Tuning the Frequencies: Robust Training for Sinusoidal Neural Networks

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impa

code

highlight

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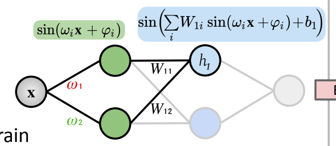
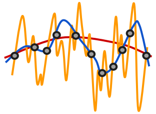
Overview

Sinusoidal MLPs are powerful *implicit neural representations* (INRs) for encoding low-dim signal on their parameters.



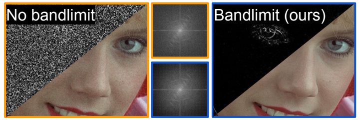
Problem: How to initialize and train such INRs with **high representation capacity** to fit the signal while controlling **their bandlimit** to avoid bypassing the sampling rate?



Contributions:

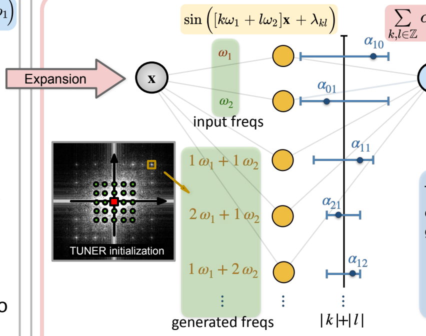
- Two novel theorems: 1) A trigonometric identity showing how sinusoidal MLPs **expand** their input freqs, offering deeper insight into their representation capacity; 2) An upper bound for the new freq amplitudes that allows bounding the model spectrum.
- Building on this analysis, we propose a novel **initialization** and **bandlimit control** schemes to improve INR training.

Prior works randomly initialize the input freqs. ω in a given range. While this allows the model to represent high freqs, it may lead to overfitting.



The lack of spectral control leads to noisy reconstruction of signal and gradient.

TUNER

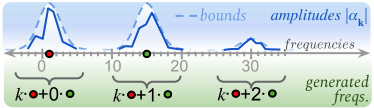


★ Layer composition introduces new freqs $k\omega_1 + l\omega_2$.

★ The matrix $\mathbf{W}$ gives the amplitudes α_{kl}.

The amplitudes α_{kl} decrease as $|k|+|l|$ grows, a consequence of

$$|\alpha_{kl}| < \frac{\left(\frac{|W_{11}|}{2}\right)^{|k|}\left(\frac{|W_{12}|}{2}\right)^{|l|}}{|k|!\,|l|!}$$

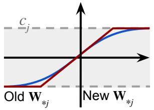


→ Bounding the matrix $\mathbf{W}$ limits the amplitudes.

→ Good input freqs allows better representing the signal spectrum.

We **initialize** ω with many low and few high frequencies chosen in $\frac{2\pi}{p}\mathbb{Z}^2$ to bypass spectral bias. They are **frozen** during training.

During training, we **bound** α_{kl} by the maximum absolute value of the hidden matrix columns.



Fixed bounds $W_{1j}\leftarrow\mathrm{clamp}(W_{1j}, c_j)$

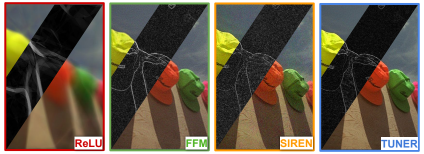
Learned bounds $W_{1j}\leftarrow c_j\tanh(W_{1j})$

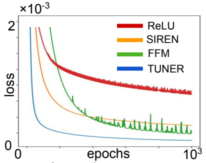
Experiments

Convergence and high order information

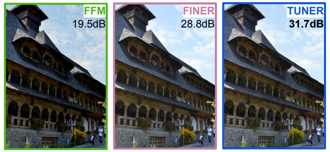
TUNER reconstructs both signal and gradient with higher PSNR avoiding overfitting on unseen pixels. We train nets with 416 input/hidden neurons over the Kodak dataset.

	Train		Test	
	signal	grad	signal	grad
SIREN	34.0	27.7	32.9	27.1
BACON	26.4	22.4	25.4	22.3
TUNER	**34.3**	**28.9**	**33.4**	**28.4**





Our initialization improves convergence compared to classic (ReLU, FFM, SIREN) and SOTA (FINER) methods.



Experiments with 256 input / hidden neurons on DIV2K dataset.

Epochs	FFM	FINER	**TUNER**
1000	29.42	30.23	**32.14**
5000	31.19	31.00	**33.16**

Frequency control

Previous methods may introduce ringing noise or artifacts.

In particular, BANF exhibit many freqs outside the bandlimit.