Supplementary Material for
ABCD : Arbitrary Bitwise Coefficient for De-quantization

1. Histogram Interpolation

In this section, we discuss the histogram analysis of ABCD. A color histogram represents the distribution of colors of an image. By representing an image's color distribution as a histogram, it becomes possible to extract important features from the image, such as dominant colors or the overall color balance. Fig. 1 shows the extreme case of histogram interpolation of ABCD results. Note that 2→8 BDE requires $\times 64$ upsampling in the histogram domain, and 8→12 BDE requires $\times 16$. Our ABCD interpolates color histograms well, even in the high-range bit-depth expansion. We demonstrate the practical application for high dynamic range (HDR) photo-editing on the right side of Fig. 1.

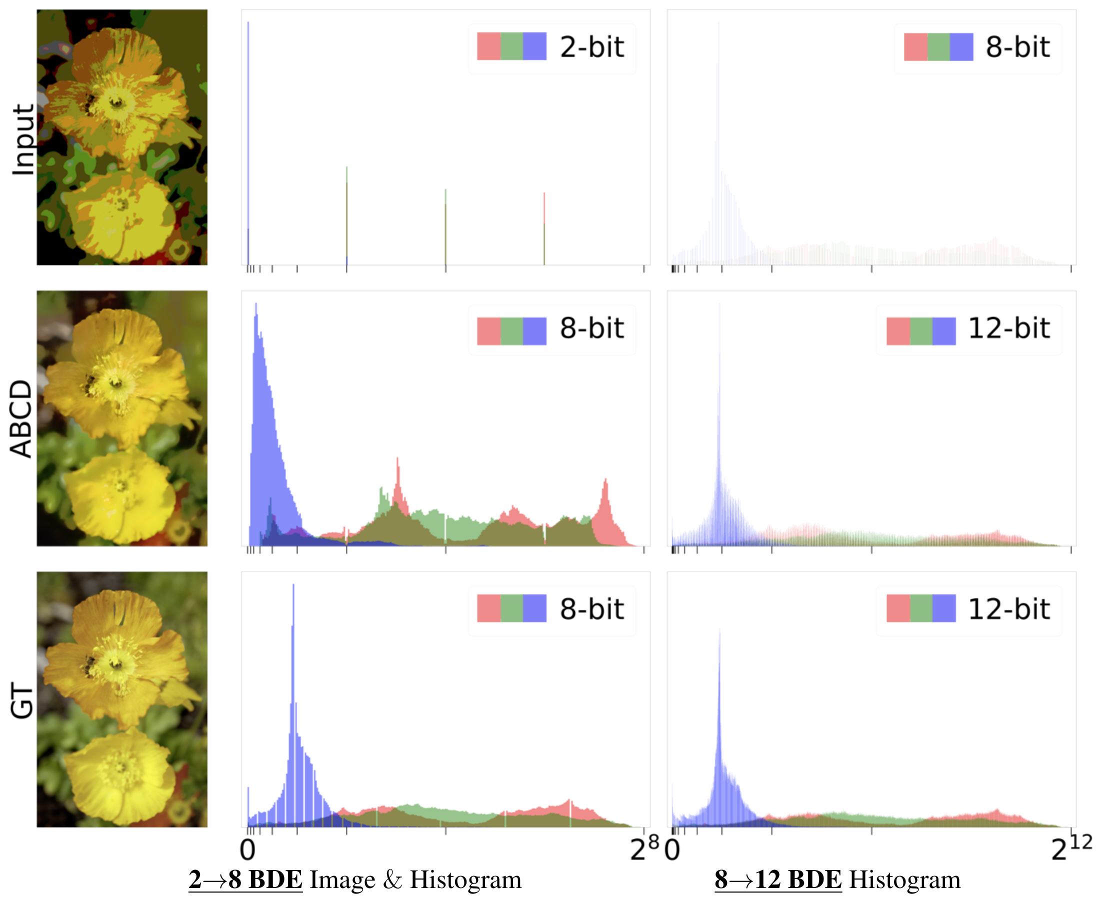

Figure 1. **Histogram analysis** of our ABCD.

2. Phasor Estimator

In this section, we present further analysis and results related to the phasor estimator. The results show that the phasor estimator significantly improves the performance of our ABCD. The phasor estimator encodes input features parsing to INR (f_θ). If we remove our phase estimator, the edge information deteriorates, leading to a performance drop.

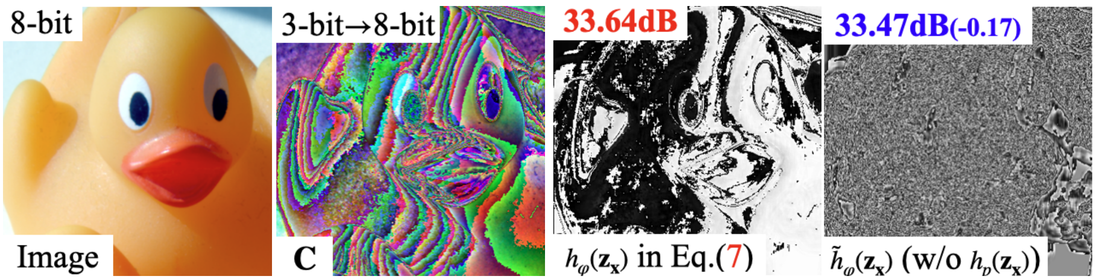

Figure 2. Feature map before forwarding MLP. Note that $\mathbf{C}$ is output label of MLP

Fig. 2 shows the impact of the phasor estimator. Note that (w/o $h_p(\mathbf{z_x})$) indicates the pre-trained model without the phasor estimator. In Fig. 2, we notice that ABCD might gain performance from detecting edges with the phase information of coefficients $\mathbf{C}$. The other motivation of the phasor estimator is representing Fourier features in latent vectors. NeRF [1] M. Tanik *et al*. [3], and SIREN [2] show that Fourier features make INR networks achieve higher performance.

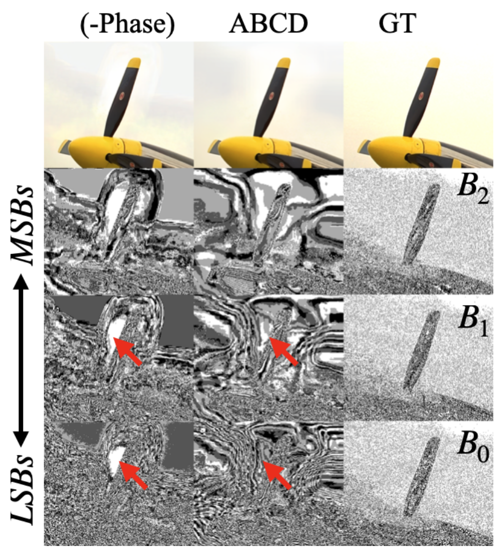

Figure 3. Qualitative comparison of phasor estimator in bitplanes for 3-bit → 8-bit BDE

Following the Fig. 8 in the main paper, we present Fig. 3 to show the impact of phase in qualitative ablation study. In LSB bitplanes, the figure shows the phasor estimator help to infer details.

3. Encoder based INR

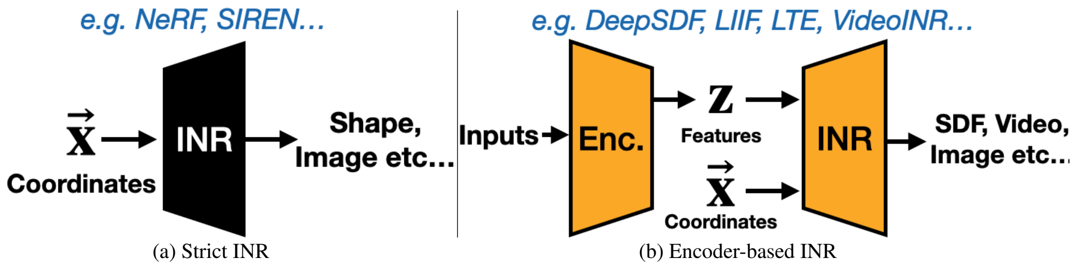

Figure 4. Overview of the strict INR and encoder-base INR.

The strict INRs (a) parameterize and overfit coordinates onto continuous signals. Instead of (a), we are inspired by (b) encoder-based INRs, which encode inputs to latent features for continuous functions. Our network follows encoder-INR, which maps both bit-wise coordinates and latent features to continuous signals. We have already tested the image-to-image regression model, which replaces the 5-layered MLP to 3×3 kernel 5-layered convolutional network :

TESTIMAGES1200	$2 \rightarrow 16$	$4 \rightarrow 16$	$6 \rightarrow 16$	$8 \rightarrow 16$	$10 \rightarrow 16$
Input(ZP)	16.68	28.83	40.95	52.92	65.04
EDSR-ABCD	**26.55**	41.65	52.78	61.78	**70.98**
EDSR-ABCD(+CNN)	**23.52**	40.94	50.22	55.09	**56.21**

Table 1. Ablation study of replacing MLP with CNN

The arbitrary BDE task is an arbitrary interpolation along with the amplitude axis. We train one BDE model with arbitrary, on-the-fly inputs like an arbitrary super-resolution task. Thus, we need to define proper amplitude-wise coordinates 's' and corresponding continuous functions $\mathbf{C}(\mathbf{I}; s)$. The regression model is inferior than our model in performance, but also it cannot infer *out-of-scales*.

4. Debanding

We will add the comparison with another approach [4]:

BBAND(↓)	360p	480p	720p	1080p	Total
Original Video	0.5525	0.4500	0.4018	0.3606	0.4316
EDSR-ABCD	0.4750	0.4180	0.3476	0.3144	0.3809
Adaband [4]	**0.3831**	**0.3139**	**0.2742**	**0.2536**	**0.2997**

We expect that the performance will improve if our network aims to solve a de-banding problem.

References

[1] Ben Mildenhall, Pratul P. Srinivasan, Matthew Tancik, Jonathan T. Barron, Ravi Ramamoorthi, and Ren Ng. NeRF: Representing Scenes as Neural Radiance Fields for View Synthesis. In *Proceedings of the European Conference on Computer Vision (ECCV)*, August 2020.

[2] Vincent Sitzmann, Julien Martel, Alexander Bergman, David Lindell, and Gordon Wetzstein. Implicit Neural Representations with Periodic Activation Functions. In H. Larochelle, M. Ranzato, R. Hadsell, M. F. Balcan, and H. Lin, editors, *Advances in Neural Information Processing Systems*, volume 33, pages 7462–7473. Curran Associates, Inc., 2020.

[3] Matthew Tancik, Pratul Srinivasan, Ben Mildenhall, Sara Fridovich-Keil, Nithin Raghavan, Utkarsh Singhal, Ravi Ramamoorthi, Jonathan Barron, and Ren Ng. Fourier Features Let Networks Learn High Frequency Functions in Low Dimensional Domains. In H. Larochelle, M. Ranzato, R. Hadsell, M. F. Balcan, and H. Lin, editors, *Advances in Neural Information Processing Systems*, volume 33, pages 7537–7547. Curran Associates, Inc., 2020.

[4] Zhengzhong Tu, Jessie Lin, Yilin Wang, Balu Adsumilli, and Alan C. Bovik. Adaptive debanding filter. *IEEE Signal Processing Letters*, 27:1715–1719, 2020.