NoiSER: Noise is All You Need for Enhancing Low-Light Images Without Task-Related Data

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Abstract

This paper is about an extraordinary phenomenon. Suppose we don’t use any low-light images as training data, can we enhance a low-light image by deep learning? Obviously, current methods cannot do this, since deep neural networks require to train their scads of parameters using copious amounts of training data, especially task-related data. In this paper, we show that in the context of fundamental deep learning, it is possible to enhance a low-light image without any task-related training data. Technically, we propose a new, magical, effective and efficient method, termed Noise SELF-Regression (NoiSER), which learns a gray-world mapping from Gaussian distribution for low-light image enhancement (LLIE). Specifically, a self-regression model is built as a carrier to learn a gray-world mapping during training, which is performed by simply iteratively feeding random noise. During inference, a low-light image is directly fed into the learned mapping to yield a normal-light one. Extensive experiments show that our NoiSER is highly competitive to current task-related data based LLIE models in terms of quantitative and visual results, while outperforming them in terms of the number of parameters, training time and inference speed. With only about 1K parameters, NoiSER realizes about 1 minute for training and 1.2 ms for inference with 600×400 resolution on RTX 2080 Ti. Besides, NoiSER has an inborn automated exposure suppression capability and can automatically adjust too bright or too dark, without additional manipulations.

1. Introduction

Unfavorable illumination is often encountered when taking photographs, and the resulted poorly illuminated photos greatly hinder understanding of their contents. Low-light image enhancement (LLIE) is a task that transforms low-light images into normal-light images, aiming at refining the illuminations in low-light images. Recent years have witnessed significant progress for LLIE [8, 9, 33, 40] and have attracted much attention in emerging applications [31, 43].

Traditional LLIE methods are mainly based on histogram equalization (HE) and retinex theory. The basic idea of HE-based methods is to widen the gray levels with a large number of pixels and to reduce the gray levels with a small number of pixels, so that the image can be enhanced. While retinex-based methods [9, 18, 33, 37] aim to estimate the illumination map to obtain reflectance (i.e., high-light image) based on the principle that low-light image can be decom-
posed into reflectance and illumination. Due to the inherent mechanisms of these methods, they will cause unpleasant artifacts and require a long processing time.

More recently, deep neural networks (DNNs) have been widely used for various computer vision tasks [3, 6, 23, 25, 27, 34, 36, 41, 42, 44] due to their strong ability to learn a general mapping from task-related training data. This also gives birth to advanced deep learning-based LLIE methods [8, 12, 15, 20, 35, 38–40], in which task-related data is a necessary condition.

Paired data, i.e., paired low-light and normal-light images (see Fig.1(b)), as strong LLIE-related data, are needed for supervised/semi-supervised models to obtain a powerful mapping to produce promising results [19, 38–40]. LLNet [19] is a pioneering method to apply deep learning for LLIE by training an auto-encoder to extract features and enhance images. KinD [39] and KinD++ [38] are based on the retinex theory, which include three deep sub-networks to handle LLIE, obtaining remarkable results compared to other traditional retinex-based methods. DCC-Net [40] discusses the chromatic aberration phenomenon in LLIE, and proposes a “divide and conquer” strategy to enhance images while retaining image color. However, paired data are costly to be collected in reality. As such, synthetic paired data are usually used by current methods, which limits their practical applications due to the weak generalization ability caused by the large gap between synthetic and real data.

Unpaired data, i.e., non-corresponding normal-light and low-light images (see Fig.1(d)), as ordinarily LLIE-related data, are used for unsupervised models, such as [12]. EnlightenGAN [12] is based on generative adversarial networks (GAN) [7], which is the first to utilize fully unpaired data to train a GAN for unsupervised LLIE. Yet, these methods usually rely on a huge number of parameters to compensate for the weak constraints caused by unpaired data, which also hinders the practical applications of LLIE.

Zero-reference data, i.e., single low-light images only (see Fig.1(f)), as the weakly LLIE-related data, facilitate a simple and elegant LLIE model that trains a simple DNN by an elaborate unsupervised loss [8, 15, 18, 20]. Zero-DCE [8] and Zero-DCE++ [15] convert the LLIE task into deep curve estimation, and obtain visually pleasing enhancement results. RUAS [18] first introduces the neural architecture search (NAS) into LLIE task and searches out an efficient network structure for LLIE. SCI [20] develops a self-calibrated illumination learning framework with remarkably enhanced results by taking into account the computational efficiency, flexibility and robustness. These methods yield surprising results using only zero-reference data, and meanwhile are far more lightweight and efficient than those methods using paired/unpaired data. However, the performance of these methods is highly dependent on training data and it is still hard to find the most suitable data.

It is worth noting that the data used in all aforementioned methods are task-related, no matter what they are strongly, ordinarily or weakly related, which is consistent with the accepted beliefs that task-related training data are always needed. So far, still no one tries to, or at least hasn’t succeeded in training a deep model for a specific task with completely task-irrelevant data, but we did. We show that just using noise can also lead to surprising LLIE results. Specifically, we build a deep model as a carrier to learn a gray-world mapping, by just sampling the noise (see Fig.1(h)) from a Gaussian distribution as training data to fit the parameters. As a result, a low-light image can be easily enhanced via the learned mapping during inference. We summarize the main contributions as follows:

- To the best of our knowledge, unlike all the current deep learning paradigms, this is the first attempt to learn a general “generalization” directly from the task-irrelevant data, instead of the common “fit → generalize” procedure. Experiments show the solution to this new paradigm has strong generalization abilities, such as stable performance on different datasets, automated exposure suppression and brightness-adaptive.

- We propose a remarkably simple and effective unsupervised LLIE model, termed NoiSER (Noise SEIf-Regression) via learning a gray-world mapping. Different from all existing LLIE methods, NoiSER is an amazing model, since it doesn’t need any task-related data for training, and just uses the randomly sampled noise from Gaussian distribution to enable the training of the model, i.e., noise is all NoiSER needs for LLIE.

- On several benchmark datasets, our NoiSER yields the highly competitive to other competitors that used different types of task-related data quantitatively and qualitatively. Without any task-related data, NoiSER can recover the low-light images accurately in detail, naturalness and color, and most importantly, it has an automated ability to turn extreme light/dark into moderates due to the learned gray-world mapping. In addition, NoiSER is extremely lightweight and efficient in both training and inference phases. Specifically, with only about 1K parameters, NoiSER achieves about 1 minute for training and 1.2 milliseconds for inference on 600x400 resolution image by a single RTX 2080 Ti.

2. Preliminaries

2.1. Image Self-Regression Principle

Image self-regression describes a process whereby the input data itself acts as a supervised signal to reconstruct the output with the same size, which is based on deep learning and falls under the category of self-supervised learning. Assuming that we have a set of identically distributed data...
\[
(x_1, x_2, \ldots), \text{ the image self-regression can be represented by minimizing the following empirical risk:}
\]
\[
\arg \min_{\theta} \mathbb{E}_x \{L(f_{\theta}(x), x)\},
\]
where \(f_{\theta}\) represents a parametric family of mapping and \(L\) denotes a loss function.

In recent years, image self-regression has been applied as a learning approach to a variety of tasks, including dimensionality reduction [11], image generation [14] and image restoration [28], with significant and far-reaching impact. Deep image prior [28], as the most relevant self-regression method, uses the corrupted image as input and supervised signal to reconstruct the natural image, which obtains stunning results in multiple tasks, such as denoising, super-resolution and inpainting, which means that a DNN has an innate ability to learn the “uncorrupted, natural” part of the image before it learns the “corrupted” part.

### 2.2. Gray-World Color Constancy Hypothesis

The gray-world color constancy hypothesis [1] (shortly, gray-world hypothesis) is a significant theory in image processing, which tells: for an image with a large number of color variations, the average of the three RGB components converges to the same gray value \(K\). In a physical sense, the gray-world hypothesis considers that the mean of the average reflection of light from a natural scene is a constant value on the whole, which is approximated as “grey”.

Recent years have also witnessed the emergence of some deep learning-based LLIE methods that use the gray-world hypothesis as a loss function, and obtain impressive LLIE performance [8, 15, 16]. Where Zero-DCE [8] is the first to come up with the idea of formulating the gray-world hypothesis as a color constancy constraint as follows:

\[
\mathcal{L}_{\text{col}} = \sqrt{\sum_{(p,q) \in S} (J^p - J^q)^2}, \quad S = \{(R, G), (R, B), (G, B)\},
\]

where \(J^p\) and \(J^q\) represent the average values of the \(p\) and \(q\) channels in the enhanced image, respectively.

### 2.3. Mirror Visual Feedback Therapy

Mirror visual feedback (MVF) therapy was first introduced in early 1990s to relieve phantom limb pain in amputees. In the field of medicine, it is increasingly being used to treat several other chronic pain and functional rehabilitation of upper limbs in hemiplegic patients [21]. Fig. 2 shows the principle of MVF therapy. During the treatment, the “affected side” of the hemiplegic patient is blocked by a flat mirror, while the patient can see the projection of the “healthy side” from the reflective surface of the mirror. As a result, when “rehabilitation training” is carried out on the “healthy side”, due to the visual feedback, the patient will believe that the “affected side” is able-bodied, and indeed, the “affected side” is also miraculously getting better. It is worth noting that the patient’s “affected side” doesn’t perform any “rehabilitation training” during this process, but even so, the “affected side” can be treated better, which intuitively is a miraculous phenomenon.

### 3. Proposed Method

#### 3.1. Motivation and Problem Statement

The current situation is that we need to enhance a low-light image via deep learning, but we have no LLIE task-related data for training, whatever type of data, including paired/unpaired/zero-reference data. In other words, we do not have a powerful paired constraint, an unpaired discriminative constraint, or even a gripper to use a non-reference constraint based on the zero-reference data. In such special case, how can we train a deep neural network to complete the task? Or do we really have hope to enhance a low-light image by deep learning without any task-related data?

A simple effective solution to this problem would probably have a major impact on the whole field of deep learning for computer vision (CV). Next, we mainly elaborate the potential impact of such a solution from two aspects.

For the LLIE task itself, this effective solution can avoid the inherent pitfalls of existing methods using task-related data, as described in Introduction. For all task-related data-based methods, the quality of the data determines the performance of the method. In other words, poor data quality leads to poor performance, which means that we need to collect good enough data, but the truth is that we have no idea what kind of data is so-called “good” for the proposed method. Thus, if this simple effective solution exists, the above pitfalls will no longer exist.

For the other CV tasks, this simple solution may allow for joint task processing in an elegant way. Recently, some works jointing LLIE with other tasks have emerged, e.g., joint with deraining [29], denoising [26], object/face
Figure 3. The training and inference pipeline of NoiSER. During training, just sampling noise \( \sim \mathcal{N} (\mu, \sigma^2) \) iteratively to train a self-regression model (SRM). During inference, the trained SRM can directly enhance the low-light images and obtain impressive results.

3.2. Our Message

At first glance, solving such an enhancement problem seems impossible, since we don’t have any available information to train a DNN. One conceivable solution for implementing deep training without task-related data is to borrow data from other similar tasks, which is exactly the idea of transfer learning [45]. For example, we can adopt the data from learning motorbikes to learn bicycles. However, this is not a real-sense solution, since the data are still needed to fine-tune the model finally. Is there really no way out?

In this paper, we will show that this problem not only can be solved, but also can be solved in an extremely elegant way. All what we need to solve this problem is just fully exploiting the three important theories in Section 2, i.e., image self-regression principle, gray-world hypothesis and mirror visual feedback therapy. We show that, based on the three theories, random noise can also exhibit great energy. A surprising message is that we will show that training a DNN by randomly sampling the noise can directly enhance a low-light image, which also perfectly solves the above problem. The following is the specific solution.

3.3. Solution?

3.3.1 Abstracting and meeting the task requirements

Let’s recall the problem, i.e., “can we enhance low-light image based on deep learning without any task-related data?”. We first decompose and abstract three requirements from the problem: 1) any task-related data can’t be used for training; 2) given an image, the output of the model should have similar content/texture to the input; 3) given a low-light image, the output of the model should be of normal light.

For the requirement (1), the easiest solution that comes to mind is to use the random noise to replace the task-related data. Thus, disregarding how to use the random noise, we at least have the determined data for training. The requirement (2) gives us a message that we need to train a model with a reconstruction capability. Considering the image self-regression principle, we can use the noise itself as supervisory signals to train the model. Now, we can meet the requirements (1) and (2) in a self-regression manner using random noise. For the requirement (3), we can force the output to satisfy the \( K \)-value gray-world hypothesis, where \( K \) should be in a normal gray range, such as 80-140 for the general 256 gray level.

Note that just meeting the above three requirements is still not enough to solve the problem, as there is one more important challenge, i.e., there is huge distribution gap between the training data (i.e., noise) and inference data (i.e., low-light images). Instead of narrowing the intractable distribution gap, the MVF therapy brings a fresh perspective, i.e., maybe we can roughly regard the forward propagation of non-task-related data as “healthy side”, take the forward propagation of low-light images as “affected side”, and see the self-regression as “rehabilitation training”. Therefore, we no longer need to bother with the gap in distribution, but only need to adjust the self-regression training to find out what is really helpful in enhancing a low-light image. As a result, if we can eventually find a proper solution in the form of the MVF therapy, all we need to do is to clarify the mechanism behind the solution.

We show the ultimate pipeline of training and inference for an intuitive observation of our approach in Fig.3. It is noteworthy that noise itself is still relatively complex data.
Thus, prior to training with noise, we introduce two types of data with much simpler structures, i.e., pure-color (Fig.4(a)) and palette (Fig.4(c)). In what follows, we present and introduce three self-regressions asymptotically.

### 3.3.2 Pure-Color Self-Regression (C-Regression)

Considering the general 256 grey level, we first define the pure-color images (shortly, pure-color) as $I_c \in \mathbb{N}^{H \times W \times 3}$ under the following constraints:

\[
\forall p_i, p_j \in I_c, \quad p_i = p_j
\[
\forall p_i \in I_c, \quad \max(p_i) \leq 255,
\]

where $p_i, p_j$ denote pixels with three channels and $\max(\cdot)$ denotes the maximum operation. Note that the “pure-” denotes an image rather than a color, e.g., pure-color image, pure-black image and pure-light-red image.

We first use pure-color for self-regression training due to two main reasons: 1) some low-light images themselves can be seen as pure-black with a degree of contrast, and 2) pure-color is very simple, which makes it easier to understand the effect of C-regression in enhancing low-light images, which is also instructive for the use of other more complex data.

Following the general image self-regression principle, as described in Eqn.1, C-regression is a process of minimizing the deviation between the model output and pure-color itself according to certain loss function:

\[
\arg \min_{\theta} \mathbb{E}_I \{L(f_{\theta}(I_c), I_c)\},
\]

where $f_{\theta}$ denotes a parametric family of mappings and $L_1$ loss is used for optimization. Please kindly note that we use the fixed pure-color for C-regression training.

We first use pure-black for training and directly use the trained model to enhance a low-light image, as shown in Fig.4(g) and Fig.4(b). We can easily see that the low-light input is crudely broken down into binary colors, i.e., black and white, which implies that pure-black can’t enhance image although it is close the dark images. However, we still got some inspiration, e.g., C-regression has roughly reconstructed the texture of the input. Thus, it is crucial to reveal the mechanism of how the input is divided into two colors.

Deep neural networks often work in black box manner and we cannot explain the intrinsic mechanism at the micro level. But at the macro level, we can still obtain a correct conclusion based on induction reasoning. Specifically, we follow the steps of incomplete induction reasoning, i.e., individual phenomenon → individual conclusion → universal conclusion → intra-domain validation. Specifically, based on the phenomenon of pure-black self-regression (i.e., dividing low-light input into black and white), we can induce an individual conclusion and then generalize it from individual to universal, and as a result, this universal conclusion can be applied to other pure-color (e.g., pure-red). Then, we need to perform self-regression training experiments using other colors, and if the experimental results also satisfy the universal conclusion, this conclusion can be proven to be correct. Prior to perform incomplete induction reasoning, we introduce the required definitions and propositions.

**Definition 1 (central grey):** For a specific range of image values $[a, b]$, the central grey is a color $C_g \in \mathbb{R}^3$ if it satisfies

\[
C_g^i = \frac{a + b}{2}, \quad i \in \{R, G, B\},
\]

where $C_g = (127.5, 127.5, 127.5)$ in the general 256 grey level (range: $[0, 255]$), while actually the channel value is replaced by 128, since only integers are allowed.

**Definition 2 (opposite color):** For a specific range of image values $[a, b]$, a color $C_1 \in \mathbb{R}^3$ is the opposite color of
the color $C_2 \in \mathbb{R}^3$ if they satisfy the following condition:

$$|C_1^i - C_g^i| = |C_2^i - C_g^i|, \quad i \in \{R, G, B\},$$

(6)

where $C_g$ denotes the central grey, and $C_1 \neq C_2$.

**Proposition 1**: Based on a model with random initialization, arbitrary C-regression tends to construct the pure-central-grey in the initial iterations.

**Validation for Proposition 1**: Given an image $I$, we use Eqn.2 to measure the distance between this image and the pure-central-grey with small modification as follows:

$$D(I) = \sqrt{\sum_{i \in S} (I^i - C_g^i)^2}, \quad S = \{R, G, B\},$$

(7)

where $I^i$ is the average value of the $i$ channel in image $I$.

In this study, we choose four pure-colors with different distances from the pure-central-grey for validation, i.e., pure-black (RGB(0,0,0)), pure-orange (RGB(255,128,0)), pure-light-red (RGB(255,128,128)) and the pure-central-grey itself (RGB(128,128,128)). Clearly, the relation of the distances satisfies: $D$(pure-black) > $D$(pure-orange) > $D$(pure-light-red) > $D$(pure-central-grey) = 0. In Fig.5, we show the iteration-distance curves based on these pure-colors during C-regression training. For non-pure-grey self-regression training, no supervised signals are pure-grey; nevertheless, the overall trend of the curves is initially down and then up rather than directly up, which indicates Proposition 1 is True. For the pure-grey self-regression training, the curve falls directly and converges gradually, which additionally proves the correctness of Proposition 1.

**Individual phenomenon.** Fig.4(a), Fig.4(g) and Fig.4(b) show an example of using pure-black self-regression training to infer a low-light image. We see from Fig.4(h) and Fig.4(b) that the trained model tends to map some colors (e.g., white and yellow) to the color used in C-regression training (i.e., black, RGB(0,0,0)), while mapping the other colors (e.g., black, red and green) to the opposite color (i.e., white, RGB(255,255,255)). This inspires us to explore the mapping relationship of the colors before and after inference. To this end, we build a palette containing rich colors as the image to be inferred. Fig.6 shows the process of inferring a low-light image and shows a palette in pure-black self-regression iterative training. We see that there are 8 colors in the palette, of which 4 colors (i.e., cyan, white, purple and yellow) are mapped to black and the other 4 colors (i.e., black, green, red and blue) are mapped to the opposite color of black, which is applicable to each pixel in the palette.

**Universal conclusion.** According to the individual conclusion.
Table 1. Illustration of the C-regression mechanism.

| (a) Individual phenomenon → Individual conclusion | (b) Universal conclusion → Intra-domain validation |
|-----------------------------------------------|-----------------------------------------------|
| ![Table 1](image)                             | ![Table 1](image)                             |

- The color binarisation of the C-regression results relies on the color homogeneity in the training samples, and it is conceivable that a more accurate texture might be reconstructed if each training sample is enriched with multiple colors and has a degree of contrast.

### 3.3.3 Palette Self-Regression (P-Regression)

In Section 3.3.2, we have used the palette for inference, and here we will illustrate that using the palette as training data for self-regression allows for a generation of normal-light image and a finer reconstruction of the image textures. Considering the general 256 grey level, we can define the palette as $I_p \in \mathbb{N}^{H \times W \times 3}$ with the following constraints:

$$
\forall q_i, q_j \in I_p, \quad grain(q_i) = grain(q_j)
$$

$$
\forall q_i \in I_p, \quad \forall p_i, p_j \in q_i, \quad p_i = p_j
$$

$$
\forall q_i \in I_p, \quad \forall p_i \in q_i, \quad max(p_i) <= 255,
$$

where $q_i,q_j$ denote non-overlapping patches, $grain(\cdot)$ denotes the grain of the patch (setting grain size to 16 in this work), $p_i,p_j$ denote pixels with three channels and $max(\cdot)$ denotes the maximum operation. From the above definition, the palette can be regarded as the coarse-grained noise and as the fine-grained pure-color. We provide the pseudo-code for building the palette in the supplementary material.

Similar to C-regression, given palettes as training data, P-regression is the process whereby the palette learns to rebuild itself according to certain loss function:

$$
\text{arg min}_\theta \mathbb{E}_{I_p} \{L(f_\theta(I_p), I_p)\},
$$

where $f_\theta$ denotes the parametric family of mappings, and we also use the $L_1$ loss for optimization.

Fig.4(g) and Fig.4(d) show an example of inferring a low-light image through P-regression. As can be seen, P-regression successfully reconstructs the texture of the given low-light image. Next, we first introduce a required propositions to seek the mechanism behind P-regression.

**Proposition 2:** Based on a model with random initialization, P-regression tends to start building the pure-central-grey at a starting point and continues until converges.
Table 2. List of RGB channel means for different datasets under the general 256 grey level. We can conclude that, for an image of normal light, the RGB channel means often fall in the range of 80-140. In addition, we also find that the RGB channel means are smaller for overdark images and larger for overexposed images.

| Sets | LOL [33] | LSRW [10] | SCIE [2] |
|------|----------|------------|----------|
|      | Normal   | Overdark   | Normal   | Overdark   | Overexposed |
| R    | 120.47   | 15.49      | 110.39   | 18.92      | 122.69      | 42.26      | 122.12 | 32.78 | 164.82 |
| G    | 113.88   | 15.22      | 98.22    | 16.39      | 124.55      | 43.19      | 121.18 | 32.71 | 161.40 |
| B    | 110.38   | 14.73      | 86.63    | 15.20      | 124.69      | 43.48      | 109.77 | 31.07 | 149.51 |

Validation for Proposition 2: Given an image $I$, similar to C-regression, we use Eqn.7 to measure the distance between this image and the pure-central-grey. The blue curve in Fig.8(a) shows the distance between the output and pure-central-grey. We see that after a certain starting point (about 61st iteration), the output gradually approaches the pure-central-grey, although we did not add any constraints to this during the training process, which means that Proposition 2 is True. Besides, we use pure-colors as inference images for validation, and obtain a consistent conclusion with Proposition 2, i.e., all outputs appear grey (see Fig.8(b)).

Proposition 3: Known $\triangledown$: The image satisfies the $K$-value gray-world hypothesis, where $K$ is approximately between 80 and 140; Known $\triangledown$: The image is of normal light. Then, $\triangledown$ is a statistically necessary condition for $\triangledown$.

Validation for Proposition 3: Table 2 shows the RGB channel means (i.e., the mean value of each color channel) for several widely-used-datasets, including two real-world datasets (LOL [33] and LSRW [10]) and a multi-exposure dataset (SCIE [2]). We conclude that: (1) all datasets satisfy gray-world hypothesis (the channel deviation is also not too large for LSRW (Huawei)-Normal); (2) the channel means of the normal datasets usually lies between 80-140. Note that (1) and (2) provide the proof of Proposition 3.

For P-regression, the training samples themselves have a degree of contrast (variation between non-overlapping patches), which ensures that P-regression can reconstruct the texture of image more accurately than C-regression. In addition, according to Propositions 2 and 3, we know that the P-regression has the ability of mapping any color to approach grey, which means that the channel means of the output meet the $K$ range (80-140) of the normal-light images. As a result, suppose that the P-regression further satisfies the gray-world hypothesis, we can use P-regression to get the normal-light output that satisfies all three requirements mentioned in Section 3.3.1. However, this supposition is valid but not strictly. We use the color constancy loss (Eqn.2) to measure the satisfaction degree towards the gray-world hypothesis (not applying it to back propagation). As the grey curves in Fig.8(a) show, the overall downward trend suffers from sharp fluctuations. Nevertheless, the P-regression can still yield a relatively favorable result.

Now, we can clarify the mechanism of P-regression and can assert the following facts:

- P-regression initially meets all the three requirements mentioned above, which means that P-regression can already enhance a low-light image properly.
- The enhancement results of P-regression are unpleasant due to the sharp fluctuations in the convergence to gray-world hypothesis. It is conceivable that a more pleasing result might be generated, if we can smooth out the sharp curve fluctuations.

3.3.4 Noise Self-Regression (NoiSER)

Considering that one possible reason for sharp curve fluctuations is the larger grain size of the patches in a palette, we attempt to use noise for self-regression training, since noise can be approximated as a fine-grained palette.

Instead of defining an additional noise, we directly sample a Gaussian noise $I_n \sim N(\mu, \sigma^2)$, and the specific regression process can be expressed as follows:

$$\arg\min_{\theta} E_{I_n} \{ L(f_\theta(I_n), I_n) \},$$

(10)

where $f_\theta$ denotes the parametric family of mappings. Similar to both C-regression and P-regression, we still use the $L_1$ loss for optimization.

Fig.4(g) and Fig.4(f) show an example of inferring a low-light image via NoiSER. As can be seen, given a low-light input, NoiSER successfully generates a visually pleasing enhanced result. We first introduce a required proposition to understand the specific mechanisms of NoiSER.
Table 3. Numerical results on the LOL dataset [33], where the best performance is marked in red and the second best one is marked in blue. Clearly, our NoiSER has significant advantages, not only for performance metrics but also for application metrics.

| Training data | Methods | Performance metrics | Application metrics |
|---------------|---------|---------------------|---------------------|
|               |         | PSNR↑  | SSIM↑ | NIQE↓ | TT ↓ (min) | IT ↓ (ms) | No.P ↓ |
| Optimization-based | -       | LIME [9] | 14.2216 | 0.5144 | 8.5828 | - | 104553.82 | - |
|                |         | Zhang et al. [37] | 14.0181 | 0.5130 | 8.6111 | - | 138127.48 | - |
| Paired        | RetinexNet [33] | 16.7740 | 0.4191 | 9.7294 | 3.17 | 95.40 | 1,333,841 |
| Unpaired      | EnlightenGAN [12] | 18.5413 | 0.6880 | 5.7111 | 90.05 | 10.91 | 6,959,553 |
| Deep learning-based |         | Zero-DCE [8] | 14.9672 | 0.5003 | 8.4228 | 16.33 | 2.24 | 79.416 |
|                |         | Zero-DCE++ [15] | 14.8039 | 0.5161 | 8.3412 | 24.12 | 1.51 | 10.561 |
|                |         | RUAS [18] | 16.4047 | 0.4996 | 5.9297 | - | 8.57 | 3.438 |
|                |         | SCI [20] | 14.0226 | 0.5080 | 8.3315 | 2563.68 | 1.12 | 258 |
| Task-irrelevant | NoiSER-FC (Ours) | 17.5748 | 0.7134 | 3.7285 | 1.10 | 1.21 | 1,323 |
|                | NoiSER-ES (Ours) | 17.0250 | 0.6563 | 3.7206 | 0.58 | 1.21 | 1,323 |
|                | NoiSER-Var3 (Ours) | 14.9257 | 0.5998 | 3.6806 | 1.10 | 1.21 | 1,323 |

Table 4. Comparison of generalization performance on the LSRW dataset [10], where the best performance is marked in red and the second best one is marked in blue. Clearly, our NoiSER has a stronger generalization ability over different datasets than all other methods.

| Training data | Methods | LSRW (Huawei) | LSRW (Nikon) |
|---------------|---------|---------------|--------------|
|               |         | PSNR↑  | SSIM↑ | NIQE↓ | PSNR↑  | SSIM↑ | NIQE↓ |
| Optimization-based | -       | LIME [9] | 15.3376 | 0.4360 | 3.0148 | 14.6362 | 0.3777 | 3.3818 |
|                |         | Zhang et al. [37] | 14.0984 | 0.4327 | 2.9228 | 13.0886 | 0.3677 | 3.4620 |
| Paired        | RetinexNet [33] | 16.8127 | 0.3948 | 4.3349 | 13.4853 | 0.2934 | 4.2774 |
| Unpaired      | EnlightenGAN [12] | 16.8448 | 0.4832 | 3.0916 | 14.9071 | 0.4065 | 3.7475 |
| Deep learning-based |         | Zero-DCE [8] | 14.2002 | 0.3958 | 3.5864 | 11.8197 | 0.3550 | 3.9127 |
|                |         | Zero-DCE++ [15] | 14.2370 | 0.4163 | 3.4862 | 11.0893 | 0.3675 | 3.7375 |
|                |         | RUAS [18] | 15.6867 | 0.4909 | 3.0399 | 12.1426 | 0.4372 | 3.9902 |
|                |         | SCI [20] | 15.2853 | 0.4233 | 3.1263 | 14.4512 | 0.4092 | 3.7864 |
| Task-irrelevant | NoiSER-FC (Ours) | 15.7268 | 0.7134 | 3.7285 | 11.5537 | 0.4687 | 3.7784 |
|                | NoiSER-ES (Ours) | 15.6968 | 0.5998 | 3.7206 | 15.7090 | 0.4584 | 3.4976 |
|                | NoiSER-Var3 (Ours) | 15.3001 | 0.5193 | 2.9714 | 15.5260 | 0.4672 | 3.5445 |

**Proposition 4:** Based on a model with random initialization, NoiSER tends to learn a gray-world mapping, i.e., learning to approach pure-central-grey while satisfying the gray-world hypothesis.

**Validation for Proposition 4:** Given an image $I$, similar to P-regression, we use Eqn.7 to measure the distance between $I$ and the pure-central-grey, and use Eqn.2 to measure the satisfaction degree towards the gray-world hypothesis. The green and red curves in Fig.8(a) demonstrate the specific iterative processes. As can be seen, although we do not apply the equation for back propagation, the curves will still converge smoothly, which demonstrate the correctness of Proposition 4. Similar to P-regression, NoiSER training can also make pure-colors appear grey (see Fig.8(b)).

Thus, it’s clear that NoiSER satisfies all the properties of P-regression while smoothing the convergence curve towards the gray-world hypothesis, which makes it possible to generate the pleasing LLIE results. In a word, our proposed NoiSER approach aims at learning a gray-world mapping during training, and the learned mapping can enhance a low-light image during inference. Finally, we demonstrate the pipelines for NoiSER training and inference, as shown in Fig.2. The specific structure of the self-regression model (SRM) is detailed in the supplementary material.

4. Experimental Results and Analysis

4.1. Experimental Descriptions

**Method description.** Training our NoiSER to full convergence (denoted as NoiSER-FC) will yield a better quantitative performance, however we observe that the visual effect appears to be obscured by a gray layer since NoiSER aims at learning a gray-world mapping. As such, we use an early stopping mechanism (denoted as NoiSER-ES), trading part of the quantitative performance for visual improvement. In addition, to obtain better visual effect, we improve the contrast between noisy neighboring pixels by raising the variance of the standard Gaussian distribution to 3 (denoted NoiSER-Var3). We will conduct extensive experiments to...
show the results of the three variants of NoiSER. Due to the special nature of NoiSER, a few hiccups are inevitable. But these hiccups are obviously trivial, since the training of our NoiSER is extremely fast, taking only about 1 minute.

**Comparison description.** Since our NoiSER does not use any task-related data for training, all the tests on different datasets are equivalent to evaluating the generalization ability of NoiSER, instead of the fitting ability. Training and testing on the same dataset is apparently against our intent, however we still use the most widely-used LOL dataset [33] (training & testing) to show that our method is competitive.

### 4.2. Experimental Settings

**Evaluated datasets.** We first conduct experiments on two real-world image datasets: LOL [33] and LSRW [10]. LOL is used to measure the fitting capability of other compared methods by training and testing on it, and LSRW is used to measure the generalization capability of all compared methods by directly testing on it using the pretrained model on LOL dataset. Besides, we use a multi-exposure dataset (SCIE [2]) to measure the overexposure suppression capability of each method. The details are as follows:

- **LOL**: LOL is the most widely-used dataset for LLIE task, including 485 training pairs and 15 testing pairs with resolution 400×600.

- **LSRW**: LSRW includes two subsets: LSRW (Huawei) and LSRW (Nikon). LSRW (Huawei) has 2,480 training pairs and 30 testing pairs with resolution 720×960, while LSRW (Nikon) contains 3,170 training pairs and 20 testing pairs with resolution 640×960.

- **SCIE**: SCIE includes 4,413 multi-exposure images with resolution between 3000×2000 and 6000×4000. It is divided into two parts, namely, “Dataset_Part1” and “Dataset_Part2”, and we only adopt the overexposed image named “7.JPG” from “Dataset_Part2” as an example in our experiments.

**Evaluated metrics.** We use three widely-used metrics to evaluate the quantitative performance of each method, including two full-reference metrics (i.e., peak signal-to-noise ratio (PSNR) and structural similarity (SSIM) [32]) and one no-reference metric (i.e., naturalness image quality evaluator (NIQE) [22]). Besides, we also use three application metrics to evaluate the possibility of each method for practical deployment and application, i.e., training time (TT), inference time (IT) and number of parameters (No.P). In all experiments, we use the ↑ to indicate the higher the better, and use the ↓ to indicate the lower the better.

**Compared methods.** Two optimization-based methods (LIME [9] and Zhang et al. [37]) and six deep learning-based methods are included for comparison. For those deep models, different types of training data are leveraged to fit the model, i.e., paired (RetinexNet [33]), unpaired data (EnlightenGAN [12]) and zero-reference data (Zero-DCE [8], Zero-DCE++ [15], RUAS [18] and SCI [20]). Note that we mainly compare with the four zero-reference methods, as they are closer to our NoiSER in terms of data constraints.

**Implementation details.** Based on PyTorch 1.10.1 [24]
Figure 10. Visual results of different enhancement methods base on the LOL dataset [33], including LIME [9], Zhang et al. [37], RetinexNet [33], EnlightenGAN [12], Zero-DCE++ [15], RUAS [18], SCI [20] and our NoiSER. Clearly, our NoiSER obtains better visualization effects, despite no task-related data has been used for training. Specifically, our NoiSER can enhance the image contents more visibly and naturally, even beyond the ground-truth, which is attributed to the ability of our method to learn a gray-world mapping.

Figure 11. Visual results of different enhancement methods based on the LSRW (Huawei) dataset [10], including Zero-DCE [8], Zero-DCE++ [15], RUAS [18], SCI [20] and our NoiSER. For each method, the top row shows the original enhanced images and the bottom row shows the zooming in of the enlarged detail in red boxes. Clearly, all other compared methods overexpose the brighter areas of the image, while our NoiSER effectively suppress the exposure and does a good job in recovering the texture detail of the image.

and Python 3.6.9, we train and evaluate our NoiSER on single NVIDIA RTX 2080 Ti GPU. We train our NoiSER for 2000 iterations (600 for NoiSER-ES) with a batch size of 1 and a fixed learning rate of 2e-4. We sample the noise from standard Gaussian distribution $\mathcal{N}(0, 1)$ ($\mathcal{N}(0, 3)$ for NoiSER-Var3) with a shape of $104 \times 104$ for training. Besides, the Adam optimizer [13] is utilized for training with $\beta_1 = 0.5$ and $\beta_2 = 0.999$. To alleviate the noise in the enhanced results, we add TV regularization during training.

The total loss function of NoiSER is defined as

$$L_{total} = L_{l_1} + L_{tv}. \quad (11)$$

4.3. Quantitative Evaluations

4.3.1 Results on LOL dataset

To examine the fitting ability of each method, we first evaluate each model on LOL, in terms of three performance metrics (PSNR, SSIM and NIQE) and three application metrics
Figure 12. Visual results of different enhancement methods based on the LSRW (Nikon) dataset [10], including Zero-DCE [8], Zero-DCE++ [15], RUAS [18], SCI [20] and our NoiSER. Because the image itself is not very dark, all other compared methods either overexpose the image or distort the color, while our NoiSER achieves a better visual result.

(TT in minutes, IT in milliseconds and No.P). The numerical results are shown in Table 1. We did not list the training time of RUAS [18], since it involves a process of neural architecture search. For the TT metric, we get the result on a single NVIDIA RTX 2080 Ti using the default configuration according to the codes provided by authors. We can find that: 1) the optimization-based methods take longer inference time for the use of CPU for computation, which will be a major impediment to real applications; 2) when training with paired/unpaired data, RetinexNet and EnlightenGAN yield better performance due to the relatively strong constraints, however, they have a larger number of parameters and slower inference speed; 3) the zero-reference methods require minimal computational resources, which are relatively efficient and have a stronger application potential; 4) although our NoiSER does not use any task-related data for training, it is still highly competitive to the other methods across all metrics. From the comparison to the zero-reference methods, our NoiSER perfectly outperforms all of them, with significantly less training time.

4.3.2 Results on LSRW dataset
To measure the generalization ability, we evaluate the methods on two test subsets, i.e., LSRW (Huawei) and LSRW (Nikon). The numerical results are shown in Table 2. We can find that: 1) the models fitted using task-related data fail to generalize well to all datasets, since they perform well on some datasets but poorly on others. For example, EnlightenGAN [12] and RetinexNet [33] obtains the best records on LSRW (Huawei), but worse on LSRW (Nikon), which is inevitable for the usage of task-related data; 2) our NoiSER generalizes generally well and is more balanced across different datasets, indicating that our approach is closer to the essence of low-light enhancement; 3) from the comparison to those zero-reference methods that are more close to ours, our NoiSER obtains significant superiority in all metrics.

4.4. Visualization Evaluations
4.4.1 Visual Analysis on LOL Dataset
NoiSER is easy to implement and yields surprising results. Considering that the test set of LOL only has 15 low-light images, we show the entire set to give a more intuitive view for the enhancement effect in Fig.9. By simply performing a noise self-regression for training, all low-light images can be enhanced with rich texture, content and color. We then compare each method on a extremely dark image (from which human eyes hardly see anything) of LOL [33] dataset in Fig.10. We see that: 1) both optimization-based methods and deep learning models using task-related data can enhance this very dark image to some extent, but the restored images are still inferior, in terms of illumination enhancement, detail recovery and color preservation; 2) our NoiSER enhances this overdark image considerably, and

\[1\]

1It means that NoiSER generalizes stably on different datasets, i.e., it is less likely to be extremely good on one, but extremely poor on the other.
the restored image is even beyond the brightness and content naturalness of the ground-truth, which can be attributed to the learned gray-world mapping that always forces the channel means of a low-light image to be close to the central grey; 3) for the visual effects of several variants of our NoiSER, NoiSER-FC < NoiSER-ES < NoiSER-Var3. As mentioned in Section 4.1, NoiSER-FC seems to be covered by a grey layer, which should be caused by the learned gray-world mapping, and NoiSER-ES shows that early stopping mechanism can alleviate this issue. To obtain the most visually pleasing effect, we can adopt the manner of increasing the variance of Gaussian distribution, since NoiSER-Var3 clearly shows a better visual effect.

4.4.2 Visual Analysis on LSRW Dataset
To evaluate the generalization ability by visual analysis, we compare the visual results of each method on LSRW [10] dataset in Figs.11 and 12. We see that: 1) when input image is not very dark, zero-reference methods tend to produce overexposure enhanced images. One possible solution to this issue is to train the model with a relatively large multi-exposure dataset, implying that appropriate training data must be picked as carefully as possible. Despite this, it is still tricky to determine which datum is so-called appropriate to handle the complex distribution of low-light images in reality: 2) owing to the simple and straightforward training process, our NoiSER has a powerful generalization power. From the comparison of the local details in Figs.11 and 12, it is clear that NoiSER recovers the texture of the images more accurately and gets a better visual effect.

4.5. Automated Overexposure Suppression
Finally, we evaluate each method to process the overexposed image of SCIE dataset. As shown in Fig.13, existing methods, i.e., Zero-DCE [8], Zero-DCE++ [15], RUAS [18], SCI [20] and our NoiSER, obtain poor results and the processed images are almost completely corrupted, since the aim of them is to learn a mapping from low to high illumination. One possible solution is to use a large scale multi-exposure dataset to train the model, so that the model can handle both overdark and overexposed images. However, it is still tricky to handle the extremely complex illumination in reality. Therefore, we are delighted to say that our NoiSER has an inborn ability to suppress the overexposure, since it learns a gray-world mapping which can automatically turn extreme light or dark into moderates, as shown in “NoiSER-Var3” in Fig.13.

5. Conclusion and Future Work
We have discussed a new problem, i.e., how to enhance a low-light image by deep learning without any task-related data? We have taken a bold and crazy perspective in thinking about the solution to the problem, but the final result offers plenty of surprises and amazing messages. We prove that the problem can easily solved by a simple and straightforward noise self-regression approach by learning a grey-world mapping. Extensive experiments demonstrate that our method yields a visually pleasing effect and obtains the competitive performance, in terms of strong learning ability, stable generalization capability, automated brightness adaptation and negligible computational consumption. In
the future, we will further think about how to optimize the noise for improving visual experience. In addition, we will prove our solution is easily embeddable and explore more possible applications by embedding our method to improve other low-level and high-level tasks in the dark.

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