Generalized Imaging Augmentation via Linear Optimization of Neurons

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Abstract

Most deep networks for computational photography tasks require large-scale training, which is time-consuming, computing-cost, and even hard to implement for certain data-unaccessible tasks. The emerging untrained convolutional networks (CNNs) rely on explicit physical models whose discrepancies and disturbances would lead to unsatisfactory performance. In response to these challenges, this work reports a generalized augmenting technique for computational photography techniques based on **LI**near **O**ptimization of **N**eurons (LION). LION linearly transforms the neurons of a pre-trained CNN and optimizes the transformation coefficients using a model-free color and texture regularization. Leveraging the inherent representation capabilities of the deep feature domain, we can enhance the quality of output images through a simple linear transformation of the pre-trained network features, without modifying network parameters or architecture. Furthermore, inspired by the concept of deep image prior, we develop a generalized workflow based on LION for augmenting untrained networks and conventional methods. A series of experiments have validated the technique's effectiveness for general imaging augmentation in underwater, low-light, and computational lensless imaging applications.

1 Introduction

Deep neural networks have achieved tremendous success in photography tasks[30, 47, 52]. In most neural-based studies, learning statistics prior from a large-scale training set has a great impact on the effectiveness. However, the performance of training-based methods will be limited for those situations that lack large-scale paired datasets. Using a pre-trained network in imaging systems with altered settings could lead to suboptimal performance without further fine-tuning or retraining. In response to these challenges, recent works have combined neural networks with model-based iterative optimization frameworks that incorporate physical constraints as fidelity. The plug-and-play (PnP) method[41, 59, 61] which treats the

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pre-trained network as the enhancing regularization in iterative optimization has achieved great success in various imaging modalities. Besides, deep unfolding[60, 62, 64] end-to-end trains an unfolded iterative optimization with a sub-network as the regularization and fixed iteration times. Ulyanov et al.[49] reported an untrained strategy dubbed deep image prior (DIP) for inverse problems. DIP constructs the objective function with a specific imaging model and updates the network's weights by the gradient-based algorithm. However, despite the current success of these frameworks, there is a need to calibrate the model with prior knowledge. The discrepancy and disturbance of models or handcraft priors would result in unsatisfactory performance.

Here, this work presents a new learning scheme that is capable of enhancing networks' performance from statistical to case optimality. It does not require additional training or calibrating an accurate physical model, which extends its applications to challenging tasks that lack data or are hard to calibrate the model. The technique is plug-and-play for existing conventional methods or CNNs without altering parameters or disrupting their structure.

The learning method we introduce demonstrates the generalized imaging augmentation technique, which works by linear optimization of neurons (LION). In this work, we show that the latent high-dimensional feature space of neural networks can establish effective constraints. From this nature, we report a generalized adaptive learning technique to further augment both traditional methods and CNNs. The core design strategy is similar to dictionary learning[48] and sparse coding[24]: optimizing the transformation of feature bases. However, the technique fully utilizes neural networks' high-dimensional feature space for encoding rather than a conventional over-complete dictionary. Optimizing in the feature domain enables improved capability for high-dimensional representation. The main contributions are as follows:

- LION is a generalized augmenting scheme for both networks and conventional computational photography methods. It can tackle the challenging tasks of hard-to-acquire large-scale data or calibrating an accurate physical model.

- By projecting feasible solutions from the spatial domain to the high-dimensional feature domain, LION linearly transforms the hidden neurons of a pre-trained CNN. It further optimizes the linear transformation in the feature domain using a model-free color and texture regularization. We demonstrate the inherited representation ability and strong constraints of the deep feature domain.

- Based on the reported LION scheme, we demonstrate a general imaging augmentation workflow suitable for various computational photography tasks such as underwater, low-light, and lensless imaging. It can further promote the performance of off-the-shelf image recovery methods. Experiments on public datasets have validated its state-of-the-art performance.

2 Related Work

2.1 Conventional computational photography methods

Conventional methods can be roughly categorized into model-free and model-based ones. Histogram equalization[1, 7, 21] is a typical model-free technique to balance the spatial illumination, improving the contrast and dynamic range for ill-exposed images. For color

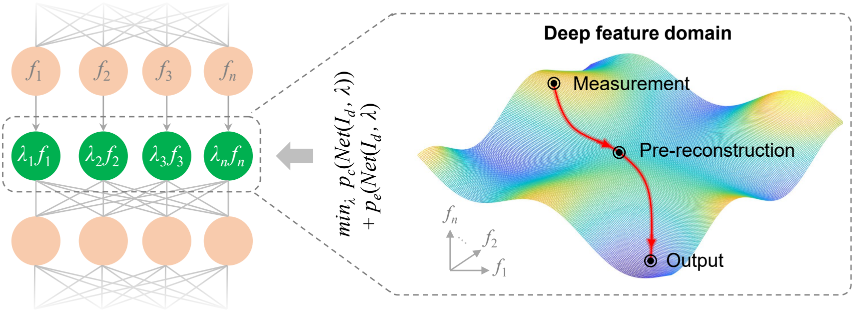

Figure 1: Principle for LION. LION linearly transforms the neurons of a CNN and tunes the transformation coefficients $\boldsymbol{\lambda}$ following the pre-defined model-free objective Eq. (2).

correction in the spectral dimension, white balance and its variants[11, 20, 34] are the most commonly used conventional methods. Besides, ref. [3, 4] combined spatial illumination balancing and color correction by fusion to deal with underwater enhancement. Traditional model-free methods are usually straightforward to implement and appropriate for real-time applications. However, they cannot be theoretically ensured to obtain the optimum. In a typical model-based reconstruction technique, an imaging model is initially created to explain how to take measurements of target scenes using geometrical or fluctuating optics. By resolving the inverse problem of the forward imaging model, it obtains the target information of interest[36]. For instance, the Retinex model is a widely applied model for photography, which decomposes an image into a reflection component and an illumination component by certain priors or regularizations[30]. For imaging in bad conditions, Nayar et al.[38] presented an atmosphere imaging model. The backscatter term in this imaging model is estimated by handcraft priors such as DCP[17], GDCP[40], and haze lines[9] to obtain sharp scenes. Akkaynak et al.[2] revised the underwater imaging model under the discovery that the attenuation coefficient is range-dependent and governs the increase in backscatter. So the accuracy of the estimated range map determines the reconstruction performance. For model-based methods, it is vital to construct a model conformed to the real-world application and employ proper regularizations. The discrepancy of preset models or inaccurate priors may cause artifacts and color deviations in output images[28, 30].

2.2 Data-driven methods

To date, training a neural network on a large-scale dataset has been proven to be an effective way for various imaging modalities[8, 45, 46, 53]. With the bloom of deep learning theories, the reconstruction network has seen the development from pure CNN to hybrid CNN-Transformer[32] architecture. However, the transferability[12] across different data distributions (such as similar imaging systems but with different settings) remains a challenge for data-driven methods, which might lead to image reconstruction degradation or hallucinations. The external generalization of a learning-based technique often requires additional transfer learning on a subset of new types of samples[19, 44]. What's more, data-driven methods will face doubts about their authenticity in scenarios where it is difficult to obtain large-scale real-captured data.

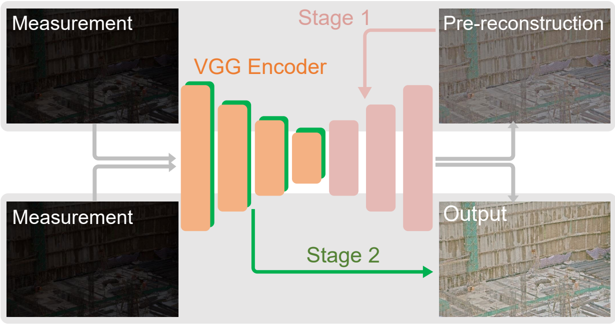

Figure 2: The generalized workflow for LION augmentation. The augmentation includes two steps. In stage 1, fitting the network (pre-trained VGG encoder + untrained decoder) to output the pre-reconstructed image with the measurement as input. Note that the first step is designed for non-learning methods. We can omit it when augmenting a pre-trained network. Next, in stage 2, tuning the linear transformation coefficients $\boldsymbol{\lambda}$ of features with fixed network parameters using the objective Eq. (2).

2.3 Combing optimization and neural networks

To combine the advantages of both the model-based and learning-based techniques, the PnP[41, 59, 61] and deep unfolding[60, 62, 64] methods have been proposed in which the neural network serves as a regularization in iterative optimization. The fidelity term in the optimization constrains the network output from deviating from the established physical model. Various iterative optimization frameworks (such as half quadric splitting (HQS)[18, 62], iterative shrinkage-thresholding algorithm (ISTA)[15, 60], and alternating direction method of multipliers (ADMM)[35, 50]) have been proven effective in these approaches. In addition, Ulyanov et al.[49] reported DIP for photography tasks. It indicates that the convolutional network has an intrinsic constraint on its output. Without the need for training, CNN can be optimized following a pre-defined objective to be an inverse model of the imaging process. DIP has shown wide applications in model-based works including deblurring[33], dehazing[25], phase imaging[51], MRI[13], dynamic PET reconstruction[58], etc. Similar to the conventional model-based approaches, these techniques suffer from inaccurate calibration of the model. Besides, deep unfolding inherits the shortcomings of learning-based methods in dealing with data-unaccessible tasks due to its end-to-end training.

3 Methodology

Next, we report a generalized workflow of LION augmentation. As presented in Fig. 1, the features f of the pre-trained encoder are encoded with linear transformation:

$$f_i \leftarrow \lambda_i f_i, \quad \text{for} \quad i \in 1 \rightarrow n. \tag{1}$$

The transformation coefficients $\boldsymbol{\lambda} = \{\lambda_1, \lambda_2, ..., \lambda_n\}$ represent the coordinates in the feature space. LION searches the optimum in the feature domain with a pre-defined model-free objective as follows:

$$min_{\lambda} \; p_c\left(Net\left(I_d, \lambda\right)\right) + p_e\left(Net\left(I_d, \lambda\right)\right), \tag{2}$$

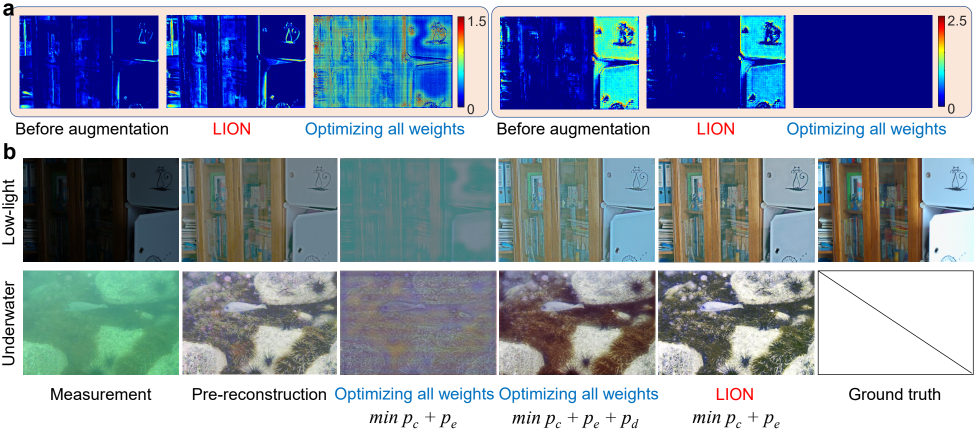

Figure 3: Comparison between LION and optimizing all the network weights. **a**, Extracted features from the decoder before and after augmentation. **b**, The reconstruction results by LION and optimizing all the weights. The fidelity regularization $p_d = \|I_o - I_p\|^2$ is used to regulate the output for optimizing all the weights, where I_o is the output image and I_p is the pre-reconstructed image. Optimizing all the weights generates nonexistent structures or gets stuck in local optima even with the fidelity regularization, whereas LION is less likely to do so.

$$p_c(z) = exp(-(s(z) + c(z) + u(z))), \tag{3}$$

$$p_e(z) = exp(-\nabla z), \tag{4}$$

where I_d denotes the input image, p_c and p_e represent the color and texture regularizations respectively. The prior p_c is inspired by the UCIQE[56] metric which is a prevalent blind image quality index. In Eq. (3), s, c, and u denote the chroma, contrast, and saturation of the output image, respectively. A lower p_c generally indicates a more visually appealing result. Besides, '∇' in Eq. (4) stands for the total variation[42] operator. A lower value of p_e corresponds to more details and textures in the output image. The feature domain optimization only adjusts the linear transformation coefficients $\boldsymbol{\lambda}$, without changing the weights of the network's filters and other hyperparameters.

Recently, encoder-decoder or UNet-like networks have proved effective for various imaging tasks[16, 29, 55]. Such networks project the input image in the high-dimensional feature domain by the encoder and reconstruct images after processing by the decoder. In the following sections, we focus on the UNet-like CNNs, separately transforming features of the encoder while retaining the form of the decoder. It efficiently reduces the calculation without affecting the augmentation effect.

We further extend the application of LION to augment conventional or DIP-based methods. Given the input degraded image I_d and pre-reconstructed image I_p obtained by any reconstruction algorithm, we build a UNet-like network and train the network's weights following DIP's procedure. For fast convergence, we take the first few layers of pre-trained VGG-19[43] (up to *relu*4_1) as the encoder as shown in Fig. 2. The decoder has 4 blocks with different resolutions, each block consisting of a ConvTranspose2d (kernel size=2, stride=2), a Conv2d (kernel size=3, padding=1, stride=1), and a LeakyReLU (gradient=0.2). From bottom to top, the kernel numbers in the Conv2d layers are 256, 128, 64, and 3, respectively.

Following UNet's architecture, the corresponding layers of the encoder and decoder are connected by skip connections. The objective is denoted as

$$min_\theta \left\|Net_\theta\left(I_d, \boldsymbol{\lambda}=\mathbf{1}\right)-I_p\right\|^2. \tag{5}$$

The weights θ of the network are trained with all the λs set as 1. After convergence, the network learns the mapping from I_d to I_p through the above fitting process. At this point, we have established a strict constraint in the feature space. With θ fixed, we then conduct the above-mentioned LION augmentation following Eq. (2).

LION transforms features as a whole, which helps maintain the structure of the features after transformation. This constraint on the feature domain regulates the structure of the output image and prevents the generation of nonexistent details. Therefore, it allows for aggressive optimization objectives (such as the reported color and texture enhancement losses) and avoids local minima. Figure 3 shows the difference between LION and optimizing all the network weights as DIP does. Figure 3**a** indicates LION's strong constraints on the feature domain. Optimizing all the weights could potentially change the feature structure (deep semantic information), but LION maintains the feature structure. The comparison of reconstruction results, as shown in 3**b** validates LION can enhance color and texture maintaining the structure of the output image. However, optimizing all the weights leads to nonexistent details or local minima, even with the extra fidelity regularization.

Overall, LION provides a powerful but easy-to-implement way for augmenting the performance of networks or traditional techniques. We consider the pre-trained features as bases of high-dimensional feature space and conduct linear optimization in the feature domain with the model-free color and texture objective. The high-dimensional feature space provides strong representation ability and strict semantic constraints. LION does not alter the semantics and textures of the output image, which ensures no information loss in the output image.

4 Experiments

We applied the reported generalized imaging augmentation technique for underwater, low-light, and computational lensless imaging. We utilized SSIM metric[63] to score the output images with the reference images. SSIM evaluates the similarity of structural details. The blind image quality index UIQM[39] is applied for images without reference images. UIQM comprehensively measures the color saturation, contrast, and sharpness of images. A higher value of UIQM indicates better visual performance. The Adam solver was utilized in the following experiments. In stage 1, all the transformation coefficients λ_i of features were set as 1. We trained the decoder with the fixed VGG encoder. In stage 2, we optimized the coefficients λ_i with the fixed encoder and decoder. The total iterations of stage 1 and stage 2 were set as 1000 (learning rate=1×10^{-4}) and 15000 (learning rate=1×10^{-5}), respectively. The reported technique was implemented using Pytorch with an NVIDIA RTX 2060 GPU. More implementation details are provided in Supplement Note 1.

4.1 Lensless imaging

Over the last decade, lensless imaging systems have provided a promising alternative for lightweight, ultra-compact, and low-cost imaging. It often places a phase[6] or amplitude[5]

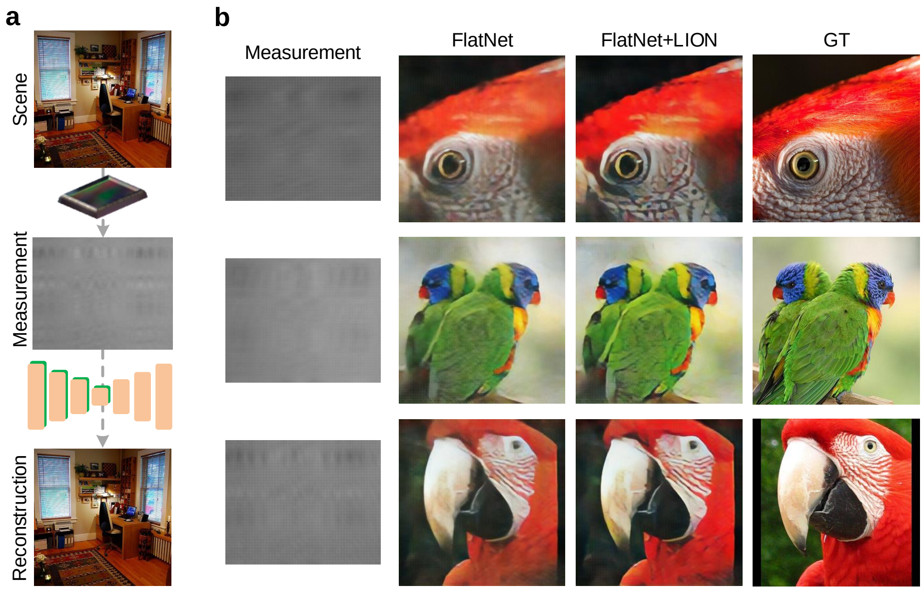

Figure 4: The lensless imaging augmentation by LION. **a**, We applied FlatNet as the base model for reconstruction from raw lensless measurements of the public dataset[23]. The channels of the Bayer measurements are arranged in the order of R-Gr-Gb-B. **b**, The visual comparisons of reconstructions w/ and w/o LION augmentation.

mask on the sensor instead of a camera lens. Without any focusing element, lensless imagers do not capture photographs of the scene. Instead, they record highly multiplexed measurements from the sensor. Thus it is essential to develop a high-fidelity reconstruction algorithm for lensless imaging systems. The state-of-the-art technique FlatNet[23] presents a UNet-like network to restore target images with raw lensless measurements. We directly applied LION to FlatNet as shown in Fig. 4 **a** and tuned $\boldsymbol{\lambda}$ with fixed pre-trained network parameters. The measurements are from ref. [23]'s public dataset which conforms to the physical model of FlatCam[6]. Figure 4 **b** demonstrates that the output images by LION's augmentation show more details and sharp textures.

4.2 Underwater imaging

To evaluate the performance of the reported technique on underwater enhancement, we tested it on the real-captured UIEB underwater dataset[27]. The reconstruction follows the workflow illustrated in Figure 2. First, we pre-enhanced underwater images via white balancing and sharpening[9]. Given an input x, the sharpening is denoted as

$$y = (x + \mathcal{N}\{x - G * x\})/2, \tag{6}$$

where $\mathcal{N}$ represents the linear normalization operator (histogram stretching) which shifts and scales pixels' values to cover the entire available dynamic range. The operator $G*$ stands for the Gaussian filtering. In practice, we iteratively performed the Eq. (6) for 30 times to obtain the pre-reconstructed image. An example of underwater pre-reconstruction is shown in Fig.

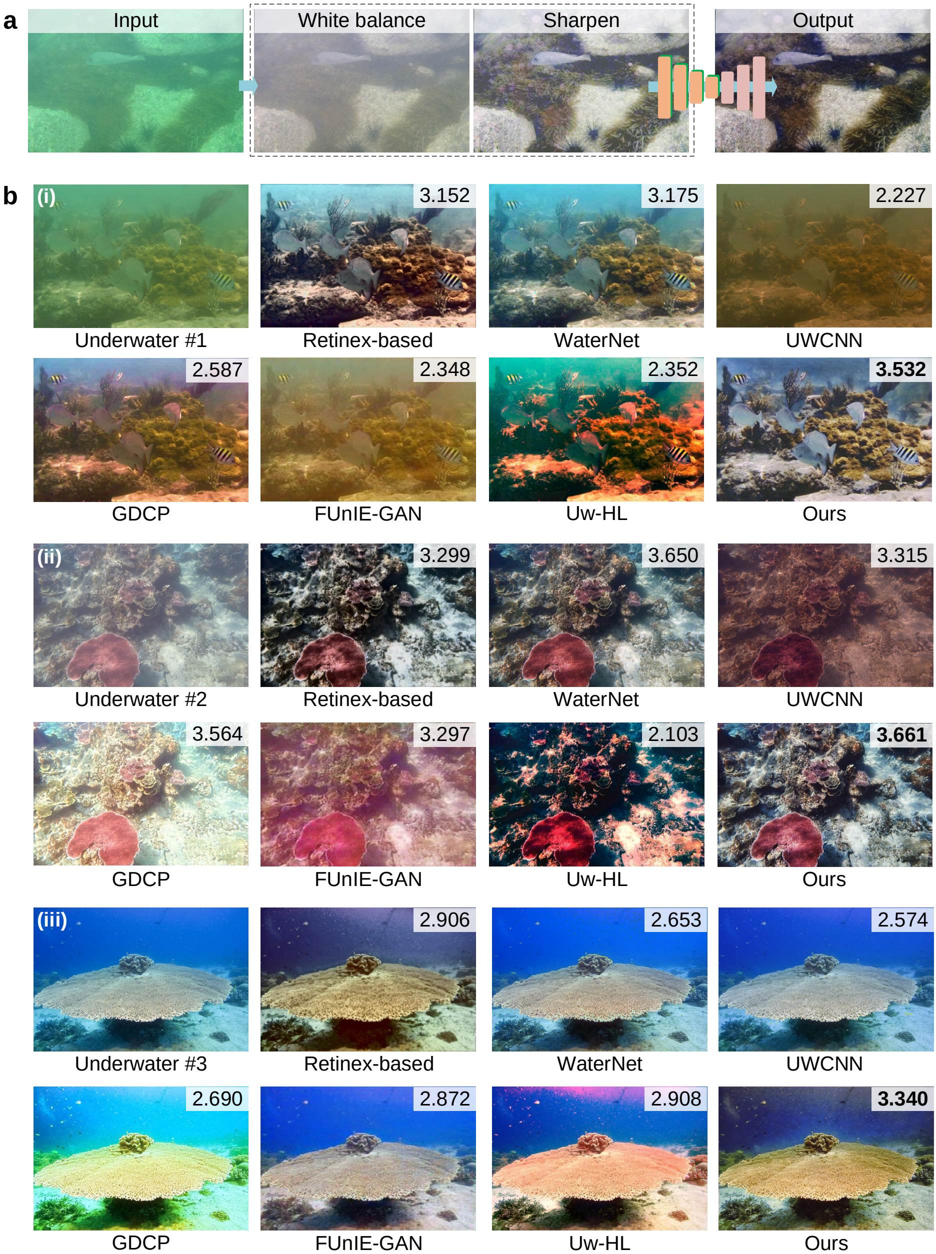

Figure 5: The underwater imaging augmentation results by LION. **a**, The pre-reconstructions are obtained by white balancing and sharpening. **b**, The exemplar underwater measurements are from the public dataset[27]. The UIQM (↑) score is listed in the upper right of each reconstructed image.

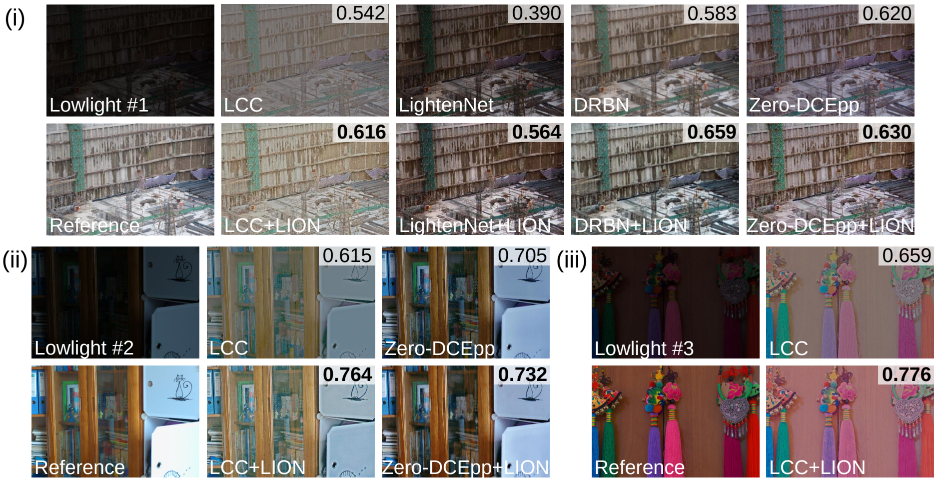

Figure 6: The low-light imaging augmentation results by LION. The exemplar low-light images are from the public dataset[54]. The SSIM (↑) score is listed in the upper right of each reconstructed image.

5 **a**. With the measurement as input, we fitted the network to output the pre-reconstruction with all the λs fixed to 1. Next, we conducted the optimization following Eq. (2) without changing the weights of the network.

We compared our technique with various underwater imaging techniques, including Retinex-based[14], WaterNet[27], UWCNN[28], GDCP[40], FUnIE-GAN[22], and Uw-HL[10]. The qualitative and quantitative comparisons of exemplar underwater enhancement results are shown in Fig. 5 **b**. Retinex-based, WaterNet, and Uw-HL can eliminate the color cast in images. However, Retinex-based and Uw-HL tend to produce over-saturated images. UWCNN, GDCP, and FUnIE-GAN introduce extra color distortion. In comparison, our method effectively removes color distortion and turbidity. As shown in Fig. 5 **b**, the qualitative and quantitative results indicate the reported technique based on LION outperforms the other methods.

4.3 Low-light enhancement

To further validate the proposed method on low-light imaging, we adopted the commonly used LOL dataset[54] for experiments. All the images are with a resolution of 600×400. Following the workflow in Fig. 2, we applied LION to augment the outputs of existing low-light imaging methods including local color correction (LCC)[37], LightenNet[26], DRBN[57], and Zero-DCEpp[31]. As shown in Fig. 6, LION can effectively augment existing methods. For the images with insufficient illumination such as Lowlight #1 - LightenNet and Lowlight #2 - LCC, LION can further enhance the ambient illumination to a suitable range. For the images with low saturation such as Lowlight #1 - DRBN and Lowlight #3 - LCC, LION is capable of enhancing the saturation. For images with the incorrect hue like Lowlight #1 - Zero-DCEpp, LION can correct the hue of the output image closer to the ground truth. Both the qualitative and quantitative results verify the effectiveness of the reported technique.

5 Conclusion

This paper reports a generalized learning scheme LION. LION performs augmentation for a pre-trained network via automatic optimum searching in the high-dimensional feature domain. The innovations of the proposed LION technique are as follows. First, compared with the existing data-driven and model-based approaches, LION does not require additional training or calibrating an accurate physical model to augment an off-the-shelf method, which extends its applications to challenging tasks that lack data or are hard to calibrate the model. Besides, this work presents a generalized imaging augmentation workflow based on LION for various computational photography techniques including conventional and learning-based ones. Experiments on underwater, low-light, and lensless imaging have validated its effectiveness for generalized imaging augmentation.

Acknowledgement

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