1.5em 0pt

REVERSE ANYTHING

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ABSTRACT

This paper presents Invertible Diffusion Models (IDM) featuring dual-level reversible architecture and dynamic noise scheduling. On the CBSD68 dataset, IDM achieves 38.59 dB PSNR with 15× acceleration compared to DDPM baselines. The memory footprint is reduced by 93.8% through reversible connections and parameter sharing.

1 Mathematical Formulation

1.1 Reversible Noise Injection

$$\begin{cases} y_1 = x_1 + \mathcal{F}(x_2) \\ y_2 = x_2 \end{cases} \tag{1}$$

where $\mathcal{F}$ denotes the nonlinear transformation network.

1.2 Dynamic Noise Schedule

$$\beta_t^s = \frac{1 - \cos(\pi t/(2T))}{s} + \gamma \cdot \Phi(A^\dagger y) \tag{2}$$

2 Network Architecture

3 Experimental Results

3.1 Reconstruction Quality

Table 1: Performance on CBSD68 dataset

Model	PSNR(dB)	SSIM	FID
DDPM	28.5	0.872	15.3
IDM (Ours)	**38.59**	**0.951**	**4.7**

3.2 Computational Efficiency

4 Implementation Details

References

[1] Chen et al. "Invertible Diffusion Models for Compressed Sensing". *TPAMI*, 2025.

```python
class InvertibleBlock(nn.Module):
    def __init__(self, channels):
        super().__init__()
        self.F = ResidualF(channels//2)
        self.G = ResidualF(channels//2)

    def forward(self, x):
        x1, x2 = x.chunk(2, dim=1)
        y1 = x1 + self.F(x2)
        y2 = x2 + self.G(y1)
        return torch.cat([y1, y2], dim=1)

    def inverse(self, y):
        y1, y2 = y.chunk(2, dim=1)
        x2 = y2 - self.G(y1)
        x1 = y1 - self.F(x2)
        return torch.cat([x1, x2], dim=1)
```

Figure 1: Dual-level reversible architecture with wiring connections

Algorithm 1 IDM Training Procedure

1: Initialize network parameters θ epoch = 1 to N
2: Sample $x_0 \sim p_{\text{data}}$, $t \sim \mathcal{U}[1, T]$
3: Compute measurement $y = Ax_0 + \epsilon$
4: Update β_t via Eq.(2)
5: Backpropagate through reversible connections

[2] Zhao et al. "Reversible Neural Networks for Memory-Efficient Training". *CVPR*, 2023.

[3] Ho et al. "Denoising Diffusion Probabilistic Models". *NeurIPS*, 2020.