DDTSE: DISCRIMINATIVE DIFFUSION MODEL FOR TARGET SPEECH EXTRACTION

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ABSTRACT

Diffusion models have gained attention in speech enhancement tasks, providing an alternative to conventional discriminative methods. However, research on target speech extraction under multi-speaker noisy conditions remains relatively unexplored. Moreover, the superior quality of diffusion methods typically comes at the cost of slower inference speed. In this paper, we introduce the **D**iscriminative **D**iffusion model for **T**arget **S**peech **E**xtraction (DDTSE). We apply the same forward process as diffusion models and utilize the reconstruction loss similar to discriminative methods. Furthermore, we devise a two-stage training strategy to emulate the inference process during model training. DDTSE not only works as a standalone system, but also can further improve the performance of discriminative models without additional retraining. Experimental results demonstrate that DDTSE not only achieves higher perceptual quality but also accelerates the inference process by 3 times compared to the conventional diffusion model.

Index Terms— target speech extraction, speech enhancement, diffusion model, discriminative model

1. INTRODUCTION

The cocktail party effect, also known as "selective hearing", is the ability to focus on a single speaker or conversation in a noisy environment [1, 2, 3]. Target Speech Extraction (TSE) aims to emulate human capability by isolating the clean speech of the target speaker from a noisy mixture. It serves as a valuable tool for enhancing downstream tasks like speech recognition and speaker verification, attracting significant research interests [4, 5, 6].

Discriminative and generative models are two different approaches for speech enhancement and target speech extraction tasks. The former learns the best mapping between inputs and outputs, while the latter learns the target distribution, allowing multiple valid estimates [7]. TSE primarily relies on discriminative methods such as DPCCN [8], SpEX [9] and Speakerbeam [10]. Despite the many advances gained from past research, discriminative methods occasionally show limited generalization abilities towards unseen noise types or speakers [11, 12].

Generative methods, particularly diffusion methods, have shown potential in producing natural and diverse speech, thereby attracting significant interest [13, 14, 15]. Previous work, such as SGMSE+ and DiffTSE [7, 12, 16, 17], has applied score-based diffusion models on speech enhancement and target speech extraction. However, the discrepancy between the forward and reverse processes of diffusion models might lead to degradation of model performance [18]. Moreover, there are few explorations for the target speech extraction task in multi-speaker noisy environments with generative models. Furthermore, enhancing inference efficiency remains a challenge for real-world deployment, due to the need for dozens or even hundreds of inference steps of diffusion models.

In this study, we introduce the **D**iscriminative **D**iffusion Model for **T**arget **S**peech **E**xtraction (DDTSE), which combines the forward processes of the diffusion model and the training objective used in the discriminative model. We design a two-stage training method and provide two usage modes. Our extensive experiments reveal that DDTSE surpasses discriminative methods in perceptual quality, particularly in noisy conditions. Furthermore, when integrated with existing models, denoted as X+DDTSE, it consistently surpasses standalone discriminative models (i.e., X) and demonstrates potential as an effective plug-in enhancement. In terms of inference efficiency, DDTSE requires only 10 steps for standalone use and 2 steps for X+DDTSE, respectively. The main contributions of the paper can be summarized as follows:

1) We introduce DDTSE, an advanced frequency domain TSE model, utilizing the forward process of the diffusion model and the reconstruction objective of the discriminative model. It is not only applicable in multi- and single-speaker scenarios but also effective in processing environmental noise.

2) We design a two-stage training process. It learns to extract the clean speech given to the target speaker embedding in the first stage and aims to bridge the gap between training and inference in the second stage.

3) We provide two usage modes for versatility. DDTSE-only operates as a standalone system for end-to-end TSE, and X+DDTSE rectifies existing discriminative models to enhance overall system performance. Audio samples[1]are available.

2. RELATED WORK

2.1. Discriminative models

For an extended period, discriminative methods have been the preferred approach for tasks related to speech enhancement and target speech extraction, such as DPCCN [8] and Speakerbeam [10]. These approaches mainly utilize supervised learning to learn an optimized

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[1] https://vivian556123.github.io/slt2024-ddtse/

deterministic mapping between corrupted speech y and the corresponding clean speech target x as in Fig.1c. However, these models may result in unpleasant speech distortions and limit generalization abilities towards unseen noise types or speakers [11].

2.2. Diffusion models

Recently, there are various diffusion models, especially score-based diffusion models, designed for speech enhancement and target speech extraction tasks [7, 12, 15, 16, 17, 19, 20]. The forward process is defined through a linear stochastic differential equation (SDE) and gradually turns data into noise. The reverse process is to sample a target data point from Gaussian noise and invert this process with a reverse-time SDE. The forward and reverse process of score-based diffusion methods is shown in Fig.1a and b.

As introduced in [12, 20], the forward process is modeled as the solution to an SDE as in Eq.1, where $\mathbf{y}$ is the spectrogram of corrupted speech, $\mathbf{x}_0$ is the spectrogram of target clean speech, $\mathbf{x}_t$ is the state of the process at time $t \in [0, T]$, $\mathbf{f}$ and g are drift and diffusion coefficient function parameterized by $\gamma, \sigma_{\max}, \sigma\text{min}$. $\mathbf{w}$ is the standard Wiener process.

$$\mathrm{d}\mathbf{x}_t = \underbrace{\gamma\left(\mathbf{y} - \mathbf{x}_t\right)}_{\mathbf{f}(\mathbf{x}_t, \mathbf{y})} \mathrm{d}t + \underbrace{\left[\sigma_{\min}\left(\frac{\sigma_{\max}}{\sigma_{\min}}\right)^t \sqrt{2\log\left(\frac{\sigma_{\max}}{\sigma_{\min}}\right)}\right]}_{g(t)} \mathrm{d}\mathbf{w} \tag{1}$$

Eq.1 describes a Gaussian process, the mean and variance of $\mathbf{x}_{t t\in[0,T]}$ can be derived as in Eq.2 and 3, when its initial conditions are known [21]. The solution for $\mathbf{x}_t$, called perturbation kernel, is shown in Eq.4. In practice, we sample each $\mathbf{x}_t$ through Eq.5, and the random noise is $\mathbf{z} \sim \mathcal{N}(0, \mathbf{I})$.

$$\mu(\mathbf{x}_0, \mathbf{y}, t) = \exp^{-\gamma t} \mathbf{x}_0 + (1 - \exp^{-\gamma t})\mathbf{y} \tag{2}$$

$$\sigma(t)^2 = \frac{\sigma_{\min}^2\left(\left(\sigma_{\max}/\sigma_{\min}\right)^{2t} - \exp^{-2\gamma t}\right)\log\left(\sigma_{\max}/\sigma_{\min}\right)}{\gamma + \log\left(\sigma_{\max}/\sigma_{\min}\right)} \tag{3}$$

$$q(\mathbf{x}_t|\mathbf{x}_0, \mathbf{y}) = \mathcal{N}(\mathbf{x}_t; \mu(\mathbf{x}_0, \mathbf{y}, t), \sigma(t)^2) \tag{4}$$

$$\mathbf{x}_t = \mu(x_0, \mathbf{y}, t) + \sigma(t)\mathbf{z} \tag{5}$$

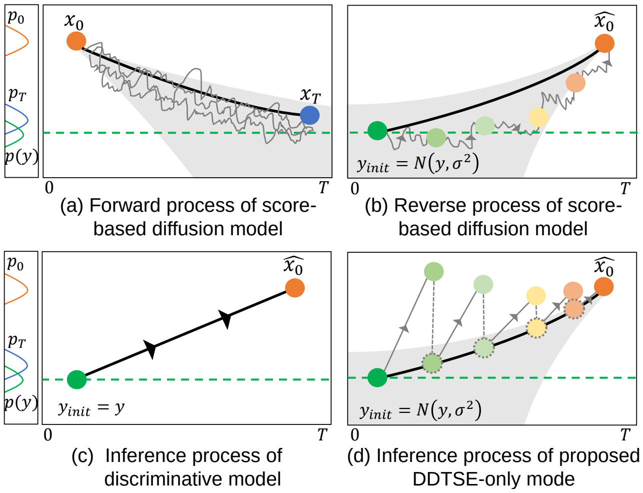
For each SDE in the form of Eq.1, the corresponding reverse-time SDE is defined by Eq.6, where $\mathrm{d}t$ is a negative timestep in the reverse process [22]. We can train a neural network to approximate $\nabla_{\mathbf{x}_t} \log p_t(\mathbf{x}_t|\mathbf{y})$, which is the score of the perturbation kernel. According to [23, 24], the loss function takes the form in Eq.8.

$$\mathrm{d}\mathbf{x}_t = \left[f\left(\mathbf{x_t}, \mathbf{y}\right) - g(t)^2 \nabla_{\mathbf{x}_t} \log p_t(\mathbf{x}_t|\mathbf{y})\right] \mathrm{d}t + g(t)\mathrm{d}\mathbf{w} \tag{6}$$

$$\mathrm{d}\mathbf{x}_t \approx \left[f\left(\mathbf{x_t}, \mathbf{y}\right) - g(t)^2 s_\theta\left(\mathbf{x}_t, \mathbf{y}, t\right)\right] \mathrm{d}t + g(t)\mathrm{d}\mathbf{w} \tag{7}$$

$$\min_\theta \mathbb{E}_{(\mathbf{x}_0, \mathbf{x}_t)\sim q(x_0)q(\mathbf{x}_t|\mathbf{x}_0, \mathbf{y}), s, t}\left[\left\|\mathbf{s}_\theta\left(\mathbf{x}_t, \mathbf{y}, t\right) + \frac{\mathbf{z}}{\sigma(t)}\right\|_2^2\right] \tag{8}$$

These diffusion methods can generate natural speech, however, as shown in Fig.1a and b, there exists a discrepancy between the terminating distribution of the forward process (the distribution of p_T for x) and the prior used for solving the reverse process at inference (the distribution of $p(y)$) [18]. This is mainly because of the exponential characteristic of Eq.2 that $x_T = \mu(x_0, \mathbf{y}, T) \neq \mathbf{y}$. Moreover, diffusion models require many inference steps to achieve good performance, and thus impose computational pressure.



(a) Forward process of score-based diffusion model

(b) Reverse process of score-based diffusion model

(c) Inference process of discriminative model

(d) Inference process of proposed DDTSE-only mode

Fig. 1. Comparison of score-based diffusion model, discriminative model and our proposed model. The x-axis represents the timestep. (a) and (b) are the forward and reverse process of score-based diffusion model [11, 12]. (c) is the inference process of discriminative method with one-step prediction. (d) is the inference process of our proposed DDTSE-only mode. The solid gray line is the model prediction in each step. The dashed gray line and the dotted circles are the results obtained by adding noise according to Eq.2 and 3.

2.3. Combination of discriminative and diffusion models

Given that diffusion and discriminative models each possess advantages and disadvantages, some researchers focus on combining them. At the architectural level, StoRM [11] and Diffiner [25] leverage preprocessed speech to guide diffusion-based model training. [26] utilizes generative and discriminative decoders and fuses them. However, they usually require fine-tuning or joint training, and cannot be used as plug-and-play models. At the objective level, WGSL [27] augments the original diffusion training objective with an L2 reconstruction loss at each diffusion time-step. To minimize the discrepancy and accelerate the inference process, [28] proposed a two-stage diffusion training method through BBED SDE [18]. In the first stage, it uses the generative denoising score matching loss, and in the second training stage it applies the predictive loss.

Inspired by these approaches, we propose DDTSE, which combines the forward process of the diffusion model and the training objective of the discriminative model. It not only improves the perceptual speech quality of discriminative models, but also achieves 3x speedup compared to the diffusion model for inference. It is applicable for both noisy and clean multi-speaker or single-speaker speech enhancement and target speech extraction. Two inference modes enable DDTSE to be utilized independently or in a rectified manner combined with other discriminative models, thereby offering a comprehensive solution for various scenarios.

3. METHODOLOGY

3.1. Training Method

The objective of TSE is to isolate the target speaker's clean speech from a mixture of multiple speakers and ambient noise. Our model processes the mixture $\mathbf{y}$ to retrieve the clean speech $\mathbf{x}_0$. We collect an enrollment speech from the target speaker to extract the speaker embedding s for model conditioning.

Our model consists of two processes: the forward process and the reverse process. The forward process $q(\mathbf{x}_t|\mathbf{x}_0, \mathbf{y})$ is the same as the score-based diffusion model [12], as shown in Fig.1a, defined in Eq.4. It gradually turns the clean speech $\mathbf{x}_0$ into the noisy mixture to simulate speech corruption with timestep $t \in [0, T]$. The reverse process is similar to the discriminative method as shown in Fig.1c, but it transforms speech with Gaussian noise $\mathbf{x}_t$ back to clean speech over timesteps, conditioned on the speaker embedding s.

Although prior works mainly focus on predicting the score function during reverse process [12, 17], the score-based objective does not properly measure the perceptual quality of the estimated clean speech because it resembles the generative loss typically utilized in unconditional diffusion models rather than supervised speech enhancement tasks [27]. To address this problem, we train the model f_θ to predict the clean speech $\mathbf{x}_0$, conditioned on the speaker embedding s by minimizing the conditional expectation as in Eq.9:

$$\min_\theta \mathbb{E}_{(\mathbf{x}_0,\mathbf{x}_t)\sim q(x_0)q(\mathbf{x}_t|\mathbf{x}_0,\mathbf{y}),s,t}\left[\|\mathbf{x}_0 - f_\theta(\mathbf{x}_t, s, t)\|_2^2\right] \tag{9}$$

In order to minimize the discrepancy caused by the exponential decay in the forward process, with this training objective, we divide the training process into two stages.

3.1.1. *First training stage*

The first stage enables DDTSE to progressively learn to extract the target speech from the conditioned target speaker embedding. Algorithm 1 shows that at each step of this stage, $\mathbf{x}_t$ is obtained through the forward process defined in Eq.4, and then the model predicts clean speech $\hat{\mathbf{x}}_{0t}$. We denote $\hat{\mathbf{x}}_{0t}$ as the predicted clean speech at the tth timestep. μ, σ are defined in Eq.2 and Eq.3, respectively. We incorporate $\lambda(t) > 0$ to control the weight of loss at different timesteps [29, 30]. d measures L2 distance.

3.1.2. *Second training stage*

Similar to conventional diffusion models [18], when comparing the first training stage (Algorithm 1) with the inference process (Algorithm 3, to be explained later), we observe two key differences. The first is the discrepancy between the terminating distribution of the forward process, which is p_T shown in Fig.1a, and the prior used for inference, which is the distribution of $p(y)$ in Fig.1d. Secondly, as indicated in blue, the substitution of the real value $\mathbf{x}_0$ with the predicted version $\hat{\mathbf{x}}_{0t+1}$ also causes mismatch.

Hence, we design the second training stage, shown in Algorithm 2, to imitate the inference process during training. This stage incorporates three strategies. Strategy A simulates the first step prediction from $\mathbf{x}_T = \mathcal{N}(\mathbf{y}, \sigma(t)^2)$ to $\hat{\mathbf{x}}_{0T}$, which ameliorates the first discrepancy. Strategy B further emulates the second step prediction, as described in Algorithm 3, making our model not only rely on real but also on predicted values at each reverse step. The probabilities, p_1 and p_2, of employing these two strategies are increased linearly with the progression of training epochs, as defined by Eq.10. Strategy C maintains consistency with the first training stage but gradually reduces its probability of sampling.

$$p_1 = p_2 = \min(0.45, \frac{\text{current training epoch}}{100}) \tag{10}$$

3.2. Inference Method

We hope that our model can not only independently realize the TSE task but also enhance the speech quality beyond the existing TSE model, so we propose two usage modes for inference.

Algorithm 1 First Training Stage

```
repeat
    Sample $\mathbf{x}_0, \mathbf{y}, t \sim \mathcal{U}[0,1], \mathbf{z} \sim \mathcal{N}(0, \mathbf{I})$
    Update $\mathbf{x}_t \leftarrow \mu(\mathbf{x}_0, \mathbf{y}, t) + \sigma(t)^2\mathbf{z}$
    Update $\hat{\mathbf{x}}_{0t} \leftarrow f_\theta(\mathbf{x}_t, s, t), \lambda(t) \leftarrow (e^t - 1)^{-1}$
    Take gradient descent step on $\nabla_\theta(\lambda(t)d(\hat{\mathbf{x}}_{0t}, \mathbf{x}_0))$
until converged
```

Algorithm 2 Second Training Stage

```
repeat
    Sample $\mathbf{x}_0, \mathbf{y}, t \sim \mathcal{U}[0,1], \mathbf{z} \sim \mathcal{N}(0, \mathbf{I}), p \sim \mathcal{U}[0,1]$
    if $p < p_1$ then
        # Strategy A
        Sample $\mathbf{x}_t \sim \mathcal{N}(\mathbf{y}, \sigma(t)^2)$
        Update $\hat{\mathbf{x}}_{0t} \leftarrow f_\theta(\mathbf{x}_t, s, t)$, $\lambda(t) \leftarrow (e^t - 1)^{-1}$
    else if $p_1 \le p < p_1 + p_2$ then
        # Strategy B
        Sample $\mathbf{x}_t \sim \mathcal{N}(\mathbf{y}, \sigma(t)^2)$
        Update $\hat{\mathbf{x}}_{0t}' \leftarrow f_\theta(\mathbf{x}_t, s, t), \mathbf{x}_t' \leftarrow \mu(\hat{\mathbf{x}}_{0t}', \mathbf{y}, t) + \sigma(t)^2\mathbf{z}$
        Update $\hat{\mathbf{x}}_{0t} \leftarrow f_\theta(\mathbf{x}_t', s, t)$, $\lambda(t) \leftarrow (e^t - 1)^{-1}$
    else
        # Strategy C
        Update $\mathbf{x}_t \leftarrow \mu(\mathbf{x}_0, \mathbf{y}, t) + \sigma(t)^2\mathbf{z}$
        Update $\hat{\mathbf{x}}_{0t} \leftarrow f_\theta(\mathbf{x}_t, s, t), \lambda(t) \leftarrow (e^t - 1)^{-1}$
    end if
    Take gradient descent step on $\nabla_\theta(\lambda(t)d(\hat{\mathbf{x}}_{0t}, \mathbf{x}_0))$
until converged
```

3.2.1. *DDTSE-only*

This mode functions as an end-to-end TSE model, delivering high-quality TSE independently. It combines the one-step prediction of the discriminative model and the randomness of the diffusion model. The inference usage mode of DDTSE-only is illustrated in Algorithm 3 and Figure 1d.

We start by sampling $\mathbf{x}_T$ from a normal distribution centered on $\mathbf{y}$, and predict target sample $\hat{\mathbf{x}}_{0T}$. The first step is similar to the one-step generation of discriminative method, and will give a coarse prediction of the clean speech. We believe that this prediction is close to the target clean speech, but it is missing in detail.

In order to continue rectifying this coarse prediction, similar to training, we introduce the forward process of the diffusion model into the DDTSE inference stage and let the model predict a more accurate target speech than the previous step. At each step, we perform the forward process to add random noise to the prediction results of the previous step $\hat{\mathbf{x}}_{0t+1}$ conditioned on $\mathbf{y}$. This simulated forward process and the sample after adding noise $\mathbf{x}_t$ are indicated by dashed gray lines and dotted circles in Figure 1d. Then we predict the clean target sample $\hat{\mathbf{x}}_{0t}$ from the sample with noise $\mathbf{x}_t$, as shown in the solid gray lines. This procedure repeats T times. Finally, the clean speech is obtained by performing iSTFT on $\hat{\mathbf{x}}_{00}$.

3.2.2. *X+DDTSE*

Based on an existing discriminative TSE model (denoted as X), X+DDTSE can achieve higher system performance and speech quality by rectifying the discriminative model's output $\mathbf{x}_{dis}$. Unlike DDTSE-only mode, X+DDTSE substitutes the first step prediction $\hat{\mathbf{x}}_{0T}$ in Algorithm 3 with $\mathbf{x}_{dis}$ in Algorithm 4 and conducts the final N steps. Since the X's prediction is quite accurate, the

Algorithm 3 Inference for DDTSE-only

```
Sample $\mathbf{x}_T \sim \mathcal{N}(\mathbf{y}, \sigma(T)^2)$
Update $\hat{\mathbf{x}}_{0T} = f_\theta(\mathbf{x}_T, s, T)$
for $t = T-1, ..., 0$ do
    Sample $\mathbf{z} \sim \mathcal{N}(0, \mathbf{I})$
    Update $\mathbf{x}_t \leftarrow \mu(\hat{\mathbf{x}}_{0t+1}, \mathbf{y}, t) + \sigma(t)^2\mathbf{z}$
    Update $\hat{\mathbf{x}}_{0t} \leftarrow f_\theta(\mathbf{x}_t, s, t)$
end for
return iSTFT$(\hat{\mathbf{x}}_{00})$
```

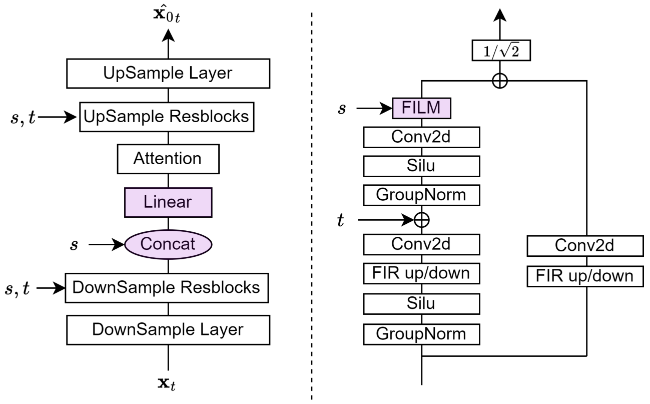


Fig. 2. The overall architecture of DDTSE. Left: The model architecture. Right: The (up/down sample) residual block in this model.

hyper-parameter N is set to a small number, with the corresponding timesteps t close to 0, in order to avoid introducing much interference in Eq.2. Due to the few steps required, X+DDTSE serves as an efficient speech quality optimizer that can be applied to various discriminative models. Moreover, different from previous work [11], X+DDTSE mode can be directly applied without any fine-tuning for model X, and the required inference steps is reduced from 50 to 2.

Algorithm 4 Inference for X+DDTSE

```
$\hat{\mathbf{x}}_{0T-N+1} = \mathbf{x}_{dis}$
for $t = T-N, ..., 0$ do
    Sample $\mathbf{z} \sim \mathcal{N}(0, \mathbf{I})$
    Update $\mathbf{x}_t \leftarrow \mu(\hat{\mathbf{x}}_{0t+1}, \mathbf{y}, t) + \sigma(t)^2\mathbf{z}$
    Update $\hat{\mathbf{x}}_{0t} \leftarrow f_\theta(\mathbf{x}_t, s, t)$
end for
return iSTFT$(\hat{\mathbf{x}}_{00})$
```

3.2.3. *Inference with ensemble*

We repeat the inference process ten times with different random seeds to get various speech signals, and then sum and normalize to get the final waveform, similar to DiffTSE [17]. This strategy leverages randomness and diversity, leading to a more accurate final waveform, as averaging these outputs can reduce anomalies.

3.3. Model architecture

Fig.2 depicts the simplified DDTSE model architecture denoted as f_θ in previous sections. It uses a modified NCSN++ network [23] as the backbone, with modified blocks indicated in purple. The model takes speech STFT spectrogram $\mathbf{x}_t$ and a speaker embedding s extracted from a pre-trained speaker verification model as input. The model operates on both real and imaginary parts of the complex spectrogram. We utilize the SiLU activation function [31]. We modify its residual block, incorporating the FiLM mechanism of a single linear layer to perceive the target speaker embedding s [32]. We also concatenate s with the hidden feature within the U-Net, positioned before the self-attention layer to enhance the feature fusion ability.

Table 1. Experimental setup for baselines and our model in standalone usage mode. We abbreviate score estimation loss as S, and clean speech reconstruction loss as R.

Scenario	Model	Objective	Noise	Steps
Multi Speaker Baseline	NCSN++ [23]	R	No	1
	DPCCN [8]	R	No	1
	DiffTSE [17]	S	Yes	30
	DiffSep [33]+SV[34]	S	Yes	30
Single Speaker Baseline	DCCRN [35]	R	No	1
	SGMSE+ [7]	S	Yes	30
	WGSL [27]	S+R	Yes	30
Ours	DDTSE	R	Yes	10

4. EXPERIMENTAL SETUP

Data: We train and evaluate our system on Libri2Mix 16kHz dataset[2] [36], which is derived from LibriSpeech signals [37] and WHAM noise [38]. The `train-360` set is used for training, with `mix_both` subset to train multi-speaker model, and `mix_single` subset to train single-speaker model. For evaluation, the multi-speaker noisy, multi-speaker clean, single-speaker clean scenarios are `mix_both`, `mix_clean` and `mix_single` test set respectively. The enrollment speech during inference is another speech of the target speaker differing from the target speech. All data are transformed into STFT representation with coefficients in [7].

Baselines: Table 1 illustrates the model configuration of our proposed DDTSE and the baseline models. In the multi-speaker scenario, we benchmark DDTSE against four baselines: NCSN++, DPCCN, DiffTSE and DiffSep+SV. We train a discriminative model NCSN++ [23], applying the same architecture as DDTSE. We reproduce DPCCN[3] [8], a widely used discriminative TSE model. We reproduce DiffSep[4] [33], a score-based speech separation model, and cascade a speaker verification model [34] after DiffSep for TSE. DiffTSE is a score-based diffusion model for TSE, but it is not accessible for independent reproduction. Our comparative analysis is based on the results reported in the original paper [17]. In single speaker scenario, we benchmark against four reproduced baselines: NCSN++, DCCRN[5] [35] , SGMSE+[6] [7], WGSL [27]. DCCRN is a conventional discriminative method, while the latter two are the latest score-based diffusion methods for speech enhancement. We re-implement WGSL by ourselves. All the speaker embedding extractor mentioned in this paper is a ResNet34 speaker verification model pre-trained on VoxCeleb2[7] [34]. The main distinction be-

[2] https://github.com/JorisCos/LibriMix
[3] https://github.com/jyhan03/dpccn
[4] https://github.com/fakufaku/diffusion-separation
[5] https://github.com/asteroid-team/asteroid
[6] https://github.com/sp-uhh/sgmse
[7] https://github.com/wenet-e2e/wespeaker

Table 2. Performance comparison in multi-speaker noisy and clean scenarios. DDTSE and NCSN++ have the same model architecture. All metrics are the higher the better.

Model	Multi-Speaker Noisy Scenario						Multi-Speaker Clean Scenario					
	PESQ	ESTOI	SI-SDR	OVRL	DNSMOS	SIM	PESQ	ESTOI	SI-SDR	OVRL	DNSMOS	SIM
Mixture	1.08	0.40	-2.0	1.63	2.71	0.46	1.15	0.54	0.0	2.65	3.41	0.54
DiffTSE[1]	/	/	/	/	/	/	/	0.76	9.5	/	/	/
DiffSep+SV	1.32	0.60	4.8	2.78	3.63	0.62	**1.85**	**0.79**	9.6	3.14	**3.83**	**0.83**
DDTSE-only	**1.60**	**0.71**	**7.6**	**3.28**	**3.74**	**0.71**	1.79	0.78	**9.9**	**3.30**	3.79	0.73
DPCCN	1.74	0.73	9.3	2.93	3.58	0.69	2.22	0.83	13.1	3.05	3.73	0.82
+DDTSE	1.88	0.75	9.7	3.19	3.80	0.76	2.27	0.85	13.3	3.29	3.91	0.82
NCSN++	1.55	0.73	9.7	3.15	3.68	0.69	2.24	0.86	13.8	3.28	3.86	0.85
+DDTSE	1.75	0.77	10.1	3.24	3.79	0.76	2.32	0.87	13.9	3.32	3.92	0.85

[1] Results were reported in [17]

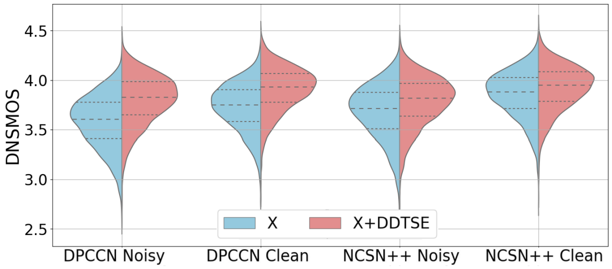


Fig. 3. Comparison of DNSMOS distribution between X+DDTSE and corresponding discriminative model (X) DPCCN and NCSN++ in noisy and clean scenarios. Values are the higher the better.

tween diffusion-based baseline models and proposed DDTSE lies in the training objectives, specifically score-based versus predicting clean data. Compared with discriminative approaches, DDTSE introduce random noise in both the training and inference stages, which brings more randomness and improves the perceptual quality of the generated samples.

Settings: Parameters defining the forward process in Eq. 1 is set to $\gamma = 1.5, \sigma_{min} = 0.05, \sigma_{max} = 0.5$. The STFT representation is processed following [12]. We use Adam optimizer and exponential moving average with a decay of 0.999. We use 8 NVIDIA TESLA V100 32GB GPUs for training, with a batch size of 3 samples per GPU. Each sample has 512 STFT frames. We train the first stage with a learning rate of 1e-4 for 500 epochs and the second stage with a learning rate of 5e-5 for 12 epochs. DDTSE-only executes 10 inference steps with linearly decreased timesteps from 1 to 0. X+DDTSE performs the last 2 steps out of a total of 10. We select the best-performing model on 20 randomly chosen samples from the dev-set for evaluation.

Evaluation metrics: We evaluate the model performance with both intrusive and non-intrusive speech quality metrics, i.e. with or without clean reference signal [39]. Intrusive metrics include Perceptual Evaluation of Speech Quality (PESQ) [40], Extended Short-Time Objective Intelligibility (ESTOI) [41], Scale-invariant Signal-to-Distortion Ratio (SI-SDR) [42]. Non-intrusive metrics, such as OVRL and DNSMOS [43, 44], are used to assess speech quality without clean reference. We use a ResNet34 model pre-trained on VoxCeleb2 to extract speaker embedding for all experiments, and we calculate the cosine speaker similarity (SIM) between speaker embedding of the enhanced speech and the target speech [34]. All metrics are the higher the better.

5. RESULTS AND ANALYSIS

5.1. Performance in multi-speaker scenarios

Table 2 shows the performance of DDTSE against both discriminative and generative baselines in scenarios involving multiple speakers under both noisy and clean conditions.

In the multi-speaker noisy scenario, DDTSE-only outperforms DiffSep+SV on all the metrics. It also demonstrates superior performance on the metrics of OVRL and DNSMOS by comparing with discriminative models, i.e., DPCCN and NCSN++. Notably, the X+DDTSE mode exhibits the highest performance on all the metrics except OVRL. X+DDTSE also improves speaker similarity score (SIM), suggesting a more accurate preservation of individual speaker characteristics during extraction.

In the multi-speaker clean scenario, DDTSE-only surpasses the score-based DiffTSE on the metrics of ESTOI and SI-SDR. Remarkably, DDTSE-only model achieves this by only using a third of the reverse iteration steps, comparing the step number reported in [17]. This indicates significant enhancements in both signal quality and efficiency. However, it's observed that the SIM obtained by the DDTSE-only model is the lowest among all the TSE models. This could potentially suggest less discrimination on speaker characteristics when compared to other models, which we will further address in our subsequent work.

Fig.3 shows the DNSMOS score distributions of various models. We observe that when combined with DPCCN and NCSN++, both models exhibit further improvements in non-intrusive speech quality. Moreover, X+DDTSE mode consistently enhances the performance in both noisy and clean conditions. This suggests that the DDTSE model has potential as a plugin in speech enhancement and extraction tasks.

5.2. Performance in single-speaker scenario

Our proposed methods can be generalized to general speech enhancement task. In the single-speaker scenario, speech extraction can be performed without requiring additional enrollment speech. We directly extract speaker embedding s from noisy speech $\mathbf{y}$. This is made possible due to the noise robustness of the speaker extrac-

Table 3. Performance comparison for speech enhancement in single speaker scenario. All metrics are the higher the better.

Model	PESQ	ESTOI	SI-SDR	OVRL	DNSMOS
Noisy speech	1.16	0.56	3.5	1.75	2.63
NCSN++	1.85	0.82	**12.7**	3.11	3.59
SGMSE+	1.99	0.82	11.1	3.12	3.60
WGSL	1.86	0.79	10.8	3.08	3.50
DDTSE-only	**2.03**	**0.83**	12.6	**3.33**	**3.84**
DDTSE-only[2]	2.01	0.82	12.2	3.25	3.75
DCCRN	2.03	0.81	13.3	2.98	3.64
+DDTSE	2.24	0.83	13.7	3.15	3.77
+DDTSE[2]	2.20	0.83	13.7	3.18	3.80

[2] This model is trained on multi-speaker data

tor [34]. The performance comparison in the single-speaker scenario is presented in Table 3. It indicates that the DDTSE-only model outperforms all other diffusion and discriminative models on all metrics, with the exception of SI-SDR. However, SI-SDR is improved to its highest value when DCCRN is integrated into the X+DDTSE model. This further highlights the potential of DDTSE in enhancing performance when used in conjunction with other models. Furthermore, the DDTSE model trained on multi-speaker data achieves comparable performance as the model trained on single-speaker data, indicating the generalization and robustness of DDTSE model. We can also employ enrollment speech, as in multi-speaker scenarios, but this only results in a marginal performance gain.

Table 4. Ablation Study of DDTSE-only in multi-speaker noisy scenario. T1 and T2 are the first and second training stages. Ensem is the Inference with ensemble strategy.

#	T1	T2	Ensem	ESTOI	SI-SDR	OVRL	DNSMOS	SIM
S0	✓	✓	✓	0.71	7.6	3.28	3.74	0.71
S1	✓	✗	✓	0.69	6.8	3.21	3.67	0.70
S2	✓	✓	✗	0.69	6.7	3.34	3.82	0.71
S3	✓	✗	✗	0.67	5.7	3.28	3.73	0.70
S4	✗	✓	✗	0.66	6.1	3.27	3.79	0.61

5.3. Ablation study

Table 4 provides an analysis of the individual contributions from the first training stage (T1), the second training stage (T2) and the inference with ensemble strategy (Ensem). These results indicate that with the same total training epochs, by omitting T2 (S1) worsens all metrics, highlighting the necessity for the second training stage. S2 shows that Ensem improves intrusive metrics but slightly reduces non-intrusive quality, suggesting that averaging speech with diversity may introduce undesired distortion. Only training with T1 or T2, as shown by S3 and S4, results in a performance decrease on intrusive metrics. Only training with T2 (S4) also causes speaker similarity degradation.

Moreover, we experimentally find that T2 cannot be trained for too many epochs. Strategy A, introduced in Section 3.1.2, provides one-step coarse prediction of the clean speech at the initial timestep, but it is not precise in detail. Strategy B integrates this prediction into diffusion forward process and deduces a more accurate result. If these strategies are over-presented as training time increases, the resulting estimation errors will lead to sub-optimal performance [15, 45]. Consequently, we limit the training of the second stage to only 12 epochs, as outlined in Section 4.

Table 5. Comparison with varying inference steps of DDTSE-only and X+DDTSE modes in multi-speaker noisy scenario.

Model	Steps	RTF	ESTOI	SI-SDR	OVRL	DNSMOS	SIM
DDTSE only	1	0.093	0.45	0.9	2.77	3.09	0.44
	5	0.273	0.64	4.9	3.20	3.59	0.66
	10	0.501	0.67	5.7	3.28	3.73	0.70
	15	0.728	0.68	5.9	3.29	3.78	0.71
	20	0.954	0.68	5.9	3.28	3.80	0.71
	30	1.415	0.67	5.6	3.24	3.81	0.71
X+ DDTSE	1	0.093	0.73	9.4	3.01	3.65	0.71
	2	0.139	0.75	9.4	3.18	3.81	0.76
	3	0.183	0.75	9.4	3.26	3.84	0.76
	4	0.234	0.76	9.2	3.29	3.83	0.75

5.4. Inference speed

Table 5 presents the Real-Time-Factor (RTF), speech quality, and speaker similarity of the generated speech across various inference steps. The RTF=$\frac{\text{processing time}}{\text{speech duration}}$ is measured on a single V100 and serves as an efficiency indicator. We notice that the performance improvements of the DDTSE-only along with the increasing number of steps tend to plateau beyond 10 steps. Furthermore, in the X+DDTSE mode, where X means DPCCN, we can achieve robust performance from as few as 2 steps, showcasing rapid processing without sacrificing quality and further eliminating the constraints of slow processing speeds of diffusion models. Utilizing our proposed DDTSE inference algorithm, we achieve significant reductions in the number of inference steps. According to the steps reported in [12] and [11], our approaches decrease the steps from 30 to 10 for the DDTSE-only mode, and from 50 to 2 for the X+DDTSE mode, respectively.

6. CONCLUSION

We present DDTSE, which combines discriminative training objective and diffusion forward process, designed for target speech extraction and enhancement in multi-speaker and single-speaker scenarios under both noisy and clean conditions. Experimental results demonstrate its effectiveness and efficiency, both as a standalone model and as an additional rectified model. In the next steps, we will further investigate its potential in other speech generation tasks.

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8. REFERENCES

[1] Adelbert W Bronkhorst, "The cocktail party phenomenon: A review of research on speech intelligibility in multiple-talker conditions," *Acta Acustica united with Acustica*, vol. 86, no. 1, pp. 117–128, 2000.

[2] Katerina Zmolikova, Marc Delcroix, Tsubasa Ochiai, Keisuke Kinoshita, Jan Černockỳ, and Dong Yu, "Neural target speech extraction: An overview," *IEEE Signal Processing Magazine*, vol. 40, no. 3, pp. 8–29, 2023.

[3] Yan-min Qian, Chao Weng, Xuan-kai Chang, Shuai Wang, and Dong Yu, "Past review, current progress, and challenges ahead on the cocktail party problem," *Frontiers of Information Technology & Electronic Engineering*, vol. 19, pp. 40–63, 2018.

[4] Marc Delcroix, Katerina Zmolikova, Keisuke Kinoshita, Atsunori Ogawa, and Tomohiro Nakatani, "Single channel target speaker extraction and recognition with speaker beam," in *ICASSP*. IEEE, 2018, pp. 5554–5558.

[5] Leying Zhang, Zhengyang Chen, and Yanmin Qian, "Enroll-aware attentive statistics pooling for target speaker verification," 2022, pp. 311–315.

[6] Quan Wang, Hannah Muckenhirn, Kevin Wilson, Prashant Sridhar, Zelin Wu, John Hershey, Rif A Saurous, Ron J Weiss, Ye Jia, and Ignacio Lopez Moreno, "Voicefilter: Targeted voice separation by speaker-conditioned spectrogram masking," in *Proc. INTERSPEECH 2019*, 2019.

[7] Jean-Marie Lemercier, Julius Richter, Simon Welker, and Timo Gerkmann, "Analysing diffusion-based generative approaches versus discriminative approaches for speech restoration," in *ICASSP*. IEEE, 2023, pp. 1–5.

[8] Jiangyu Han, Yanhua Long, Lukáš Burget, and Jan Černockỳ, "Dpccn: Densely-connected pyramid complex convolutional network for robust speech separation and extraction," in *ICASSP*. IEEE, 2022, pp. 7292–7296.

[9] Chenglin Xu, Wei Rao, Eng Siong Chng, and Haizhou Li, "Spex: Multi-scale time domain speaker extraction network," *IEEE/ACM transactions on audio, speech, and language processing*, vol. 28, pp. 1370–1384, 2020.

[10] Kateřina Žmolíková, Marc Delcroix, Keisuke Kinoshita, Tsubasa Ochiai, Tomohiro Nakatani, Lukáš Burget, and Jan Černockỳ, "Speakerbeam: Speaker aware neural network for target speaker extraction in speech mixtures," *IEEE Journal of Selected Topics in Signal Processing*, vol. 13, no. 4, pp. 800–814, 2019.

[11] Jean-Marie Lemercier, Julius Richter, Simon Welker, and Timo Gerkmann, "Storm: A diffusion-based stochastic regeneration model for speech enhancement and dereverberation," *IEEE/ACM Transactions on Audio, Speech, and Language Processing*, 2023.

[12] Julius Richter, Simon Welker, Jean-Marie Lemercier, Bunlong Lay, and Timo Gerkmann, "Speech enhancement and dereverberation with diffusion-based generative models," *IEEE/ACM Transactions on Audio, Speech, and Language Processing*, 2023.

[13] Linfeng Yu, Wangyou Zhang, Chenpeng Du, Leying Zhang, Zheng Liang, and Yanmin Qian, "Generation-based target speech extraction with speech discretization and vocoder," in *ICASSP*. IEEE, 2024, pp. 12612–12616.

[14] Huy Phan, Ian V McLoughlin, Lam Pham, Oliver Y Chén, Philipp Koch, Maarten De Vos, and Alfred Mertins, "Improving gans for speech enhancement," *IEEE Signal Processing Letters*, vol. 27, pp. 1700–1704, 2020.

[15] Wenxin Tai, Yue Lei, Fan Zhou, Goce Trajcevski, and Ting Zhong, "Dose: Diffusion dropout with adaptive prior for speech enhancement," *Advances in Neural Information Processing Systems*, vol. 36, 2024.

[16] Simon Welker, Julius Richter, and Timo Gerkmann, "Speech enhancement with score-based generative models in the complex stft domain," in *Proc. Interspeech 2022*, pp. 2928–2932.

[17] Naoyuki Kamo, Marc Delcroix, and Tomohiro Nakatan, "Target speech extraction with conditional diffusion model," *arXiv preprint arXiv:2308.03987*, 2023.

[18] Bunlong Lay, Simon Welker, Julius Richter, and Timo Gerkmann, "Reducing the prior mismatch of stochastic differential equations for diffusion-based speech enhancement," 2023.

[19] Hao Yen, François G Germain, Gordon Wichern, and Jonathan Le Roux, "Cold diffusion for speech enhancement," in *ICASSP*. IEEE, 2023, pp. 1–5.

[20] Theodor Nguyen, Guangzhi Sun, Xianrui Zheng, Chao Zhang, and Philip C Woodland, "Conditional diffusion model for target speaker extraction," *arXiv preprint arXiv:2310.04791*, 2023.

[21] Simo Särkkä and Arno Solin, *Applied stochastic differential equations*, vol. 10, Cambridge University Press, 2019.

[22] Brian DO Anderson, "Reverse-time diffusion equation models," *Stochastic Processes and their Applications*, vol. 12, no. 3, pp. 313–326, 1982.

[23] Yang Song, Jascha Sohl-Dickstein, Diederik P Kingma, Abhishek Kumar, Stefano Ermon, and Ben Poole, "Score-based generative modeling through stochastic differential equations," in *International Conference on Learning Representations*, 2021.

[24] Pascal Vincent, "A connection between score matching and denoising autoencoders," *Neural computation*, vol. 23, no. 7, pp. 1661–1674, 2011.

[25] Ryosuke Sawata, Naoki Murata, Yuhta Takida, Toshimitsu Uesaka, Takashi Shibuya, Shusuke Takahashi, and Yuki Mitsufuji, "A versatile diffusion-based generative refiner for speech enhancement," in *Proc. INTERSPEECH 2023*, 2023.

[26] Hao Shi, Kazuki Shimada, Masato Hirano, Takashi Shibuya, Yuichiro Koyama, Zhi Zhong, Shusuke Takahashi, Tatsuya Kawahara, and Yuki Mitsufuji, "Diffusion-based speech enhancement with joint generative and predictive decoders," in *ICASSP*. IEEE, 2024, pp. 12951–12955.

[27] Jean-Eudes Ayilo, Mostafa Sadeghi, and Romain Serizel, "Diffusion-based speech enhancement with a weighted generative-supervised learning loss," in *ICASSP*. IEEE, 2024, pp. 12506–12510.

[28] Bunlong Lay, Jean-Marie Lermercier, Julius Richter, and Timo Gerkmann, "Single and few-step diffusion for generative speech enhancement," in *ICASSP*. IEEE, 2024, pp. 626–630.

[29] Jonathan Ho, Ajay Jain, and Pieter Abbeel, "Denoising diffusion probabilistic models," *Advances in neural information processing systems*, vol. 33, pp. 6840–6851, 2020.

[30] Yibin Lu, Zhongjian Wang, and Guillaume Bal, "Understanding the diffusion models by conditional expectations," *arXiv preprint arXiv:2301.07882*, 2023.

[31] Stefan Elfwing, Eiji Uchibe, and Kenji Doya, "Sigmoid-weighted linear units for neural network function approximation in reinforcement learning," *Neural networks*, vol. 107, pp. 3–11, 2018.

[32] Ethan Perez, Florian Strub, Harm De Vries, Vincent Dumoulin, and Aaron Courville, "Film: Visual reasoning with a general conditioning layer," in *Proceedings of the AAAI conference on artificial intelligence*, 2018, vol. 32.

[33] Robin Scheibler, Youna Ji, Soo-Whan Chung, Jaeuk Byun, Soyeon Choe, and Min-Seok Choi, "Diffusion-based generative speech source separation," in *ICASSP*. IEEE, 2023, pp. 1–5.

[34] Hongji Wang, Chengdong Liang, Shuai Wang, Zhengyang Chen, Binbin Zhang, Xu Xiang, Yanlei Deng, and Yanmin Qian, "Wespeaker: A research and production oriented speaker embedding learning toolkit," in *ICASSP*. IEEE, 2023, pp. 1–5.

[35] Yanxin Hu, Yun Liu, Shubo Lv, Mengtao Xing, Shimin Zhang, Yihui Fu, Jian Wu, Bihong Zhang, and Lei Xie, "Dccrn: Deep complex convolution recurrent network for phase-aware speech enhancement," in *Proc. INTERSPEECH 2020*, 2020.

[36] Joris Cosentino, Manuel Pariente, Samuele Cornell, Antoine Deleforge, and Emmanuel Vincent, "Librimix: An open-source dataset for generalizable speech separation," *arXiv preprint arXiv:2005.11262*, 2020.

[37] Vassil Panayotov, Guoguo Chen, Daniel Povey, and Sanjeev Khudanpur, "Librispeech: an asr corpus based on public domain audio books," in *2015 IEEE international conference on acoustics, speech and signal processing (ICASSP)*. IEEE, 2015, pp. 5206–5210.

[38] Gordon Wichern, Joe Antognini, Michael Flynn, Licheng Richard Zhu, Emmett McQuinn, Dwight Crow, Ethan Manilow, and Jonathan Le Roux, "Wham!: Extending speech separation to noisy environments," in *Proc. INTERSPEECH 2019*, 2019.

[39] Hannes Gamper, Chandan KA Reddy, Ross Cutler, Ivan J Tashev, and Johannes Gehrke, "Intrusive and non-intrusive perceptual speech quality assessment using a convolutional neural network," in *2019 IEEE Workshop on Applications of Signal Processing to Audio and Acoustics*. IEEE, 2019, pp. 85–89.

[40] Antony W Rix, John G Beerends, Michael P Hollier, and Andries P Hekstra, "Perceptual evaluation of speech quality (pesq)-a new method for speech quality assessment of telephone networks and codecs," in *2001 International Conference on acoustics, speech, and signal processing. Proceedings (Cat. No. 01CH37221)*. IEEE, 2001, vol. 2, pp. 749–752.

[41] Jesper Jensen and Cees H Taal, "An algorithm for predicting the intelligibility of speech masked by modulated noise maskers," *IEEE/ACM Transactions on Audio, Speech, and Language Processing*, vol. 24, no. 11, pp. 2009–2022, 2016.

[42] Jonathan Le Roux, Scott Wisdom, Hakan Erdogan, and John R Hershey, "Sdr–half-baked or well done?," in *ICASSP*. IEEE, 2019, pp. 626–630.

[43] Chandan KA Reddy, Vishak Gopal, and Ross Cutler, "Dnsmos: A non-intrusive perceptual objective speech quality metric to evaluate noise suppressors," in *ICASSP*. IEEE, 2021, pp. 6493–6497.

[44] Chandan KA Reddy, Vishak Gopal, and Ross Cutler, "Dnsmos p. 835: A non-intrusive perceptual objective speech quality metric to evaluate noise suppressors," in *ICASSP*. IEEE, 2022, pp. 886–890.

[45] Rongjie Huang, Zhou Zhao, Huadai Liu, Jinglin Liu, Chenye Cui, and Yi Ren, "Prodiff: Progressive fast diffusion model for high-quality text-to-speech," in *Proceedings of the 30th ACM International Conference on Multimedia*, 2022, pp. 2595–2605.