D4AM: A GENERAL DENOISING FRAMEWORK FOR DOWNSTREAM ACOUSTIC MODELS

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ABSTRACT

The performance of acoustic models degrades notably in noisy environments. Speech enhancement (SE) can be used as a front-end strategy to serve automatic speech recognition (ASR) systems. However, existing training objectives SE methods are not fully effective at integrating speech-text and noise-clean paired data for training toward unseen ASRs. In this study, we propose a general denoising framework for various downstream acoustic models, called D4AM. Our framework fine-tunes the SE model with the backward gradient according to a specific acoustic model and the corresponding classification objective. At the same time, our method aims to take the regression objective as an auxiliary loss to make the SE model generalize to other unseen acoustic models. To jointly train an SE unit with regression and classification objectives, D4AM uses an adjustment scheme to directly estimate suitable weighting coefficients instead of going through a grid search process with additional training costs. The adjustment scheme consists of two parts: gradient calibration and regression objective weighting. Experimental results show that D4AM can consistently and effectively provide improvements to various unseen acoustic models and outperforms other combination setups. Specifically, when evaluated on the Google ASR API with real noisy data completely unseen during SE training, D4AM achieves a relative WER reduction of 24.65% compared to directly feeding noisy speech input. To the best of our knowledge, this is the first work that deploys an effective combination scheme of regression (denoising) and classification (ASR) objectives to derive a general pre-processor applicable to various unseen ASR systems.

1 INTRODUCTION

Speech enhancement (SE) aims to extract speech components from distorted speech signals to obtain enhanced signals with better properties (Loizou, 2013). Recently, various deep learning models (Wang et al., 2020; Lu et al., 2013; Xu et al., 2015; Zheng et al., 2021; Nikzad et al., 2020) have been used to formulate mapping functions for SE, which treat SE as a regression task trained with noisy-clean paired speech data. Typically, the objective function is formulated using a signal-level distance measure (e.g., L1 norm (Pandey & Wang, 2018; Yue et al., 2022), L2 norm (Ephraim & Malah, 1984; Yin et al., 2020; Xu et al., 2020), SI-SDR (Le Roux et al., 2019; Wisdom et al., 2020; Lee et al., 2020), or multiple-resolution loss (Défossez et al., 2020)). In speech-related applications, SE units are often used as key pre-processors to improve the performance of the main task in noisy environments. To facilitate better performance on the main task, some studies focus on deriving suitable objective functions for SE training.

For human-human oral communication tasks, SE aims to improve speech quality and intelligibility, and enhancement performance is usually assessed by subjective listening tests. Because large-scale listening tests are generally prohibitive, objective evaluation metrics have been developed to objectively assess human perception of a given speech signal (Rix et al., 2001; Taal et al., 2010; Jensen & Taal, 2016; Reddy et al., 2021). Perceptual evaluation of speech quality (PESQ) (Rix et al., 2001) and short-time objective intelligibility (STOI) (Taal et al., 2010; Jensen & Taal, 2016) are popular objective metrics designed to measure speech quality and intelligibility, respectively. Recently, DNSMOS (Reddy et al., 2021) has been developed as a non-instructive assessment tool that predicts human ratings (MOS scores) of speech signals. In order to obtain speech signals with improved speech quality and intelligibility, many SE approaches attempt to formulate objective

functions for SE training directly according to speech assessment metrics (Fu et al., 2018; Fu et al., 2019; 2021). Another group of approaches, such as deep feature loss (Germain et al., 2019) and HiFi-GAN (Su et al., 2020), propose to perform SE by mapping learned noisy latent features to clean ones. Experimental results show that the deep feature loss can enable the enhanced speech signal to reach higher human perception scores compared to the conventional L1 and L2 distances.

Another prominent application of SE is to improve automatic speech recognition (ASR) in noise (Seltzer et al., 2013; Weninger et al., 2015b; Li et al., 2014; Cui et al., 2021). ASR systems perform sequential classification, mapping speech utterances to sequences of tokens. Therefore, the predictions of ASR systems are highly dependent on the overall structure of the input utterance. When it comes to noisy signals, ASR performance will degrade significantly because noise interference corrupts the content information of the structure. Without modifying the ASR model, SE models can be trained separately and "universally" used as a pre-processor for ASR to improve recognition accuracy. Several studies have investigated the effectiveness of SE's model architecture and objective function in improving the performance of ASR in noise (Geiger et al., 2014a; Wang et al., 2020; Zhang et al., 2020; Chao et al., 2021; Meng et al., 2017; Weninger et al., 2015a; Du et al., 2019; Kinoshita et al., 2020; Meng et al., 2018). The results show that some specific designs, including model architecture and input format, are beneficial to improving ASR performance. However, it has also been reported that improved recognition accuracy in noise is not always guaranteed when the ASR objective is not considered in SE training (Geiger et al., 2014b). To tune the SE model parameters toward the main ASR task, one possible approach is to prepare the data of (noisy) speech-text pairs and backpropagate gradients on the SE model according to the classification objective provided by the ASR model. That is, SE models can be trained on a regression objective (using noisy-clean paired speech data) or/and a classification objective (using speech-text paired data). Ochiai et al. (2017a;b) proposed a multichannel end-to-end (E2E) ASR framework, where a mask-based MVDR (minimum variance distortionless response) neural beamformer is estimated based on the classification objective. Experimental results on CHiME-4 (Jon et al., 2017) confirm that under noisy conditions, the estimated neural beamformer can achieve significant ASR improvements. Meanwhile, Chen et al. (2015) and Ma et al. (2021) proposed to train SE units by considering both regression and classification objectives, and some work (Chen et al., 2015; Ochiai et al., 2017a;b) proposed to train SE models with E2E-ASR classification objectives. A common way to combine regression and classification objectives is to use weighting coefficients to combine them into a joint objective for SE model training.

Despite promising results, the use of combined objectives in SE training has two limitations. First, how to effectively combine regression and classification objectives still remains an issue. A large-scale grid search is often employed to determine optimal weights for regression and classification objectives, which requires exhaustive computational costs. Second, ASR models are often provided by third parties and may not be accessible when training SE models. Moreover, due to various training settings in the acoustic model, such as label encoding schemes (e.g., word-piece (Schuster & Nakajima, 2012), byte-pair-encoding (BPE) (Gage, 1994; Sennrich et al., 2016), and character), model architectures (e.g., RNN (Chiu et al., 2018; Rao et al., 2017; He et al., 2019; Sainath et al., 2020), transformer (Vaswani et al., 2017; Zhang et al., 2020), and conformer (Gulati et al., 2020)), and objectives (e.g., Connectionist Temporal Classification (CTC) (Graves et al., 2006), Attention (NLL) (Chan et al., 2016), and their hybrid version (Watanabe et al., 2017)), SE units trained according to a specific acoustic model may not generalize well to other ASR systems. Based on the above limitations, we raise the question: *Can we effectively integrate speech-text and noisy-clean paired data to build a denoising pre-processor that generalizes well to unseen ASR systems?*

In this work, we derive a novel denoising framework, called D4AM, to be used as a "universal" pre-processor to improve the performance of various downstream acoustic models in noise. To achieve this goal, the proposed framework focuses on preserving the integrity of clean speech signals and trains SE models with regression and classification objectives jointly. By using the regression objective as an auxiliary loss, we do not require additional training costs to grid search the appropriate weighting coefficients for the regression and classification objectives; instead, D4AM applies an adjustment scheme to determine the appropriate weighting coefficients automatically and efficiently. The adjustment scheme is inspired by the following ideas: (1) we attempt to adjust the gradient yielded by a proxy ASR model so that the SE unit can be trained to improve the general recognition ability; (2) we treat the weighted regression objective as a regularizer, thus avoiding over-fitting when training the SE unit. For (1), we derive a coefficient α_{gclb} (abbreviation for gradient calibration)

according to whether the classification gradient conflicts with the regression gradient. When the inner product of the two gradient sets is negative, α_{gclb} is the projection of the classification gradient on the regression gradient; otherwise, it is set to 0. For (2), we derive a coefficient α_{srpr} (abbreviation for surrogate prior) based on an auxiliary learning method called ARML (auxiliary task reweighting for minimum-data learning) (Shi et al., 2020) and formulate the parameter distribution induced by the weighted regression objective as the surrogate prior when training the SE model. From the experimental results on two standard speech datasets, we first notice that by properly combining regression and classification objectives, D4AM can effectively improve the recognition accuracy of various unseen ASR systems and outperform the SE models trained only with the classification objective. Next, by taking the regression objective as an auxiliary loss, D4AM can be efficiently trained to avoid over-fitting even with limited speech-text paired data. Finally, compared to grid search, D4AM performs mostly better. The main contribution of this study is two-fold: (1) to the best of our knowledge, this is the first work that derives a general denoising pre-processor applicable to various unseen ASR systems; (2) we deploy a rational coefficient adjustment scheme for the combination strategy and link it to the motivation for better generalization ability.

2 Motivation and Main Idea

Noise Robustness Strategies for ASR. Acoustic mismatch, often caused by noise interference, is a long-standing problem that limits the applicability of ASR systems. To improve recognition performance, multi-condition training (MCT) (Parihar et al., 2004; Rajnoha, 2009; Zhang et al., 2020) is a popular approach when building practical ASR systems. MCT takes noise-corrupted utterances as augmented data and jointly trains an acoustic model with clean and noisy utterances. In addition to noise-corrupted utterances, enhanced utterances from SE models can also be included in the training data for MCT training. Recently, Prasad et al. (2021) studied advanced MCT training strategies and conducted a detailed investigation of different ASR fine-tuning techniques, including freezing partial layers (Zhang et al., 2020), multi-task learning (Saon et al., 2017; Prasad et al., 2021), adversarial learning (Serdyuk et al., 2016; Denisov et al., 2018; Zhang et al., 2020), and training involving enhanced utterances from various SE models (Braithwaite & Kleijn, 2019; Zhang et al., 2020; Défossez et al., 2020). The results reveal that recognition performance in noise can be remarkably improved by tuning the parameters in the ASR system. However, an ASR system is generally formed by a complex structure and estimated with a large amount of training data. Also, for most users, ASR systems provided by third parties are black-box models whose acoustic model parameters cannot be fine-tuned to improve performance in specific noisy environments. Therefore, tuning the parameters in an ASR system for each specific test condition is usually not a feasible solution for real-world scenarios.

In contrast, employing an SE unit to process noisy speech signals to generate enhanced signals, which are then sent to the ASR system, is a viable alternative to externally improve the recognition accuracy in noise as a two-stage strategy of noise robustness. The main advantage of this alternative is that SE units can be pre-prepared for direct application to ASR systems without the need to modify these ASR systems or to know the system setups. Furthermore, ASR is usually trained with a large amount of speech-text pairs, requiring expensive annotation costs; on the contrary, for SE, the required large number of noisy-clean training pairs can be easily synthesized. In this study, we propose to utilize the regression objective as a regularization term, combined with the classification objective, for SE unit training to reduce the need for speech-text data and improve the generalization ability.

Regression Objective as an Auxiliary Loss. Since our proposed framework focuses on improving ASR performance in noise, the classification objective is regarded as the main task, and the regression objective is used as an auxiliary loss. Generally, an auxiliary loss aims to improve the performance of the main task without considering the performance of the auxiliary task itself. The auxiliary task learning framework searches for adequate coefficients to incorporate auxiliary information and thus improve the performance of the main task. Several studies (Hu et al., 2019; Chen et al., 2018; Du et al., 2018; Lin et al., 2019; Dery et al., 2021; Shi et al., 2020) have investigated and confirmed the benefits of auxiliary task learning. In D4AM, given the SE model parameter θ, we take the classification objective $\mathcal{L}_{cls}(\theta)$ as the main task and the regression objective $\mathcal{L}_{reg}(\theta)$ as the auxiliary task. Then, we aim to jointly fine-tune the SE model with $\mathcal{L}_{cls}(\theta)$ and $\mathcal{L}_{reg}(\theta)$, where their corresponding training data are $\mathcal{T}_{cls}$ (speech-text paired data) and $\mathcal{T}_{reg}$ (noisy-clean paired

speech data), respectively. Here, D4AM uses $-\log p(\mathcal{T}_{cls}|\theta)$ and $-\log p(\mathcal{T}_{reg}|\theta)$, respectively, as the classification objective $\mathcal{L}_{cls}(\theta)$ and the regression objective $\mathcal{L}_{reg}(\theta)$. Fig. 1a shows the overall training flow of D4AM. Notably, D4AM is partially different from traditional auxiliary task learning algorithms, where the main and auxiliary tasks commonly share the same model parameters. In D4AM, the main task objective $\mathcal{L}_{cls}(\theta)$ cannot be obtained by the SE model alone. Instead, a proxy acoustic model ϕ is employed. That is, the true classification objective $\mathcal{L}_{cls}(\theta)$ is not reachable, and alternatively, with the proxy acoustic model ϕ, a surrogate term $-\log p(\mathcal{T}_{cls}|\theta, \phi)$, termed $\mathcal{L}^{\phi}_{cls}(\theta)$, is used to update the SE parameters. Since there is no guarantee that reducing $\mathcal{L}^{\phi}_{cls}(\theta)$ will reduce $\mathcal{L}_{cls}(\theta)$, a constraint is needed to guide the gradient of $\mathcal{L}^{\phi}_{cls}(\theta)$ toward improving general recognition performance.

Meanwhile, we believe that, for any particular downstream acoustic recognizer, the best enhanced output produced by the SE unit from any noisy speech input is the corresponding clean speech. Therefore, any critical point of $\mathcal{L}_{cls}(\theta)$ should be "covered" by the critical point space of $\mathcal{L}_{reg}(\theta)$, and we just need guidance from speech-text paired data to determine the critical point in the $\mathcal{L}_{reg}(\theta)$ space. That is, when an update of SE model parameters θ decreases both $\mathcal{L}^{\phi}_{cls}(\theta)$ and $\mathcal{L}_{reg}(\theta)$, that update should be beneficial to general ASR systems. On the other hand, compared to $\mathcal{L}_{cls}(\theta)$, the calculation of $\mathcal{L}_{reg}(\theta)$ does not require the proxy model when we use it to update SE model parameters. Accordingly, we derive the update of θ at the t-th step as:

$$\theta^{t+1} = \arg\min_{\theta} \mathcal{L}^{\phi}_{cls}(\theta) \quad \text{subject to} \quad \mathcal{L}_{reg}(\theta) \leq \mathcal{L}_{reg}(\theta^t). \tag{1}$$

As pointed out in Lopez-Paz & Ranzato (2017) and Chaudhry et al. (2019), the model function is supposed to be locally linear around small optimization steps. For ease of computation, we replace $\mathcal{L}_{reg}(\theta) \leq \mathcal{L}_{reg}(\theta^t)$ with $\langle \nabla\mathcal{L}^{\phi}_{cls}(\theta^t), \nabla\mathcal{L}_{reg}(\theta^t)\rangle \geq 0$. That is, we take the alignment between $\nabla\mathcal{L}^{\phi}_{cls}(\theta^t)$ and $\nabla\mathcal{L}_{reg}(\theta^t)$ as the constraint to guarantee the generalization ability to unseen ASR systems at each training step. When the constraint is violated, $\nabla\mathcal{L}^{\phi}_{cls}(\theta^t)$ needs to be calibrated. Following the calibration method proposed in Chaudhry et al. (2019) to search for the closest non-violating candidate to the original $\nabla\mathcal{L}^{\phi}_{cls}(\theta^t)$, we formulate the calibrated gradient g^* as:

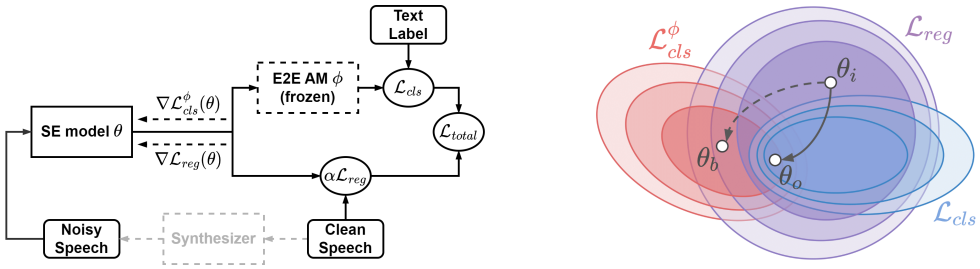
$$g^* = \arg\min_{g} \frac{1}{2}\|g - \nabla\mathcal{L}^{\phi}_{cls}(\theta^t)\|^2 \ \text{ subject to } \ \langle g, \nabla\mathcal{L}_{reg}(\theta^t)\rangle \geq 0. \tag{2}$$

In addition to guiding SE unit training toward improving ASR performance, D4AM also aims to alleviate over-fitting in the classification task. In ARML (Shi et al., 2020), auxiliary task learning is formulated as the problem of minimizing the divergence between the surrogate prior and the true prior. It is shown that when a suitable surrogate prior is identified, the over-fitting issue caused by the data limitation of the main task can be effectively alleviated. Following the concept of ARML, D4AM aims to estimate an appropriate coefficient of $\mathcal{L}_{reg}$ to approximate the log prior of the main task objective $\mathcal{L}_{cls}$ to alleviate over-fitting. Finally, D4AM combines the calibrated gradient g^* and auxiliary task learning (ARML) to find a critical point that ensures better generalization to unseen ASR systems and alleviates over-fitting in the classification task. In Sec. 3, we will illustrate the details of our proposed framework.

3 METHODOLOGY

D4AM aims to estimate an SE unit that can effectively improve the recognition performance of general downstream ASR systems. As shown in Fig. 1a, the overall objective consists of two parts, the classification objective $\mathcal{L}^{\phi}_{cls}(\theta)$ given the proxy model ϕ and the regression objective $\mathcal{L}_{reg}(\theta)$. As shown in Fig. 1b, we intend to guide the update of the model from θ_i to θ_o with the regression objective $\mathcal{L}_{reg}(\theta)$ to improve the performance of ASR in noise. In this section, we present an adjustment scheme to determine a suitable weighting coefficient to combine $\mathcal{L}^{\phi}_{cls}(\theta)$ and $\mathcal{L}_{reg}(\theta)$ instead of a grid search process. The adjustment scheme consists of two parts. First, we calibrate the direction of $\nabla\mathcal{L}^{\phi}_{cls}(\theta)$ to promote the recognition accuracy, as described in Eq. 2. Second, we follow the ARML algorithm to derive a suitable prior by weighting the regression objective. Finally, the gradient descent of D4AM at the t-th step for SE training is defined as:

$$\theta^{t+1} \leftarrow \theta^t - \epsilon_t(\nabla\mathcal{L}^{\phi}_{cls}(\theta^t) + (\alpha_{gclb} + \alpha_{srpr}) \cdot \nabla\mathcal{L}_{reg}(\theta^t)) + \eta_t, \tag{3}$$



(a) Training flowchart

(b) Schematic diagram of training trajectory

Figure 1: (a) The training flow of D4AM. Given a proxy acoustic model (AM) parameterized by ϕ, θ is updated by training with both $\mathcal{L}_{cls}$ and $\mathcal{L}_{reg}$ weighted by α. (b) The illustration of the training trajectories. The dashed line (from θ_i to θ_b) represents the training process without considering $\mathcal{L}_{reg}$. The solid line (from θ_i to θ_o) represents the training process considering $\mathcal{L}_{reg}$.

where ϵ_t is the learning rate, and $\eta_t \sim \mathcal{N}(0, 2\epsilon_t)$ is a Gaussian noise used to formulate the sampling of θ. The coefficient α_{gclb} is responsible for calibrating the direction of gradient when $\mathcal{L}^{\phi}_{cls}(\theta^t)$ does not satisfy $\langle \nabla\mathcal{L}^{\phi}_{cls}(\theta^t), \nabla\mathcal{L}_{reg}(\theta^t)\rangle \geq 0$. Mathematically, α_{gclb} is the result of projecting $\nabla\mathcal{L}^{\phi}_{cls}(\theta^t)$ into the space formed by using $\nabla\mathcal{L}_{reg}(\theta^t)$ as a basis. The connection between the projection process and the constraint $\langle \nabla\mathcal{L}^{\phi}_{cls}(\theta^t), \nabla\mathcal{L}_{reg}(\theta^t)\rangle \geq 0$ will be introduced in Section 3.1. The coefficient α_{srpr} is responsible for weighting $\mathcal{L}_{reg}(\theta^t)$ to approximate the log prior of parameters and is estimated to minimize the divergence between the parameter distributions of the surrogate and true priors. The determination of α_{srpr}, the mechanism of the sampling of θ, and the overall framework proposed in ARML will be described in Section 3.2. Finally, in Section 3.3, we will introduce the implementation of the D4AM framework.

3.1 Gradient Calibration for Improving General Recognition Ability

This section details the gradient calibration mechanism. First, we assume that any critical point of $\mathcal{L}_{cls}(\theta)$ is located in the critical point space of $\mathcal{L}_{reg}(\theta)$. When the derived g^* satisfies $\langle g^*, \nabla\mathcal{L}_{reg}(\theta^t)\rangle \geq 0$, the direction of g^* can potentially bring recognition improvements to general acoustic models. The constrained optimization problem described in Eq. 2 can be solved in a closed form while considering only a mini-batch of samples. We then design a criterion $\mathcal{C} = \langle \nabla\mathcal{L}^{\phi}_{cls}(\theta^t), \nabla\mathcal{L}_{reg}(\theta^t)\rangle$ to check the direction of the gradient and formulate the solution as:

$$g^* = \nabla\mathcal{L}^{\phi}_{cls}(\theta^t) + \alpha_{gclb} \cdot \nabla\mathcal{L}_{reg}(\theta^t) \text{ , where } \alpha_{gclb} = -[\![\mathcal{C} < 0]\!] \cdot \frac{\mathcal{C}}{\|\nabla\mathcal{L}_{reg}(\theta^t)\|_2^2}, \tag{4}$$

where $[\![.]\!]$ is an indicator function whose output is 1 if the argument condition is satisfied; otherwise, the output is 0. The derivation of α_{gclb} is based on the Lagrangian of the constrained optimization problem. The details of the derivation can be found in Appendix A.6.

3.2 Regression Objective Weighting as the Surrogate Prior

In this section, we discuss the relation of classification and regression objectives to the main ASR task. A weighted regression objective is derived to approximate the log prior for SE training by modifying the ARML (Shi et al., 2020) algorithm, which takes the weighted sum of auxiliary losses as a surrogate prior and proposes a framework for reweighting auxiliary losses based on minimizing the divergence between the parameter distributions of the surrogate and true priors. We aim to find a coefficient α_{srpr} such that $\alpha_{srpr} = \arg\min_{\alpha} \mathbb{E}_{\theta\sim p^*}[\log p^*(\theta) - \alpha \cdot \log(p(\mathcal{T}_{reg}|\theta))]$, where p^* is the true prior distribution of θ, and $p^{\alpha_{srpr}}(\mathcal{T}_{reg}|\theta)$ is the surrogate prior corresponding to the weighted regression objective $-\alpha_{srpr} \cdot \log(p(\mathcal{T}_{reg}|\theta))$. However, $p^*(\theta)$ is not practically available. To overcome the unavailability of $p^*(\theta)$, ARML uses an alternative solution for $p^*(\theta)$ and a sampling scheme of θ in $p^*(\theta)$. For the alternative solution of $p^*(\theta)$, ARML assumes that the main task distribution $p(\mathcal{T}_{cls}|\theta)$ will cover $p^*(\theta)$ since the samples of θ from $p^*(\theta)$ likely induce high values in $p(\mathcal{T}_{cls}|\theta)$. Thus, ARML takes $\log p(\mathcal{T}_{cls}|\theta)$ as the alternative of $\log p^*(\theta)$. For the sampling scheme of θ in $p^*(\theta)$, due to convenience, ARML takes the derived parameters from the joint loss at each

training step and combines them with Langevin dynamics (Neal et al., 2011; Welling & Teh, 2011) to approximate the sampling of θ with an injected noise $\eta_t \sim \mathcal{N}(0, 2\epsilon_t)$. Thus, the optimization problem of α_{srpr} becomes $\min_\alpha \mathbb{E}_{\theta^t \sim p^J}[\log(p(\mathcal{T}_{cls}|\theta^t)) - \alpha \cdot \log(p(\mathcal{T}_{reg}|\theta^t))]$, where p^J represents the distribution for sampling θ from the above described joint training process with respect to the original sampling. More details about the ARML algorithm can be found in Shi et al. (2020). Finally, at the t-th step, the overall parameter change $\Delta\theta(g)$ of the auxiliary learning framework given an arbitrary gradient g of the main task (ASR) can be written as:

$$\Delta\theta(g) = \epsilon_t(g + \alpha_{srpr} \cdot \nabla\mathcal{L}_{reg}(\theta^t)) + \eta_t. \tag{5}$$

Yet, the aforementioned problem still remains: we can only obtain $\nabla\mathcal{L}^{\phi}_{cls}(\theta^t)$ instead of the ideal ASR task gradient $\nabla\mathcal{L}_{cls}(\theta^t)$. Therefore, the gradient should be calibrated, as described in Section 3.1. To this end, we accordingly update θ by taking $\Delta\theta(g^*)$, as described in Eq. 3.

Algorithm 1 D4AM (A General Denoising Framework for Downstream Acoustic Models)

Learnable-Parameter: model parameter θ (initialized by θ^0); task weight α_{srpr} (initialized by 1)
Hyper-Parameter: learning rate of the t-th iteration ϵ_t, learning rate of task weight β

1: **for** iteration $t = 0$ to $T - 1$ **do**
2: $\quad\alpha_{gclb} \leftarrow \text{project}(\nabla\mathcal{L}^{\phi}_{cls}(\theta^t), \nabla\mathcal{L}_{reg}(\theta^t))$
3: $\quad\theta^{t+1} \leftarrow \theta^t - \epsilon_t(\nabla\mathcal{L}^{\phi}_{cls}(\theta^t) + (\alpha_{gclb} + \alpha_{srpr}) \cdot \nabla\mathcal{L}_{reg}(\theta^t)) + \eta_t$
4: $\quad g_\alpha \leftarrow \frac{\partial}{\partial\alpha_{srpr}}\|\nabla\mathcal{L}^{\phi}_{cls}(\theta^t) + (\alpha_{gclb} - \alpha_{srpr}) \cdot \nabla\mathcal{L}_{reg}(\theta^t))\|_2^2$
5: $\quad\alpha_{srpr} \leftarrow \alpha_{srpr} - \beta \cdot \text{clamp}(g_\alpha, \max = +1, \min = -1)$
6: **end for**

3.3 Algorithm

In this section, we detail the implementation of the proposed D4AM framework. The complete algorithm is shown in Algorithm 1. The initial value of α_{srpr} was set to 1, and the learning rate β was set to 0.05. We first update θ^t by the mechanism presented in Eq. 3 and collect θ samples at each iteration. As described in Section 3.2, α_{srpr} is optimized to minimize the divergence between $p^*(\theta)$ and $p^{\alpha_{srpr}}(\mathcal{T}_{reg}|\theta)$. Referring to ARML (Shi et al., 2020), we use the Fisher divergence to measure the difference between the surrogate prior and the true prior. That is, we optimize α by $\min_\alpha \mathbb{E}_{\theta^t \sim p^J}[\|\nabla\mathcal{L}_{cls}(\theta^t) - \alpha \cdot \nabla\mathcal{L}_{reg}(\theta^t))\|_2^2]$. Because we can only obtain $\mathcal{L}^{\phi}_{cls}(\theta^t)$, we use the calibrated version g^* as the alternative of $\nabla\mathcal{L}_{cls}(\theta^t)$. Then, the optimization of α becomes $\min_\alpha \mathbb{E}_{\theta^t \sim p^J}[\|\nabla\mathcal{L}^{\phi}_{cls}(\theta^t) + (\alpha_{gclb} - \alpha) \cdot \nabla\mathcal{L}_{reg}(\theta^t))\|_2^2]$. In addition, we use gradient descent to approximate the above minimization problem, since it is not feasible to collect all θ samples. Practically, we only have access to one sample of θ per step, which may cause instability when updating α_{srpr}. Therefore, to increase the batch size of θ, we modify the update scheme by accumulating the gradients of α_{srpr}. The update period of α_{srpr} was set to 16 steps. Unlike ARML (Shi et al., 2020), we did not restrict the value of α_{srpr} to the range 0 to 1, because $\mathcal{L}^{\phi}_{cls}$ and $\mathcal{L}_{reg}$ have different scales. In addition, we clamp the gradient of α_{srpr} with the interval $[-1, 1]$ while updating α_{srpr} to increase training stability. Further implementation details are provided in Section 4 and Supplementary Material.

4 Experiments

4.1 Experimental Setup

The training datasets used in this study include: noise signals from DNS-Challenge (Reddy et al., 2020) and speech utterances from Librispeech (Panayotov et al., 2015). DNS-Challenge, hereinafter DNS, is a public dataset that provides 65,303 background and foreground noise signal samples. Librispeech is a well-known speech corpus that includes three training subsets: Libri-100 (28,539 utterances), Libri-360 (104,014 utterances), and Libri-500 (148,688 utterances). The mixing process (of noise signals and clean utterances) to generate noisy-clean paired speech data was conducted during training, and the signal-to-noise ratio (SNR) level was uniformly sampled from -4dB to 6dB.

The SE unit was built on DEMUCS (Défossez et al., 2019; 2020), which employs a skip-connected encoder-decoder architecture with a multi-resolution STFT objective function. DEMUCS has been

shown to yield state-of-the-art results on music separation and SE tasks, We divided the whole training process into two stages: pre-training and fine-tuning. For pre-training, we only used $\mathcal{L}_{reg}$ to train the SE unit. At this stage, we selected Libri-360 and Libri-500 as the clean speech corpus. The SE unit was trained for 500,000 steps using the Adam optimizer with β_1 = 0.9 and β_2 = 0.999, learning rate 0.0002, gradient clipping value 1, and batch size 8. For fine-tuning, we used both $\mathcal{L}_{reg}$ and $\mathcal{L}_{cls}^{\phi}$ to re-train the SE model initialized by the checkpoint selected from the pre-training stage. We used Libri-100 to prepare the speech-text paired data for $\mathcal{L}_{cls}^{\phi}$ and all the training subsets (including Libri-100, Libri-360, and Libri-500) to prepare the noisy-clean paired speech data for $\mathcal{L}_{reg}$. The SE unit was trained for 100,000 steps with the Adam optimizer with β_1 = 0.9 and β_2 = 0.999, learning rate 0.0001, gradient clipping value 1, and batch size 16. For the proxy acoustic model ϕ, we adopted the conformer architecture and used the training recipe provided in the SpeechBrain toolkit (Ravanelli et al., 2021). The model was trained with all training utterances in Librispeech, and the training objective was a hybrid version (Watanabe et al., 2017) of CTC (Graves et al., 2006) and NLL (Chan et al., 2016).

Since the main motivation of our study is to appropriately adjust the weights of the training objectives to better collaborate with the noisy-clean/speech-text paired data, we focus on comparing different objective combination schemes on the same SE unit. To investigate the effectiveness of each component in D4AM, our comparison includes: (1) without any SE processing (termed ***NOIS***), (2) solely trained with $\mathcal{L}_{reg}$ in the pre-training stage (termed ***INIT***), (3) solely trained with $\mathcal{L}_{cls}^{\phi}$ in the fine-tuning stage (termed ***CLSO***), (4) jointly trained with $\mathcal{L}_{cls}^{\phi}$ and $\mathcal{L}_{reg}$ by solely taking α_{gclb} in the fine-tuning stage (termed ***GCLB***), and (5) jointly trained with $\mathcal{L}_{cls}^{\phi}$ and $\mathcal{L}_{reg}$ by solely taking α_{srpr} in the fine-tuning stage (termed ***SRPR***). Note that some of the above schemes can be viewed as partial comparisons with previous attempts. For example, ***CLSO*** is trained only with the classification objective, the same as (Ochiai et al., 2017a;b); ***SRPR***, ***GCLB***, and ***D4AM*** use joint training, the same as (Chen et al., 2015; Ma et al., 2021), but (Chen et al., 2015; Ma et al., 2021) use predefined weighting coefficients. In our ablation study, we will show that our adjustment achieves optimal results without additional training costs compared to grid search. Since our main goal is to prepare an SE unit as a pre-processor to improve the performance of ASR in noise, the word error rate (WER) was used as the main evaluation metric. Lower WER values indicate better performance.

To fairly evaluate the proposed D4AM framework, we used CHiME-4 (Jon et al., 2017) and Aurora-4 (Parihar et al., 2004) as test datasets, which have been widely used for robust ASR evaluation. For CHiME-4, we evaluated the performance on the development and test sets of the 1-st track. For Aurora-4, we evaluated the performance on the noisy parts of the development and test sets. There are two types of recording process, namely wv1 and wv2. The results of these two categories are reported separately for comparison. For the downstream ASR systems, we normalized all predicted tokens by removing all punctuation, mapping numbers to words, and converting all characters to their upper versions. To further analyze our results, we categorized the ASR evaluation into out-of-domain and in-domain scenarios. In the out-of-domain scenario, we aim to verify the generalization ability of ASR when the training and testing data come from different corpora. That is, in this scenario, the testing data is unseen to all downstream ASR systems. In the in-domain scenario, we aim to investigate the improvements achievable in standard benchmark settings. Therefore, we set up training and testing data for ASR from the same corpus. Note that ASR systems typically achieve better performance in the in-domain scenarios than in the out-domain scenario (Likhomanenko et al., 2021).

4.2 Experimental Results

D4AM Evaluated with Various Unseen Recognizers in the Out-of-Domain Scenario. We first investigated the D4AM performance with various unseen recognizers. We prepared these recognizers by the SpeechBrain toolkit with all the training data in Librispeech. The recognizers include: (1) a conformer architecture trained with the hybrid loss and encoded by BPE-5000 (termed ***CONF***), (2) a transformer architecture trained with the hybrid loss and encoded by BPE-5000 (termed ***TRAN***), (3) an RNN architecture trained with the hybrid loss and encoded by BPE-5000 (termed ***RNN***), and (4) a self-supervised wav2vec2 (Baevski et al., 2020) framework trained with the CTC loss and encoded by characters (termed ***W2V2***). To avoid potential biases caused by language models, ***CONF***, ***TRAN***, and ***RNN*** only decoded results from their attention decoders, while ***W2V2*** greedily decoded

Table 1: WER (%) results on CHiME-4 and Aurora-4.

	CHiME-4															
	dt05-real				dt05-simu				et05-real				et05-simu			
	CONF	TRAN	RNN	W2V2	CONF	TRAN	RNN	W2V2	CONF	TRAN	RNN	W2V2	CONF	TRAN	RNN	W2V2
NOIS	40.53	34.56	56.76	29.84	45.40	38.86	58.75	35.37	57.23	46.10	72.16	45.61	52.06	44.96	64.93	44.10
INIT	30.98	29.61	38.61	26.93	35.02	32.49	41.76	31.84	40.32	38.77	49.67	39.37	42.78	40.51	49.83	41.04
CLSO	**26.66**	27.83	35.25	24.63	**29.09**	29.89	38.00	29.16	34.00	35.19	46.02	36.08	**35.02**	36.62	45.66	37.23
SRPR	26.88	26.73	34.83	24.51	30.12	29.22	38.73	29.86	34.53	33.93	46.08	35.21	36.68	36.55	46.27	38.80
GCLB	26.76	26.51	34.62	23.55	29.28	28.73	37.55	28.54	34.18	33.76	45.75	35.15	35.69	36.09	45.37	**37.18**
D4AM	26.70	**26.07**	**34.43**	**23.30**	29.45	**28.61**	**37.49**	**28.40**	**33.71**	**33.20**	**45.07**	**34.43**	35.97	**35.75**	**45.36**	37.30
	Aurora-4															
	dev-wv1				dev-wv2				test-wv1				test-wv2			
	CONF	TRAN	RNN	W2V2	CONF	TRAN	RNN	W2V2	CONF	TRAN	RNN	W2V2	CONF	TRAN	RNN	W2V2
NOIS	21.69	19.66	27.36	14.44	31.56	27.96	42.12	25.47	19.27	17.64	23.98	13.60	29.77	27.54	38.91	26.37
INIT	18.97	18.24	21.71	13.59	27.85	26.16	34.58	24.38	16.76	16.25	18.45	12.26	26.55	25.23	31.98	24.65
CLSO	17.75	18.23	20.98	13.31	24.76	25.05	33.08	23.48	**15.43**	17.03	17.53	12.16	24.24	25.85	32.33	25.79
SRPR	17.77	17.20	20.40	12.97	24.67	23.20	31.66	21.57	15.52	15.50	16.82	11.89	23.83	23.00	29.74	22.95
GCLB	**17.70**	17.16	20.35	12.91	24.65	22.99	31.73	21.92	15.51	15.66	**16.82**	12.11	24.51	23.19	30.39	23.36
D4AM	17.73	**17.08**	**20.30**	**12.84**	**24.31**	**22.78**	**31.06**	**20.90**	15.55	**15.44**	17.18	**11.66**	**23.35**	**22.68**	**29.65**	**22.02**

Table 2: WER (%) results of CHiME-4's baseline ASR system.

method	NOIS	INIT	CLSO	SRPR	GCLB	D4AM
dt05-real	11.57	10.28	7.95	8.28	8.15	**7.94**
dt05-simu	12.98	11.80	10.07	10.28	9.56	**9.48**
et05-real	23.71	19.91	16.28	16.33	16.32	**15.66**
et05-simu	20.85	20.39	18.37	18.18	16.86	**16.31**

results following the CTC rule. Table 1 shows the WER results under different settings. Note that we cascaded ***CONF*** to train our SE model, so ***CONF*** is not a completely unseen recognizer in our evaluation. Therefore, we marked the results of ***CONF*** in gray and paid more attention to the results of other acoustic models. Obviously, ***NOIS*** yielded the worst results under all recognition and test conditions. ***INIT*** performed worse than others because it did not consider the ASR objective in the pre-training stage. ***CLSO*** was worse than ***GCLB***, ***SRPR***, and ***D4AM***, verifying that training with $\mathcal{L}_{cls}^{\phi}$ alone does not generalize well to other unseen recognizers. Finally, ***D4AM*** achieved the best performance on average, confirming the effectiveness of gradient calibration and using regression objective weighting as a surrogate prior in improving general recognition ability.

D4AM Evaluated with a Standard ASR System in the In-Domain Scenario. In this experiment, we chose the official baseline ASR system from CHiME-4, a DNN-HMM ASR system trained in an MCT manner using the CHiME-4 task-specific training data, as the evaluation recognizer. This baseline ASR system is the most widely used to evaluate the performance of SE units. As seen in Table 2, the result of ***INIT*** is comparable to the state-of-the-art results of CHiME-4. Meanwhile, ***D4AM*** achieved notable reductions in WER compared to ***NOIS***. This trend is similar to that observed in Table 2 and again validates the effectiveness of D4AM.

D4AM Evaluated with a Practical ASR API. We further evaluated D4AM using the Google ASR API, a well-known black-box system for users. To prepare a "real" noisy testing dataset, we merged the real parts of the CHiME-4 development and test sets. Table 3 shows the average WER values obtained by the Google ASR API. From the table, we observe similar trends to those observed in Table 1, but two points are particularly noteworthy. First, ***NOIS*** still yielded the worst result, confirming that all SE units contribute to the recognition accuracy of the Google ASR API on our testing data. Second, ***CLSO*** was worse than ***INIT***, confirming that an SE unit trained only by the

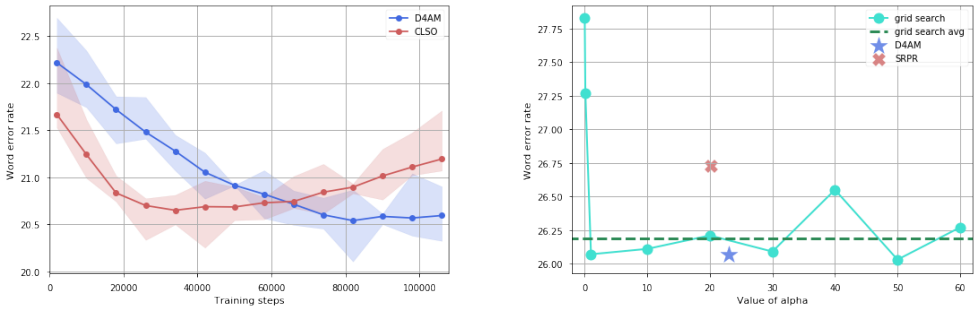
Table 3: WER (%) results of the Google ASR API on the CHiME-4 real sets.

method	NOIS	INIT	CLSO	SRPR	GCLB	D4AM
WER (%)	35.09	28.02	29.26	26.79	26.54	**26.44**

classification objective according to one ASR model is not guaranteed to contribute to other unseen recognizers. In contrast, improved recognition results (confirmed by the improvements produced by ***SRPR***, ***GCLB***, and ***D4AM***) can be obtained by well considering the combination of objectives.

4.3 Ablation Studies

Regression Objective Weighting for Handling Over-fitting. As mentioned earlier, ARML addresses the over-fitting issue caused by the limited labeled data of the main task by introducing an appropriate auxiliary loss. For D4AM, we treat the regression objective as an auxiliary loss to alleviate the over-fitting issue. To verify this feature, we reduced the speech-text paired data to only 10% (2853 utterances) of the Libri-100 dataset. The WER learning curves of ***CLSO*** and ***D4AM*** on a privately mixed validation set within 100,000 training steps are shown in Fig. 2a. From the figure, we can see that the learning curve of ***CLSO*** rises after 50,000 training steps, which is a clear sign of over-fitting. In contrast, ***D4AM*** has no such trend. Fig. 2a confirms the effectiveness of using the regression objective to improve generalization and mitigate over-fitting.



(a) Learning curves.

(b) WER (%) results of grid search, SRPR, and D4AM.

Figure 2: (a) Learning curves of CLSO and D4AM trained with 10% transcribed data of Libri-100. (b) Comparison of WER (%) results of grid search, SRPR, and D4AM. The dashed line represents the average performance of the best seven results of grid search.

D4AM versus Grid Search. One important feature of D4AM is that it automatically and effectively determines the weighting coefficients to combine regression and classification objectives. In this section, we intend to compare this feature with the common grid search. Fig. 2b compares the performance of ***D4AM***, ***SRPR***, and grid search with different weights on the CHiME-4 dt05-real set. For the grid search method, the figure shows the results for different weights, including 0, 0.1, 1.0, 10, 20, 30, 40, 50, and 60. The average performance of the best seven results is represented by the dashed green line. From Fig. 2b, we first note that ***D4AM*** clearly outperforms ***SRPR***. Furthermore, the result of ***D4AM*** is better than most average results of grid search. The results confirm that D4AM can efficiently and effectively estimate coefficients without an expensive grid search process.

To further investigate its effectiveness, we tested D4AM on high SNR testing conditions, MCT-trained ASR models, and another acoustic model setup. Additionally, we tested human perception assessments using the D4AM-enhanced speech signals. All the experimental results confirm the effectiveness of D4AM. Due to space limitations, these results are reported in APPENDIX.

5 Conclusion

In this paper, we have proposed a denoising framework called D4AM, which aims to serve as a pre-processor for various unseen ASR systems to boost their performance in noisy environments. D4AM employs gradient calibration and regression objective weighting to guide SE training to improve ASR performance while avoiding over-fitting. Experimental results first verify that D4AM can effectively reduce WERs for various unseen recognizers, even a practical ASR application (Google API). Meanwhile, D4AM can alleviate the over-fitting issue by effectively and efficiently combining classification and regression objectives without the exhaustive coefficient search. The promising results confirm that separately training an SE unit to serve existing ASR applications may be a feasible solution to improve the performance robustness of ASR in noise.

REPRODUCIBILITY STATEMENT

The source code for additional details of the model architecture, training process, and pre-processing steps, as well as a demo page, are provided in the supplemental material. Additional experiments are provided in Appendix.

REFERENCES

Alexei Baevski, Yuhao Zhou, Abdelrahman Mohamed, and Michael Auli. wav2vec 2.0: A framework for self-supervised learning of speech representations. In *Proc. NeurIPS*, 2020.

D.T. Braithwaite and W. Bastiaan Kleijn. Speech enhancement with variance constrained autoencoders. In *Proc. Interspeech*, 2019.

William Chan, Navdeep Jaitly, Quoc Le, and Oriol Vinyals. Listen, attend and spell: A neural network for large vocabulary conversational speech recognition. In *Proc. ICASSP*, 2016.

Fu-An Chao, Shao-Wei Fan-Jiang, Bi-Cheng Yan, Jeih-Weih Hung, and Berlin Chen. Tenet: A time-reversal enhancement network for noise-robust asr. *arXiv preprint arXiv:2107.01531*, 2021.

Arslan Chaudhry, Marc'Aurelio Ranzato, Marcus Rohrbach, and Mohamed Elhoseiny. Efficient lifelong learning with a-GEM. In *Proc. ICLR*, 2019.

Zhao Chen, Vijay Badrinarayanan, Chen-Yu Lee, and Andrew Rabinovich. Gradnorm: Gradient normalization for adaptive loss balancing in deep multitask networks. In *Proc. ICML*, 2018.

Zhuo Chen, Shinji Watanabe, Hakan Erdogan, and John R. Hershey. Speech enhancement and recognition using multi-task learning of long short-term memory recurrent neural networks. In *Proc. Interspeech*, 2015.

Chung-Cheng Chiu, Tara Sainath, Yonghui Wu, Rohit Prabhavalkar, Patrick Nguyen, Zhifeng Chen, Anjuli Kannan, Ron Weiss, Kanishka Rao, Ekaterina Gonina, Navdeep Jaitly, Bo Li, Jan Chorowski, and Michiel Bacchiani. State-of-the-art speech recognition with sequence-to-sequence models. In *Proc. ICASSP*, 2018.

Xiaodong Cui, Songtao Lu, and Brian Kingsbury. Federated acoustic modeling for automatic speech recognition. In *Proc. ICASSP*, 2021.

Alexandre Défossez, Nicolas Usunier, Léon Bottou, and Francis Bach. Music source separation in the waveform domain. *arXiv preprint arXiv:1911.13254*, 2019.

Alexandre Défossez, Gabriel Synnaeve, and Yossi Adi. Real time speech enhancement in the waveform domain. In *Proc. Interspeech*, 2020.

Pavel Denisov, Ngoc Thang Vu, and Marc Ferras. Unsupervised domain adaptation by adversarial learning for robust speech recognition. In *ITG Symposium on Speech Communication*, 2018.

Lucio M. Dery, Yann Dauphin, and David Grangier. Auxiliary task update decomposition: The good, the bad and the neutral. In *Proc. ICLR*, 2021.

Yunshu Du, Wojciech M Czarnecki, Siddhant M Jayakumar, Mehrdad Farajtabar, Razvan Pascanu, and Balaji Lakshminarayanan. Adapting auxiliary losses using gradient similarity. *arXiv preprint arXiv:1812.02224*, 2018.

Zhihao Du, Xueliang Zhang, and Jiqing Han. Investigation of monaural front-end processing for robust speech recognition without retraining or joint-training. In *Proc. APSIPA ASC*, 2019.

Y. Ephraim and D. Malah. Speech enhancement using a minimum-mean square error short-time spectral amplitude estimator. *IEEE/ACM Transactions on Audio, Speech, and Language Processing*, pp. 1109–1121, 1984.

S. Fu, T. Wang, Y. Tsao, X. Lu, and H. Kawai. End-to-end waveform utterance enhancement for direct evaluation metrics optimization by fully convolutional neural networks. *IEEE/ACM Transactions on Audio, Speech, and Language Processing*, pp. 1570–1584, 2018.

Szu-Wei Fu, Chien-Feng Liao, Yu Tsao, and Shou-De Lin. MetricGAN: Generative adversarial networks based black-box metric scores optimization for speech enhancement. In *Proc. ICML*, 2019.

Szu-Wei Fu, Cheng Yu, Tsun-An Hsieh, Peter Plantinga, Mirco Ravanelli, Xugang lu, and Yu Tsao. MetricGAN+: An improved version of MetricGAN for speech enhancement. In *Proc. Interspeech*, 2021.

Philip Gage. A new algorithm for data compression. *C Users Journal*, 12(2):23–38, 1994.

Jürgen T Geiger, Jort F Gemmeke, Björn Schuller, and Gerhard Rigoll. Investigating NMF speech enhancement for neural network based acoustic models. In *Proc. Interspeech*, 2014a.

Jürgen T. Geiger, Felix Weninger, Jort F. Gemmeke, Martin Wöllmer, Björn Schuller, and Gerhard Rigoll. Memory-enhanced neural networks and NMF for robust asr. *IEEE/ACM Transactions on Audio, Speech, and Language Processing*, pp. 1037–1046, 2014b.

François Germain, Qifeng Chen, and Vladlen Koltun. Speech denoising with deep feature losses. In *Proc. Interspeech*, 2019.

Alex Graves, Santiago Fernández, Faustino Gomez, and Jürgen Schmidhuber. Connectionist temporal classification: Labelling unsegmented sequence data with recurrent neural networks. In *Proc. ICML*, 2006.

Anmol Gulati, Chung-Cheng Chiu, James Qin, Jiahui Yu, Niki Parmar, Ruoming Pang, Shibo Wang, Wei Han, Yonghui Wu, Yu Zhang, and Zhengdong Zhang. Conformer: Convolution-augmented transformer for speech recognition. In *Proc. Interspeech*, 2020.

Yanzhang He, Tara N. Sainath, Rohit Prabhavalkar, Ian McGraw, Raziel Álvarez, Ding Zhao, David Rybach, Anjuli Kannan, Yonghui Wu, Ruoming Pang, Qiao Liang, Deepti Bhatia, Yuan Shangguan, Bo Li, Golan Pundak, Khe Chai Sim, Tom Bagby, Shuo yiin Chang, Kanishka Rao, and Alexander Gruenstein. Streaming end-to-end speech recognition for mobile devices. *Proc. ICASSP*, 2019.

Guoning Hu and DeLiang Wang. A tandem algorithm for pitch estimation and voiced speech segregation. *IEEE/ACM Transactions on Audio, Speech, and Language Processing*, pp. 2067–2079, 2010.

Hanzhang Hu, Debadeepta Dey, Martial Hebert, and J. Andrew Bagnell. Learning anytime predictions in neural networks via adaptive loss balancing. In *Proc. AAAI*, 2019.

J. Jensen and C. H. Taal. An algorithm for predicting the intelligibility of speech masked by modulated noise maskers. *IEEE/ACM Transactions on Audio, Speech, and Language Processing*, pp. 2009–2022, 2016.

Barker Jon, Marxer Ricard, Vincent Emmanuel, and Watanabe Shinji. The third 'CHiME' speech separation and recognition challenge: Analysis and outcomes. *Computer Speech & Language*, pp. 605–626, 2017.

Keisuke Kinoshita, Tsubasa Ochiai, Marc Delcroix, and Tomohiro Nakatani. Improving noise robust automatic speech recognition with single-channel time-domain enhancement network. In *Proc. ICASSP*, 2020.

Jonathan Le Roux, Scott Wisdom, Hakan Erdogan, and John R Hershey. SDR-half-baked or well done? In *Proc. ICASSP*, 2019.

Chi-Chang Lee, Yu-Chen Lin, Hsuan-Tien Lin, Hsin-Min Wang, and Yu Tsao. SERIL: noise adaptive speech enhancement using regularization-based incremental learning. In *Proc. Interspeech*, 2020.

Jinyu Li, Li Deng, Yifan Gong, and Reinhold Haeb-Umbach. An overview of noise-robust automatic speech recognition. *IEEE/ACM Transactions on Audio, Speech, and Language Processing*, pp. 745–777, 2014.

Tatiana Likhomanenko, Qiantong Xu, Vineel Pratap, Paden Tomasello, Jacob Kahn, Gilad Avidov, Ronan Collobert, and Gabriel Synnaeve. Rethinking Evaluation in ASR: Are Our Models Robust Enough? In *Proc. Interspeech*, 2021.

Xingyu Lin, Harjatin Baweja, George Kantor, and David Held. Adaptive auxiliary task weighting for reinforcement learning. In *Proc. NeurIPS*, 2019.

Philipos C. Loizou. *Speech Enhancement: Theory and Practice*. CRC Press, Inc., USA, 2nd edition, 2013. ISBN 1466504218.

David Lopez-Paz and Marc' Aurelio Ranzato. Gradient episodic memory for continual learning. In *Proc. NeurIPS*, 2017.

Xugang Lu, Yu Tsao, Shigeki Matsuda, and Chiori Hori. Speech enhancement based on deep denoising autoencoder. In *Proc. Interspeech*, 2013.

Duo Ma, Nana Hou, Van Tung Pham, Haihua Xu, and Eng Siong Chng. Multitask-based joint learning approach to robust asr for radio communication speech. In *Proc. APSIPA ASC*, 2021.

Zhong Meng, Shinji Watanabe, John R. Hershey, and Hakan Erdogan. Deep long short-term memory adaptive beamforming networks for multichannel robust speech recognition. In *Proc. ICASSP*, 2017.

Zhong Meng, Jinyu Li, Yifan Gong, and Biing-Hwang (Fred) Juang. Cycle-consistent speech enhancement. In *Proc. Interspeech*, 2018.

Radford M Neal et al. Mcmc using hamiltonian dynamics. *Handbook of markov chain monte carlo*, 2(11):2, 2011.

Mohammad Nikzad, Aaron Nicolson, Yongsheng Gao, Jun Zhou, Kuldip K. Paliwal, and Fanhua Shang. Deep residual-dense lattice network for speech enhancement. In *Proc. AAAI*, 2020.

Tsubasa Ochiai, Shinji Watanabe, Takaaki Hori, and John R. Hershey. Multichannel end-to-end speech recognition. In *Proc. ICML*, 2017a.

Tsubasa Ochiai, Shinji Watanabe, and Shigeru Katagiri. Does speech enhancement work with end-to-end asr objectives?: Experimental analysis of multichannel end-to-end asr. In *Proc. IEEE 27th International Workshop on Machine Learning for Signal Processing (MLSP)*, 2017b.

Vassil Panayotov, Guoguo Chen, Daniel Povey, and Sanjeev Khudanpur. Librispeech: an asr corpus based on public domain audio books. In *Proc. ICASSP*, 2015.

Ashutosh Pandey and DeLiang Wang. A new framework for supervised speech enhancement in the time domain. In *Proc. Interspeech*, 2018.

N. Parihar, J. Picone, D. Pearce, and H. G. Hirsch. Performance analysis of the Aurora large vocabulary baseline system. In *Proc. The 12th European Signal Processing Conference*, 2004.

Archiki Prasad, Preethi Jyothi, and Rajbabu Velmurugan. An investigation of end-to-end models for robust speech recognition. In *Proc. ICASSP*, 2021.

Josef Rajnoha. Multi-condition training for unknown environment adaptation in robust ASR under real conditions. 2009.

Kanishka Rao, Haşim Sak, and Rohit Prabhavalkar. Exploring architectures, data and units for streaming end-to-end speech recognition with rnn-transducer. In *Proc. ASRU*, 2017.

Mirco Ravanelli, Titouan Parcollet, Peter Plantinga, Aku Rouhe, Samuele Cornell, Loren Lugosch, Cem Subakan, Nauman Dawalatabad, Abdelwahab Heba, Jianyuan Zhong, Ju-Chieh Chou, Sung-Lin Yeh, Szu-Wei Fu, Chien-Feng Liao, Elena Rastorgueva, François Grondin, William Aris, Hwidong Na, Yan Gao, Renato De Mori, and Yoshua Bengio. Speechbrain: A general-purpose speech toolkit. *arXiv preprint arXiv:2106.04624*, 2021.

Chandan KA Reddy, Vishak Gopal, Ross Cutler, Ebrahim Beyrami, Roger Cheng, Harishchandra Dubey, Sergiy Matusevych, Robert Aichner, Ashkan Aazami, Sebastian Braun, et al. The interspeech 2020 deep noise suppression challenge: Datasets, subjective testing framework, and challenge results. In *Proc. Interspeech*, 2020.

Chandan KA Reddy, Vishak Gopal, and Ross Cutler. Dnsmos: A non-intrusive perceptual objective speech quality metric to evaluate noise suppressors. In *Proc. ICASSP*, 2021.

A. W. Rix, J. G. Beerends, M. P. Hollier, and A. P. Hekstra. Perceptual evaluation of speech quality (PESQ)-a new method for speech quality assessment of telephone networks and codecs. In *Proc. ICASSP*, 2001.

Tara N Sainath, Yanzhang He, Bo Li, Arun Narayanan, Ruoming Pang, Antoine Bruguier, Shuo-yiin Chang, Wei Li, Raziel Alvarez, Zhifeng Chen, et al. A streaming on-device end-to-end model surpassing server-side conventional model quality and latency. In *Proc. ICASSP*, 2020.

George Saon, Gakuto Kurata, Tom Sercu, Kartik Audhkhasi, Samuel Thomas, Dimitrios Dimitriadis, Xiaodong Cui, Bhuvana Ramabhadran, Michael Picheny, Lynn-Li Lim, Bergul Roomi, and Phil Hall. English conversational telephone speech recognition by humans and machines. In *Proc. Interspeech*, 2017.

Mike Schuster and Kaisuke Nakajima. Japanese and korean voice search. In *Proc. ICASSP*, 2012.

Michael L. Seltzer, Dong Yu, and Yongqiang Wang. An investigation of deep neural networks for noise robust speech recognition. In *Proc. ICASSP*, 2013.

Rico Sennrich, Barry Haddow, and Alexandra Birch. Neural machine translation of rare words with subword units. In *Proc. ACL*, 2016.

Dmitriy Serdyuk, Kartik Audhkhasi, Philémon Brakel, Bhuvana Ramabhadran, Samuel Thomas, and Yoshua Bengio. Invariant representations for noisy speech recognition. *arXiv preprint arXiv:1612.01928*, 2016.

Baifeng Shi, Judy Hoffman, Kate Saenko, Trevor Darrell, and Huijuan Xu. Auxiliary task reweighting for minimum-data learning. In *Proc. NeurIPS*, 2020.

Jiaqi Su, Zeyu Jin, and Adam Finkelstein. HiFi-GAN: High-fidelity denoising and dereverberation based on speech deep features in adversarial networks. In *Proc. Interspeech*, 2020.

C. H. Taal, R. C. Hendriks, R. Heusdens, and J. Jensen. A short-time objective intelligibility measure for time-frequency weighted noisy speech. In *Proc. ICASSP*, 2010.

Andrew Varga and Herman J. M. Steeneken. Assessment for automatic speech recognition: II. NOISEX-92: A database and an experiment to study the effect of additive noise on speech recognition systems. *Speech Communication*, pp. 247–251, 1993.

Ashish Vaswani, Noam Shazeer, Niki Parmar, Jakob Uszkoreit, Llion Jones, Aidan N Gomez, Łukasz Kaiser, and Illia Polosukhin. Attention is all you need. In *Proc. NeurIPS*, 2017.

Peidong Wang, Ke Tan, and De Liang Wang. Bridging the gap between monaural speech enhancement and recognition with distortion-independent acoustic modeling. *IEEE/ACM Transactions on Audio, Speech, and Language Processing*, pp. 39–48, 2020.

S. Wang, W. Li, S. M. Siniscalchi, and C. Lee. A cross-task transfer learning approach to adapting deep speech enhancement models to unseen background noise using paired senone classifiers. In *Proc. ICASSP*, 2020.

Shinji Watanabe, Takaaki Hori, Suyoun Kim, John R Hershey, and Tomoki Hayashi. Hybrid ctc/attention architecture for end-to-end speech recognition. *IEEE Journal of Selected Topics in Signal Processing*, pp. 1240–1253, 2017.

Max Welling and Yee W Teh. Bayesian learning via stochastic gradient langevin dynamics. In *Proc. ICML*, 2011.

Felix Weninger, Hakan Erdogan, Shinji Watanabe, Emmanuel Vincent, Jonathan Le Roux, John R. Hershey, and Björn Schuller. Speech enhancement with lstm recurrent neural networks and its application to noise-robust asr. In *International Conference on Latent Variable Analysis and Signal Separation*, pp. 91–99, 2015a.

Felix Weninger, Hakan Erdogan, Shinji Watanabe, Emmanuel Vincent, Jonathan Le Roux, John R Hershey, and Björn Schuller. Speech enhancement with LSTM recurrent neural networks and its application to noise-robust asr. In *International Conference on Latent Variable Analysis and Signal Separation*, 2015b.

Scott Wisdom, Efthymios Tzinis, Hakan Erdogan, Ron Weiss, Kevin Wilson, and John Hershey. Unsupervised sound separation using mixture invariant training. In *Proc. NeurIPS*, 2020.

Ruilin Xu, Rundi Wu, Yuko Ishiwaka, Carl Vondrick, and Changxi Zheng. Listening to sounds of silence for speech denoising. In *Proc. NeurIPS*, 2020.

Y. Xu, J. Du, L. Dai, and C. Lee. A regression approach to speech enhancement based on deep neural networks. *IEEE/ACM Transactions on Audio, Speech, and Language Processing*, 2015.

Dacheng Yin, Chong Luo, Zhiwei Xiong, and Wenjun Zeng. PHASEN: A phase-and-harmonics-aware speech enhancement network. In *Proc. AAAI*, 2020.

Huanjing Yue, Wenxin Duo, and Jingyu Yang. Reference-based speech enhancement via feature alignment and fusion network. In *Proc. AAAI*, 2022.

Q. Zhang, A. Nicolson, M. Wang, K. K. Paliwal, and C. Wang. DeepMMSE: A deep learning approach to MMSE-based noise power spectral density estimation. *IEEE/ACM Transactions on Audio, Speech, and Language Processing*, pp. 1404–1415, 2020.

Qian Zhang, Han Lu, Hasim Sak, Anshuman Tripathi, Erik McDermott, Stephen Koo, and Shankar Kumar. Transformer transducer: A streamable speech recognition model with transformer encoders and RNN-T loss. In *Proc. ICASSP*, 2020.

S. Zhang, C. T. Do, R. Doddipatla, and S. Renals. Learning noise invariant features through transfer learning for robust end-to-end speech recognition. In *Proc. ICASSP*, 2020.

Shucong Zhang, Cong-Thanh Do, Rama Doddipatla, and Steve Renals. Learning noise invariant features through transfer learning for robust end-to-end speech recognition. In *Proc. ICASSP*, 2020.

Chengyu Zheng, Xiulian Peng, Yuan Zhang, Sriram Srinivasan, and Yan Lu. Interactive speech and noise modeling for speech enhancement. In *Proc. AAAI*, 2021.

A Appendix

A.1 D4AM Evaluated on High SNR Data

Most SE research focuses on "average" denoising on the target ASR task, which means that if the distortion caused by the SE model is low enough, we consider it tolerable. Accordingly, we conducted additional experiments using cleaner speech utterances as testing data. The WERs of the Google ASR API are shown in Table 4, where test-clean represents the clean LibriSpeech test set, and the others are test-clean mixed with noisex92 (Varga & Steeneken, 1993) and Nonspeech (Hu & Wang, 2010) noise sources, uniformly sampled at high SNR levels between 10dB to 20dB (average 15 dB). From Table 4, it can be seen that the WER of the clean speech processed by D4AM is only slightly higher than that of the original clean speech (ORIG). The result is 16.61% versus 16.27%. However, for both types of high SNR noisy speech, using D4AM reduced the WER (19.24% versus 19.67% for noisex92 (Varga & Steeneken, 1993) and 20.19% versus 20.55% for Nonspeech (Hu & Wang, 2010)). The results show that D4AM can yield comparable (better) performance than using the original clean (high SNR noisy) speech.

A.2 D4AM Evaluated with MCT-trained ASR models

The results of the Google ASR API in Table 3 are supposed to be representative results of the MCT-trained ASR systems. We conducted additional ASR experiments on CHiME-4 with **MCT-CONF**, **MCT-W2V2**, and **MCT-TRAN** corresponding to the ASR model architectures in Table 1 and trained

Table 4: WER (%) results on high SNR test sets.

method	test-clean	test-noisex	test-nonspeech
ORIG	16.27	19.67	20.55
D4AM	16.61	19.24	20.19

on the LibriSpeech and DNS noise datasets with the SNR levels -4 to 6. Note that ***W2V2*** consists of a wav2vec2 module and a linear layer. During training, the wav2vec2 module was fixed and used as a feature extractor, and only the linear layer was updated. It is clear from Table 5 that ***D4AM*** consistently outperforms ***NOIS*** for all MCT-trained ASR models.

Table 5: WER (%) results of MCT-trained ASR models on the CHiME-4 dt-05 real set.

method	MCT-CONF	MCT-W2V2	MCT-TRAN
NOIS	25.69	28.86	22.82
D4AM	24.22	22.89	22.59

A.3 D4AM Trained with Another Acoustic Model

We chose the conformer-based ASR model as the proxy acoustic model because it has the lowest memory requirement compared with other model architectures in SpeechBrain. In terms of implementation, especially for researchers like us with limited computing resources, model complexity is a major concern. We believe our claim that any critical point of $\mathcal{L}_{cls}(\theta)$ should be "covered" by the critical point space of $\mathcal{L}_{reg}(\theta)$ applies to most cases. By taking this appropriately, we can reduce the bias of different settings of the proxy acoustic model used for training. Also, previous work (Ochiai et al., 2017a;b) has shown empirically that training an SE unit with one acoustic model can improve another ASR system. To show that the proposed D4AM is insensitive to the choice of proxy acoustic model, we conducted additional experiments using the W2V2-CTC model as the proxy acoustic model. The results evaluated with a LibriSpeech-trained ASR system on the CHiME-4 dt-05 real set are shown in Table 6, where Proxy-CONF and Proxy-W2V2-CTC denote conformer- and W2V2-CTC-based proxy acoustic models, respectively.

Table 6: WER (%) results of different setups on the CHiME-4 dt-05 real set.

method	CONF	TRAN	RNN
Proxy-CONF-CLSO	26.66	27.83	35.25
Proxy-CONF-SRPR	26.88	26.73	34.83
Proxy-CONF-GCLB	26.76	27.51	34.62
Proxy-CONF-D4AM	26.7	26.07	34.43
Proxy-W2V2-CTC-CLSO	30.61	28.98	40.30
Proxy-W2V2-CTC-SRPR	29.09	27.57	36.67
Proxy-W2V2-CTC-GCLB	29.25	27.91	36.92
Proxy-W2V2-CTC-D4AM	28.46	26.89	35.33
INIT	30.98	29.61	38.61

As shown in Table 6, D4AM can effectively reduce the bias between proxy acoustic models and notably improve the performance. Since Conformer and W2V2-CTC have different model architectures and use different label types, the results confirm that D4AM can consistently produce promising results using different types of proxy acoustic models.

A.4 HUMAN PERCEPTION EVALUATION

Finally, we evaluate the enhanced speech signal using an objective perceptual metric, DNSMOS (Reddy et al., 2021). The DNSMOS value represents the perception score of human hearing, with higher scores indicating better quality. Table 7 shows the DNSMOS scores of enhanced speech produced by various SE methods. The real sets of CHiME-4 described in Section 4.2 were used as the testing data. From Table 7, we note that ***D4AM*** produces the highest DNSMOS score among all models trained with the ASR objective, and its DNSMOS score is only slightly lower than that of ***INIT*** (only considering the regression objective for training). The result again proves our conjecture that any critical point of $\mathcal{L}_{cls}(\theta)$ should be "covered" by the critical point space of $\mathcal{L}_{reg}(\theta)$.

Table 7: DNSMOS results on the CHiME-4 real sets.

method	NOIS	INIT	CLSO	SRPR	GCLB	D4AM
DNSMOS	2.5574	3.2401	2.7665	3.0598	3.0398	**3.1450**

A.5 THE CHANGE IN THE α_{srpr} VALUE DURING TRAINING

Fig. 3 shows the change in the α_{srpr} value with and without gradient calibration applied over training steps. It is clear that the α_{srpr} values of both ***SRPR*** and ***D4AM*** converge rapidly, indicating that their learning process is stable.

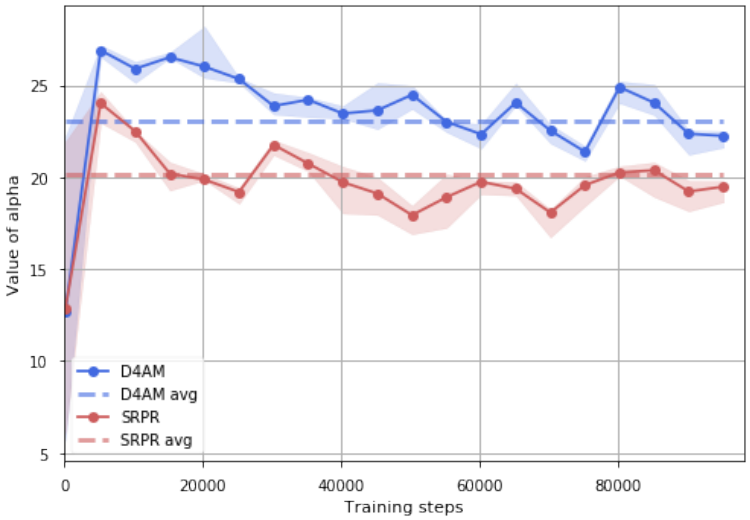


Figure 3: The change in the α_{srpr} value during training. The dashed lines represent the average α_{srpr} values.

A.6 THE DERIVATION OF α_{gclb}

For the derivation of α_{gclb}, the Lagrangian of the constrained optimization problem defined in Eq. 2 can be written as:

$$\mathcal{L}(g, \alpha) = \frac{1}{2}\|g - \nabla\mathcal{L}^{\phi}_{cls}(\theta^t)\|^2 - \alpha\langle g, \nabla\mathcal{L}_{reg}(\theta^t)\rangle \tag{6}$$

To find the optimal value $g^* = \arg\min_g \mathcal{L}(g, \alpha)$, we set the derivatives of $\mathcal{L}(g, \alpha)$ with respect to g to 0. By solving for $\nabla_g\mathcal{L}(\alpha, g) = 0$, we will get $g = \nabla\mathcal{L}^{\phi}_{cls}(\theta^t) + \alpha \cdot \nabla\mathcal{L}_{reg}(\theta^t)$. Then, we can substitute $g = \nabla\mathcal{L}^{\phi}_{cls}(\theta^t) + \alpha \cdot \nabla\mathcal{L}_{reg}(\theta^t)$ into $\mathcal{L}(\alpha, g)$ and get the minimum $\mathcal{L}^*(\alpha)$:

$$\mathcal{L}^*(\alpha) = -\alpha\langle\nabla\mathcal{L}^{\phi}_{cls}(\theta^t), \nabla\mathcal{L}_{reg}(\theta^t)\rangle - \frac{1}{2}\alpha^2\|\nabla\mathcal{L}_{reg}(\theta^t)\|_2^2 + const \tag{7}$$

where $const$ is the summation of those terms regardless of α. Here, the solution of α_{gclb} will be the critical point of $\mathcal{L}^*(\alpha)$. Therefore, by deriving α such that $\nabla_\alpha \mathcal{L}^*(\alpha) = 0$, we can get the final result of α_{gclb}:

$$\alpha_{gclb} = -[\![\langle \nabla \mathcal{L}_{cls}^{\phi}(\theta^t), \nabla \mathcal{L}_{reg}(\theta^t) \rangle < 0]\!] \cdot \frac{\langle \nabla \mathcal{L}_{cls}^{\phi}(\theta^t), \nabla \mathcal{L}_{reg}(\theta^t) \rangle}{\|\nabla \mathcal{L}_{reg}(\theta^t)\|_2^2} \tag{8}$$