Learning Fine-Grained Bimanual Manipulation with Low-Cost Hardware

RSS 2023

양현서

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About

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- Conference: RSS 2023

Motivation

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- However, designers also vastly use **vectorized** images in practice like SVG (Scalable Vector Graphics)

- Training diffusion model to generate vectorized images is theoritically possible but practically challenging

Challenges of training diffusion models for vectorized images

- Most labeled datasets are for rasterized images

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- Vectorized images’ data structure is more complex (hierarchical and variable-lengthed) than rasterized images’

Baselines

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Challenges

- Diffusion Models often generate **too complex** rasterized images to be vectorized
- Automated conversion **loses details**

VectorFusion

- Differentiable vector graphics renderer

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- Score Distillation Sampling

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- SVG-Specific regularization

Background: Vector representation and rendering pipeline

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<svg width="200" height="200" xmlns="http://www.w3.org/2000/svg">
  <circle cx="50" cy="50" r="40" stroke="black" stroke-width="3" fill="red" />
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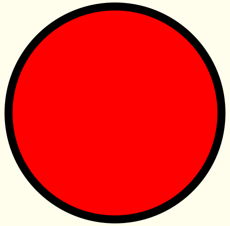

Background: SVG Path

- **`M x,y`: Move to the point (x, y)**
- `L x,y`: Draw a line to the point (x, y)
- `H x`: Draw a horizontal line to x
- `V y`: Draw a vertical line to y
- **`C x1, y1, x2, y2, x, y`: Draw a cubic Bezier curve**
- `Q x1, y1, x, y`: Draw a quadratic Bezier curve
- **`Z`: Close the path**

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```
  <svg width="200" height="200" xmlns="http://www.w3.org/
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    <path d="M10 80 C 40 10, 160 10, 190 80" stroke="black"
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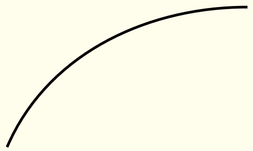

Vector Grapchic Parameterization

- s: number of segments
- n: number of paths to add

Background: Diffusion Models Training

- $\mathcal{L}_{\text{DDPM}}(\phi, \mathtt{x}) = \mathbb{E}_{t,\epsilon}\left[w(t)\|\epsilon_\phi(\alpha_t \mathtt{x} + \sigma_t \epsilon) - \epsilon\|_2^2\right]$ [1]

[1] $\alpha_t = \sqrt{1-\beta_t}$, $\sigma_t = \sqrt{\beta_t}$

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Background: Diffusion Models Sampling

1. Sample $\mathtt{x}_t$ from a prior.
2. Predict noise $\epsilon_\phi(\mathtt{x}_t)$.
3. Compute $\hat{\mathtt{x}}$.

   $\hat{\mathtt{x}} = \frac{\mathtt{x}_t - \sigma_t \epsilon_\phi(\mathtt{x}_t)}{\alpha_t}$

4. Compute $\mathtt{x}_{t-1}$ and feed to the next step.

   $\mathtt{x}_{t-1} = \alpha_{t-1}\hat{\mathtt{x}} + \sigma_{t-1}\epsilon_\phi(\mathtt{x}_t)$

Background: Classifier Free Guidance

$$\hat{\epsilon}_\phi(\mathtt{x}, y) = (1 + \omega) * \epsilon_\phi(\mathtt{x}, y) - \omega * \epsilon_\phi(\mathtt{x})$$

- Generate both conditional and unconditional prediction for the noise. $\epsilon_\phi(\mathtt{x}, y)$ and $\epsilon_\phi(\mathtt{x})$

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- This enhances the model's ability to generate images with the desired class.

Score Distillation Sampling

$$\mathcal{L}_{\mathrm{SDS}} = \mathbb{E}_{t,\epsilon}\left[\frac{\sigma_t}{\alpha_t} w(t)\,\mathrm{KL}\Big(q(\mathtt{x}_t|g(\theta);y,t)\|\; p_\phi(\mathtt{x}_t;y,t)\Big)\right]$$

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- q is a unimodal gaussian centered at a learned image $g(\theta)$
- The larger $\frac{\sigma_t}{\alpha_t}$, the more the model prediction is important

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$$\nabla_\theta \mathcal{L}_{\mathrm{SDS}} = \mathbb{E}_{t,\epsilon}\left[w(t)(\hat{\epsilon}_t(\mathtt{x}_t; y, t) - \epsilon)\frac{\partial \mathtt{x}}{\partial \theta}\right]$$

Method

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Provide "minimal flat 2d vector icon. lineal color. on a white background. trending on artstation" as a prompt.

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Rejection Sampling

Sample $K = 4$ images, select best by CLIP ViT-B/16 score

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   4. Compute $\mathbf{z}_t = \alpha_t \mathbf{z} + \sigma_t \epsilon$
   5. Remove the noise using the noise prediction model
   6. Update the parameters using SDS loss

VectorFusion: Details

- Sample t from $t \sim \mathrm{Uniform}(50, 950)$
- Use fp16 precision
  - Use fp32 precision for $\frac{\partial \mathtt{z}}{\partial \mathtt{x}_{\mathrm{aug}}}$ for stability
- Apply self intersection regularizer loss also[7]

$$\mathcal{L}_{\mathrm{Xing}} = D_1(\mathrm{ReLU}(-D_2) + (1 - D_1)(\mathrm{ReLU}(D_2)))$$

- Reinitialize low opacity or shrinked paths

[7] $D_1 = \mathbb{I}\left(\overrightarrow{AB} \cdot \overrightarrow{BC}\right)$, $D_2 = \frac{\overrightarrow{AB} \cdot \overrightarrow{CD}}{\|\overrightarrow{AB}\|\|\overrightarrow{CD}\|}$

VectorFusion: Architecture

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No test dataset available for vector graphics

Therefore, use CLIP as an evaluation metric

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R-Precision

For 128 SVGs, assign the captions by the CLIP score and check if it was the correct caption. Get the fraction of correct captions.

- Used rejection sampling (K in the table)

Evaluation

- CLIPDraw performed best, but **qualitative results are poor**
- Therefore, also use OpenCLIP score
- Effect of rejection sampling $\sim$ caption consistency

Qualitative Results

Discussion

- Utilizes pretrained diffusion models **without captioned SVG datasets**
- Effectively shows the **distillation of generative models** compared to contrastive models

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- Utilizes pretrained diffusion models **without captioned SVG datasets**
- Effectively shows the **distillation of generative models** compared to contrastive models

- Computationally more **expensive** than CLIP-based approaches
- **Limited** by the quality and biases of the pretrained diffusion model

References

- DiffVG
- LIVE
- VectorFusion