Unsupervised Deep Learning for Phase Retrieval via Teacher-Student Distillation

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Abstract

Phase retrieval (PR) is an important nonlinear inverse problem in scientific imaging. It aims at reconstructing the phase of a signal from its intensity measurements. Recently, there is an increasing interest in deep learning-based PR. Motivated by the challenge of collecting ground-truth (GT) images in many domains, this paper proposes an unsupervised learning approach for PR, which trains a deep end-to-end model without using any GT image. The unsupervised learning from intensity measurements is done via a teacher-student online distillation framework. A teacher model is trained using a self-expressive loss with noise resistance, and a student model is trained with a consistency loss on augmented data to exploit the teacher's dark knowledge for improvement. An enhanced unfolding neural network is also developed for both the teacher and student models. Extensive experiments show that, the proposed approach not only outperforms existing unsupervised PR methods with higher computational efficiency, but also performs competitively against the supervised ones.

Introduction

Phase retrieval (PR) refers to reconstructing the phase of a signal from its intensity measurements, which finds a wide range of applications in scientific imaging. Formally, PR requires solving a nonlinear ill-posed problem as follows:

$$\boldsymbol{y} = |\mathbf{A}\boldsymbol{x}_{\text{gt}}| + \boldsymbol{n}, \tag{1}$$

where $\boldsymbol{x}_{\text{gt}} \in \mathbb{C}^N$ denotes the signal (image) to reconstruct, $\boldsymbol{y} \in \mathbb{R}^M$ the intensity measurements, $\boldsymbol{n} \in \mathbb{R}^M$ the measurement noise, $|\cdot|$ the element-wise modulus operator, and $\mathbf{A} \in \mathbb{C}^{M\times N}$ some complex-valued linear transform, *e.g.*, discrete Fourier transform (DFT).

In recent years, deep learning (DL) has emerged as one promising tool for PR. Most existing studies leverage supervised DL and train an end-to-end neural network (NN) over a paired set of ground-truth (GT) images and their intensity measurements. Recent works (Cha et al. 2021; Zhang et al. 2021b) allow training an NN using an unpaired set. Plug-and-Play (PnP) approaches use a pre-trained denoising NN (Metzler et al. 2018; Wu et al. 2019; Shi, Lian, and Chang 2020; Wei et al. 2020; Chen et al. 2022b) or a pre-trained generative NN (Hand, Leong, and Voroninski 2018; Shamshad and Ahmed 2020; Hyder et al. 2019; Liu, Ghosh, and Scarlett 2021; Liu et al. 2021) to regularize prediction.

These DL-based PR methods require the acquisition of a large number of GT images in target domains. In many fields, capturing latent images with a high signal-to-noise ratio (SNR) as the GTs is expensive or even infeasible. Although PnP methods can use GT images from other domains, their generality is often limited by domain shifts, *e.g.*, statistical priors learned from digital photographs of natural scenes may not match images of biology or material science.

Built upon the deep image prior (DIP) (Ulyanov, Vedaldi, and Lempitsky 2018) that a convolutional NN (CNN) has a good inductive bias towards regular image structures in its prediction, the DIP-based unsupervised DL methods (Jagatap and Hegde 2019; Bostan et al. 2020; Wang et al. 2020; Chen et al. 2022a) avoid training data collection by using an untrained CNN for regularization. Although being free from training datasets, these methods are computationally expensive because NN models are learned separately for different test samples. In addition, their performance is not as good as the supervised DL methods in the existing literature, probably due to the lack of knowledge learned from external data.

Motivated by the challenges of GT collection for supervised methods and the limitations of dataset-free unsupervised methods, we study a dataset-based unsupervised DL approach for PR with the following three features:

- No prerequisite on GT images or pre-trained NN models.
- Training a universal model for different test samples.
- Providing competitive performance against existing supervised DL-based methods.

Main Idea and Contributions

Unsupervised DL of PR can be interpreted as a weakly semi-supervised learning problem. Consider the image acquisition process in (1). A GT image $\boldsymbol{x}_{\text{gt}}$ is composed by a part $\boldsymbol{x}_{\text{gt}}^{\text{l}}$ which is completely captured by the intensity measurements $|\mathbf{A}\boldsymbol{x}_{\text{gt}}|$ and the other part $\boldsymbol{x}_{\text{gt}}^{\text{u}}$ which is completely lost during image acquisition. These two parts are sufficient for reconstructing $\boldsymbol{x}_{\text{gt}}$. Since $\boldsymbol{y}$ is a noisy version of $|\mathbf{A}\boldsymbol{x}_{\text{gt}}|$, it

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is used as a noisy label of $\boldsymbol{x}_{\mathrm{gt}}^{\mathrm{l}}$ for weakly supervised learning. However, there is no label regarding $\boldsymbol{x}_{\mathrm{gt}}^{\mathrm{u}}$. Therefore, the training data for unsupervised PR can be viewed as having partial weak (noisy) labels encoded by $\boldsymbol{y}$, where weakly semi-supervised learning applies.

The interpretation above inspired us to develop a teacher-student DL approach for unsupervised PR. Teacher-student learning is an emerging semi-supervised learning technique in high-level vision tasks, where teacher models are trained on labeled data for initial prediction, and student models are trained to mimic the predictions of teachers on augmented unlabeled data for regularization and improvement; see *e.g.* (Tarvainen and Valpola 2017; Tang et al. 2021). It is also known as online self-supervised knowledge distillation in existing literature (Anil et al. 2018; Wang and Yoon 2021), *i.e.*, teacher and student models are jointly end-to-end trained for knowledge refinement and mutual improvement.

In the proposed approach, the learning regarding $\boldsymbol{x}_{\mathrm{gt}}^{\mathrm{l}}$ is conducted by a teacher model using a self-expressive loss with noise resistance. This loss is extended from the R2R self-supervised Gaussian denoiser (Pang et al. 2021) to measurement noise removal for nonlinear inverse problems and to handling non-Gaussian noise, *e.g.* Poisson noise often seen in PR. Together with the image prior from the inductive bias of a deep NN (Tayal et al. 2020; Manekar et al. 2020b,a; Dittmer et al. 2020), the proposed loss can train the teacher model to have a reasonable prediction accuracy.

For improvement, a student model is trained together with the teacher model using a consistency loss to encourage the predictions of the student model match that of the teacher model, *i.e.* the so-called knowledge distillation. The consistency loss is measured on a set of paired samples formed by the image estimates from the teacher model, with data augmentation via noise injection, image transformation, and exploitation of intermediate estimates from an unfolding NN.

The motivation of using consistency learning for the student model is two-fold. One is that consistency learning is an effective semi-supervised learning technique (Hendrycks et al. 2019; Englesson and Azizpour 2021), which improves noise robustness in both training and testing by perturbing the input. The other is that knowledge distillation can exploit the *dark knowledge* from the teacher model via implicit ensemble (Allen-Zhu and Li 2020). Concretely, we empirically found that the samples generated via data augmentation for student training contain multiple diverse estimates of each GT image (patch), *i.e.* one kind of dark knowledge. Since the teacher model will suffer from overfitting with large prediction variance caused by the weak supervision from its training data, the ensemble of those estimates can noticeably reduce the prediction variance. The student model trained to predict all those estimates of a GT image can implicitly learn such an effective ensemble. In addition, through consistency learning, the different predictions of the teacher and student models can be integrated to reduce solution ambiguity.

NN architecture is also important for the performance of a DL-based PR method. Based on proximal gradient, we implement a deep unfolding NN for both the teacher and student models, with two modules introduced for improvement. One is a condition-aware module for training a universal model that adapts to imaging conditions (*e.g.*, noise level and compression ratio). The other is a long short-term memory (LSTM) module to form a highway across the NN for more efficient feature delivery, and it is the first time to integrate memory into unfolding NNs for PR. These two modules lead to a powerful unfolding NN for PR.

The performance of the proposed approach is extensively evaluated under various settings. The results show that, in terms of reconstruction accuracy, the proposed approach outperforms existing GT-free methods by a large margin and provides competitive performance against latest GT-based methods. Moreover, it has advantages in terms of computational complexity compared to DIP-based unsupervised methods. The main technical contributions of this paper are:

- The first work on end-to-end unsupervised (GT-free) deep learning for PR in noisy settings.
- A self-supervised teacher-student learning approach to unsupervised PR, with state-of-the-art performance.
- A self-supervised loss with strong noise resistance for teacher models and an effective knowledge distillation scheme for student models.
- A deep unfolding NN enhanced for end-to-end PR.

Related Works

It is a prominent approach to regularize the PR process via image priors. Sparsity prior induced by a transform (dictionary) is often used in existing works and usually implemented by ℓ_1-variational models; see *e.g.* (Tillmann, Eldar, and Mairal 2016; Qiu and Palomar 2017; Chang et al. 2018; Shi et al. 2018a; Shi, Lian, and Fan 2019). Patch recurrence is another often-used prior, usually implemented by incorporating a non-local denoiser into an iterative PR process; see *e.g.* (Metzler, Maleki, and Baraniuk 2016; Shi et al. 2018b).

There is an increasing interest in end-to-end DL for PR. The supervised methods (Rivenson et al. 2018; Işıl, Oktem, and Koç 2019; Naimipour, Khobahi, and Soltanalian 2020; Hyder, Cai, and Asif 2020; Yang et al. 2022; Zhang et al. 2021a; Shi and Lian 2022) train an end-to-end NN over a paired dataset. Most of them adopt an unfolding NN constructed via replacing the regularization-related steps in an unfolded iterative process by learnable modules. Based on pre-trained deep denoisers, Wei et al. (2020) proposed an end-to-end trained NN with reinforcement learning blocks to predict the hyper-parameters involved in an unfolded process. The unpaired DL-based methods (Cha et al. 2021; Zhang et al. 2021b) inspired by CycleGAN (Zhu et al. 2017) weaken the prerequisite on training data, from paired samples to the unpaired ones. Cha et al. (2021) developed a PhaseCut-based loss for improving generator training. Zhang et al. (2021b) introduced the physics of image formation and a Fourier loss to improve cycle learning.

Instead of end-to-end training, PnP methods utilize pre-trained models from other domains as regularizers. Many PnP methods incorporate deep denoisers pre-trained on noisy/clean image pairs into an unfolding NN. Metzler et al. (2018) unfolded the RED (Romano, Elad, and Milanfar 2017) with the FASTA algorithm (Goldstein, Studer, and Baraniuk 2014) and plugged pre-trained DnCNN models (Zhang et al. 2017). Chen et al. (2022b) plugged pre-trained complex-valued NNs into RED. Shi, Lian, and Chang (2020) unfolded a sparse model embedded with a well-designed PnP denoiser. The success of these methods depends on how correlated the images for pre-training are to target images. Another PNP approach leverages deep generative model for regularization; see *e.g.* (Hand, Leong, and Voroninski 2018; Shamshad and Ahmed 2020; Hyder et al. 2019; Liu, Ghosh, and Scarlett 2021; Liu et al. 2021). The latent image is represented by a pre-trained generative model with a specific input code. Then, the NN is trained by optimizing the code to fit the model's output *w.r.t.* observed measurements. As generative models are domain-specific, these methods usually do not generalize well to unseen domains.

Recently, dataset-free DL has made rapid progress in PR; see *e.g.* (Jagatap and Hegde 2019; Bostan et al. 2020; Sun and Bouman 2021; Wang et al. 2020; Chen et al. 2022a; Wang, Li, and Ji 2022). Taking an untrained NN with random initialization, these methods adjust the NN weights such that the intensity measurements of the output image match the observed ones. The noise sensitivity and the solution ambiguity are addressed by the inductive bias of a CNN.

This paper is one of the very few works on dataset-based unsupervised DL of end-to-end NNs for PR which avoids the issues of DIP-based dataset-free DL. The related studies (Tayal et al. 2020; Manekar et al. 2020b,a) showed the fundamental difficulty of supervised learning on images with strong symmetry and addressed it by self-supervised learning with a regularized reconstructive loss on noiseless intensity measurements. In comparison, our approach considers measurement noise and leverages teacher-student distillation for improvement on addressing solution ambiguity.

Methodology

Given a set of measurement samples, but without their GT images, the goal is to train an end-to-end NN for reconstruction. Each measurement sample $\boldsymbol{y}$ relates to its GT $\boldsymbol{x}_{\mathrm{gt}}$ by $\boldsymbol{y} = |\mathbf{A}\boldsymbol{x}_{\mathrm{gt}}| + \boldsymbol{n}$, with measurement noise $\boldsymbol{n}$. Our main idea discussed in previous sections is implemented as follows.

Teacher-Student Distillation Framework

The teacher-student self-supervised knowledge distillation framework of the proposed approach is outlined in Figure 1. There are a teacher model f_{T} and a student model f_{S}, which are simultaneously end-to-end trained. The teacher model will prepare multiple estimates of the latent images with reasonable accuracy by some scheme, and these estimates will be passed to the student for knowledge distillation. Afterward, the student model will be used for testing.

Noise-resistant learning of teacher model The teacher model is trained through partial weak supervision provided by the measurements themselves. There are two issues to address: the existence of measurement noise and the solution ambiguity caused by the missing phase in training samples.

To address the issue caused by measurement noise, the following self-supervised loss is introduced:

$$\mathcal{L}_{\mathrm{T}} = \mathbb{E}_{\boldsymbol{\eta}} \| |\mathbf{A} f_{\mathrm{T}}(\boldsymbol{y}+\boldsymbol{\eta})| - (\boldsymbol{y}-\boldsymbol{\eta}) \|_2^2, \tag{2}$$

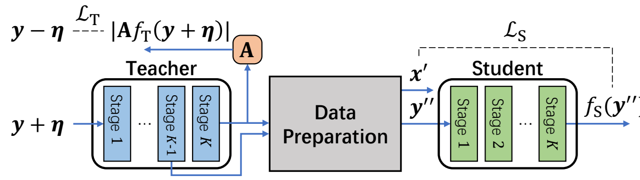


Figure 1: Proposed framework for unsupervised DL of PR.

where $\boldsymbol{\eta}$ is drawn from $\mathcal{P}_{\boldsymbol{n}}$, the distribution of $\boldsymbol{n}$. The loss is defined on a pair of re-corrupted measurements $(\boldsymbol{y}+\boldsymbol{\eta}, \boldsymbol{y}-\boldsymbol{\eta})$, and the rationale comes from the following proposition.

Proposition 1. *Suppose $\boldsymbol{\eta}|\boldsymbol{x}$ and $\boldsymbol{n}|\boldsymbol{x}$ are independent and identically distributed (i.i.d.). Then*

$$\mathbb{E}_{\boldsymbol{y}}\mathcal{L}_{\mathrm{T}} = \mathbb{E}_{\boldsymbol{x}_{\mathrm{gt}},\boldsymbol{n},\boldsymbol{\eta}} \| |\mathbf{A} f_{\mathrm{T}}(\boldsymbol{y}+\boldsymbol{\eta})| - |\mathbf{A}\boldsymbol{x}_{\mathrm{gt}}| \|_2^2 + \text{const.}. \tag{3}$$

Proposition 1 states that $\mathcal{L}_{\mathrm{T}}$ is immune to measurement noise, as it provides an unbiased estimate of the loss defined on the noise-free measurements $|\mathbf{A}\boldsymbol{x}_{\mathrm{gt}}|$. In other words, the loss $\mathcal{L}_{\mathrm{T}}$ can effectively remove the negative impact caused by $\boldsymbol{n}$. However, it cannot remove other solution ambiguity, as it only considers the fitting error on intensity measurements. However, as a CNN architecture is likely to have a good inductive bias for natural images (Tayal et al. 2020; Manekar et al. 2020b,a; Dittmer et al. 2020), the teacher model can alleviate solution ambiguity with the loss $\mathcal{L}_{\mathrm{T}}$.

Consistent learning of student model During learning, the teacher model prepares a set of image estimates $\{\boldsymbol{x}'\}_{\boldsymbol{x}'}$ as follows. (i) Noise injection: For each measurement $\boldsymbol{y}$, the teacher model takes $\boldsymbol{y}' := \boldsymbol{y} + \boldsymbol{z}$ as input with randomly added $\boldsymbol{z} \sim \mathcal{P}_{\boldsymbol{n}}$, and outputs multiple image estimates $\boldsymbol{x}' = f_{\mathrm{T}}(\boldsymbol{y}')$. (ii) Intermediate reusing: As the teacher model is an unrolling NN with multiple stages where each stage outputs an intermediate estimate, we take the estimates from the last N stages as $\boldsymbol{x}'$, which provides various corrupted versions of latent images. (iii) Image data augmentation: we apply random rotation and random cropping on those image estimates to enlarge the set of $\boldsymbol{x}'$. Flipping is not used, as it will generate images with the same measurements and training the student model to predict different images from the same measurements will lead to contradiction.

The three schemes above enable the teacher model to have multiple estimates of the target image from different perspectives. Afterward, many pairs of training samples $\{(\boldsymbol{y}'', \boldsymbol{x}')|\boldsymbol{y}'' = |\mathbf{A}\boldsymbol{x}'| + \boldsymbol{n}'\}_{\boldsymbol{x}',\boldsymbol{n}'\sim\mathcal{P}_{\boldsymbol{n}}}$ are formed and used to train student model for consistency regularization and knowledge distillation via the following loss:

$$\mathcal{L}_{\mathrm{S}} = \mathbb{E}_{\boldsymbol{y}''} \| f_{\mathrm{S}}(\boldsymbol{y}'') - \boldsymbol{x}' \|_2^2. \tag{4}$$

Total training loss We impose the losses $\mathcal{L}_{\mathrm{T}}, \mathcal{L}_{\mathrm{S}}$ on the output of every stage of the unfolding NNs, which are denoted by $\mathcal{L}_{\mathrm{T}}^k, \mathcal{L}_{\mathrm{S}}^k$ respectively. Then, the teacher and student models are jointly trained by

$$\mathcal{L} := \lambda_{\mathrm{T}} \sum_{k=1}^{K} \gamma_k \mathcal{L}_{\mathrm{T}}^k + \lambda_{\mathrm{S}} \sum_{k=1}^{K} \gamma_k \mathcal{L}_{\mathrm{S}}^k, \tag{5}$$

where $\lambda_{\mathrm{T}}, \lambda_{\mathrm{S}} \in \mathbb{R}^+$ and $\gamma_k = 1/(K-k+1)$.

Network Architecture

Similar to standard CNNs, an unfolding NN based on proximal gradient descend also has an inductive bias (Dittmer et al. 2020) to facilitate unsupervised DL. Therefore, for both the teacher and student models, we construct an NN with K stages via unfolding the proximal gradient descend solver (Combettes and Pesquet 2011) for a regularized variational problem: $\min_{\boldsymbol{x}} \|\boldsymbol{y} - |\mathbf{A}\boldsymbol{x}|\|_2^2 + \phi(\boldsymbol{x})$. Starting from an initial point $\boldsymbol{x}_0$, the proximal gradient descend iterates:

$$\begin{aligned} \boldsymbol{z}_k &= \boldsymbol{x}_{k-1} - q_k \nabla\mathcal{D}(\boldsymbol{x}_{k-1}; \boldsymbol{y}, \mathbf{A}), \\ \boldsymbol{x}_k &= \mathrm{Prox}_{\phi}^{q_k}(\boldsymbol{z}_k) := \mathrm{argmin}_{\boldsymbol{x}} \{\phi(\boldsymbol{x}) + \frac{q_k}{2}\|\boldsymbol{x} - \boldsymbol{z}_k\|_2^2\}, \end{aligned} \tag{6}$$

where $q_k \in \mathbb{R}^+$ is a step size, $\mathcal{D}(\boldsymbol{x}; \boldsymbol{y}, \mathbf{A}) = \|\boldsymbol{y} - |\mathbf{A}\boldsymbol{x}|\|_2^2$, and $\mathrm{Prox}_{\phi}^{q_k}(\boldsymbol{z})$ denotes the proximal operator. We replace $\mathrm{Prox}_{\phi}^{q_k}$ by a so-called proximal module (PM) without weight sharing across stages, which is a U-Net with two enhancements. See Figure 2 for the resulting NN architecture.

Imaging condition awareness Imaging conditions such as noise level and sampling ratio can vary for different samples. Many existing methods, *e.g.* (Metzler, Maleki, and Baraniuk 2016; Metzler et al. 2018; Wei et al. 2020; Yang et al. 2022), include them as known hyper-parameters or an additional input. Instead, we introduce a condition-aware block (CAB) to utilize imaging conditions for better prediction, which also allows training a single model that generalizes well on the samples with varying imaging conditions. Let $\boldsymbol{\theta} = [\beta, \rho]$ store the noise level β (*e.g.*, standard deviation for Gaussian noise and strength for Poisson noise) and the sampling ratio ρ. The CAB is a stack of fully-connected layers, which maps $\boldsymbol{\theta}$ to the step sizes $\{q_k\}_{k=1}^K$ used in (6) as well as to a set of feature values $\{p_k\}_{k=1}^K$ incorporated into the PMs at different stages. Concretely, p_k is repeated to form a map of the size of $\boldsymbol{x}$ and used as the additional input of the kth PM.

Cross-stage feature delivery In a PM, an input image is mapped to features and then transformed back to an image for output. Then, an unrolling NN constructed via (6) alternates between the image and feature domains. Since the PMs at different stages play a similar role (*i.e.* proximal operators), their extracted features should be highly correlated and the features from the previous PM could benefit the process of next one. However, the aforementioned features-image-features pipeline is not efficient which may form a bottleneck for feature delivery through the whole NN, particularly when the image size is much less than the feature size.

To address the bottleneck issue of feature delivery, similar to the work for compressed sensing (Song, Chen, and Zhang 2021), we introduce convolutional long short-term memory (ConvLSTM) cells (Shi et al. 2015) on top of the CNNs, which creates a path that allows interactions and feature delivery across different stages. Then, the pipeline of our unfolding NN reads as follows: for $k = 1, \cdots, K$,

$$\begin{aligned} \boldsymbol{z}_k &= \boldsymbol{x}_{k-1} - q_k \nabla\mathcal{D}(\boldsymbol{x}_{k-1}; \boldsymbol{y}, \mathbf{A}), \\ \boldsymbol{x}_k &= \mathrm{PM}_k(p_k, \boldsymbol{h}_{k-1}, \boldsymbol{z}_k), \\ [\boldsymbol{h}_k, \boldsymbol{c}_k] &= \mathrm{ConvLSTM}(\boldsymbol{t}_k, \boldsymbol{h}_{k-1}, \boldsymbol{c}_{k-1}), \text{ if } k \le K-1, \end{aligned}$$

where q_k, p_k are the output of CAB, $\boldsymbol{t}_k$ is the intermediate features drawn in the kth PM (*i.e.*, PM_k), and $\boldsymbol{h}_k, \boldsymbol{c}_k$ are the

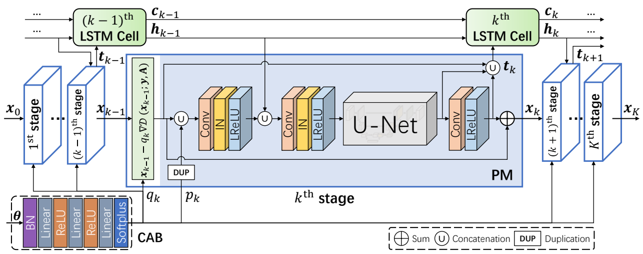


Figure 2: NN architecture for teacher and student models.

hidden and cell states respectively in the kth ConvLSTM cell, with $\boldsymbol{h}_0$ and $\boldsymbol{c}_0$ set to zeros. To fully exploit feature delivery, we draw intermediate features from three parts of PM_k to form $\boldsymbol{t}_k$, as shown in Figure 2. We insert a ConvLSTM cell between every two adjacent stages so as to reduce the cell number from K to $K-1$, which differs from (Song, Chen, and Zhang 2021). In addition, a ConvLSTM cell in our NN consumes features from multiple layers, rather than a single layer like (Song, Chen, and Zhang 2021).

Experiments

Performance evaluation is conducted on three types of measurements: coded diffraction patterns (CDPs), holographic patterns, and ptychographic patterns. Through the experiments, we set $K = 5$ for both NNs and $\lambda_{\mathrm{T}} = \lambda_{\mathrm{S}} = 1, N = 2$ for training. The teacher and student models are jointly trained using the Adam optimizer with 200 epochs and batch size of 8. The learning rate is initialized to 5×10^{-4} when the measurement number is two times larger than the pixel number, and 1×10^{-3} otherwise. It is then decayed every 100 epochs with the factor of 0.5. To simulate practical scenarios, for each GT image, only one intensity measurement sample is generated to form the data for unsupervised learning. The trained student model is used for inference.

Evaluation on Coded Diffraction Patterns

CDPs in coded diffraction imaging are generated with $\mathbf{A} = \left[(\mathbf{F}\mathbf{D}_1)^\top, \cdots, (\mathbf{F}\mathbf{D}_J)^\top\right]^\top$, where $\mathbf{F}$ is a DFT matrix, and $\mathbf{D}_1, \cdots, \mathbf{D}_J$ are defined as $\mathbf{D}_j\boldsymbol{x} \to \boldsymbol{d}_j \odot \boldsymbol{x},\ j = 1, \cdots, J$. Here $\odot$ denotes the Hadamard product, and $\boldsymbol{d}_j \in \mathbb{C}^N$ is an illumination mask set to uniform masks or bipolar masks: the former for non-compressive CDPs and the both for compressive CDPs. A uniform mask is generated through drawing its elements uniformly from the cell circle in the complex plane. A bipolar mask is generated through drawing its elements from $\{1, -1\}$ with the Bernoulli distribution $\mathcal{B}(1/2)$. The mask number is set to $J = 1, 2, 4$ respectively.

PR from non-compressive uniform CDPs The training data setting for PR varies in existing works. Following the representative work (Wei et al. 2020), our training set consists of the 400 images of the Berkeley segmentation dataset (BSD) (Martin et al. 2001) and the 5600 images selected randomly from the PASCAL VOC dataset (Everingham et al. 2015). Each of these 6000 images is resized to 128×128 and used to generate the CDPs via (1), with Poisson noise simulated by the scheme of (Metzler et al. 2018): $\boldsymbol{y}^2 = |\mathbf{A}\boldsymbol{x}|^2 + \boldsymbol{\epsilon}$,

Table 1: Quantitative results on uniform CDPs in terms of PSNR(dB). The best and second best results at each row are **boldfaced** and underlined respectively. Left part of methods: GT-dependent; Right part of methods: GT-free.

	J	γ	prDeep	PPR	DPSR	TFPnP	prCom	Dolpin	B-GAMP	conPR	DDec	DMMSE	E2E	Ours
prDeep12	1	9	35.29	33.29	33.33	**36.05**	35.59	26.29	35.10	32.81	33.33	34.04	30.31	35.94
		27	26.39	28.71	28.98	30.15	29.75	25.16	29.07	26.80	28.09	29.46	25.56	**30.17**
		81	22.08	24.04	23.92	24.42	23.52	17.47	22.96	20.44	22.55	23.53	17.24	**25.00**
	2	9	37.61	35.92	35.90	38.53	38.06	30.89	37.75	35.09	33.21	37.01	34.27	**38.58**
		27	31.26	30.63	30.66	32.07	32.15	25.69	30.96	29.48	28.71	30.06	24.66	**32.16**
		81	25.20	25.39	25.59	26.37	25.90	17.70	23.96	24.07	24.55	25.82	17.45	**26.40**
	4	9	39.70	37.55	37.69	40.33	40.60	31.24	40.32	36.39	37.60	40.58	37.53	**41.09**
		27	33.54	31.67	32.30	33.90	34.10	27.45	32.85	30.88	31.36	33.97	27.69	**34.23**
		81	26.90	27.02	26.73	27.23	27.60	20.22	25.43	25.87	25.19	27.12	18.58	**28.29**
BSD68	1	9	34.83	33.46	33.44	**35.46**	34.37	27.43	34.62	32.98	32.24	33.97	29.61	35.37
		27	25.92	28.59	28.75	**29.88**	28.75	25.54	29.05	26.93	28.11	29.67	24.41	29.85
		81	21.49	24.08	23.97	24.68	23.09	16.58	23.01	20.52	22.16	24.42	16.35	**24.99**
	2	9	37.22	35.55	35.57	37.96	37.11	32.17	37.35	35.46	32.01	36.72	34.27	**37.99**
		27	30.92	30.34	30.25	31.69	30.03	26.35	30.94	29.60	28.23	31.40	25.50	**31.69**
		81	24.70	25.35	25.38	26.28	24.94	16.54	23.98	24.10	23.73	25.54	16.59	**26.46**
	4	9	39.41	37.16	37.25	40.40	39.63	32.81	40.00	37.37	36.33	39.31	37.49	**40.52**
		27	33.14	31.53	31.87	33.63	33.19	28.52	32.82	31.05	30.67	33.12	28.64	**33.70**
		81	26.49	26.38	26.47	27.94	26.53	19.76	24.99	25.95	24.44	26.56	19.91	**28.05**
Time(sec.)			9.05	1.72	5.13	0.02	7.56	10.09	16.96	3.61	22.18	267	0.02	**0.02**

where $\epsilon \sim \mathcal{N}(\mathbf{0}, \gamma^2 \text{Diag}(|\mathbf{A}\boldsymbol{x}|^2))$ and a larger γ indicates a lower SNR. The value of γ is uniformly sampled from $\{9, 27\}$. For test, the images of the prDeep12 dataset (Metzler et al. 2018) and BSD68 (Martin et al. 2001) are used as GTs for generation of measurements, with Poisson noise of $\gamma = 9, 27, 81$ added respectively.

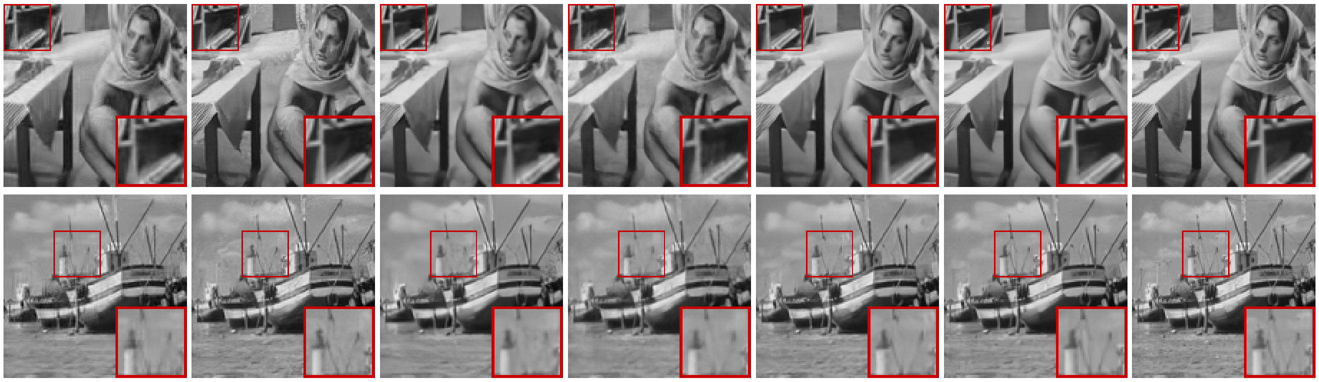
Totally eleven methods are selected for performance comparison, including DOLPHIn (Tillmann, Eldar, and Mairal 2016), B-GAMP (Metzler, Maleki, and Baraniuk 2016), ConPR (Shi et al. 2018b), prDeep (Metzler et al. 2018), PPR (Shi, Lian, and Fan 2019), DDec (Jagatap and Hegde 2019), DPSR (Shi, Lian, and Chang 2020), E2E (Manekar et al. 2020a) TFPnP (Wei et al. 2020), prCom (Chen et al. 2022b) and DMMSE (Chen et al. 2022a). Their results are quoted from (Chen et al. 2022b,a) whenever possible and otherwise obtained with their published codes. Specifically, DOLPHIn, B-GAMP and ConPR are learning-free methods, DDec and DMMSE are DIP-based dataset-free unsupervised methods, and E2E is a dataset-based unsupervised method. All of them are GT-free. In comparison, prDeep, PPR, DPSR, prCom and TFPnP are GT-dependent: the former four are PnP methods, and the last one is an end-to-end DL-based method. For fair comparison and for PNSR improvement, we replace the U-Net used in E2E by ours.

See Table 1 for the quantitative results of all compared methods measured by Peak-Signal-to-Noise Ratio (PSNR). Among all GT-free methods, ours is the best performer. By leveraging teacher-student learning, our approach noticeably outperformed the very recent DIP-based unsupervised method DMMSE and the very recent PnP method prCom. It also performs much better than the dataset-based unsupervised method E2E. Surprisingly, it even performed competitively against the representative supervised method TFPnP, with better results in more than one half settings. See Figure 3 for visual comparison on some reconstructed images. The visual quality of our results is competitive against that of the supervised methods. All above results have demonstrated the effectiveness of our approach.

Computational efficiency Table 1 also lists the inference time of different methods in reconstructing a 128×128 image with a uniform mask, run on an RTX Titan GPU. The TFPnP, E2E, DDec, DMMSE and our model are all implemented with PyTorch. It can be seen that our model, E2E and TFPnP have nearly the same inference time which is much less than the DIP-based methods DDec and DMMSE. This showed the computational efficiency advantage of our dataset-based unsupervised approach over the dataset-free ones. Other methods are not implemented with PyTorch and require more stages/iterations in their processing, and their running time is much higher than ours.

PR from compressive uniform or bipolar CDPs Compressive PR considers an additional compression process during measuring, which can be expressed as $\mathbf{A} = \mathbf{CFD}$, where $\mathbf{C}$ is a $M \times N$ matrix produced by randomly sampling M rows of an $N \times N$ identity matrix, and $\mathbf{D}$ is a diagonal matrix associated with a single illumination mask. The sampling ratio ρ is defined as $\rho = M/N$. Two types of noise are considered respectively: the Poisson noise simulated by the scheme of (Metzler et al. 2018) with strength γ and the additive white Gaussian noise (AWGN) with strength measured by the SNR of input measurements. Three sampling ratios $\rho = 0.3, 0.4, 0.5$ are used respectively.

Following Yang et al. (2022), we randomly crop 6000 patches of size 128×128 from 400 images of BSD to



B-GAMP prDeep DPSR prCom TFPnP Ours GT

Figure 3: Reconstructed images on uniform CDPs with $\gamma = 27$. Upper: $J = 2$; Bottom: $J = 4$.

Table 2: Performance comparison of PR from compressive uniform or bipolar CDPs on prDeep12 dataset, in terms of PSNR(dB). The best result at each column is **boldfaced**.

	ρ	0.50		0.40		0.30	
Uniform	γ	10	30	10	30	10	30
	B-GAMP	32.33	27.85	31.94	27.78	30.53	27.33
	prDeep	32.43	22.29	30.90	23.80	30.55	25.10
	PPR	29.91	27.31	28.51	26.48	26.20	25.07
	DPUNet	33.18	28.63	**32.34**	28.37	30.96	27.76
	Ours	**33.19**	**28.86**	32.30	**28.52**	**31.09**	**28.12**
Bipolar	SNR	10	20	10	20	10	20
	B-GAMP	23.75	28.45	23.22	27.74	22.10	26.75
	prDeep	19.51	28.27	18.49	27.77	17.04	26.89
	PPR	**24.46**	27.17	23.69	26.16	22.72	24.33
	Ours	24.35	**28.62**	**23.71**	**27.94**	**23.13**	**26.99**

generate the measurements for training. The Poisson noise of training data has its strength uniformly sampled from [0,50], while the AWGN has its SNR uniformly sampled from [10,50]. For test, the images from prDeep12 are used as GTs. The strength of Poisson noise is set to 10 and 30 respectively, and the SNR of AWGN is set to 10 and 20 respectively. A single model is trained for dealing varying ρ.

Three baseline methods including B-GAMP, prDeep and PPR, are used for comparison, with results generated from their released codes. In addition, the DPUNet (Yang et al. 2022), a supervised end-to-end NN, is introduced for the comparison on uniform masks, with quoted results. See Table 2 for the quantitative results. Our approach is the top performer through all settings except for two cases where it performed slightly worse than two GT-based methods, DPUNet and PPR, respectively. Such results again demonstrated the effectiveness of our approach.

Evaluation on Other Patterns

PR from holographic patterns In holography, the measurements are generated with $\mathbf{A} : \boldsymbol{x} \to [(\mathbf{F}\boldsymbol{x})^\top, (\mathbf{F}(\boldsymbol{x} + \mathscr{D}^{s_1,s_2}\boldsymbol{x}))^\top, (\mathbf{F}(\boldsymbol{x} - i\mathscr{D}^{s_1,s_2}\boldsymbol{x}))^\top]^\top$, where $(\mathscr{D}^{s_1,s_2}\boldsymbol{x})(t_1 + t_2 n_1) = \exp(\frac{2\pi i s_1 t_1}{n_1} + \frac{2\pi i s_2 t_2}{n_2})\boldsymbol{x}(t_1 + t_2 n_1), 0 \leq t_j \leq n_j - 1$ for $j = 1, 2$, and $i = \sqrt{-1}$. Both the s_1 and s_2 are set to 0.5 according to (Chang et al. 2018). Poisson noise defined by $|\boldsymbol{y}| \sim \alpha \cdot \text{Poisson}(|\mathbf{A}\boldsymbol{x}|/\alpha)$ is added where a larger α indicates a lower SNR. We randomly select 6000 (100) images from the public fashion product image dataset (Aggarwal 2019) to form the training (test) set. All the images are converted to gray-scale, resized and cropped centrally to 128×128 for generating the measurements. The Poisson noise strength α is uniformly sampled from $\{3, 9\}$ for training data, and set to 3 and 9 respectively on test data.

Table 3: PSNR(dB) results of PR from holographic patterns and ptychographic patterns respectively.

	α	prDeep	DPSR	PPR	prCom	TFPnP	TFPnP*	Ours
Holo	3	31.73	25.79	25.85	31.03	32.18	33.13	**33.81**
	9	28.70	24.88	24.96	27.93	28.52	29.58	**30.28**
Pty	3	25.37	20.93	20.93	23.99	24.46	25.12	**25.68**
	9	18.78	19.94	19.90	20.37	22.57	23.30	**24.08**

prDeep TFPnP Ours GT

Figure 4: Reconstructed images from holographic patterns (up) and ptychographic patterns (bottom) with $\alpha = 9$.

PR from ptychographic patterns Ptychography is an emerging application of PR. Following (Chang et al. 2018), we define $\mathbf{A} : \boldsymbol{x} \to [(\mathbf{F}(\omega \odot \mathbf{R}_1\boldsymbol{x}))^\top, (\mathbf{F}(\omega \odot \mathbf{R}_2\boldsymbol{x}))^\top, \cdots, (\mathbf{F}(\omega \odot \mathbf{R}_L\boldsymbol{x}))^\top]^\top$, where $\mathbf{R}_l$ is a binary matrix that selects a window of $\boldsymbol{x}$ and $L = 9$, and the ω denotes the coded pattern generated by a 64×64 zone plate len. We select 82 (20) cell images from public microscope cell image dataset (Payyavula 2018) to form the training (test) set. The training images are cropped to 6012 patches of size 128×128 for measurement generation, and the test images are cropped to 128×128. The previous noise setting is used.

Results and analysis We select prDeep (Metzler et al. 2018), PPR (Shi, Lian, and Fan 2019), DPSR (Shi, Lian, and Chang 2020), prCom (Chen et al. 2022b), and TF-PnP (Wei et al. 2020) for comparison. To simulate the scenarios where GTs are unavailable, for these compared methods we directly call their models trained on CDPs of natural images. See Table 3 for the quantitative results. Our approach achieved the best results among all compared methods. Due to the domain gap between natural images and cell images, most PnP methods did not work well. When TF-PnP is retrained on the cell images (denoted by TFPnP*), its performance has a noticeable increase but is still worse than ours overall. See Figure 4 for visualization comparison. Our approach preserved more structural details, while other two methods produced over-smoothing patterns or flecked backgrounds. These results have justified the value of our unsupervised learning approach for PR.

Ablation Studies

We construct the following baselines for ablation studies. (a) Teacher: using the teacher model for test; (b) w/o $\mathcal{L}_{\rm T}$: replace $\mathcal{L}_{\rm T}$ with the one used in (Manekar et al. 2020a): $\||\mathbf{A} f_{\rm T}(\boldsymbol{y})| - \boldsymbol{y}\|_2^2$; (c) w/o Inject (w/o Inter, w/o Augment): Noise injection (Intermediate reusing, image data augmentation) is disabled respectively when the teacher model prepares the data for student learning; (d) w/o CAB: all CABs are disabled; (e) w/o LSTM: all the ConvLSTM cells are replaced by a series of convolutional layers of nearly the same parameter number; (f) supervised: training the student model using paired data with MSE loss. All baselines are retrained with the same strategy stated in CDPs for fair comparison.

See Table 4 for the quantitative comparison. Each component of the proposed approach contributes to performance improvement. Particularly, (i) benefiting from the proposed noise-resistant self-expressive loss and the inductive bias of the unfolding NN architecture, the teacher model already has a not bad performance, which is further improved noticeably with larger than 0.72dB PSNR gain; (ii) the proposed noise-resistant loss $\mathcal{L}_{\rm T}$ is critical to the success of the learning; (iii) the three strategies used in the data preparation process can improve the effectiveness of student learning and distillation; (iv) our approach performed even slightly better than its supervised counterpart, which is probably due to the difficulty of supervised learning of PR on the training data with certain symmetry (Tayal et al. 2020).

Table 4: Results of ablation studies in PSNR(dB), conducted on uniform CDPs with J=1,4 on prDeep12 dataset, in the presence of Poisson noise with $\gamma = 9$.

J	Teacher	w/o $\mathcal{L}_{\rm T}$	w/o Inject	w/o Inter	Original
1	35.21	35.22	35.62	35.76	35.94
4	40.29	40.35	40.72	40.85	41.09
J	w/o Augment	w/o CAB	w/o LSTM	Supervised	Original
1	35.73	35.34	35.43	35.90	35.94
4	40.81	40.66	40.55	41.02	41.09

Analysis on Noise Model Mismatch

Like many existing approaches, *e.g.* (Metzler et al. 2018; Wei et al. 2020), one key of our scheme requires the knowledge of noise. We investigate the influence of mismatch between the noise model used in our training scheme and that of both training and test data. This is done by adding Poisson-Gaussian mixed noise simulated by the scheme of (Khademi et al. 2021) to the training and test samples. The strengths of Poisson and Gaussian noise are set to 10 and 30 respectively. In training, the Poisson noise instead of the Poisson-Gaussian mixed one is used for our unsupervised loss and noise injection, with its strength γ sampled from $9, 27, 81$. As a result, the noise characteristics are inconsistent between data and our assumption. We include five selected methods for comparison. These methods are also blind to the noise characteristics of test data, with their models trained on Poisson noise directly applied.

See Table 5 for the results of CDPs on prDeep12. We also include our result with matched noise statistic, denoted as "Ours*". Our method has an around 0.5dB PSNR drop but still better than prDeep, DPSR, DMMSE and E2E. The performance of our approach with noise model mismatch does not come up to that of TFPnP. This is probably because the noise robustness of TFPnP comes from the image prior learned from GTs and the noise model for synthesizing noisy images. In comparison, same as other unsupervised methods, ours does not access any GT and its noise robustness comes from the training loss whose effectiveness relies on noise model match.

Table 5: Performance comparison of CDPs (J=4) in PSNR(dB) when trained with a mismatched noise model.

prDeep	DPSR	TFPnP	DMMSE	E2E	Ours	Ours*
25.73	27.11	28.42	25.36	24.44	28.12	28.61

Conclusion

To extend the applicability of deep learning to the PR scenarios where collecting GT images is challenging, in this paper, we proposed a self-supervised teacher-student distillation approach to unsupervised learning for PR. It contains a teacher model trained with a noise-resistant loss and a student model performing consistent learning using the paired samples generated by the teacher model. With the implementation of an unrolling NN with specific modules, the proposed approach demonstrated its effectiveness and efficiency in the extensive experiments with various settings. In future, we will investigate other frameworks and strategies of teacher-student learning and distillation for improvement.

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