Anatomically-Controllable Medical Image Generation with Segmentation-Guided Diffusion Models

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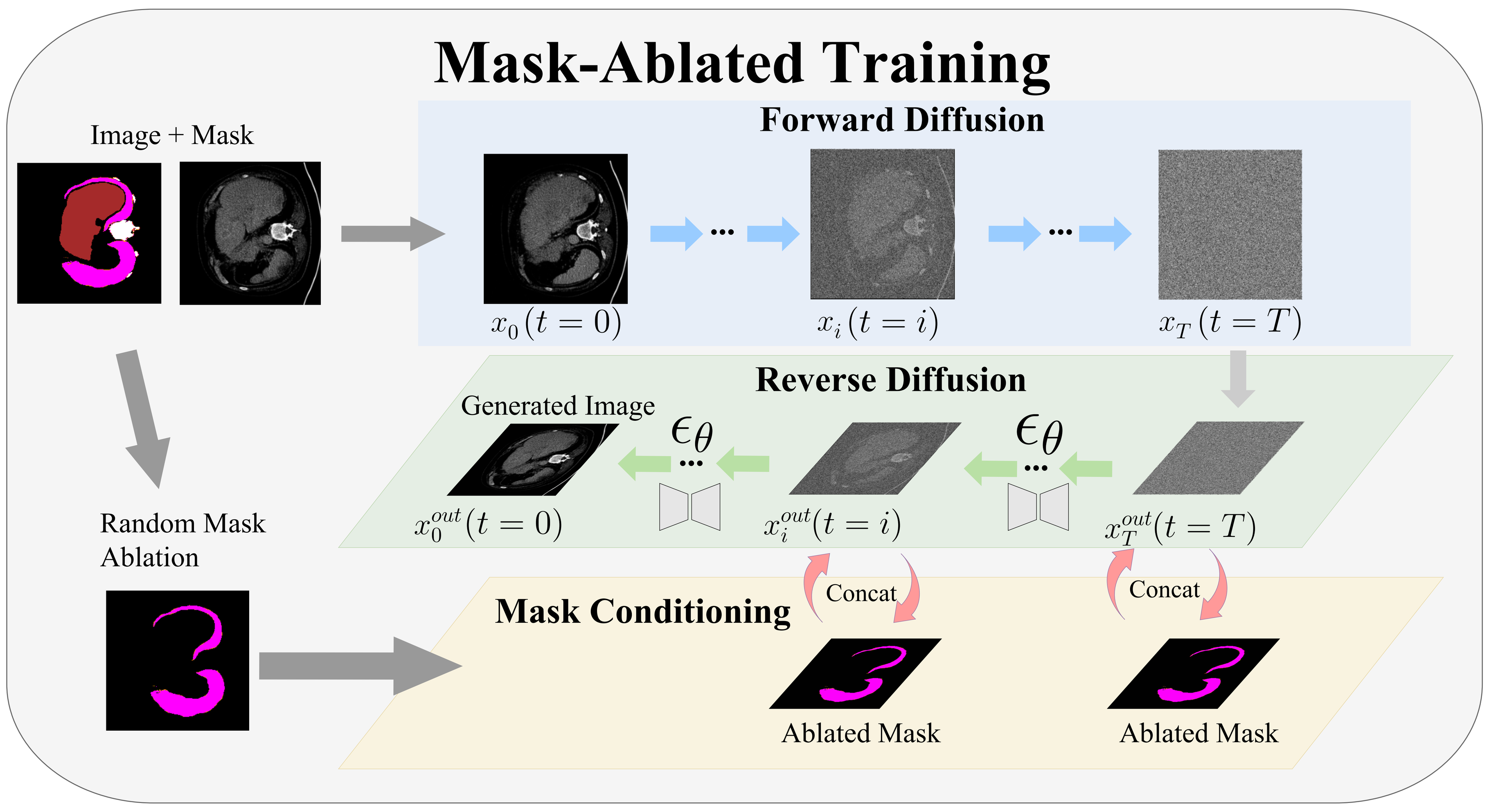
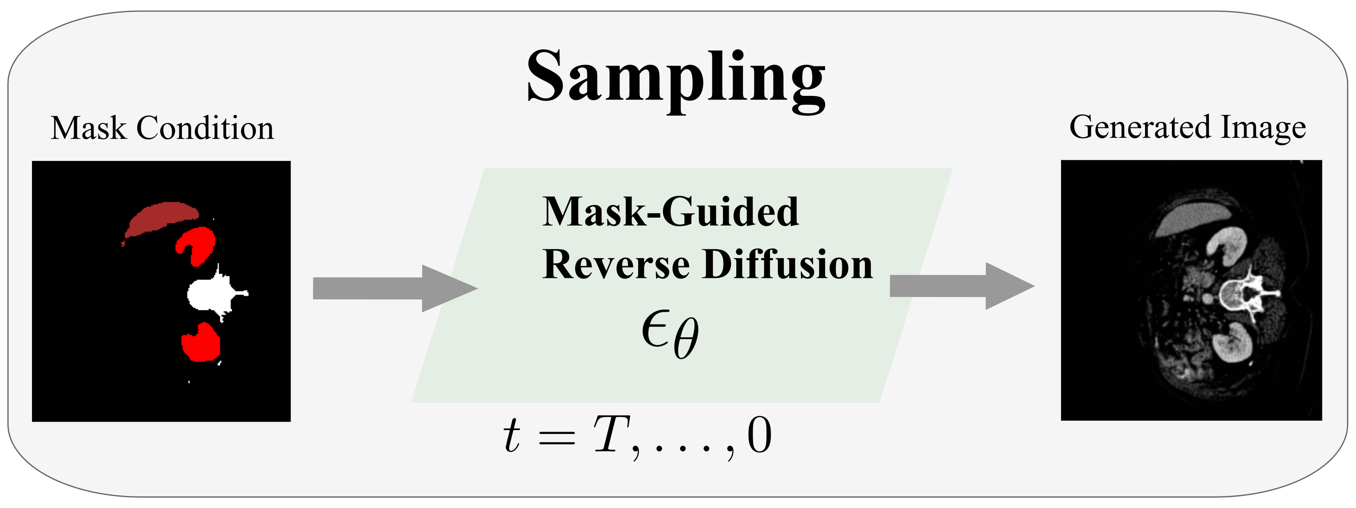
Background

- **Can we precisely control the anatomy in artificially-generated medical images, while maintaining quality?**
- **Applications:** generation of rare cases, generation of anatomically-paired data, cross-modality image translation, etc.
- Enter: ***Segmentation-Guided Diffusion Models*** with mask-ablated training!

Model Diagram





Mask-Ablated Training

- Random chance to remove each class from mask condition in training.
- Teaches the model to be able to generate from masks with missing classes.

Algorithm 1: Segmentation-guided model training with mask ablation.

Input: number of mask classes C, dataset $p(x_0, m)$.
repeat
  $x_0, m \sim p(x_0, m)$
  for $c = 1, \dots, C-1$ **do**
    $\delta \sim \mathrm{Bernoulli}(0.5)$
    if $\delta = 1$ **then**
      $m[m = c] = 0$
  end
  $\epsilon \sim \mathcal{N}(0, I_n)$; $t \sim \mathrm{Uniform}(\{1, \dots, T\})$
  $x_t = \sqrt{\bar{\alpha}_t}x_0 + \sqrt{1-\bar{\alpha}_t}\epsilon$
  Update θ with $\nabla_\theta \left\|\epsilon - \epsilon_\theta(x_t, t|m)\right\|^2$
until *converged*;

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Check out the codebase!

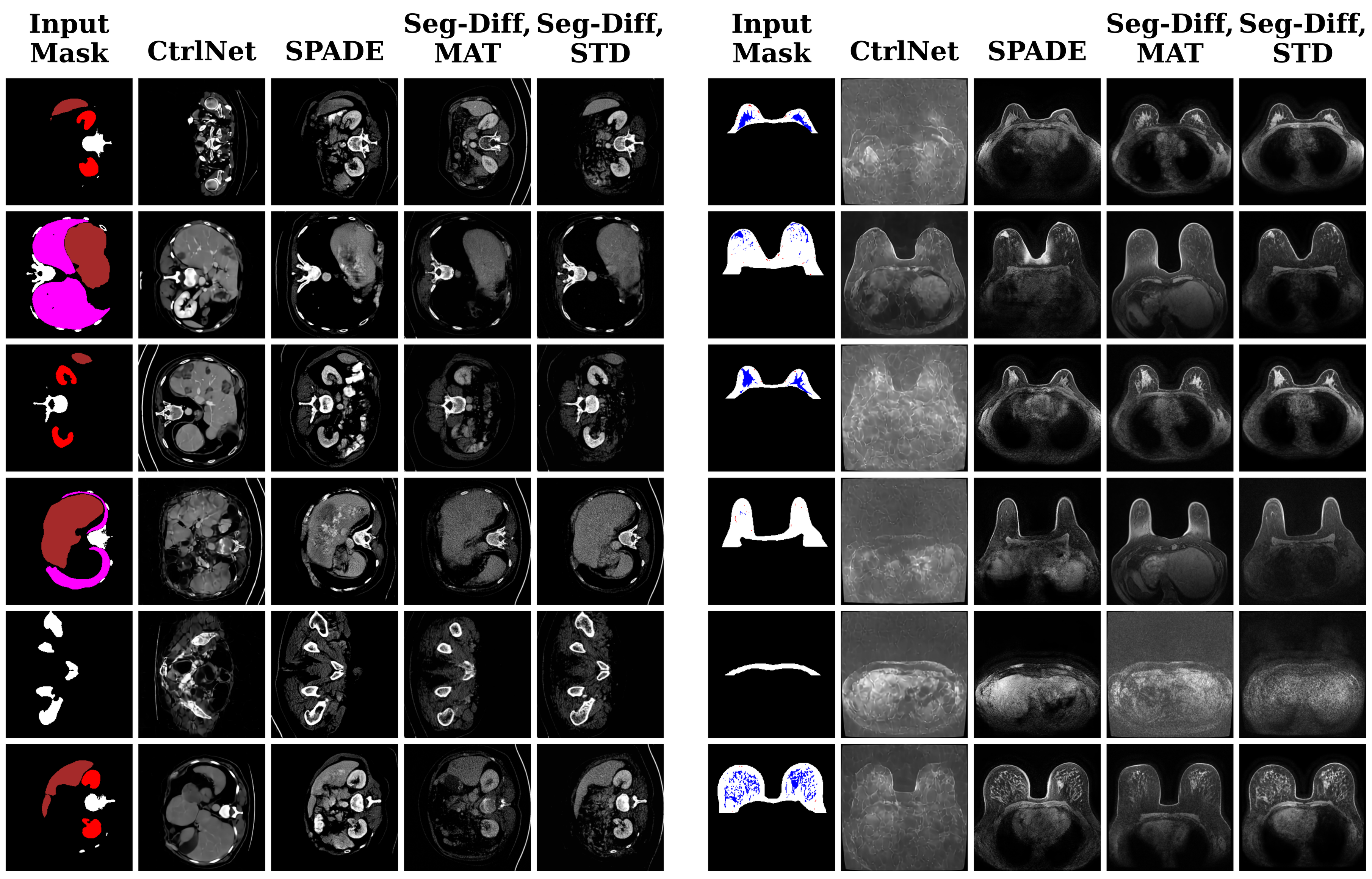
https://github.com/mazurowski-lab/segmentation-guided-diffusion

- ✓ 80+ stars
- ✓ Easy to use out-of-the-box
- ✓ Actively maintained and documented
- ✓ Pretrained models
- ✓ Generated paired breast MRI dataset

Datasets

1. **CT Organ** (liver, bladder, lung, kidney, and bone masks)
2. **Breast MRI** (Breast, dense tissue, and blood vessel masks)

Results



1. **New SOTA in faithfulness of generated images to input masks:**

	Breast MRI		CT Organ	
Model	Dice(m^{pred}_{gen}, m)	Dice($m^{pred}_{gen}, m^{pred}_{real}$)	Dice(m^{pred}_{gen}, m)	Dice($m^{pred}_{gen}, m^{pred}_{real}$)
ControlNet (ICCV '23)	0.3636	0.3604	0.1132	0.1126
SPADE (CVPR '19)	0.8473	0.8477	0.8771	0.8603
Ours	**0.9027**	**0.8593**	**0.8980**	**0.8797**

2. **Strong general anatomical realism:**

	Real training set	*Synthetic training set:* ControlNet	SPADE	**Ours**
Breast MRI	0.8376	0.7570	**0.8333**	0.7934
CT Organ	0.9075	0.0000	0.8932	**0.8981**

Performance (Dice) of a segmentation model on real data that was trained on each model's generated data

Precisely Adjustable Anatomy

- How else can we take advantage of the generation flexibility gained by mask-ablated training?
- Via interpolating in a mask-ablated trained model's latent space, with $\lambda \in (0,1)$.