SIREN

Implicit Neural Representations with Periodic Activation Functions

https://arxiv.org/abs/2006.09661

MI2RL 장령우

Implicit Neural Network

- Goal : Find Φ s.t.

$$F(x, \Phi, \nabla_x \Phi, \nabla_x^2 \Phi, \cdots) = 0, \quad \Phi : x \mapsto \Phi(x))$$

- Thus, Φ is implicitly defined by the relation defined by F -> Implicit Neural Network

Implicit Neural Network

- What does Implicit means?
  - The set of parameters of each NN will be representation/encoding of the corresponding image
  - Φ is an implicit representation of an image.
- What is advantage of implicit representation?
  - We get a continuous mapping from pixel locations to pixel values.
  - Network can also learn its gradients.

Formulation

- Find Φ w.r.t. M constraints :

  $$\{C_m(a(x), \Phi(x), \nabla\Phi(x), \cdots)\}_{m=1}^{M}$$

- This can be expressed as minimizing

  $$\mathcal{L} = \int_\Omega \sum_{i=1}^{M} 1_\Omega ||C_m(a(x), \Phi(x), \nabla\Phi(x), \cdots)|| dx$$

Periodic Activations for Implicit Neural Representations

- This paper suggests periodic activation function :
  $$\Phi(x) = W_n(\phi_{n-1} \circ \phi_{n-2} \circ \cdots \circ \phi_0)(x) + b_n, \quad x_i \mapsto \phi_i(x_i) = \sin(W_i x_i + b_i)$$
- Any derivative of a SIREN is itself a SIREN -> $\frac{d(\sin x)}{dx} = \cos x = \sin(\frac{\pi}{2} - x)$

Simple Example: Fitting an Image

- Consider finding a function $\Phi : \mathbb{R}^2 \rightarrow \mathbb{R}^3$
- Image defines a dataset $\mathcal{D} = \{(x_i, f(x_i))\}_i$ of pixel coordinates $x_i = (\mathrm{x}_i, \mathrm{y}_i)$ associated with their RGB colors $f(x_i)$
- Here, $C(f(x_i), \Phi(x)) = \Phi(x_i) - f(x_i)$ and $\tilde{\mathcal{L}} = \sum_i ||\Phi(x_i) - f(x_i)||^2$

Simple Example: Fitting an Image

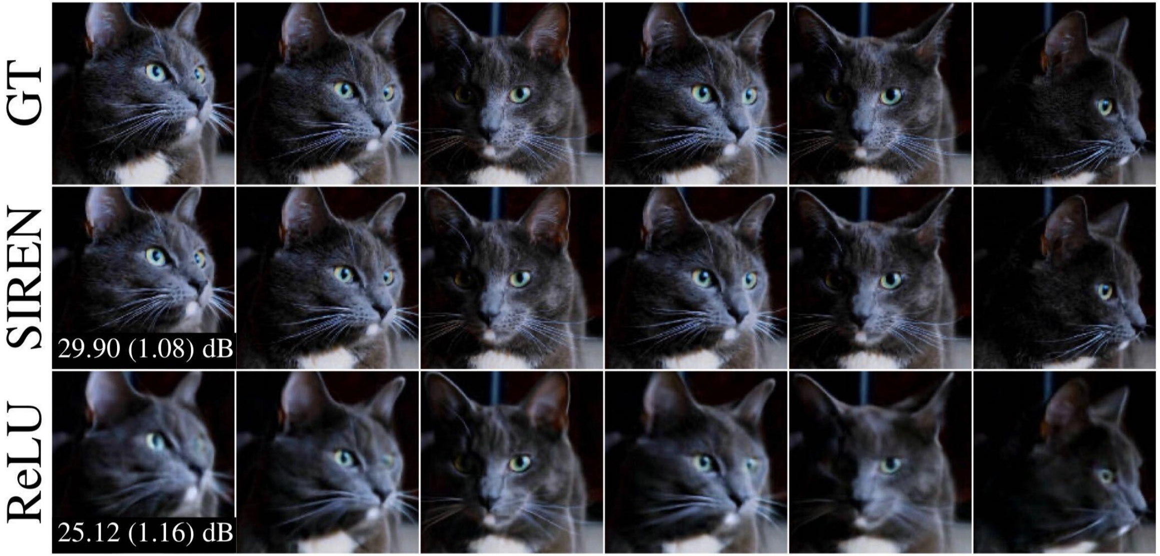


Figure 2: Example frames from fitting a video with SIREN and ReLU-MLPs. Our approach faithfully reconstructs fine details like the whiskers. Mean (and standard deviation) of the PSNR over all frames is reported.

Solving the Poisson Equation

- Poisson Equation : $\nabla^2 \varphi = f$
- Loss term : $\mathcal{L}_{\text{grad}} = \int_{\Omega} ||\nabla_x \Phi(x) - \nabla_x f(x)||dx, \quad \text{or} \quad \mathcal{L}_{\text{lapl}} = \int_{\Omega} ||\Delta \Phi(x) - \Delta f(x)||dx$

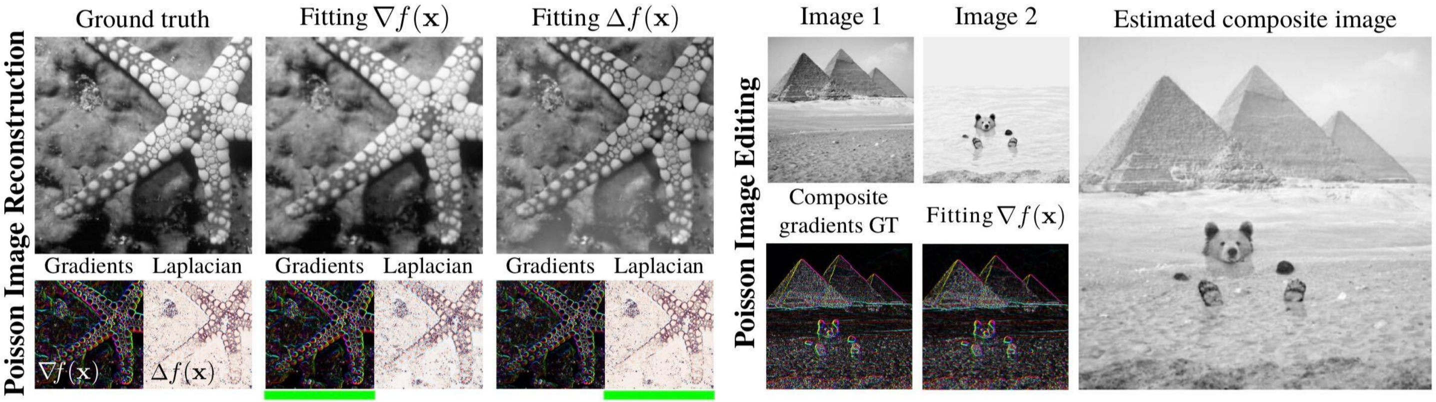


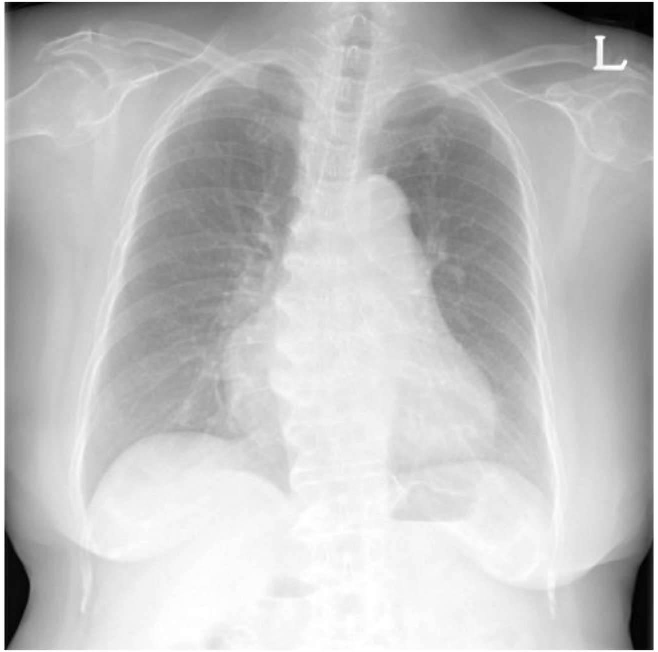
Figure 3: **Poisson image reconstruction:** An image (left) is reconstructed by fitting a SIREN, supervised either by its gradients or Laplacians (underlined in green). The results, shown in the center and right, respectively, match both the image and its derivatives well. **Poisson image editing:** The gradients of two images (top) are fused (bottom left). SIREN allows for the composite (right) to be reconstructed using supervision on the gradients (bottom right).

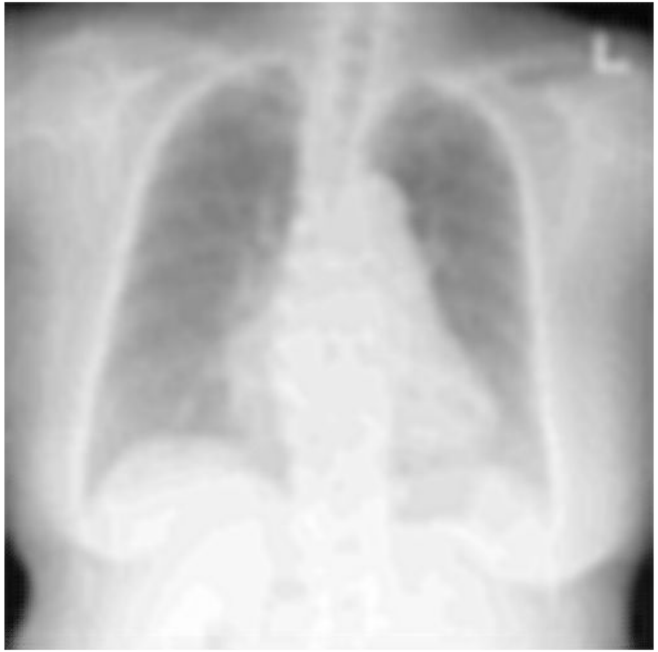
What is advantage of SIREN?

- SIREN can fit anything that can be formulated that relate the input of the function to its output or any of the derivatives of the output.

My result

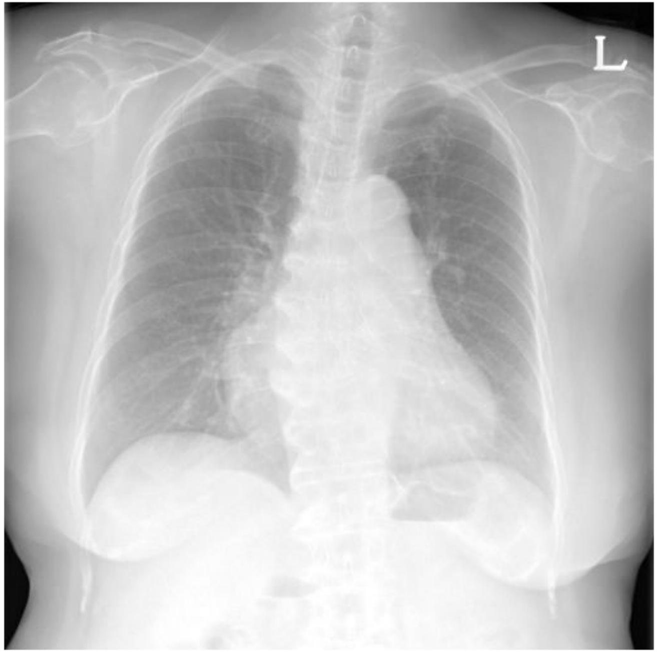
- VQVAE 2 with ReLU activation

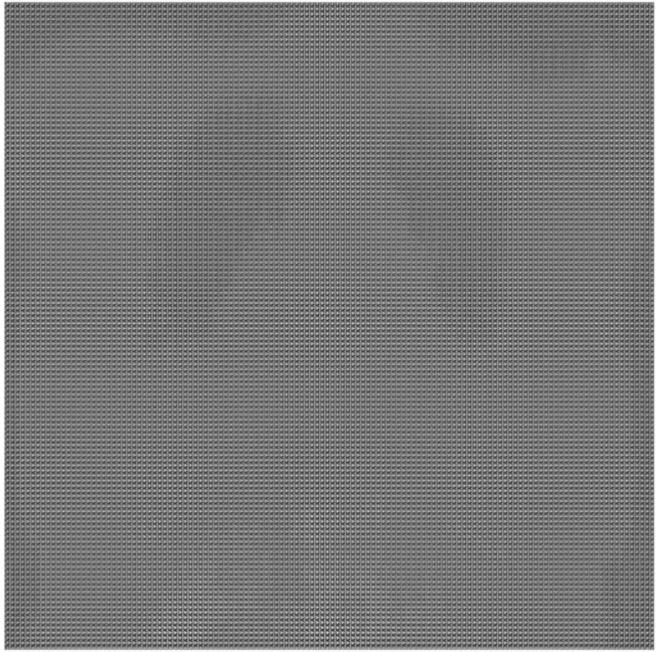




My result

- VQVAE 2 with SIREN activation





Why SIREN does not work?

1. Only assumed SIREN would enforce edge component better than ReLU.
2. There was no consideration about whether AutoEncoder satisfies condition of SIREN.