Unsupervised Speech Enhancement with Diffusion-based Generative Models

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What is speech enhancement?

- In practice, speech is recorded in noisy environments $\rightarrow$ **speech enhancement** (SE)

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- Complex-valued short-time Fourier transform domain

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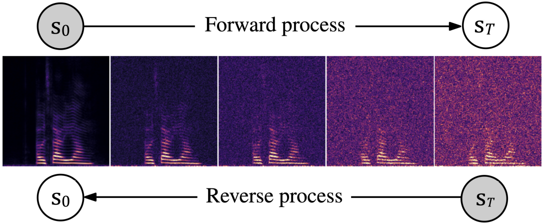
- Inference - Model $p_\phi(\mathbf{x}|\mathbf{s})$, and infer $\mathbf{s}$ using $p_\theta(\mathbf{s})$

☞ May offer superior generalization

Score-based generative models for SE

▷ **Previous (supervised) diffusion-based work: SMGSE+** [1]

- Gradually corrupt clean speech with both Gaussian and environmental noise



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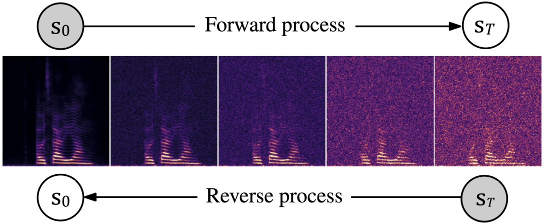

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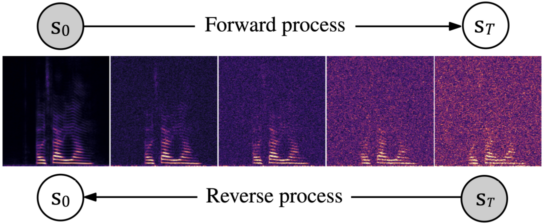

- Processes can be modelled as a *Stochastic Differential Equation (SDE)*

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Estimate clean speech **s** by directly sampling from the **intractable** posterior:

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$$p_\phi(\mathbf{x}|\mathbf{s}) = \mathcal{N}_\mathbb{C}\Big(\mathbf{s}, \mathrm{diag}(\mathbf{v}_\phi)\Big)$$

  - $\mathbf{v}_\phi = \mathrm{vec}(\mathbf{WH}) \leftarrow$ non-negative matrix factorisation (NMF)

Inference framework: Expectation-maximisation

- Iterative **Expectation Maximisation**-based inference $(k = 1, \ldots, K)$:

1. **E-step:** *Draw posterior sample*

$$\hat{\mathbf{s}}_k \sim p_{\Theta_{k-1}}(\mathbf{x}|\mathbf{s}) \quad \rightarrow \text{reverse diffusion}$$

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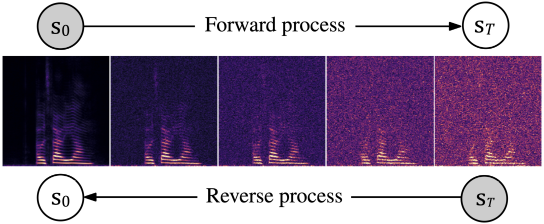
2. **M-step:** *Maximise likelihood*

$$\phi_k \leftarrow \underset{\phi}{\text{argmax}} \ \log p_{\phi}(\mathbf{x}|\hat{\mathbf{s}}_k) \quad \rightarrow \text{NMF update}$$

Prior: Diffusion-based speech generative model

▷ *Unconditional* (prior) diffusion model for complex-valued clean speech STFT:

- **Noising (forward) SDE:** [2] $\mathrm{d}\mathbf{s}_t = \mathbf{f}(\mathbf{s}_t)\mathrm{d}t + g(t)\mathrm{d}\mathbf{w}, \quad \mathbf{f}(\mathbf{s}_t) = -\gamma\mathbf{s}_t$



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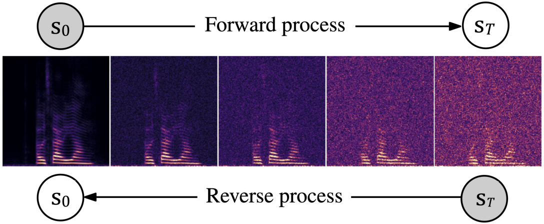

- **Denoising (reverse) SDE:** $\mathrm{d}\mathbf{s}_t = [\mathbf{f}(\mathbf{s}_t) - g(t)^2 \nabla_{\mathbf{s}_t} \log p_t(\mathbf{s}_t)]\mathrm{d}t + g(t)\mathrm{d}\mathbf{w}$

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Prior: Approximating the score

Knowing the score function enables sampling from the prior. Approximate it instead:

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1. Learn $\mathbf{S}_\theta(\mathbf{s}_t, t)$:

$$\theta^* = \operatorname*{argmin}_\theta \mathbb{E}_{t,\mathbf{s},\zeta,\mathbf{s}_t|\mathbf{s}} \left[\left\| \mathbf{S}_\theta(\mathbf{s}_t, t) + \frac{\zeta}{\sigma(t)} \right\|_2^2 \right], \quad \zeta \sim \mathcal{N}_\mathbb{C}(\mathbf{0}, \mathbf{I})$$

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2. Numerically sample from the prior $p_\theta(\mathbf{s})$

☞ The above SDE can be solved by the *Predictor-Corrector (PC) sampler*

SE phase as EM approach

Once the prior *score model* is trained, SE is performed via EM:

E-step: Approximate the conditional reverse SDE:

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

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⚠ *Intractable*, time-dependent likelihood!

Approximation by the *"noise-perturbed pseudo-likelihood score"*[3] $\nabla_{\mathbf{s}_t} \log \tilde{p}_\phi(\mathbf{x}|\mathbf{s}_t)$

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$$\tilde{p}_\phi(\mathbf{x}|\mathbf{s}_t) \sim \mathcal{N}_{\mathbb{C}}\left(\frac{\mathbf{s}_t}{\delta_t}, \frac{\sigma(t)^2}{\delta_t^2}\mathbf{I} + \mathrm{diag}(\boldsymbol{v}_\phi)\right), \qquad \delta_t = \mathrm{e}^{-\gamma t}$$

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- λ: weighting parameter to balance prior and likelihood terms.

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M-step:

$$\phi^* \leftarrow \underset{\mathbf{v}_\phi(i)\geq 0}{\operatorname{argmax}} \log p_\phi(\mathbf{x}|\hat{\mathbf{s}})$$

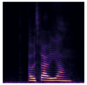
$$= \underset{\mathbf{v}_\phi(i)\geq 0}{\operatorname{argmin}} \sum_i \frac{(\mathbf{x}-\hat{\mathbf{s}})_i^*(\mathbf{x}-\hat{\mathbf{s}})_i}{\mathbf{v}_\phi(i)} + \log(\mathbf{v}_\phi(i))$$

UDiffSE pipeline

Pre-training		Posterior sampling		Output
$p_\theta(\mathbf{s})$	$\cdot$	$p_\phi(\mathbf{x}\|\mathbf{s})$	$\propto$	$p_\Theta(\mathbf{s}\|\mathbf{x})$

Clean speech estimate
(posterior sample)

$\hat{\mathbf{s}}$



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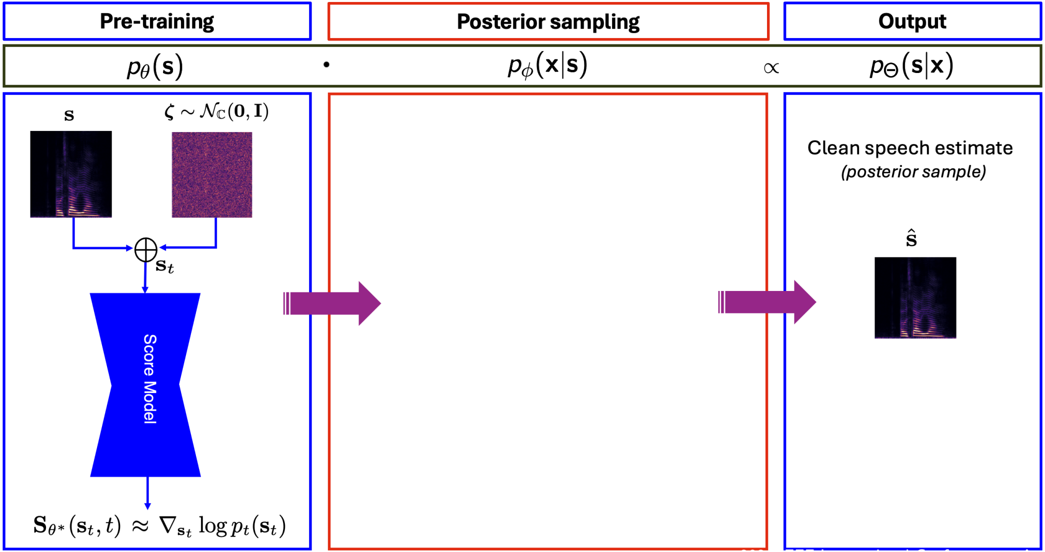

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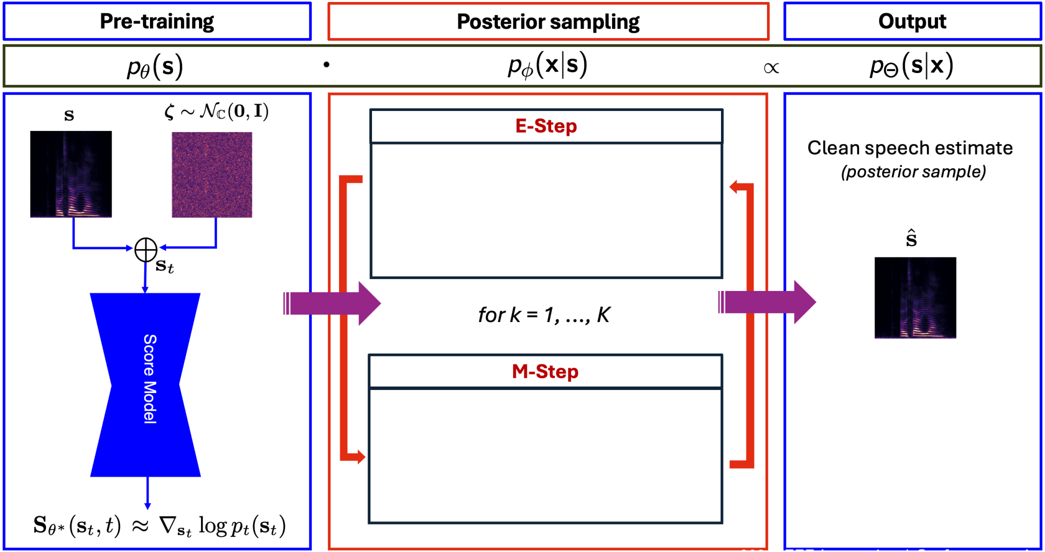

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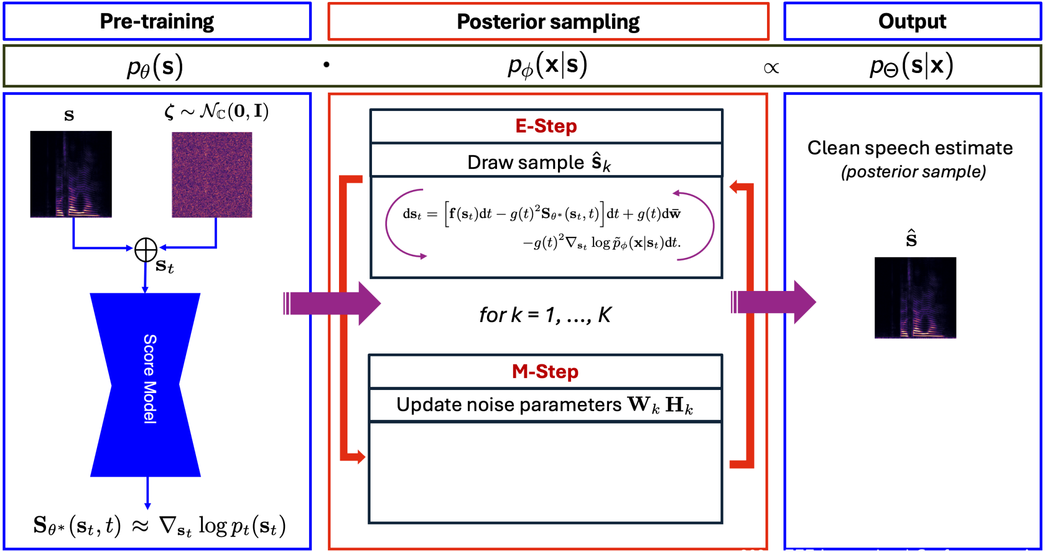

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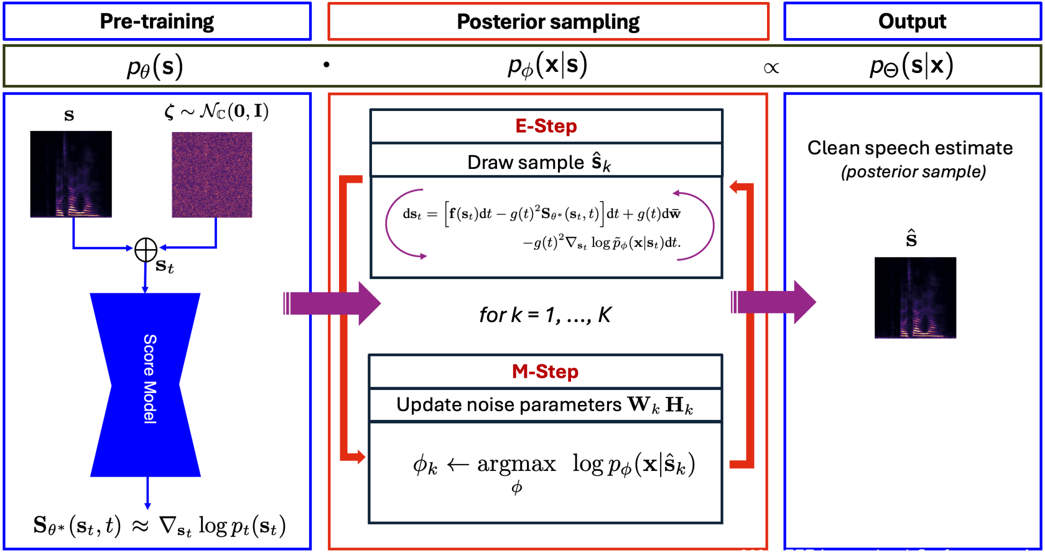
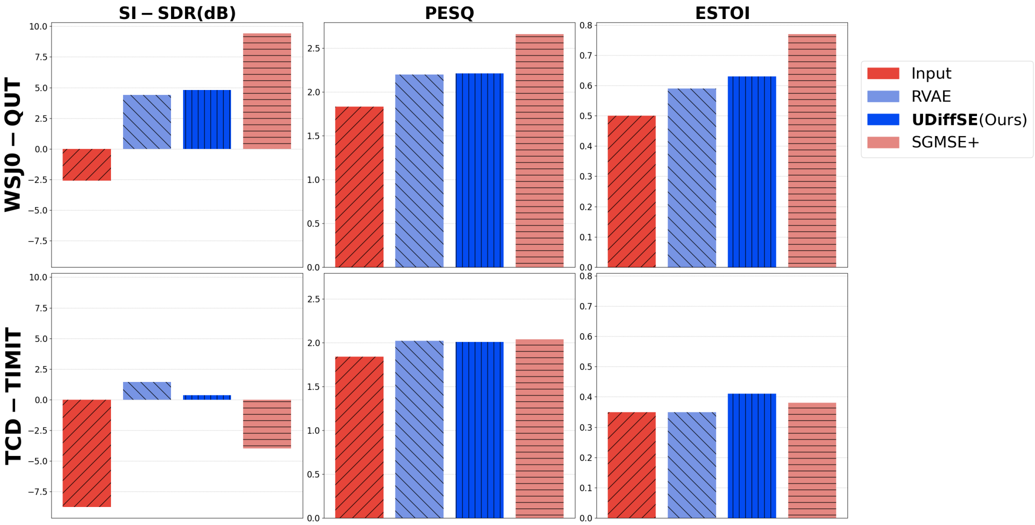


Experiments

- **Datasets**.
  - Training: WSJ0 ($\sim$ 25hrs)
  - Testing: WSJ0-QUT (1.5hrs), TCD-TIMIT (45mins)
  - Noise levels (dB): $[-5, 0, 5]$.
  - Noise types: *Café*, *Home*, *Street*, and *Car*
- **Evaluation Metrics**.
  - Objective measures: SI-SDR, ESTOI, PESQ
  - (Pseudo)-subjective measures: DNS-MOS (SIG, BAK, OVRL)
- **Baselines**. RVAE, SGMSE+ (pre-trained).
- **Models architecture**. Multi-resolution U-Net as in SGMSE+.
- **EM settings**. NMF rank 4. $K = 5$ EM iterations. Averaging over $b = 4$ parallel sample batches. Weighting parameter $\lambda = 1.5$.

Results


SI – SDR(dB)
PESQ
ESTOI
WSJ0 – QUT
TCD – TIMIT
10.0
7.5
5.0
2.5
0.0
−2.5
−5.0
−7.5
0.5
1.0
1.5
2.0
0.0
0.1
0.2
0.3
0.4
0.5
0.6
0.7
0.8
Input
RVAE
UDiffSE(Ours)
SGMSE+

Conclusion & next directions

▷ **Conclusions**

- UDiffSE: *Proof of concept*
- Learning an *implicit prior* distribution over clean speech data
- An EM approach to generate clean speech & learn the noise parameters *at the same time*
- Better *generalisation* & outperforms VAE (also less artifacts)

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- **Next steps**
  1. Speeding up inference
  2. Investigating generalisational capability
  3. Improving prior

Further resources

GitHub

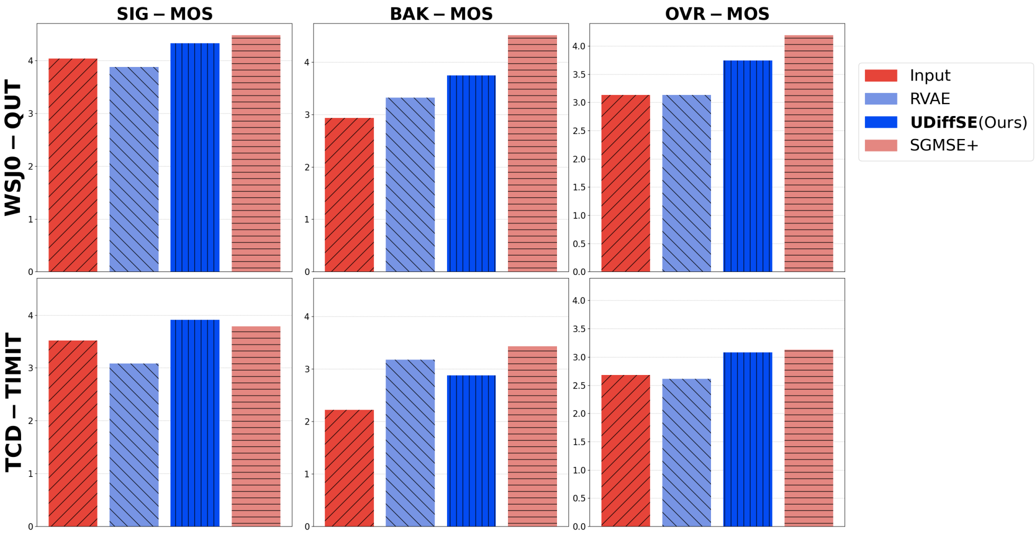
`https://github.com/joanne-b-nortier/udiffse`

Demo

`https://team.inria.fr/multispeech/demos/udiffse/`

Additional resources

Results II



SIG – MOS
BAK – MOS
OVR – MOS
WSJ0 – QUT
TCD – TIMIT
0
1
2
3
4
0.0
0.5
1.0
1.5
2.0
2.5
3.0
3.5
4.0
Input
RVAE
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SGMSE+

Algorithm

Algorithm 2 Posterior sampling (E-step) of UDiffSE

Require: $\mathbf{x}, N, \ell, \lambda, r$ (signal-to-noise ratio)

$\mathbf{s}_1 \sim \mathcal{N}_{\mathbb{C}}(\mathbf{x}, \mathbf{I}), \Delta\tau \leftarrow \frac{1}{N}$

for $i = N, \dots, 1$ **do**

  $\tau \leftarrow \frac{i}{N}$

  $\epsilon_\tau \leftarrow (\sigma_\tau \cdot r)^2$

  $\boldsymbol{\zeta}_c \sim \mathcal{N}_{\mathbb{C}}(\mathbf{0}, \mathbf{I})$ ▷ *(Corrector)*

  $\mathbf{s}_\tau \leftarrow \mathbf{s}_\tau + \epsilon_\tau \mathbf{S}_{\theta^*}(\mathbf{s}_\tau, \tau) + \sqrt{2\epsilon_\tau}\boldsymbol{\zeta}_c$

  $\boldsymbol{\zeta}_p \sim \mathcal{N}_{\mathbb{C}}(\mathbf{0}, \mathbf{I})$ ▷ *(Predictor)*

  $\mathbf{s}_\tau \leftarrow \mathbf{s}_\tau - \mathbf{f}_\tau \Delta\tau + g_\tau^2 \mathbf{S}_{\theta^*}(\mathbf{s}_\tau, \tau)\Delta\tau + g_\tau \sqrt{\Delta\tau}\boldsymbol{\zeta}_p$

  if $i \equiv 0 \pmod{\ell}$ **then** ▷ *(Posterior)*

    $\nabla_{\mathbf{s}_\tau} \log \tilde{p}_\phi(\mathbf{x}|\mathbf{s}_\tau) \leftarrow \frac{1}{\delta_\tau}\left[\frac{\sigma_\tau^2}{\delta_\tau^2}\mathbf{I} + \mathrm{diag}(\boldsymbol{v}_\phi)\right]^{-1}(\frac{\mathbf{s}_\tau}{\delta_\tau} - \mathbf{x})$

    $\mathbf{s}_\tau \leftarrow \mathbf{s}_\tau + \lambda g_\tau^2 \nabla_{\mathbf{s}_\tau} \log \tilde{p}_\phi(\mathbf{x}|\mathbf{s}_\tau)\Delta\tau$

  end if

end for

return $\hat{\mathbf{s}} = \mathbf{s}_0$