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Physics-informed Unsupervised Learning for Single Photon Imaging

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Abstract: By embedding imaging physics, we develop an unsupervised framework to enable image restoration learning for single photon imaging with only the training data degraded by the blurring effect, Poisson noise, and readout noise. © 2025 The Author(s)

1. Introduction

Owing to high photon sensitivity, single photon imaging sensors, such as the quanta image sensor (QIS) [1], have the ability of detecting each arriving photon. Different from conventional detectors that directly measure and output the light intensity, single photon image sensors count the arriving photons and encodes the photon number into a binary single-bit signal, with "1" for the case where the photon number exceeds a threshold and "0" for the other case. Therefore, an effective decoding algorithm is indispensable for such a sensor to accurately obtain the light intensity. Existing methods can be classified into two categories, *i.e.*, the model-based method (*e.g.*, [2]) and the learning-based method (*e.g.*, [3]). The former one is developed by explicitly modeling the imaging process and the image prior distribution. These methods hold inferior performance since their models are generally oversimplified, lacking a comprehensive characterization of imaging physics and image statistics. In contrast, the learning-based method determines an implicit mapping function to achieve image restoration. Although it can achieve superior results, its performance heavily relies on the data collection that is laborious or even infeasible under challenging scenarios. To alleviate the data collection burden and enhance the practicability, we develop a physics-informed unsupervised framework to enable network learning directly with binary signals detected with the single photon image sensor.

2. Method

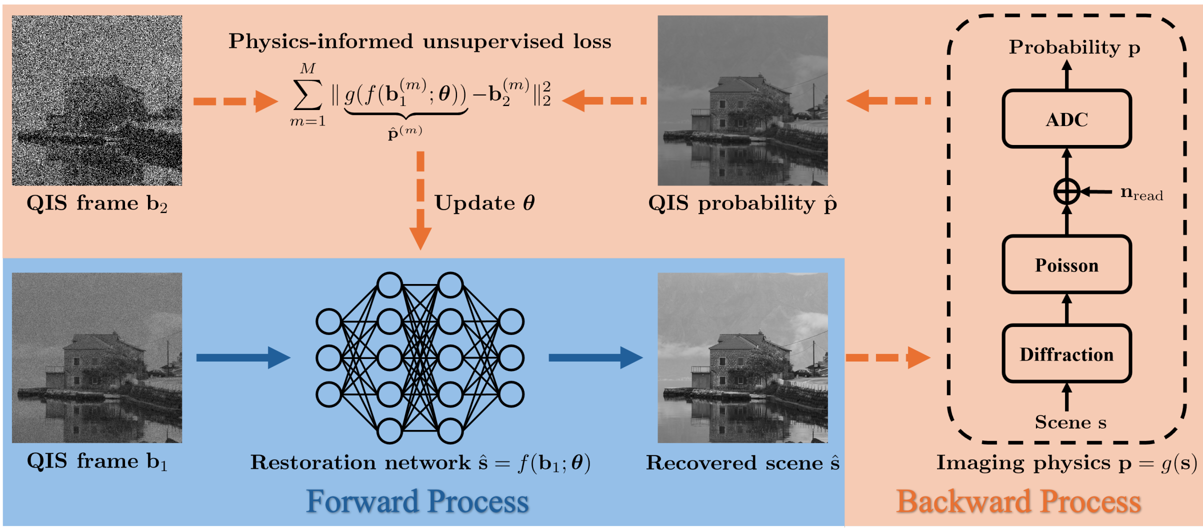

Fig. 1: Physics-informed unsupervised learning framework for single photon imaging.

Statistically speaking, the binary signal $\mathbf{b}$ output by single photon image sensors follows a Bernoulli distribution, *i.e.*, $\mathbf{b} \sim \text{Ber}(\mathbf{p})$, where the probability parameter $\mathbf{p} = \mathbb{E}[\mathbf{b}]$ is determined by the light intensity of the target scene $\mathbf{s}$ and the imaging process. For the QIS, its imaging process involves the diffraction-limited blurring, the Poisson

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process, the readout process influence by Gaussian noise noise, and the Analog-to-Digital Converter (ADC), which can be modeled by

$$\mathbf{b} = \mathrm{ADC}\{\underbrace{\mathrm{Poisson}(\overbrace{\mathbf{s}*\mathbf{h}}^{\text{Diffraction}})}_{\text{Poisson process}} + \underbrace{\mathrm{Gaussian}(0, \sigma_{\text{read}}^2)}_{\text{read noise}}\}, \tag{1}$$

where $*$ denotes the convolution operator, $\mathbf{h}$ denotes the blur kernel, and σ_{read}^2 denotes the noise level. For such an imaging process, we observe that there is a relation between the probability $\mathbf{p}$ and the light intensity $\mathbf{s}$ as

$$\mathbf{p} = g(\mathbf{s}) = p_{\text{flip}} e^{-\mathbf{s}*\mathbf{h}} + (1 - p_{\text{flip}})(1 - e^{-\mathbf{s}*\mathbf{h}}), \tag{2}$$

where $p_{\text{flip}} = erfc\left(\frac{1}{2\sqrt{2}\sigma_{\text{read}}}\right)$ denotes the bit-flip error result from the read noise. The $erfc(\cdot)$ denotes the complementary error function. With this observation, we further develop a physics-informed unsupervised loss as $L(\boldsymbol{\theta}) = \sum_{m=1}^{M} \|g(f(\mathbf{b}_1^{(m)};\boldsymbol{\theta})) - \mathbf{b}_2^{(m)}\|_2^2$ to enable the learning of a network $f(\cdot;\boldsymbol{\theta})$ with M pairs of QIS outputs, as illustrated in Fig. 1. When the paired outputs $\mathbf{b}_1^{(m)}$ and $\mathbf{b}_2^{(m)}$ are independently captured from the same scene $\mathbf{s}^{(m)}$, this unsupervised loss is statistically equivalent to the supervised loss, since there is

$$\mathbb{E}[\|g(f(\mathbf{b}_1^{(m)};\boldsymbol{\theta})) - \mathbf{b}_2^{(m)}\|_2^2] = \|g(f(\mathbf{b}_1^{(m)};\boldsymbol{\theta})) - \mathbb{E}[\mathbf{b}_2^{(m)}]\|_2^2 + \mathrm{C}. \tag{3}$$

3. Results

Our method is evaluated with simulated experiments where the binary QIS frames are generated with source images from publicaly available datasets according to the imaging process modeled by (1). For each training input $\mathbf{b}_1^{(m)}$, we generate and accumulate 64 binary frames to obtain a multi-bit QIS frame. For each training target $\mathbf{b}_2^{(m)}$, a single-bit binary QIS frame is synthesized. The source images used for training and test are different. Experimental results on two example test images are shown in Fig. 2. It can be observed that network trained with our method can successfully recover image with clear textures from the QIS frames, even when the training target is a single-bit frame corrupted by various degradations.

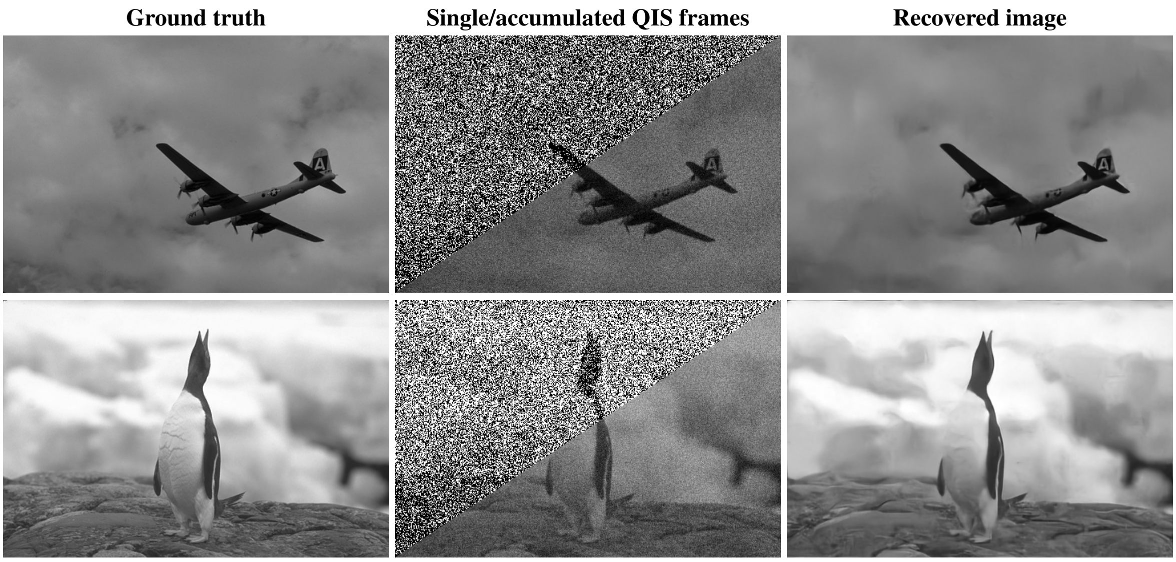

Fig. 2: Visual results of the proposed unsupervised method

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