^0 \) and \( \tilde{y}_2^0 \) stemmed from the same pseudo-source. We express these objectives as a positive pair loss function \( \mathcal{L}_p \) in the following form:

\[
\mathcal{L}_p = \mathcal{E}(s^0||\tilde{y}_1^0) + \mathcal{E}(s^0||\tilde{y}_2^0) + \lambda_p \mathcal{E}(\tilde{y}_1^0||\tilde{y}_2^0),
\]

where \( \lambda_p \) scales the contribution of the contrastive loss term.

In a negative pair, each mixture is made from a different noisy source (\( \tilde{s}_1^0 \neq \tilde{s}_2^0 \)), but with a shared deformation, i.e., \( \tilde{x}_1^0 = \tilde{s}_1^0 + n^0 \) and \( \tilde{x}_2^0 = \tilde{s}_2^0 + n^0 \); in other words, the negative pair mixing process makes the inputs more similar to one another. Accordingly, in addition to the source-wise denoising objectives, the dissimilarity between the estimates \( \tilde{y}_1^0 \) and \( \tilde{y}_2^0 \) must be enforced. We express these objectives as a negative pair loss function \( \mathcal{L}_n \) in the following form:

\[
\mathcal{L}_n = \mathcal{E}(s_1^0||\tilde{y}_1^0) + \mathcal{E}(s_2^0||\tilde{y}_2^0) + \lambda_n \left[ \mathcal{E}(s_1^0||s_2^0) - \mathcal{E}(\tilde{y}_1^0||\tilde{y}_2^0) \right]^2,
\]

where \( \lambda_n \) controls the contribution of the contrastive loss term. Note that this term is defined as a squared error between the difference of the target pseudo-sources and that of the reconstruction pair. The squared error associates the difference between \( \tilde{y}_1^0 \) and \( \tilde{y}_2^0 \) with that of the original difference between the pseudo-sources \( s_1^0 \) and \( s_2^0 \), rather than enforcing an unbounded difference.

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 SE loss while the latter regularizes through the proposed contrastive mixtures process. The model ultimately minimizes the sum of these two losses, i.e.,

\[
\mathcal{L}_{CM} = \sum_{t=1}^T \mathcal{L}_p(t) + \sum_{t=1}^T \mathcal{L}_n(t) \quad \text{where} \quad T \quad \text{the number of positive or negative pairs within the batch and} \quad \mathcal{L}_p(t) \quad \text{and} \quad \mathcal{L}_n(t) \quad \text{the loss for the t-th pair. If the regularizing contrastive terms are omitted, i.e.} \quad \lambda_p = 0 \quad \text{and} \quad \lambda_n = 0, \quad \text{it can be shown that} \quad \mathcal{L}_{CM} \quad \text{reduces to Eq. (6). We empirically found that scaling the estimate-to-estimate errors with} \quad \lambda_p = 0.05 \quad \text{and} \quad \lambda_n = 0.0001 \quad \text{minimized training loss.}
\]

The proposed CM approach differs from the SimCLR model in multiple regards: (a) it uses a more advanced data augmentation process to mimic the noisy speech mixture generation process, i.e. sophisticated non-stationary noise injection; (b) the introduction of the negative pairs reflects
the source separation concept underlying our SE problem and yields a more discriminative feature than a positive pair only; and, (c) our interpretation of having the contrastive loss as a regularizer enriches the total loss function allowing the traditional SE loss to prevent trivial solution: very similar \( \tilde{y}_1 \) and \( \tilde{y}_2 \) that do not recover the pseudo-sources.

3. Experiment Setup

3.1. Model Architectures

We evaluate the four initialization schemes using two types of neural networks that are with smaller architectures to prove our efficiency-related claim. The first model consists of a two-layer gated recurrent unit network (GRU) (Cho et al., 2014) followed by a dense layer. We set the number of GRU hidden units to be either 64, 128, and 256, which exponentially varies the total number of model parameters. The GRU-based model is trained to perform speech denoising through time-frequency ratio mask estimation (Narayanan & Wang, 2013). The second model is the recently proposed ConvTasNet (CTN) speech separation system with the smallest suggested configuration, i.e. \( N = 128 \) filters (Luo & Mesgarani, 2019). The number of total parameters in each of these architectures is listed in Table 2.

The GRU-based models process batches of 128 mixtures, while the ConvTasNet model batches contain 8 mixtures. Because the CM pretraining is done pairwise, batches are built using 64 and 4 pairs respectively. A batch of mixtures \( x \) is made using 1 sec long, randomly offset clips from the appropriate speech and noise sets. Inputs to the ConvTasNet model remain in the time-domain; however, inputs to the GRU-based models are converted to the time-frequency domain using the short-time Fourier transform (STFT) with a Hann window of 1024 samples and 75% overlap. The estimated ratio mask is applied onto the input mixture spectrogram to obtain a denoised estimate spectrogram.

All parameter updates are made using the Adam optimizer (Kingma & Ba, 2015) with various learning rates specific to each system configuration in comparison. These learning rates, in addition to the CM regularizer weights \( \lambda_p \) and \( \lambda_n \), were identified using Tune, which optimized for validation loss (Liaw et al., 2018).

3.2. Metrics

In a study surveying various speech enhancement loss functions, it was found that functions which are based on negative scale-invariant signal-to-distortion ratio (SI-SDR) proved to be optimal for neural network training (Roux et al., 2018; Kolbæk et al., 2020). SI-SDR augments conventional SDR with 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:

\[
\text{SI-SDR}(v|\hat{v}) = 10 \log_{10} \left[ \frac{\sum_i (\alpha v_i)^2}{\sum_i (\alpha v_i - \hat{v}_i)^2} \right],
\]

where \( \alpha = \frac{\hat{v}^\top v}{v^\top v} \). We use this metric to evaluate denoising performance during validation and testing. However, our models use the scale-dependent variant for the training loss to account for cases of improper output scaling. It is defined similar to Eq. (11) but omits the \( \alpha \) value in the denominator. Because SD-SDR is a similarity metric between two signals, it must be negated to be used as a loss function, i.e. \( \mathcal{E} = -\text{SD-SDR}(v|\hat{v}) \).

3.3. Data Preparation

Our experiments combine audio data from three public corpora: Librispeech (Panayotov et al., 2015), MUSAN (Snyder et al., 2015), and DEMAND (Thiemann et al., 2013).

We denote two partitions for MUSAN: \( \mathbb{N}_{\text{tr}} \) as training noises from the free-sound subset, and \( \mathbb{N}_{\text{te}} \) for evaluation noises from the sound-bible subset. We use the ch01 subset from DEMAND exclusively when adding premixture noise which we denote as \( \mathbb{N}_{\text{pm}} \).

Of the 251 speakers in the LibriSpeech train-clean-100 subset, we designate 20 to be test-time users, i.e. each test speaker \( k \) has their own utterance set \( \mathbb{S}^{(k)} \) (we will omit speaker index for brevity). The remaining speakers make up speaker-agnostic set \( \mathbb{G} \). Each speaker-specific set contains \( |\mathbb{S}_{\text{tr}}^k| < 180 \text{ sec} \) from which we sample a few seconds of clean speech utterances for finetuning, and \( |\mathbb{S}_{\text{te}}| < 1320 \text{ sec} \), the larger subset representing the entirety of the test speaker’s speech, made inaccessible to the models. Instead, we use its noisy version to construct the speaker-specific premixture signals, i.e. \( \mathbb{S}_{\text{pm}} = \mathbb{S}_{\text{te}} \times \mathbb{N}_{\text{pm}} \) (Eq. (4)).

All competing models are finetuned using artificial mixtures \( x \in \mathbb{S}_{\text{tr}} \times \mathbb{N}_{\text{tr}} \), and their denoising performance is evaluated on unseen mixtures \( x \in \mathbb{S}_{\text{te}} \times \mathbb{N}_{\text{te}} \). The mixing SNR is randomly chosen between \(-5 \text{ dB}\) and \(5 \text{ dB}\) per sample in a training batch (Eq. (1)). We vary the size of the clean speech set \( S_{\text{tr}} \) to be either 0, 3, 5, 10, 30, or 60 sec in total duration; this controls the fiveness of our posed few-shot learning scenario.

For pretraining, the baseline model is trained using mixtures made from the speaker-agnostic set, i.e. \( x \in \mathbb{G} \times \mathbb{N}_{\text{tr}} \). Through multi-speaker initialization, the model processes \( x \) and generates clean speech estimates \( \hat{s} \) (Eq. (2)). Our proposed pretraining schemes PseudoSE and CM procedures differ in that they rely on the speaker-specific noisy utterance set \( \mathbb{S}_{\text{pm}} \). Signals for noise injection are sampled from \( \mathbb{N}_{\text{tr}} \) (Eq. (5)). As conjectured in Section 2.3, how degraded \( \mathbb{S}_{\text{pm}} \) will impact the model’s ability to learn speaker-specific fea-
We note that CM consistently outperforms PseudoSE in all architectures. We see that across all architectures, a PSE model pretrained using either proposed self-supervised method universally outperforms models which are pretrained using the baseline fully-supervised method, contingent on the unlabeled dataset $\tilde{S}_{ne}$ having a premixture SNR of at least 10 dB. We also found that the proposed methods quickly achieve high performance with only a small amount of clean speech, earlier than the baseline. For example, for the GRU 256×2 architecture, CM improves the pretrained model from 10.14 to 10.96 dB (8.1% increase) while the baseline improves from 9.75 to 10.02 (2.8%) when both are using only 3 seconds of clean speech for finetuning. Or, as for ConvTasNet, the PseudoSE’s improvement is by 16.2% while the baseline’s only 6.2%. However, the robustness to the few-shot learning scenario is maximized when the models are larger as also reported in SimCLR (Chen et al., 2020). We note that CM consistently outperforms PseudoSE in all the GRU-based models. The gap between the two models explain the merit of the additional contrastive loss that works as a regularizer. This did not hold true with ConvTasNet, which saw PseudoSE slightly outperforming CM. Our future work may investigate whether alternate choices for $\lambda_p$ and $\lambda_n$ are needed for ConvTasNet.

Models pretrained using 5 dB premixtures usually underperforms the 10 dB mixtures, meaning premixture signals’ quality matters for a successful SSL feature training. However, the proposed models pretrained on the 5 dB premixtures remain competitive with the multi-speaker-based models.

As discussed in Section 1, a model with a small number of parameters achieving comparable performance to a model made up of many more parameters suggests that the smaller model is more advantageous on devices with limited resources. There is an inherent tradeoff between model compression and our overarching FSL objective, i.e., we want to minimize the use of clean speech, while the more of it results in a better performance. But overall, the usage of a self-supervised initialization method allows smaller PSE models to exceed the performance of larger baseline models. For example, a CM-pretrained GRU: 128×2 model using 10 dB premixtures requires only 5 sec of clean speech from the target user before it can outperform a baseline-pretrained ConvTasNet model—an almost 70% reduction in model parameters is made possible using self-supervised pretraining and a modest amount of clean speech from the test-time speaker.

With the individual speaker’s PSE results shown in Figure 4, we can immediately observe how the baseline model—which during pretraining is speaker-agnostic—sometimes struggles to adapt to certain test speakers; two notable cases of this are speaker #83 and #200. The proposed SSL initialization methods remedy these case successfully. There are few anomalous cases where the baseline model does not adapt competitively or even superlatively compared to the SSL methods when the model is the smallest (GRU 64×2), but the average trend shows the self-supervised models universally personalizing. Matching our initial hypothesis, the generalist model does not comprehensively generalize to this 20 speaker test set, showing that the peculiarities of certain speakers do require an efficient specialist model. This trend is more obvious when the clean set is limited, suggesting that the SSL methods are a more robust solution in the FSL context.

## 5. Related Work

In this section, we address prior works which motivated our investigation of the personalized speech enhancement task.

**Model Adaptation** Prior works have shown that adaptive speech denoising autoencoders (Kim & Smaragdis, 2015) and modularized SE systems (Kim, 2017) can increase performance through test-time adaptation at the cost of increased model complexity. Ensemble networks have been used to compress the test-time adapted SE models using a no-shot non-personalized context (Sivaraman & Kim, 2020). There is also prior research on speaker-aware SE systems in the single-channel (Wang et al., 2018) and multi-channel (Žmolíková et al., 2017; Delcroix et al., 2018) formulations. In all these works, a generalist SE model is conditioned using a speaker-identifying feature vector. As discussed in Section 1, the single-speaker enhancement task is a subset of the broader speaker-agnostic enhancement task; therefore, conditioning a generalist model does not
Table 2. Mean SI-SDR improvement (in dB) with standard deviation in parentheses. Averages are computed over twenty test speakers from the LibriSpeech corpus. Columns compare the amount of clean speech from the test speaker used to finetune the model ($|S_n|$). Rows compare the three discussed PSE model initialization methods. Premixure SNR applies to the two proposed methods which involve training on the large set of noisy speech from the test speaker ($|S_n|$). The four tested architectures are arranged by model size, i.e. in order of number of parameters. Note that only the Multi-Speaker models with 0 sec of finetuning are non-personalized.

| Initialization Method | Premixture SNR (dB) | GRU: 64 × 2 (169k params.) | GRU: 128 × 2 (412k params.) | GRU: 256 × 2 (1.1m params.) | ConvTasNet (1.4m params.) |
|-----------------------|---------------------|-----------------------------|-----------------------------|-----------------------------|---------------------------|
|                       | 0 sec    | 3 sec    | 5 sec    | 10 sec   | 30 sec   | 60 sec   | 0 sec    | 3 sec    | 5 sec    | 10 sec   | 30 sec   | 60 sec   | 0 sec    | 3 sec    | 5 sec    | 10 sec   | 30 sec   | 60 sec   |
| Multi-Speaker         | n/a      | 8.32 (0.710) | 8.60 (0.813) | 8.68 (0.809) | 8.98 (0.781) | 9.36 (0.699) | 9.58 (0.737) | 8.75 (0.616) | 9.44 (0.723) | 9.52 (0.738) | 9.80 (0.727) | 10.13 (0.690) | 10.14 (0.698) | 9.75 (0.687) | 10.02 (0.758) | 10.09 (0.754) | 10.36 (0.791) | 10.80 (0.784) | 10.91 (0.773) |
| PseudoSE              | 5        | 7.63 (0.660) | 8.70 (0.785) | 8.82 (0.764) | 9.02 (0.810) | 9.25 (0.806) | 9.37 (0.789) | 8.09 (0.599) | 9.44 (0.685) | 9.56 (0.656) | 9.71 (0.669) | 9.93 (0.650) | 9.96 (0.684) | 9.60 (0.623) | 9.59 (0.718) | 9.72 (0.708) | 9.91 (0.725) | 10.14 (0.724) | 10.23 (0.723) |
|                      | 10       | 8.51 (0.632) | 9.15 (0.730) | 9.24 (0.744) | 9.37 (0.749) | 9.50 (0.725) | 9.59 (0.694) | 9.27 (0.649) | 10.01 (0.687) | 10.04 (0.670) | 10.13 (0.697) | 10.25 (0.689) | 10.28 (0.694) | 8.46 (0.623) | 9.59 (0.718) | 9.72 (0.708) | 9.91 (0.725) | 10.14 (0.724) | 10.23 (0.723) |
| Contrastive Mixtures  | 5        | 7.95 (0.612) | 8.81 (0.760) | 8.96 (0.712) | 9.16 (0.770) | 9.36 (0.802) | 9.50 (0.760) | 8.78 (0.637) | 9.20 (0.721) | 9.30 (0.730) | 9.46 (0.760) | 9.62 (0.791) | 9.70 (0.729) | 9.51 (0.581) | 10.06 (0.701) | 10.14 (0.683) | 10.24 (0.720) | 10.38 (0.725) | 10.46 (0.715) |
|                      | 10       | 8.78 (0.637) | 9.20 (0.721) | 9.30 (0.730) | 9.46 (0.760) | 9.62 (0.791) | 9.70 (0.729) | 10.14 (0.621) | 8.93 (0.703) | 10.49 (0.710) | 10.68 (0.730) | 10.90 (0.736) | 11.08 (0.732) | 10.91 (0.621) | 10.49 (0.710) | 10.68 (0.730) | 11.08 (0.736) | 11.13 (0.647) | 11.20 (0.732) |

Pretext Tasks This paper formulate the PSE task as a unique opportunity to apply self-supervised learning (Schmidhuber, 1990) which has gained significant traction in image and video processing research communities (Wang & Gupta, 2015; Veit et al., 2017). 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 visual object classification, various pretext tasks have shown promising performances, e.g., colorization and rotation (Dosovitskiy et al., 2015; Gidaris et al., 2018; Zhang et al., 2015), by predicting relative positions of local patches (Doersch et al., 2015; Noroozi & Favaro, 2016), and by sharing network weights between supervised and self-supervised models (Zhai et al., 2019; Sun et al., 2019). Stochastic masking has also been shown to add robustness to the learned self-supervised features; this was proven using denoising autoencoders (Vincent et al., 2008) and bidirectional encoder representations from transformer (BERT) (Devlin et al., 2019). Among the many studied pretext tasks, contrastive learning has gained recent popularity as it directly competes with features learned through fully-supervised means (van den Oord et al., 2018; He et al., 2020; Chen et al., 2020). Our CM pretraining extends the insights from these works.

exploit the benefit of reducing model capacity.
Data Augmentation Data augmentation is frequently seen in audio signal processing research. With musical instrument source separation, one can generate vast amounts of incoherent unrealistic mixtures from random musical stems to augment training data (Manilow et al., 2019). 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 (Wisdom et al., 2020). 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 (Wang et al., 2020b). In all prior works, the exact amount of data augmentation is left unquantified—more specifically, minimizing the required amount of speaker-specific clean speech data is not addressed. In contrast to these works, for personalized speech enhancement, we constraint our finetuning procedure to a small fixed amount of clean speech data from the test-time user.

6. Conclusion

In this work, we presented two self-supervised learning approaches towards personalized speech enhancement, highlighting their ability to quickly adapt using only a few seconds of test-user clean speech data. Compared with the naïve 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, promoting the use of robust privacy-preserving speech processing applications.

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