Enhancing Implicit Neural Representations via Symmetric Power Transformation

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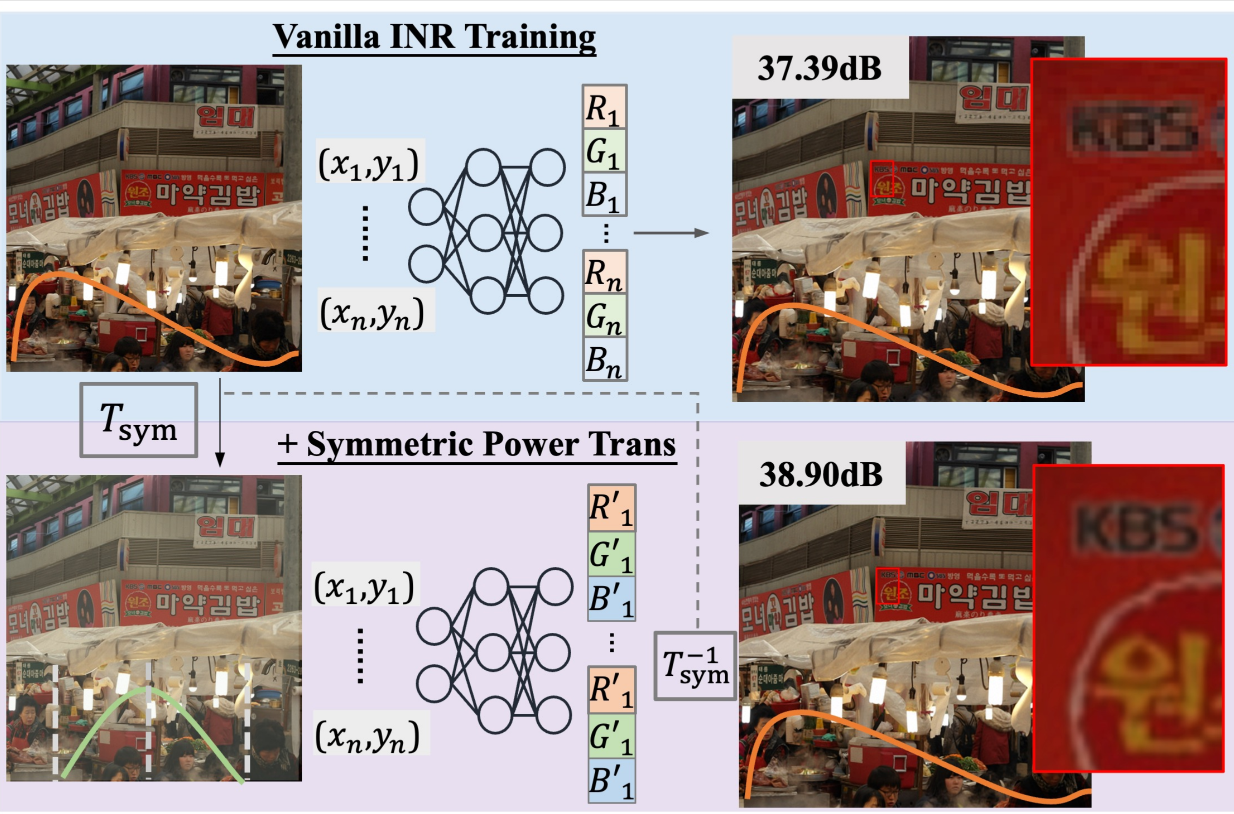
Background

Implicit Neural Representations (INRs) have been proposed for continuously representing signals using neural networks, which has garnered significant attention in the data representation.

Challenge:
Encoding signals into neural representations is resource-intensive, requiring training a neural network to fit natural signals.

Overview

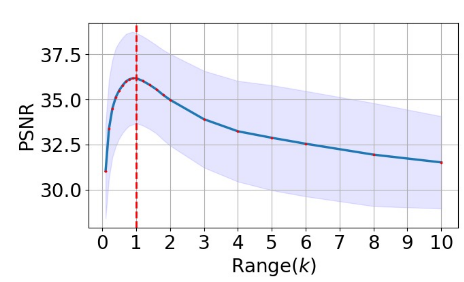


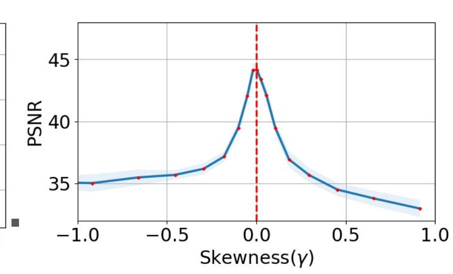
Contributions

- We observe that scaling the data to a specific **range** and ensuring a **symmetric** distribution benefits the training of INRs.
- We propose Symmetric Power Transformation to enhance implicit neural representation. We also introduce deviation-aware calibration and adaptive soft boundary to further improve the robustness of the method.
- We verify the effectiveness of our method through extensive experiments, including 1D audio fitting, 2D image fitting, and 3D video fitting task.

Range-Defined Symmetric Hypothesis

Given an INR F_θ with a bounded periodic activation function $\sigma(\cdot) \sim I$ and an input signal $\mathbf{y}$ with distribution $\boldsymbol{G}$, satisfying the following conditions can enhance the expressive ability of INRs: (1) **Range-Defined:** the bound of $\mathbf{y}$ is approximately I. (2) **Symmetric:** the skewness of $\boldsymbol{G}$ is approximately 0.





Symmetric Power Transformation

- **Basic Form:**

$$T_{\text{sym}}(\mathbf{y}) = (b-a)\mathbf{y}_0^{\beta} + a, \quad \mathbf{y}_0 = \frac{\mathbf{y} - \min(\mathbf{y})}{\max(\mathbf{y}) - \min(\mathbf{y})}$$

C.D.F.

$$\beta = \frac{\log \lambda}{\log(Q_\lambda)}, \quad F_Y(Q_\lambda) = P(Y \le Q_\lambda) = \lambda$$

COST-FREE Acceleration for INR's Training!

- **Deviation-Aware Calibration**:

$$\beta^{+} = \beta - \Delta\beta = \beta - \xi \int_0^{\tau} [f_{\text{sym}}(y) - f(y)]\mathrm{d}y$$

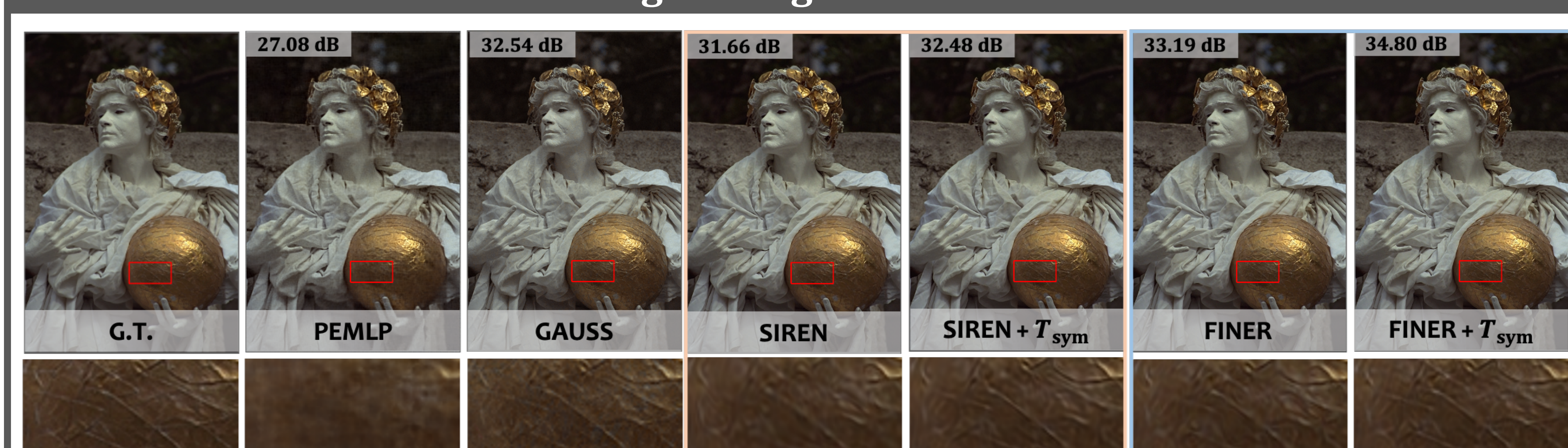
To calibrate extreme deviation boosting

- **Adaptive Soft Boundary:**

$$\mathbf{y}_0^{+} = \frac{\mathbf{y} - [1+\kappa f(0)]\min(\mathbf{y})}{[1+\kappa f(1)]\max(\mathbf{y}) - [1+\kappa f(0)]\min(\mathbf{y})}$$

To mitigate continuity-breaking at boundaries

Visualization for 2D natural image fitting



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