SRTNET: TIME DOMAIN SPEECH ENHANCEMENT VIA STOCHASTIC REFINEMENT

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ABSTRACT

Diffusion model, as a new generative model which is very popular in image generation and audio synthesis, is rarely used in speech enhancement. In this paper, we use the diffusion model as a module for stochastic refinement. We propose SRTNet, a novel method for speech enhancement via stochastic refinement in complete time domain. Specifically, we design a joint network consisting of a deterministic module and a stochastic module, which makes up the “enhance-and-refine” paradigm. We theoretically demonstrate the feasibility of our method and experimentally prove that our method achieves faster training, faster sampling and higher quality. Our code is available at https://github.com/zhibinQiu/SRTNet.git

Index Terms— speech enhancement, time domain, diffusion model, enhance-and-refine, joint training

1. INTRODUCTION

Speech enhancement (SE) using generative models has great potential. Typical generative methods for SE are GAN-based methods [1, 2, 3, 4, 5, 6, 7], flow-based methods [8, 9] and VAE-based methods [10, 11, 12, 13, 14, 15]. Diffusion model is another generative model which is very popular recently [16, 17]. However, it is rarely used for speech enhancement. The SE methods in time domain not only avoid the distortions caused by inaccurate phase information [18], but also avoid the extra overhead of computing the T-F representation. [19] proposed a method for SE in time domain using the diffusion model, but it relies on the speech spectrogram of noisy, so it is not a complete time-domain method. Moreover, in [19], the diffusion model directly estimates the distribution of clean speech by optimizing the evidence lower bound (ELBO), which puts a large computational overhead on the diffusion model and leads to a lot of time consumption during the training phase. [20], a method of image deblurring, proposed the predict-and-refine approach to reduce the computational pressure of the diffusion model while guaranteeing the quality of the image generation. Inspired by this, a joint network paradigm is designed, namely “enhance-and-refine” which is comprised of two sub-modules, deterministic module and stochastic module, respectively. The two modules are connected by the residual structure, and the noisy speech is initially enhanced after passing through the deterministic module. Afterward, the initial enhanced result passes through the residual structure and into the stochastic module for detailed refinement. We refer to the network consisting of these two modules as SRTNet. SRTNet allows the diffusion model to act as a stochastic module to learn the residual distribution instead of the distribution of data directly, which significantly reduces the computational overhead of the diffusion model. In addition, SRTNet is a network entirely in time domain and does not depend on any Fourier transform. Our main contributions are as follows:

• We innovatively apply the diffusion model as a stochastic refinement module for SE task and possess theoretical correctness.

• We introduce an “enhance-and-refine” paradigm and use a joint network to implement it, which results in faster convergence and better speech quality.

2. PROPOSED METHODS

Existing diffusion model based SE methods generally trained directly on the original speech. Motivated by [20], it is also reasonable for the SE task to learn the residual data. In the idea of “enhance-and-refine”, we add a deterministic module \( D_0 \) to the original conditional diffusion model. The block diagram of the overall structure is illustrated in Fig. 1. The noisy speech \( y \) is initially enhanced by \( D_0 \) and we call its output \( y_{\text{init}} \). Then the residual operations are enforced on the clean speech \( x \) and the noisy speech \( y \) with \( y_{\text{init}} \) and the residuals \( x_0, y_0 \) are fed to stochastic module \( S_0 \). Because the output of the noisy speech passing through \( D_0 \) during sampling is deterministic when the parameters are determined, we call the \( D_0 \) deterministic module. Whereas in \( S_0 \), we need to sample from Gaussian distribution in diffusion model, which could produce different outputs, so we call the \( S_0 \) stochastic module.
2.1. Diffusion and Reverse process of SRTNet

Diffusion. The diffusion process takes $y_0$ as a condition, and the noise in diffusion process contains not only Gaussian noise but also non-Gaussian noise in $y_0$ which is the residual of $y$ and $y_{init}$. The conditional diffusion process $q(x_t|x_0, y_0)$ is defined as:

$$q(x_t|x_0, y_0) = N(x_t; (1 - m_t)\sqrt{\alpha_t} x_0 + m_t \sqrt{\alpha_t y_0}, \delta_t I),$$  

where $\alpha_t = \prod_{i=1}^t \alpha_i$, the noise schedule. $\alpha_i$ is defined as:

$$\alpha_i = (1 - \bar{\alpha}_i) - m^2 \bar{\alpha}_i.$$  

Reverse. In the reverse process, we start from $x_T$, with the condition $y$ and the variance $\delta_T$:

$$p(x_T|y_0) = N(x_T; \sqrt{\alpha_T} y_0, \delta_T I).$$  

The reverse process also follows a Markov chain, so we can gradually obtain $x_0$ from $x_T$ by continuously executing the reverse process. The parameterised conditional reverse process $p_{\theta}(x_{t-1}|x_t, y_0)$ is denoted as:

$$N(x_{t-1}; c^x_t x_t + c^y_t y_0 + c^\epsilon_t \phi(x_t, y_0, t), \delta_t I).$$  

Note that the mean is parameterized as a linear combination of $x_t$, residual noisy speech $y_0$, and estimated noise $\phi$. The coefficients $c^x_t, c^y_t$ and $c^\epsilon_t$ are derived as follows:

$$c^x_t = \frac{1 - m_t}{1 - m_{t-1}} \delta_{t-1} \sqrt{\alpha_t} + (1 - m_{t-1}) \frac{\delta_t}{\delta_{t-1}} \frac{1}{\sqrt{\alpha_t}};$$

$$c^y_t = \frac{m_t(1 - m_{t-1})}{1 - m_{t-1}} \alpha_t \delta_{t-1} \frac{1}{\delta_t};$$

$$c^\epsilon_t = \frac{1 - m_t}{1 - m_{t-1}} \delta_{t-1} \frac{1}{\sqrt{\alpha_t}}.$$  

The variance $\delta_t$ in Eq. (5) can be derived from reverse diffusion process $p(x_{t-1}|x_t, x_0, y_0)$, and the detailed derivation is given in [19]:

$$\tilde{\delta}_t = \delta_{t-1} - \left(1 - \frac{m_t}{1 - m_{t-1}}\right)^2 \alpha_t \frac{\delta_{t-1}}{\delta_t}.$$  

2.2. Training and Sampling of SRTNet

Training. The training process of the SRTNet is described in Algorithm 1. During the training phase, all parameters of diffusion process will depend on the noise level $\bar{\alpha}$ which is obtained by hierarchical sampling rather than time steps used in [19]. Specifically, a segment $(l_{i-1}, l_i)$ is sampled from $s \sim U(\{1, \ldots, S\})$ where $S$ is the length of the noise level schedule. Then the noise level $\bar{\alpha}$ is obtained from this segment by sampling from the uniform distribution. The benefit of the diffusion model relying on the noise level in the training phase is that it allows us to sample with an arbitrary noise level schedule. The effectiveness of this approach is verified in [16]. Therefore, in Eq. (1), the interpolation ratio $m$ is denoted as:

$$m = (1 - \bar{\alpha})/\sqrt{\bar{\alpha}},$$  

and the variance $\delta$ is:

$$\delta = (1 - \bar{\alpha}) - m^2 \bar{\alpha}.$$  

Therefore, the expression of $x_t$ through reparameterizing the diffusion process Eq. (1) can be denoted as:

$$x_t = (1 - m) \sqrt{\alpha_t} x_0 + m \sqrt{\alpha_t y_0} + \sqrt{\delta} \epsilon.$$  

To optimize the ELBO, we can directly model the mean of reverse process Eq. (5). But in practice, we generally model the noise added at a certain noise level, which is an unweighted variant of ELBO [21]. The objective function is defined as:

$$\mathbb{E} \| \epsilon_* - \epsilon_\phi(x_t, y_0, \sqrt{\alpha_t}) \|^2_2,$$  

where $\epsilon_*$ is the noise from the combination of Gaussian noise $\epsilon$ and the noise in $y_0$:

$$\epsilon_* = \frac{m \sqrt{\alpha_t}}{1 - \alpha_t} (y_0 - x_0) + \frac{\sqrt{\delta}}{\sqrt{1 - \alpha_t}} \epsilon.$$  

Sampling. The sampling process of the SRTNet is described in Algorithm 2. Through training, our model is able to efficiently model the noise at different noise levels. The noisy speech $y$ is first fed into the deterministic model $D_{\theta}$ to obtain $y_{init}$. Unlike the training process, here we obtain the noise level from the noise level schedule rather than hierarchical sampling. By iterating over the noise level schedule, we can run the reverse process through the reverse Markov chain. Afterwards, we obtain the residual clean speech $x_0$. The final enhanced speech will be obtained by summing $x_0$ and $y_{init}$.

2.3. Structure of deterministic and stochastic module

The deterministic module and the stochastic module have a similar structure as in [22, 19]. Note that the conditioner and the noise level encoding here are only for the stochastic module. Moreover, we have made some other modifications to the structure. Unlike [22, 19], we have modified the structure with two main changes:

Firstly, we directly use the waveform of the noisy speech $y$ as the conditioner instead of spectrogram. As a result, a complete time-domain SE is achieved. Moreover, it is also experimentally found that our model can converge faster, the detail in Sec. 3.

Secondly, we replace the time step encoding with a noise level

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Algorithm 1 SRTNet Training.

```
repeat
    Sample (x, y)~qdata, \epsilon \sim N(0, I), s \sim \text{Uniform}\{1, \cdots, S\}, \text{and} \sqrt{\alpha} \sim \text{Uniform}(l_{i-1}, l_i)
    Get y_{init} through the deterministic module D_{\theta}, y_{init} = D_{\theta}(y)
    Get two Residual: x_0 = x - y_{init} and y_0 = y - y_{init}
    Get x_t according to Eq. (12)
    Take gradient descent step on
    \nabla_\theta \| \frac{\sqrt{\alpha_t}}{\sqrt{\alpha_t}} (m \sqrt{\alpha_t} (y_0 - x_0) + \sqrt{\delta} \epsilon) - \epsilon_\phi(x_t, y_0, \sqrt{\alpha_t}) \|_2^2
    until converged
```

Algorithm 2 SRTNet Sampling.

```
Get y_{init} through the deterministic module D_{\theta}, y_{init} = D_{\theta}(y)
Get Residual y_0 = y - y_{init}
Sample x_T \sim N(x_T; \sqrt{\alpha_T} y_0, \delta_T I),
for i = T, T-1, \cdots, 1 do
    Compute c^x_t, c^y_t and c^\epsilon_t using Eq. (6), (7), and (8)
    Sample x_{t-1} \sim p_{\theta}(x_{t-1}|x_t, y_0) =
    N(x_{t-1}; c^x_t x_t + c^y_t y_0 + c^\epsilon_t \phi(x_t, y_0, \sqrt{\alpha_t}), \delta_t I)
end for
return x_0 + y_{init}
```
encoding. But our encoding method differently from both in [17, 16], the encoding method can be expressed by:

\[ \sqrt{\alpha_{\text{encoding}}} = \sin \left(10^{-\frac{63}{10} \alpha_i} \sqrt{\alpha} \right), \ldots, \sin \left(10^{-\frac{63}{10} \alpha_{400k} \sqrt{\alpha}} \right), \]

\[ \cos \left(10^{-\frac{63}{10} \alpha_i} \sqrt{\alpha} \right), \ldots, \cos \left(10^{-\frac{63}{10} \alpha_{400k} \sqrt{\alpha}} \right). \] (15)

Through this, we can obtain different encoding results with different noise level conditions as part of the input to the diffusion model.

3. EXPERIMENTS

3.1. Experimental setup

3.1.1. Datasets

The VoiceBank-DEMAND corpus [23], which includes 30 speakers from different accent regions in the UK and the US, is selected to evaluate the proposed method, with 28 speakers selected for training and 2 others for testing. The training set consists of 11, 572 single channel speech samples, while the test set contains 824 utterances from 2 speakers (one male and one female). The signal-to-noise ratios (SNRs) of the training set are 0 dB, 5 dB, 10 dB, 15 dB. The test set mixes with five unseen test noise types (all from the DEMAND database [24]) selected at 2.5 dB, 7.5 dB, 12.5 dB, 17.5 dB. For the experiments, the original waveform is sub-sampled from 48 kHz to 16 kHz. CHiME-4 [25] is another dataset commonly used for SE tasks. The test set in CHiME-4 is synthesized from noises recorded from four real-life scenes and four speakers, and as in [19], we also take the signal from the fourth microphone to evaluate the generalization performance of our model.

3.1.2. Performance metrics

Four common SE evaluation metrics are used: perceptual evaluation of speech quality (PESQ) [26], background intrusiveness (CBAK), prediction of the signal distortion (CSIG), and overall speech quality (COVL) [27]. The PESQ score ranges from -0.5 to 4.5, and the rest of the metrics range from 1 to 5. Higher score means better speech enhancement performance.

3.1.3. Training and sampling

We train SRTNet 800k steps on two NVidia 3090 GPUs with Adam optimizer, learning rate is \(2 \times 10^{-4}\) and the batch size is set to 32. The inference noise level schedule is same to [19]. In order to recover the high frequency speech we combine the sampling results with the noisy speech with a ratio of 0.2 at the end of the reverse process [28, 29]. Moreover, to avoid randomness, we infer the results several times and take the average value as the final result. For other models, we follow the training setups as in the original papers.

3.2. Results

3.2.1. Results from generative models in matched condition

SRTNet and other recent generative models are trained on the VoiceBank-DEMAND dataset, and tested on the matched condition (training and testing on the same dataset). We can find that our method is the strongest generative model in Table 1. Compared to other generative methods, we further narrow the gap with the regression-based discriminative models. In addition, compared with our baseline [19], not only do we achieve better performance, but also greatly improve the convergence speed of the model. For example, when we train them 800k steps, the two models have almost converged. SRTNet consumes only one-fifth of the training time of [19] as shown in Fig. 2.

| Method                     | PESQ↑ | CSIG↑ | CBAK↑ | COVL↑ |
|----------------------------|-------|-------|-------|-------|
| Unprocessed                | 1.97  | 3.35  | 2.44  | 2.63  |
| SEGAN [1]                  | 2.16  | 3.48  | 2.94  | 2.80  |
| SASEGAN [6]                | 2.36  | 3.54  | 3.08  | 2.93  |
| DSEGAN [30]                | 2.39  | 3.46  | 3.11  | 2.90  |
| SE-Flow [9]                | 2.28  | 3.70  | 3.03  | 2.97  |
| DiffuSE [22]               | 2.41  | 3.61  | 2.81  | 2.99  |
| CDiffuSE [19](Base)        | 2.44  | 3.66  | 2.83  | 3.03  |
| CDiffuSE [19](Large)       | 2.52  | 3.72  | 2.91  | 3.10  |
| SRTNet (Ours)              | 2.69  | 4.12  | 3.19  | 3.39  |

3.2.2. Results on generalizability to mismatched condition

To verify that our model as a generative model has greater potential in generalizability than the discriminative model, we have done experiments on mismatched condition. The test set is obtained from CHiME-4 test set. Table 2 shows the results. The performance of the discriminative models degrade greatly and our model has a significant advantage. The main reason is that the generative methods learn information about the data distribution rather than a mapping relationship learned by reducing a certain distance such as \(L_p\) - loss. This feature allows SRTNet as a generative model to perform better.

| Method                     | PESQ↑ | CSIG↑ | CBAK↑ | COVL↑ |
|----------------------------|-------|-------|-------|-------|
| Unprocessed                | 1.27  | 2.61  | 1.93  | 1.88  |
| WaveCRN [31]               | 1.43(-1.20) | 2.53(-1.42) | 2.03(-1.03) | 1.91(-1.38) |
| Demucs [28]                | 1.38(-1.27) | 2.50(-1.49) | 2.08(-1.25) | 1.88(-1.44) |
| Conv-TasNet [32]           | 1.63(-1.21) | 1.70(-0.63) | 1.82(-0.80) | 1.54(-0.97) |
| CDiffuSE(Large) [19]       | 1.66(-0.86) | 2.98(-0.74) | 2.19(-0.72) | 2.27(-0.83) |
| SRTNet (Ours)              | 1.87(-0.82) | 3.37(-0.75) | 2.49(-0.70) | 2.67(-0.72) |

3.2.3. Speech waveform and spectrogram analysis

Fig. 3 illustrates the waveforms and spectrograms of SRTNet output at different phases. By observing the waveforms, we can find that
3.2.4. Ablation experiments

Here we carry out ablation tests to achieve deeper investigation into the contribution of each individual controlling factor. When the best PESQ is obtained, we record the corresponding time consumption of training and sampling. Table 3 demonstrates the experimental results. The first experiment replaces the conditioner noisy waveform with noisy spectrogram as in [19]. The enhanced speech quality reduces from 2.69 to 2.59, indicating the effectiveness of the time-domain conditioning. We also see significant fast convergence and sampling speed in this setup. This is partly due to the absence of Fourier transform, and partly due to the time of up-sampling the speech spectrogram within the diffusion model. The second experiment replaces the noise level with time step compare to Eq. (5) and the objective function expression is:

$$\mathbb{E} \left\| \epsilon_s - \epsilon_0(x_t, y_0, t) \right\|^2_2.$$

By the results we can find that using continuous noise level can effectively reduce the sampling time. The third experiment removes the deterministic module and we see a significant degradation of the enhanced speech quality, indicating the gain by “enhance-and-refine”. However, we also see the deterministic module increases the convergence time to some extent, because it adds an additional generation process. In summary, the deterministic module and time-domain conditioning contribute the most to the performance improvement.

Table 3. Ablation experiments. The PESQ and the relative convergence/sampling time as metrics for our experiments. The original SRTNet convergence and sampling time to 1.0.

| Method                        | PESQ(↑) | Convergence/Sampling time(↓) |
|-------------------------------|---------|-------------------------------|
| SRTNet                        | 2.69    | 1.0 / 1.0                     |
| - waveform conditioner        | 2.59    | 4.86 / 1.22                   |
| - continuous noisy level      | 2.63    | 1.34 / 3.66                   |
| - deterministic module        | 2.58    | 0.83 / 0.88                   |

4. CONCLUSION AND FUTURE DIRECTIONS

We propose SRTNet, a joint network for complete time domain speech enhancement. Our model achieves state-of-the-art performance for SE task in generative models while significantly reducing the time consumption of training. However, our model also has some limitations, which we will investigate in our next work. When the noise situation is more complex and the signal-to-noise ratio is extremely low, our model may appear to be under-exerted, i.e., the initial enhancement of the noise interference in the deterministic module is not very thorough, resulting in the stochastic module that does not recover the clean speech well.

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