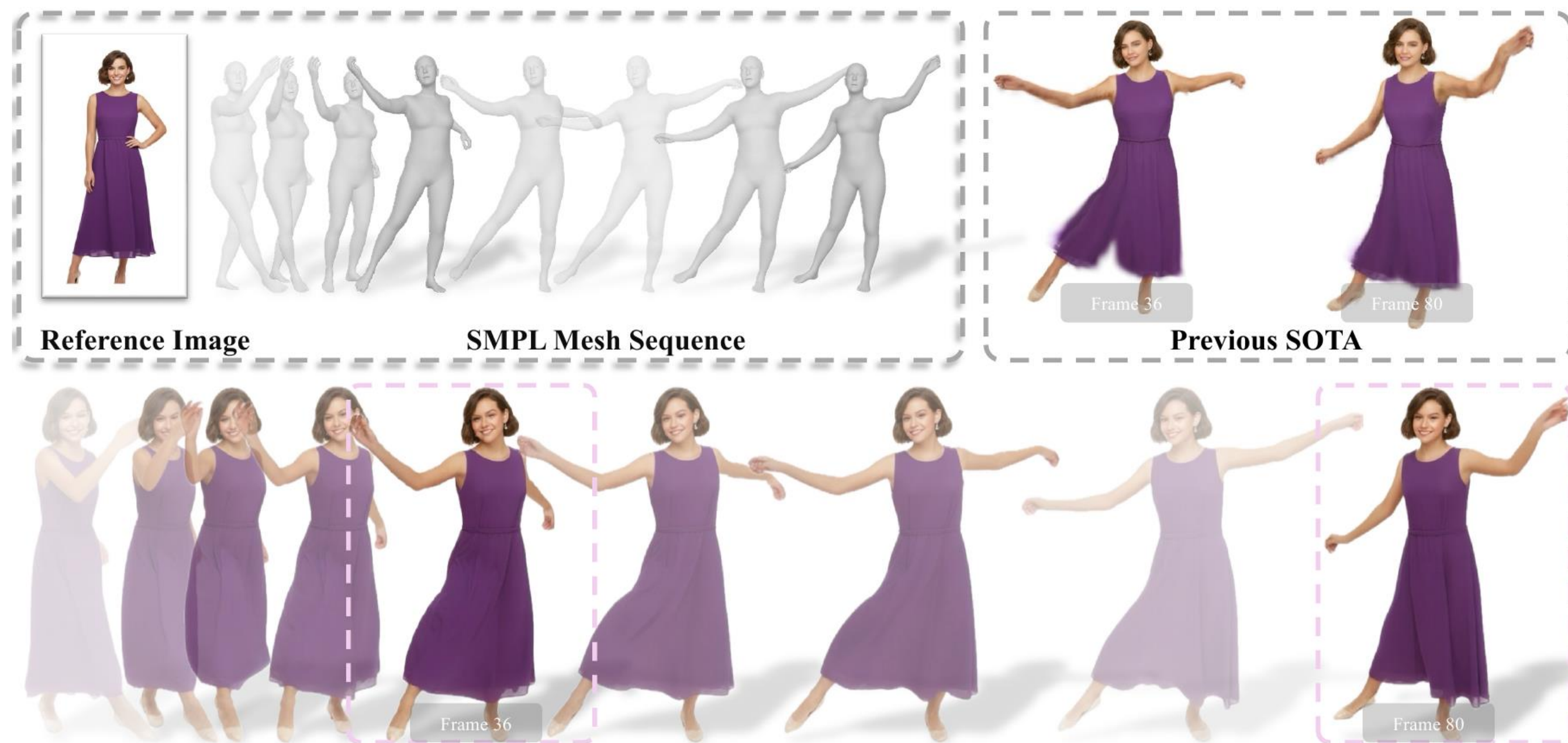


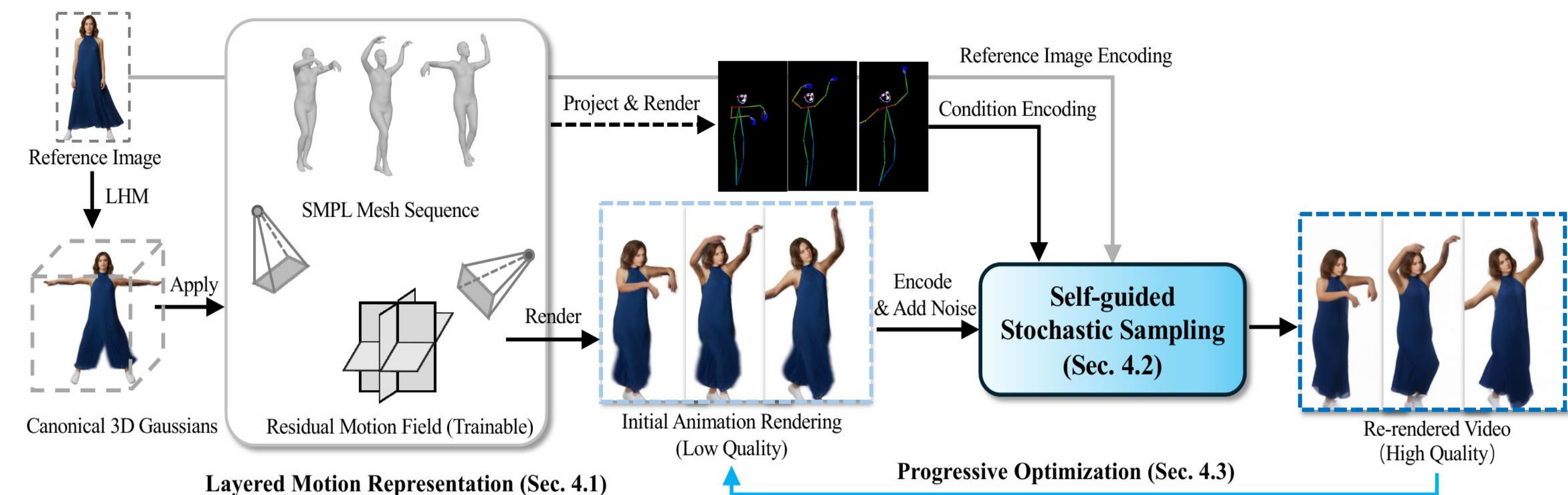


Abstract

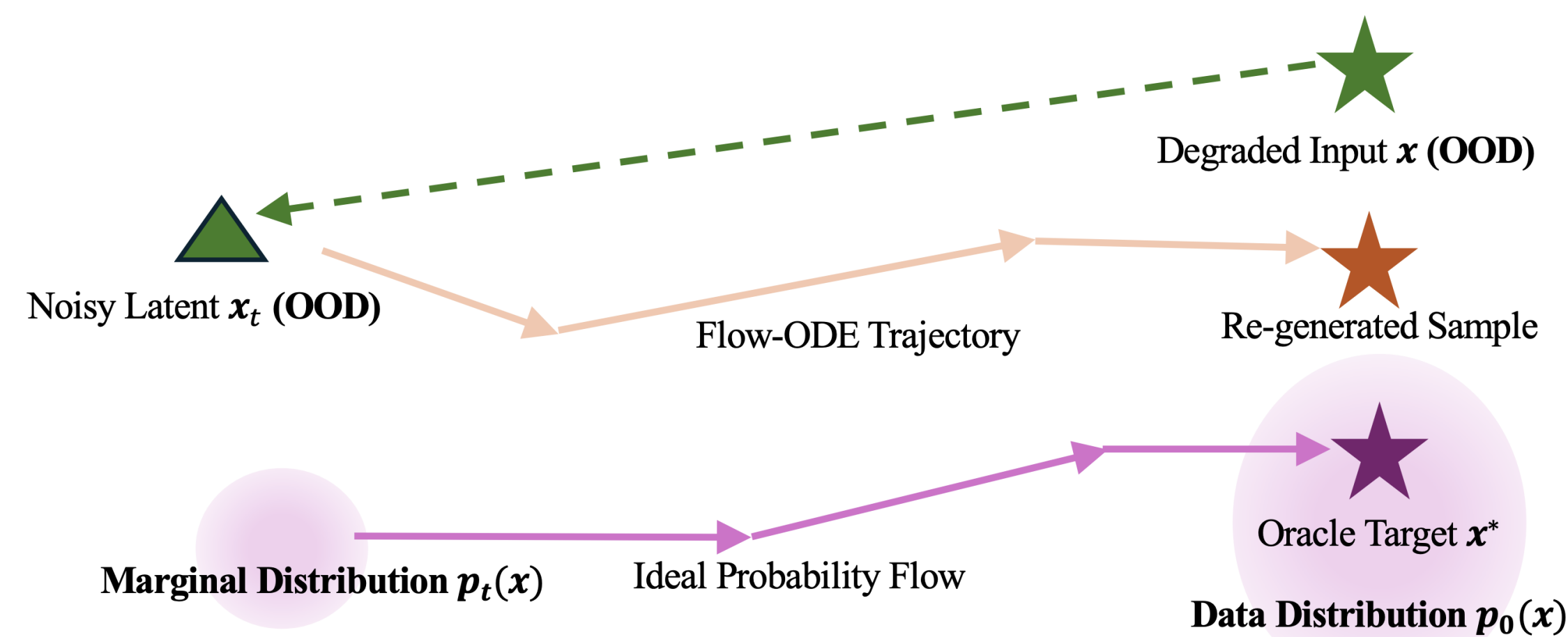
- **Input:** One image + SMPL motion
- **Output:** 4D human Gaussian sequence
- **Motion representation:** rigid body control + non-rigid dynamics.
- **Core Algorithm:** Self-guided stochastic sampling preserves identity and restores realism with *video diffusion prior*.



Framework



How it Works?



Distribution mismatch in deterministic flow matching

Algorithm 1 Self-guided Stochastic Sampling (Practical)

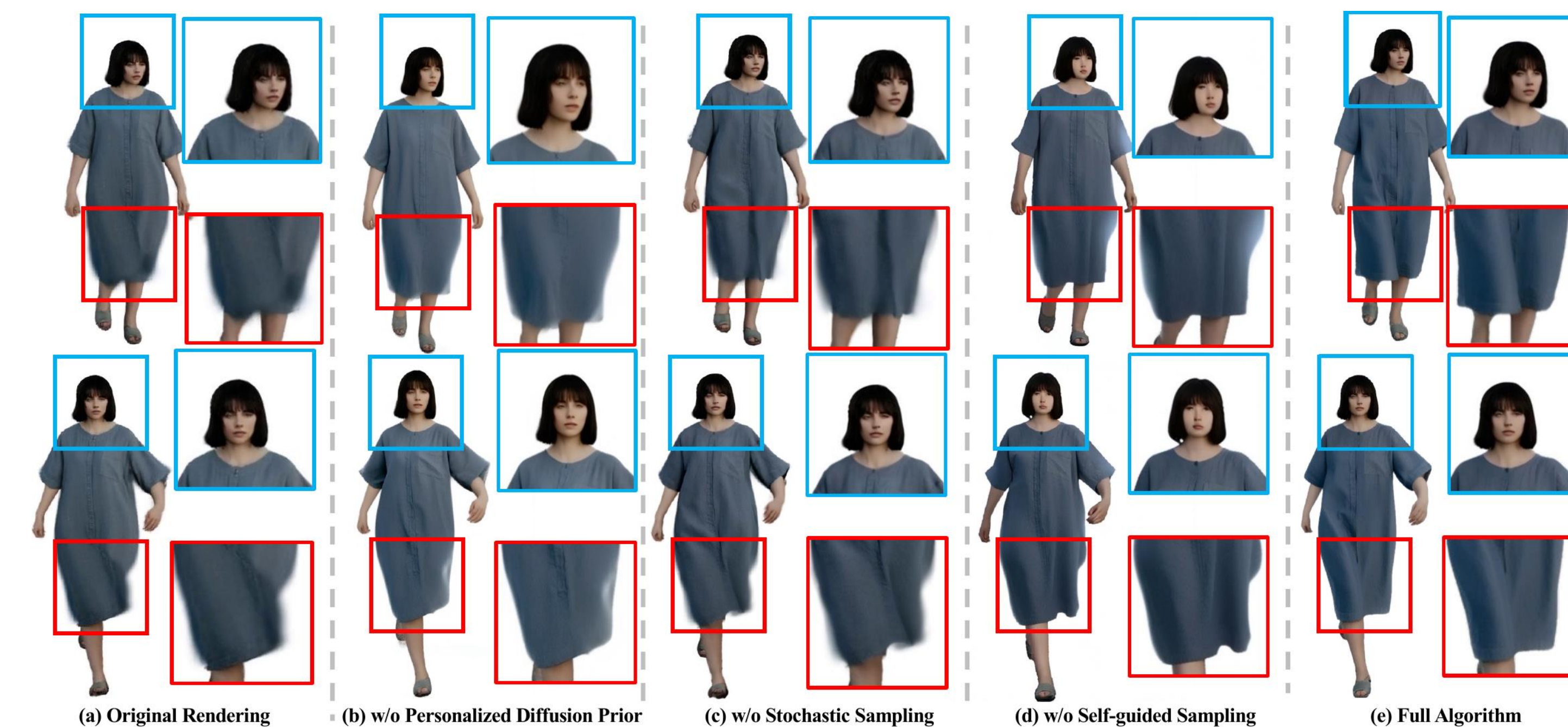
Require: Low-quality video y ; Pre-trained flow-based model v_θ ; Preserved region \mathcal{M} ; Initial noise step t_0 , constant step size λ ;

Ensure: Desirable high-quality video x^*

- 1: **Sample** $\epsilon \sim \mathcal{N}(0, \mathbf{I})$
- 2: $\mathbf{x}_t = \sigma_{t_0} \epsilon + (1 - \sigma_{t_0}) \mathbf{y}$ ▷ Eq. (6)
- 3: **for** $t : t_0 \rightarrow 0$ **do** ▷ Sampling loop
- 4: $\hat{\mathbf{x}}_{0|t} \leftarrow \mathbf{x}_t - \sigma_t v_\theta(\mathbf{x}_t, t)$ ▷ Eq. (3)
- 5: $\hat{\mathbf{x}}_{1|t} \leftarrow \mathbf{x}_t + (1 - \sigma_t) v_\theta(\mathbf{x}_t, t)$ ▷ Eq. (4)
- 6: $\hat{\mathbf{x}}_{0|t} \leftarrow \hat{\mathbf{x}}_{0|t} - \lambda \nabla_{\mathbf{x}_t} \|\mathcal{M} \odot (\mathbf{y} - \hat{\mathbf{x}}_{0|t})\|^2$ ▷ Eq. (10)
- 7: **Sample** $\epsilon \sim \mathcal{N}(0, \mathbf{I})$
- 8: $\hat{\mathbf{x}}_{1|t} \leftarrow \sqrt{1 - \sigma_t} \hat{\mathbf{x}}_{1|t} + \sqrt{\sigma_t} \epsilon$ ▷ Eq. (8)
- 9: $\mathbf{x}_{t_{\text{next}}} \leftarrow (1 - \sigma_{t_{\text{next}}}) \hat{\mathbf{x}}_{0|t} + \sigma_{t_{\text{next}}} \hat{\mathbf{x}}_{1|t}$ ▷ Eq. (5)
- 10: **end for**
- 11: **Return** $x^* = x_t|_{t=0}$

■ Eq(10) – DPS-style gradient guidance
■ Eq(8) – introduce stochasticity in sampling

Ablation – Self-guided Stochastic Sampling



Comparison with SOTA

