Appendix for Submission # 6611

A Additional Verification for Empirical Studies

In this section, we provide additional verification of our empirical studies (Sec.2.2) and INR representation experiments (Sec.4.1). We conduct experiments on the Kodak dataset [14], maintaining all configurations identical to those described in Sec. 4.1. The quantitative results are presented in Tab. 4. The configurations Standard, Bias Free, H_1Bias, Output Bias, and Input Bias align with those in Tab. 1. Additionally, we include H_2 Bias and H_3 Bias, representing networks with bias terms exclusively in the second and third layers, respectively. Settings without underlines represent standard SIREN implementations, while underlined settings correspond to FINER. The symbol ⊘ indicates reconstructions exhibiting *spatial aliasing*. For each configuration block, we report averaged metrics both with and without bias term backpropagation. Complementary results on the DIV2K dataset are presented in Tab. 5, supplementing the findings in Tab. 1. The results in Tab. 5 and Tab. 4 further validate our observations from Sec. 2.2 and conclusions from Sec. 4.1. These findings substantiate both the magnitude of bias terms' impact in INRs and the effects of their gradient optimization, lending additional support to Proposition 1. This reinforces our claim that the primary role of bias terms in neural representations is to eliminate *spatial aliasing* arising from the symmetry of coordinate space and activation functions.

Table 4: Results of 2D image fitting tasks with varying bias configurations (Kodak dataset)

Settings	1k Iterations PSNR ↑	1k Iterations SSIM↑	3k Iterations PSNR↑	3k Iterations SSIM↑	5k Iterations PSNR↑	5k Iterations SSIM↑
Standard	30.05 / 30.05	0.832 / 0.832	33.93 / 33.92	0.912 / 0.912	35.24 / 35.23	0.929 / 0.929
Bias Free⊘	15.06 / 15.06	0.599 / 0.599	15.09 / 15.09	0.620 / 0.620	15.10 / 15.10	0.626 / 0.626
H_1 Bias	29.67 / 29.68	0.822 / 0.822	33.25 / 33.25	0.902 / 0.902	34.44 / 34.45	0.919 / 0.919
H_2 Bias	29.96 / 29.96	0.831 / 0.831	33.33 / 33.32	0.903 / 0.903	34.41 / 34.42	0.918 / 0.918
H_3 Bias	30.07 / 30.05	0.829 / 0.829	33.17 / 33.16	0.895 / 0.894	34.18 / 33.17	0.910 / 0.910
Output Bias⊘	16.34 / 16.04	0.613 / 0.610	17.03 / 16.78	0.641 / 0.639	17.31 / 17.02	0.648 / 0.646
Input Bias	30.78 / 30.78	0.854 / 0.854	34.31 / 34.30	0.917 / 0.917	35.42 / 35.42	0.930 / 0.930
Standard	32.05 / 32.06	0.880 / 0.881	36.18 / 36.18	0.940 / 0.940	37.52 / 37.53	0.952 / 0.952
Bias Free⊘	15.09 / 15.09	0.617 / 0.617	15.11 / 15.11	0.632 / 0.632	15.11 / 15.11	0.636 / 0.636
H_1 Bias	30.83 / 30.82	0.853 / 0.853	34.46 / 34.45	0.921 / 0.921	35.82 / 35.81	0.935 / 0.935
H_2 Bias	31.28 / 31.28	0.866 / 0.866	34.74 / 34.75	0.924 / 0.924	35.66/ 35.67	0.934 / 0.935
H_3 Bias	31.37 / 31.36	0.865 / 0.864	34.60 / 34.60	0.919 / 0.919	35.60 / 35.59	0.931 / 0.931
Output Bias⊘	16.19 / 16.07	0.628 / 0.627	16.82 / 16.79	0.652 / 0.651	17.10 / 17.04	0.655 / 0.657
Input Bias	33.06 / 33.05	0.901 / 0.900	36.81 / 36.80	0.948 / 0.950	37.92 / 37.91	0.955 / 0.955

Table 5: Results of 2D image fitting tasks with varying bias configurations (DIV2K dataset)

Settings	1k Iterations PSNR ↑	1k Iterations SSIM↑	3k Iterations PSNR↑	3k Iterations SSIM↑	5k Iterations PSNR↑	5k Iterations SSIM↑
Standard	30.30 / 30.30	0.882 / 0.882	34.68 / 34.69	0.946 / 0.946	36.17 / 36.18	0.956 / 0.959
Bias Free⊘	13.98 / 13.98	0.556 / 0.556	14.00 / 14.00	0.574 / 0.574	14.03 / 14.03	0.577 / 0.577
H_1 Bias	29.88 / 29.87	0.872 / 0.872	34.02 / 34.00	0.938 / 0.938	35.33 / 35.34	0.950 / 0.950
H_2 Bias	30.14 / 30.13	0.875 / 0.875	33.98 / 33.96	0.935 / 0.935	35.20 / 35.19	0.946 / 0.946
H_3 Bias	30.18 / 30.14	0.871 / 0.869	33.65 / 33.63	0.927 / 0.926	34.77 / 34.76	0.934 / 0.933
Output Bias⊘	14.67 / 14.49	0.567 / 0.562	15.11 / 14.96	0.593 / 0.583	15.11 / 15.13	0.586 / 0.588
Input Bias	31.20 / 31.18	0.903 / 0.902	35.33 / 35.32	0.953 / 0.953	36.61 / 36.63	0.962 / 0.962
Standard	32.26 / 32.25	0.916 / 0.916	36.84 / 36.83	0.962 / 0.962	38.47 / 38.47	0.971 / 0.971
Bias Free⊘	13.99 / 13.99	0.568 / 0.568	14.01 / 14.01	0.581 / 0.581	14.03 / 14.03	0.583 / 0.583
H_1 Bias	31.06 / 31.08	0.894 / 0.894	35.21 / 35.23	0.950 / 0.949	36.63 / 36.62	0.958 / 0.958
H_2 Bias	31.49 / 31.49	0.901 / 0.901	35.28 / 35.24	0.948 / 0.947	36.62 / 36.60	0.957 / 0.957
H_3 Bias	31.66 / 31.60	0.901 / 0.899	35.21 / 35.18	0.946 / 0.944	36.32 / 36.30	0.952 / 0.951
Output Bias⊘	14.55 / 14.51	0.577 / 0.573	15.13 / 14.98	0.599 / 0.590	15.22 / 15.14	0.595 / 0.594
Input Bias	33.39 / 33.38	0.933 / 0.932	37.95 / 37.90	0.968 / 0.968	39.30 / 39.29	0.974 / 0.974

B Additional Experiments for Feat-Bias

In this section, we present additional experiments to validate the effectiveness of Feat-Bias (Sec.3). Following prior work[59, 19, 15], we evaluate our method on INR classification tasks using MNIST and F-MNIST datasets. In addition to the baselines discussed in Sec.D, we include comparisons with recent methods including Inr2Vec[28], DWS [33], and NG-GNN [23]. Feat-Bias$_{[\text{ViT}]}$ and Feat-Bias$_{[\text{DINOV2}]}$ represent our method using features extracted from ViT [10] and DINOv2 [34], respectively. We maintain identical configurations as described in Sec. D, employing a 3×256 MLP downstream network, training for 1000 iterations with a cosine scheduler and learning rate of $1\text{e}{-3}$. The quantitative results are presented in Tab. 6. Our Feat-Bias$_{[\text{DINOV2}]}$ achieves the highest classification accuracy on both datasets, surpassing the recent state-of-the-art MWT-L. Notably, on F-MNIST, our method improves accuracy from 87.32% to 92.38%, demonstrating significant advancement in INR downstream tasks.

Table 6: INR classification on MNIST and Fashion-MNIST Datasets

Method	MNIST	F-MNIST	Method	MNIST	F-MNIST
MLP	17.55±0.01	19.91±0.47	Inr2Vec [28]	23.69±0.10	22.33±0.41
NFN_{NP} [59]	78.50±0.23	68.19±0.28	NFN_{HNP} [59]	79.11±0.84	68.94±0.64
DWS [33]	85.71±0.57	67.06±0.29	NG-GNN [23]	91.40±0.60	68.00±0.20
ScaleGMN [19]	96.57±0.10	80.46±0.32	ScaleGMN-B [19]	96.59±0.24	80.78±0.16
WT [15]	93.08±2.26	73.81±1.43	$\text{MWT}_{\text{Mid-Task}}$ [15]	95.57±0.30	77.23±0.56
MWT [15]	96.58±0.32	83.86±0.91	MWT-L [15]	98.33±0.13	87.32±0.16
Feat-Bias$_{[\text{ViT}]}$	95.79±0.04	90.13±0.49	Feat-Bias$_{[\text{DINOV2}]}$	98.48±0.05	92.38±0.06

C Additional Experiments for Ablation Studies

We present additional ablation studies to further verify the source of *spatial aliasing*. All experimental settings strictly align with those in Sec. 4.3. Tab 7 present ablation result for spatial aliasing on Kodak dataset, demonstrating consistency with the findings presented in Tab. 3.

Table 7: Ablation study for *spatial aliasing* (Kodak Dataset)

Settings	standard	w/o coord. sym.	w/o act. sym. $(+1)$	w/o act. sym. (-1)
Full-Bias	35.23 / 0.929 / 0.089	32.23 / 0.880 / 0.191	30.38 / 0.838 / 0.257	30.44 / 0.840 / 0.254
Bias-Free	**15.10 / 0.626 / 0.461**	32.17 / 0.877 / 0.200	30.11 / 0.832 / 0.258	30.11 / 0.832 / 0.259

D Additional Experiments for classification task

Experimental Settings. In this section, we further evaluate the effectiveness of our proposed Feat-Bias (Sec. 3) on INR downstream tasks. The downstream network of Feat-Bias consists of a lightweight 3×256 MLP classifier. Since the CIFAR-100 dataset is more complex than CIFAR-10, the number of iterations is changed to 5000, using a cosine scheduler with a learning rate of $1\mathrm{e}{-3}$. In addition, the iteration count of MWT has also been modified to 20 epochs. In tab 8, we list the performance metrics at 10 epochs (i.e., the original default setting) and 20 epochs. All experiments are repeated three times, reporting both mean and standard deviation.

Quantitative Results. Tab. 8 shows the classification results for CIFAR-100 dataset [24], where we also adopt Implicit-Zoo's default configuration with a 1×64 SIREN network like the settings in the main text to ensure consistent experimental conditions across all comparisons. Since Implicitly Zoo does not provide the INR dataset of CIFAR-100, only MWT is compared with our method here. As evidenced by the results, our method achieves superior performance across accuracy, precision, and F1 score metrics meanwhile greatly reduces the training time,further demonstrating Feat-Bias's effectiveness in INR post-processing tasks.

Table 8: INR classification on CIFAR-100 Datasets

Method	***Classification Task***					***INRs***	
	Accuracy (%) ↑	Precision (%) ↑	F1 ↑	Time ↓	Params (kilo #) ↓	PSNR (dB) ↑	SSIM ↑
$\text{WT}_{\text{10epochs}}$ [15]	$12.21_{\pm 0.89}$	$10.90_{\pm 0.62}$	$10.09_{\pm 0.87}$	$73.52_{\pm 1.78}$ (min)	261	32.33	0.942
$\text{WT}_{\text{20epochs}}$ [15]	$15.83_{\pm 0.71}$	$13.82_{\pm 0.85}$	$13.84_{\pm 0.79}$	$151.78_{\pm 2.93}$ (min)	261	34.89	0.964
$\text{MWT}_{\text{Mid-Task-10epochs}}{}^{\ddagger}$ [15]	$15.81_{\pm 0.44}$	$14.94_{\pm 0.86}$	$13.86_{\pm 0.74}$	$83.41_{\pm 1.55}$ (min)	261	30.17	0.910
$\text{MWT}_{\text{Mid-Task-20epochs}}{}^{\ddagger}$ [15]	$19.87_{\pm 0.21}$	$17.88_{\pm 0.11}$	$18.06_{\pm 0.15}$	$169.42_{\pm 2.80}$ (min)	261	33.06	0.948
$\text{MWT}_{\text{10epochs}}$ [15]	$19.46_{\pm 0.88}$	$18.09_{\pm 0.58}$	$17.67_{\pm 0.69}$	$83.74_{\pm 0.97}$ (min)	261	24.45	0.752
$\text{MWT}_{\text{20epochs}}$ [15]	$23.29_{\pm 0.57}$	$21.56_{\pm 0.67}$	$21.78_{\pm 0.65}$	$168.0_{\pm 1.27}$ (min)	261	25.80	0.806
$\text{Feat-Bias}_{\text{[ViT]}}$	$74.83_{\pm 0.07}$	$75.03_{\pm 0.09}$	$74.79_{\pm 0.07}$	$144.70_{\pm 1.83}$ (sec)	151	/	/
$\text{Feat-Bias}_{\text{[DINOV2]}}$	$78.51_{\pm 0.16}$	$78.71_{\pm 0.13}$	$78.46_{\pm 0.15}$	$145.38_{\pm 1.65}$ (sec)	151	/	/

‡ denotes ω_{task} reported in MWT [15].

E Additional visualizations for *spatial aliasing*

Figure 5: Visualization for *spatial aliasing*: reconstructed signals demonstrate central symmetry, manifesting as aliasing artifacts between distinct regions of the input. Green and Pink denote the ground truth and reconstructed signals with *spatial aliasing*, respectively.

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