Supplementary Material for
Deep learning phase recovery: data-driven, physics-driven, or combining both?

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To explore the tolerance of methods to defocus distances, we generate holograms with propagation distances from 15mm to 25mm and infer them using neural networks trained on the 20mm dataset. The SSIM of the inference results and the corresponding samples are shown in Fig. S1. It can be seen that DD is more tolerant than tPD, while CD neutralizes them.

We test all methods using holograms of tissue slices. The results are shown in Fig. S2. Compared with DD, as a joint strategy of data and physics, CD also infers more high-frequency information like tPD, see the yellow arrow of Fig. S2. Since the inferences go through multiple cycles, the results of uPD and tPDr contain richer information, see the green arrow of Fig. S2.

We provide a hyperparameter “pad” in the code to eliminate edge diffraction effects through padding and cropping. As shown in Fig. S3, a hologram is generated directly through numerical propagation (the upper part), or “padding and cropping” is added to eliminate edge diffraction effects (the lower part).

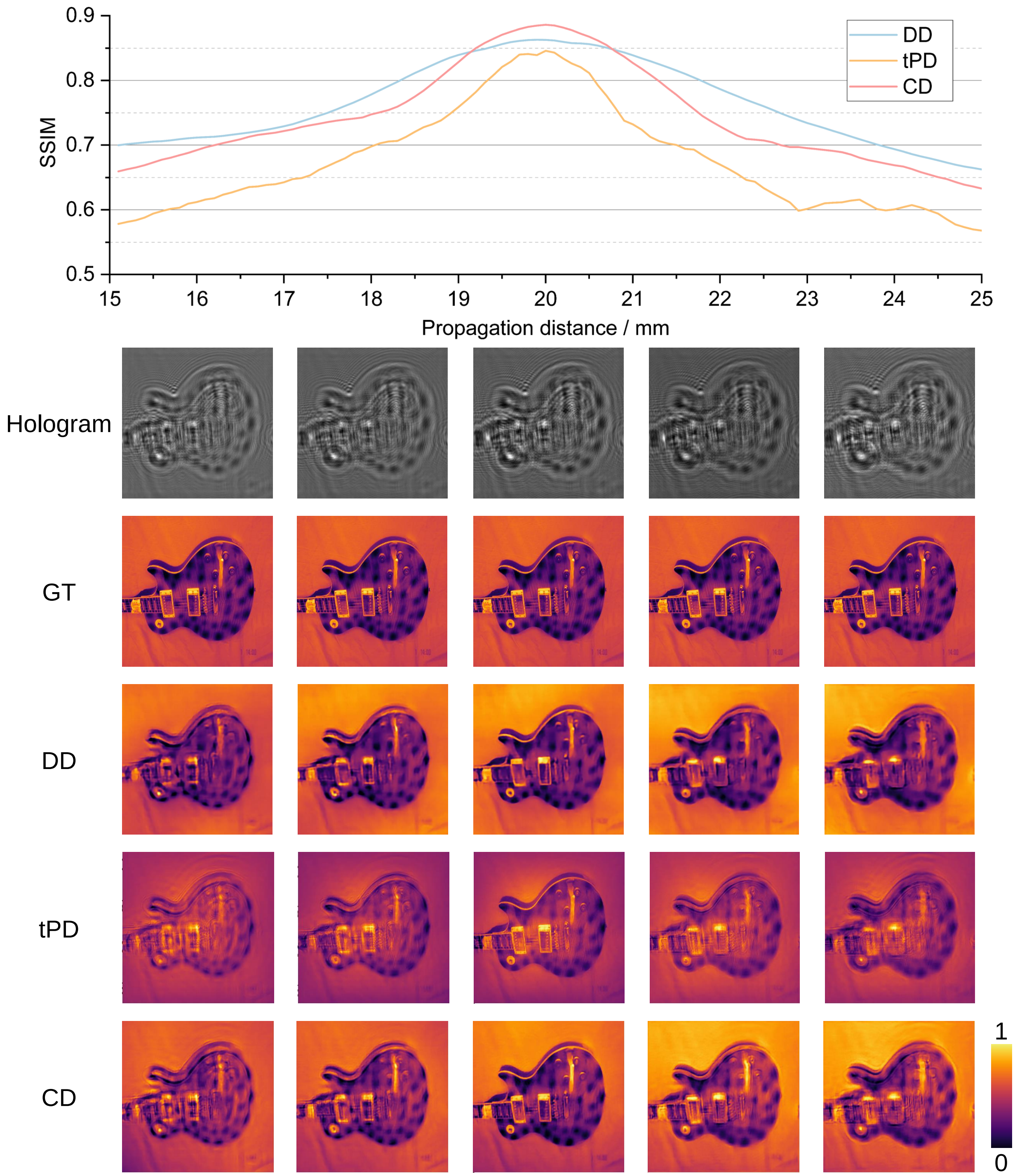

Fig S1 Defocus distance tolerance tests of DD, tPD, and CD.

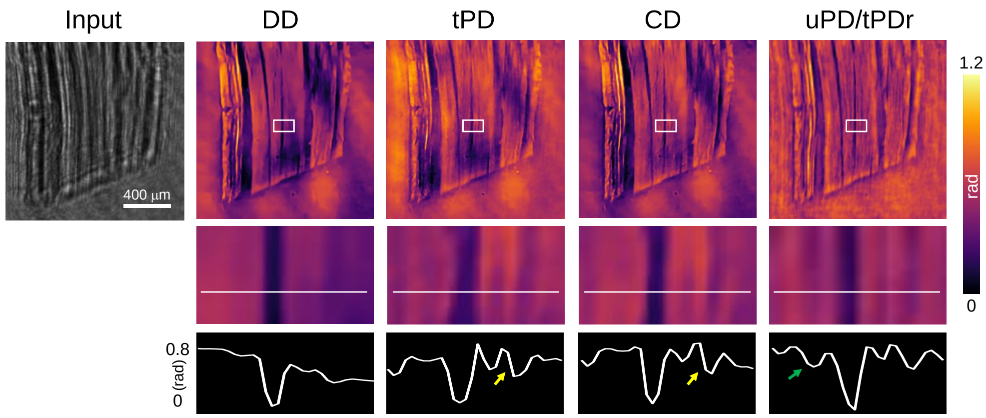

Fig S2 Experimental tests of DD, tPD, CD, and uPD(tPDr) for tissue slices.

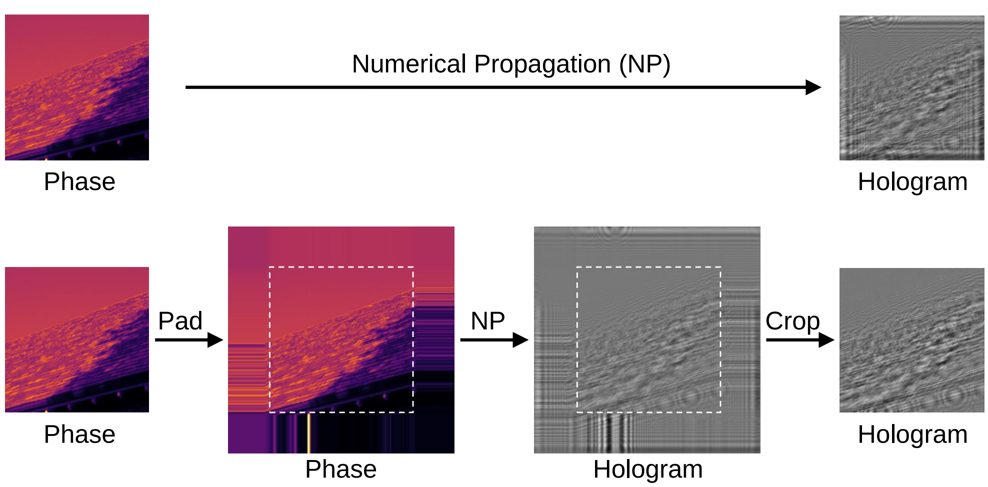

Fig S3 An example of hologram generation. Generate holograms directly by numerical propagation (upper part) or use "padding and cropping" to eliminate edge diffraction effects (lower part).