Paper Digest Meeting

Score Distillation via Reparametrized DDIM

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Problem Definition

Goal: Generate high-detail 3D objects from input text prompts.

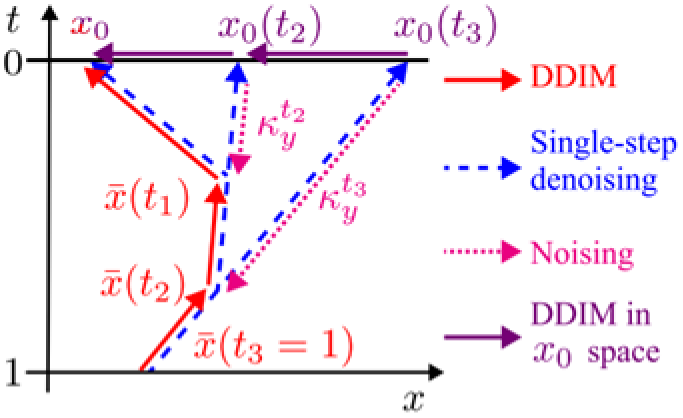
Insight: 2D diffusion models generate realistic, high-detail images whereas SDS produces cartoon-like, over-smoothed images.

a) DDIM (CFG=7.5) b) 2D SDS (CFG=7.5) c) 2D ours (CFG = 7.5)

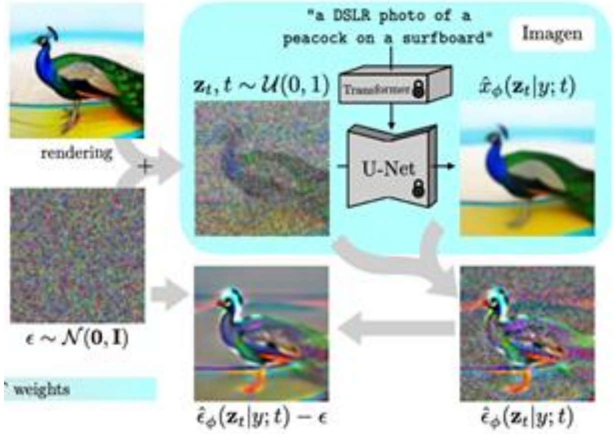
Reparametrization of SDS shows a resemblance to high-variance version of DDIM.
→ A better noise prediction to reduce the variance and improve the output quality.

Key Ideas

DDIM uses the **same predicted noise** for both single-step denoising and noising.
SDS samples random noise at every iteration which unnecessarily increases the variance.



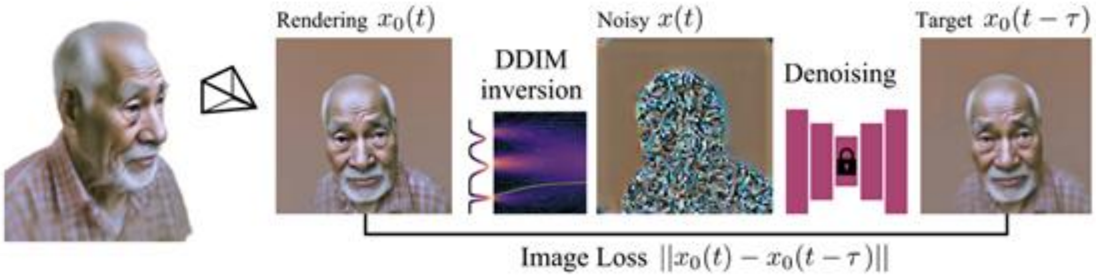
DDIM



SDS

Method

Use DDIM inverted noise to guide SDS as DDIM.



Algorithm 1 Dreamfusion (SDS)

Input: $\psi \in \mathbb{R}^N$ - parametrized 3D shape
$\mathcal{C}$ - set of cameras around the 3D shape
y - text prompt
$g : \mathbb{R}^N \times \mathbb{C} \to \mathbb{R}^{n \times n}$ - differentiable renderer
$\epsilon_\theta^{(t)} : \mathbb{R}^{n \times n} \to \mathbb{R}^{n \times n}$ - trained diffusion model
Output: 3D shape ψ of y

procedure DREAMFUSION(y)
  for i in range(n_iters) **do**
    $t \leftarrow$ Uniform(0, 1)
    $c \leftarrow$ Uniform($\mathcal{C}$)
    $\epsilon \leftarrow$ Normal(0, I)
    $x_t \leftarrow \sqrt{\alpha(t)}g(\psi, c) + \sqrt{1-\alpha(t)}\epsilon$
    $\nabla_\psi \mathcal{L}_{SDS} = \sigma(t)\left[\epsilon_\theta^{(t)}(x_t, y) - \epsilon\right]\frac{\partial g}{\partial \psi}$
    Backpropagate $\nabla_\psi \mathcal{L}_{SDS}$
    SGD update on ψ

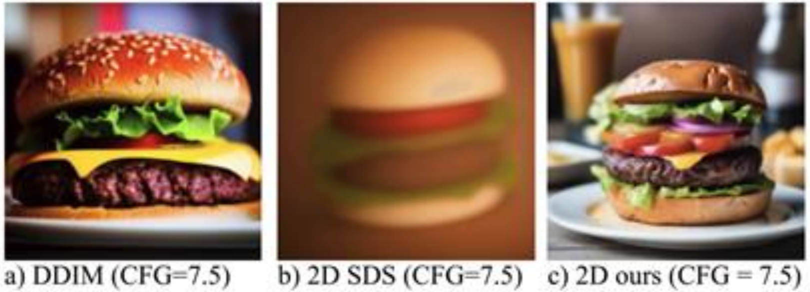
Algorithm 2 Ours (SDI)

Input: $\psi \in \mathbb{R}^N$ - parametrized 3D shape
$\mathcal{C}$ - set of cameras around the 3D shape
y - text prompt
$g : \mathbb{R}^N \times \mathbb{C} \to \mathbb{R}^{n \times n}$ - differentiable renderer
$\epsilon_\theta^{(t)} : \mathbb{R}^{n \times n} \to \mathbb{R}^{n \times n}$ - trained diffusion model
Output: 3D shape ψ of y

procedure OURS(y)
  for i in range(n_iters) **do**
    $t \leftarrow 1 - i/n\_iters$
    $c \leftarrow$ Uniform($\mathcal{C}$)
    $\epsilon \leftarrow \kappa_y^{t+\tau}(g(\psi, c))$
    $x_t \leftarrow \sqrt{\alpha(t)}g(\psi, c) + \sqrt{1-\alpha(t)}\epsilon$
    $\nabla_\psi \mathcal{L}_{SDS} = \sigma(t)\left[\epsilon_\theta^{(t)}(x_t, y) - \epsilon\right]\frac{\partial g}{\partial \psi}$
    Backpropagate $\nabla_\psi \mathcal{L}_{SDS}$
    SGD update on ψ

Experiments

2D Generation - Almost the same as DDIM



3D Generation - Outperform, comparable results to previous methods