Back to the future: a night photography rendering ISP without deep learning

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Abstract

Rendering night photography pictures is a challenging task that requires advanced processing techniques. Although deep learning-based Image Signal Processing (ISP) pipelines have shown promising results, current limitations are set by the lack of proper nighttime image datasets, their high computational requirements, and low explainability. In this paper, we propose a traditional ISP pipeline for rendering visually pleasing photographs of night scenes. Our pipeline is comprised of various algorithms addressing the different challenges presented by night images, and it is characterized by a shallow structure, explainable steps, and a low parameter count, resulting in computationally efficient processing. Moreover, it does not require training data. Experiments show that our pipeline can produce more pleasing results compared to other deep learning-based ISP pipelines, as it won first place in people's choice track and third place in photographer's choice track in the NTIRE 2023 Night Photography Rendering Challenge.

1. Introduction

Night photography is a non-trivial task, due to the technical challenges associated with low-light imaging conditions. Longer shutter speeds and higher ISO settings are required to capture the image when compared to daytime imaging, which may introduce noise and blur artifacts. The light sources at night are usually artificial, and their intensity and direction can vary unpredictably, making it difficult to control the color balance of the image. In addition, the dynamic range of a night scene can be very high, with bright light sources such as streetlights and deep shadows in the surrounding environment, which can make it difficult to capture a well-exposed image that accurately renders the scene contents.

An Image Signal Processing pipeline (ISP) pipeline is a combination of processing steps that are applied to the RAW image data captured by a digital sensor to generate a high-quality, visually appealing image [9]. It is a critical component of a digital camera system and plays a key role in determining the image quality of the captured images. A

(a) RAW input image (demosaiced and delinearized for visualization)

(b) RGB output image rendered by our ISP pipeline

Figure 1. Rendering results of the proposed ISP pipeline.

traditional ISP pipeline usually consists of various processing modules, including demosaicing, noise reduction, contrast enhancement, sharpening and white balancing, each of which is responsible for a specific aspect of image processing [19, 32].

Due to the success of deep learning in many computer vision fields, deep learning-based ISP pipelines have been proposed with the aim of replacing the algorithms from a traditional pipeline with neural networks [17, 23, 27, 36, 41]. Compared to traditional pipelines, they typically require a large amount of paired RAW-RGB data to learn how to map the RAW input image into the final rendered RGB image. However, most of the existing datasets for ISP are collected during daytime, limiting their applicability for nighttime applications because of the significant differences in illumination between day and night [22]. The lack of datasets of nighttime images, along with their high computational requirements and low explainability represent serious limitations.

In this paper, we present a traditional ISP pipeline for rendering visually pleasing photographs of night scenes. Our pipeline is composed of several algorithms, addressing denoising, color and contrast enhancement, sharpening and white balancing, to deal with the challenges presented by images captured at night, and it is characterized by a shallow structure and by a low parameter count. Our pipeline does not require training data, which is a significant aspect to address the problem of the lack of nighttime image datasets. Figure 1 shows an example of images rendered by our pipeline. The main modules are designed on the basis of our knowledge of the mechanisms of human vision and the main limitations of traditional imaging devices. The few required parameters are heuristically set by our personal preferences, without any reference to existing enhancement datasets corrected by human experts or automatic approaches. This means that our pipeline is flexible, as it can be easily tuned to match individual users' preferences.

Our main contributions can be summarized as follows:

- We present a traditional ISP pipeline for rendering visually pleasant photographs of night scenes by applying various adjustments to the image, including denoising, contrast and color enhancement, sharpening and white balancing. The pipeline is characterized by a shallow structure, a low parameter count, and does not require training data.

- We show that the proposed pipeline can produce better results than existing deep learning-based ISP methods, as also confirmed by the ranking of our solution in the NTIRE 2023 Night Photography Rendering Challenge [37], where we won first place in people's choice track and third place in photographer's choice track.

2. Related work

An ISP pipeline applies a combination of algorithms to the RAW image signal captured by a digital sensor, with the goal of improving the image quality and producing a visually pleasing rendering. The common modules of a traditional ISP pipeline include demosaicing, denoising, white balancing, sharpening and contrast enhancement [9, 32]. Demosaicing is the process used to convert a single-channel RAW image into a full-color RGB image by interpolating the RAW color filter array image with repetitive mosaic pattern [21, 40]. Denoising aims to remove acquisition noise from the image while preserving details to improve its quality, using techniques such as spatial filtering, frequency domain filtering, and wavelet-based methods [2, 6, 8]. White balancing is used to adjust the colors in the image to accurately represent the true colors of the scene being captured, by removing any unwanted color casts caused by the lighting conditions [1, 20, 31]. Image sharpening is a processing technique that enhances the edges and details in an image, making it appear clearer and more defined by increasing the contrast of edges to make them more prominent [9, 24, 29]. Contrast enhancement increases the visual difference between light and dark areas in an image, and it is often achieved using image processing techniques such as histogram equalization [7, 15] or local contrast correction [5, 28, 35].

Recently, deep learning-based ISP pipelines have been proposed [17, 23, 27, 36, 41]. These solutions set the goal of replacing the different algorithms in a traditional ISP pipeline with a single neural network. Using paired datasets [4, 17] for RAW-RGB images, they learn to process the RAW input images to produce the final rendered RGB image. However, these datasets mainly contain scenes captured during daytime, which are very different from nighttime images due to different lighting conditions. Punnappurath et al. [30] proposed a method to synthesize nighttime images starting from daytime ones, in order to cope with this problem. Nevertheless, the authors did not consider extreme low-light scenarios, which are likely to occur in scenes captured at night.

In the context of night photography, both traditional and deep learning-based ISP pipelines have been recently proposed [12, 22, 26, 37, 42]. Zini et al. [42] developed a traditional pipeline that cascades a sequence of algorithms to process the RAW input images. Liu et al. [26] proposed a three-stage framework applying denoising [33], white balancing [14] and conversion from RAW to sRGB [16, 25]. Li et al. [22] created a dataset annotated by experts to cope with the lack of paired data for night scene enhancement. Using this dataset, they developed a framework consisting of a neural network to estimate illumination colors and, after a color correction step, a neural network for brightness adjustment based on histogram matching.

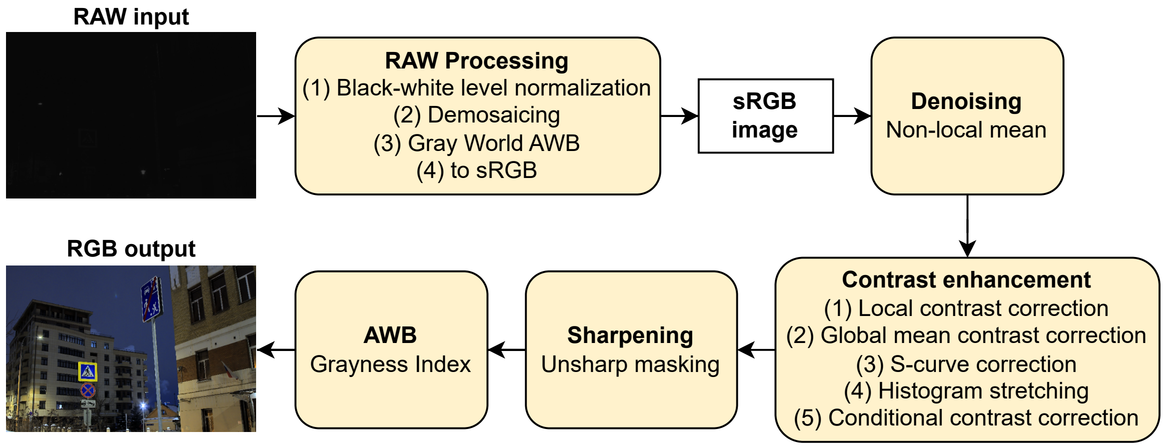


Figure 2. Overview of the proposed ISP pipeline for night photography rendering.

Although deep learning-based ISP pipelines have shown promising results, they also present major limitations. First, they require large training datasets to learn specific processing tasks. Second, they can be computationally expensive and may require significant computational resources. Finally, their limited explainability makes it hard to understand why they produce a specific output image, and how to control specific image aspects. Compared to deep learning-based ISP pipelines, our solution is computationally efficient, it is explainable, and does not require any training procedure, thus removing the requirement for large training datasets.

3. Proposed method

In this paper, we propose a traditional ISP pipeline for the rendering of visually pleasing photographs of night scenes, illustrated in Figure 2. There are five main steps, each of which addresses a specific aspect of the image. After a sequence of corrections to the RAW input image, the pipeline applies image denoising to remove acquisition noise, contrast enhancement to improve image dynamic range and color appearance, followed by edge sharpening and white balancing to remove unwanted color casts. In the following, we describe these steps in detail.

RAW Processing. The RAW processing step is used to apply a sequence of corrections to the image in the RAW domain. In this stage, image metadata provided by the camera are used to normalize the image based on its nominal black and white levels. According to the color filter array of the image, demosaicing is used to convert the single-channel RAW image into a full-color image. Here, the Gray World algorithm [3] is applied to perform white balancing, which provides an initial approximate correction of the image cast. The resulting image is then converted from the camera-specific color space to the XYZ color space (using the inverse of color matrix provided in the image metadata), and finally to the sRGB color space using a standard transformation that uses D65 as reference white.

Denoising. The second step of our pipeline is image denoising. In particular, we use the Non-local means algorithm [2] due to its proven excellent trade-off between denoising performance and efficiency: despite high processing speed not being a requisite for the challenge, we set an internal goal to produce a computationally lightweight solution. The intensity of the denoising operation varies depending on the noise in the image, and it is here measured using the wavelet-based estimator of Gaussian noise standard deviation proposed in [10]. In our pipeline, we decompose the image into its luminance and chroma components (in the YCbCr color space), and we apply stronger denoising to chroma channels in order to effectively remove color noise while preserving image details and edges.

This approach is based on the rationale that noise impacts differently the luminance and chroma components. On the one hand, chroma channels contain less information about image details, and chroma noise is considered more noticeable and distracting than luminance noise because it creates unnatural color patterns in the image, which can be particularly noticeable in areas with smooth color gradients [13]. On the other hand, the luminance channel contains more information about image details [39], which should be preserved by the denoising process.

Contrast enhancement. The contrast enhancement step involves different algorithms to enhance the image contrast by manipulating the corresponding histogram statistics.

The first operation we apply is the Local Contrast Correction (LCC) algorithm proposed in [28] (step 1 in the contrast enhancement block of Figure 2). LCC applies a pixel-wise gamma correction to the luminance channel Y of the image so that very dark regions are brightened and very bright regions are darkened. In order to obtain spatially varying corrections, the parameters for the pixel-wise gamma correction are determined using a mask M obtained by applying a Gaussian filter to the luminance channel of the image in the YCbCr color space. The resulting $\hat{Y}$ luminance channel is computed as

$$\hat{Y} = Y^{\gamma^{\frac{0.5-(1-M)}{0.5}}}, \tag{1}$$

where Y is the input luminance channel, $1 - M$ is the complement of the mask previously described, and γ is the value of the exponent for gamma correction. Note that γ has different values for each pixel, and depends on the values in M. Following Schettini et al. [35], we compute γ as

$$\gamma = \begin{cases} \dfrac{\ln(0.5)}{\ln(\bar{Y})} & \text{if } \bar{Y} \geq 0.5 \\ \dfrac{\ln(\bar{Y})}{\ln 0.5} & \text{otherwise} \end{cases}, \tag{2}$$

where $\bar{Y}$ is the average value of the luminance channel. Since $1 - M$ reverses the mask values, bright regions are darkened ($\gamma > 1$) while dark regions are brightened ($\gamma < 1$).

As noticed by Schettini et al. [35], LCC tends to reduce the global image contrast and saturation. Therefore, we apply contrast and saturation fixing operations as described by the authors. The contrast fixing operation adaptively stretches the image histogram depending on variations in the distribution of dark pixels before and after the application of LCC. A dark pixel is defined as a pixel whose luminance value and chroma radius are lower than 0.14 and 0.07, respectively. If there is at least one dark pixel in Y and $\hat{Y}$, the lower range is computed as the difference of the bins corresponding to 30% of dark pixels in the cumulative histogram of $\hat{Y}$ and Y. Otherwise, it is defined as the second percentile of the pixel values in $\hat{Y}$. The upper range for histogram stretching always corresponds to the 98th percentile of pixel values in $\hat{Y}$. For both ranges, the maximum number of bins to clip is 50. Using the determined range, the image histogram is stretched and the histogram bins that fall outside are clipped. Every computed histogram has 256 bins. For the saturation fixing step, we correct each RGB channel as suggested in [34]:

$$\hat{C} = 0.5 \times \frac{\hat{Y}}{Y} \times (C + Y) + C - Y, \tag{3}$$

where C corresponds to a RGB channel, $\hat{C}$ is the corresponding output channel, $\hat{Y}$ and Y are the output and input luminance channels used in Equation 1.

We then apply four operations to improve the overall image color appearance. The global mean contrast operation (step 2 in the contrast enhancement block of Figure 2) adjusts the image contrast by stretching the pixel values of each RGB channel by a factor β around their mean μ as follows:

$$\hat{C} = \mu + \beta * (C - \mu), \tag{4}$$

where C is a RGB channel, $\hat{C}$ is the corresponding output channel, μ is the mean pixel value and β is the amplification factor. The S-curve correction (step 3 in the contrast enhancement block of Figure 2) applies to each RGB channel the S-curve proposed in [18], which is defined as

$$\hat{C} = \begin{cases} \alpha + (1-\alpha) * \left(\dfrac{C-\alpha}{1-\alpha}\right)^{\lambda} & \text{if } C \geq \alpha \\ \alpha - \alpha * \left(1 - \dfrac{C}{\alpha}\right)^{\lambda} & \text{otherwise} \end{cases} \tag{5}$$

where C is a RGB channel, $\hat{C}$ is the corresponding output channel, α and λ are two parameters controlling the inflection point and the amplitude of the curve, respectively. The histogram stretching operation (step 4 in the contrast enhancement block of Figure 2) stretches the image histogram, increasing the dynamic range and improving the overall contrast. Finally, the conditional contrast correction operation (step 5 in the contrast enhancement block of Figure 2), consists of an extra contrast correction operation depending on the mean value μ of the luminance channel. If μ is lower than a lower threshold, then the image is considered too dark and an additional S-curve correction, described in Equation 5, is applied. Instead, if μ is higher than an upper threshold, then the image is considered too bright and a gamma correction is used to darken it. This operation improves visibility for very dark images and restores the mood of nighttime scenes when images are too bright.

Sharpening. The previous step of image denoising occasionally flattens certain image details. Hence, we apply image sharpening using unsharp masking to boost high frequency content, increasing the perceived contrast between edges and flat regions. The unsharp masking operation is applied to each RGB channel as

$$\hat{C} = C + (C - Gaussian(C, \sigma)), \tag{6}$$

where C is an input RGB channel, $\hat{C}$ is the same channel processed by the sharpening operation, and $Gaussian$ is the function that applies a Gaussian filter with a specified σ value.

White balancing. In the RAW processing stage of the pipeline, white balancing correction is done using a von Kries-like transform [38]. Illuminant estimation is performed using the Gray World algorithm [3]. This white balancing step is applied to reduce the image color cast typical of night scenes. However, in some challenging scenarios with multiple light sources, it may not be sufficient. To address this problem we include a second, more sophisticated, white balancing operation, based on the detection of

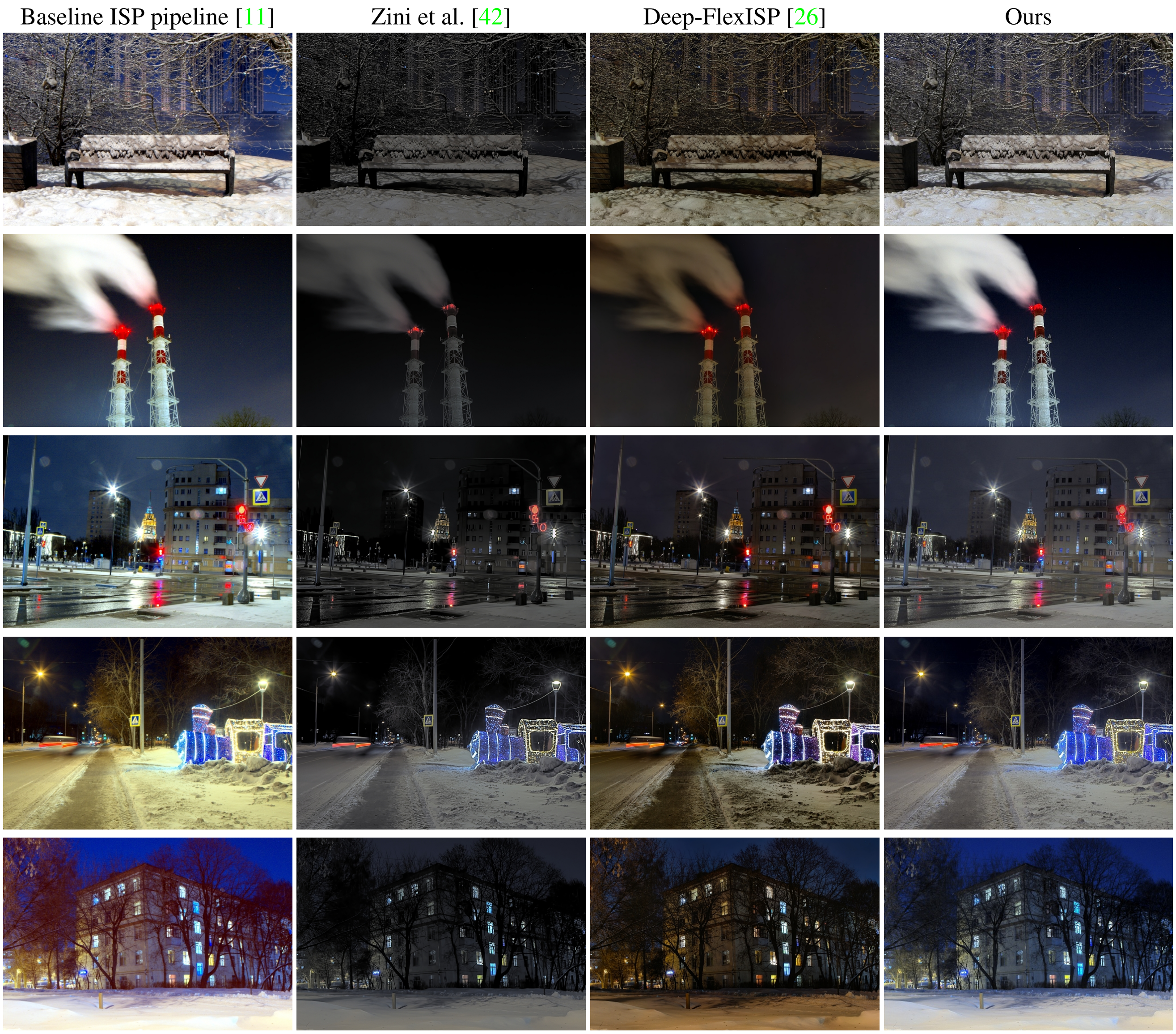


Figure 3. Visual comparison between rendered results by other ISP pipelines and ours.

achromatic pixels through the computation of Grayness Index [31].

4. Experiments

In this section, we describe the dataset used for our experiments and the results obtained. Then, we substantiate the importance of each step of our pipeline showing its impact on the final result.

4.1. Dataset

We used the dataset provided in the NTIRE 2023 Night Photography Rendering Challenge [37], which contains 200 RAW images of night scenes captured using a Canon EOS 7D device. Each RAW image has a resolution of 3464×5202 pixels. Ground truth images are not available due to the nature of the challenge. According to the challenge setup, 50 images are provided as training set, 50 as first validation set, 50 as second validation set, and the remaining 50 as final validation set. Since our solution does not need a training procedure, we use the training set to develop our pipeline and to empirically select the few required parameters, and we use all validation sets to validate our renderings.

4.2. Results

We compare the proposed ISP pipeline with other solutions for night image rendering, including a simple baseline provided by the challenge organizers [11], the method by Zini et al. [42] and Deep-FlexISP [26]. The first two methods are traditional ISP pipelines, while the last one is based on deep learning. Note that Zini et al. [42] and Deep-FlexISP [26] won fifth and first place in people's choice track of the NTIRE 2022 Night Photography Rendering Challenge [12], respectively. Some results are shown in Figure 3. Overall, images rendered with our solution present better contrast and better brightness distribution, improving visibility in dark areas with respect to the compared solutions. The simple mechanisms of the baseline pipeline [11] lead to occasional unrealistic results due to excessive saturation enhancement, as can be observed in the last two rows. Depending on the scene, untreated visible noise can be observed in the sky due to a lack of adequate noise removal, while high-frequency details look overall blurred. Moreover, illuminated snow and spotlights tend to be over-exposed, resulting in a loss of details in the surrounding areas. For comparison, image saturation is well balanced throughout all our images, which are also characterized by a significant reduction of sensor noise. Both Zini et al. [42] and Deep-FlexISP [26] produce excessively dark results, with the latter also failing to remove a general yellow color cast.

4.3. NTIRE 2023 Night Photography Rendering Challenge

The NTIRE 2023 Night Photography Rendering Challenge [37] has the goal of developing a solution for creating realistic and visually pleasing photographs of night scenes. The competition has two tracks: people's choice and photographer's choice. In the first track, evaluation is done by people using Mean Opinion Score (MOS) through visual comparison on the Yandex Toloka platform. In the second track, a professional photographer is asked to judge the images and to provide his selection. Table 1 reports the final leaderboard of the competition for the people's choice track. Here our solution won first place, obtaining 2.5% and 4.4% more votes than the second-ranked and third-ranked solutions, respectively, which are based on deep learning. It also received considerably more votes than the solution whose images were manually enhanced by non-professional photographers. Moreover, it won third place in the photographer's choice track, obtaining a better ranking with respect to other entries of the challenge based on deep learning.

4.4. Analysis of pipeline steps

As discussed in Section 3, we apply stronger denoising to the chroma component with respect to the luminance component to remove color noise while preserving image details. Figure 4 shows the impact of this approach: as we can see, denoising applied to luminance and chroma channels separately (Figure 4c) tends to preserve high-frequency details while effectively removing the sensor noise that is present in the original signal. Figure 4b shows the result of the application of the denoising operation to the RGB image, a process that results in a heavier loss of details.

The contrast enhancement stage of our pipeline applies several manipulations to the image histogram to enhance image contrast and colors. To better visualize such manipulations, Figure 5 shows the intermediate results of each algorithm within this stage, accompanied by the corresponding image histogram. We can see that the resulting histogram after the application of LCC has a limited dynamic range, even after the application of contrast and satura-

Rank	Team	Score	Votes
1	**IVLTeam**	**0.67**	**1843**
2	DH_ImageAlgo	0.645	1774
3	MiAlgo	0.626	1722
4	BSSC	0.606	1667
5	DH-AISP	0.583	1603
6	Manual Enhancement	0.491	1350
7	OzUVGL	0.453	1246
8	The Majestic Mavericks	0.444	1221
9	JMUCVLAB	0.439	1207
10	NTU607	0.376	1034
11	Baseline [11]	0.345	949

Table 1. Final leaderboard of people's choice track in the NTIRE 2023 Night Photography Rendering Challenge [37]. All submissions (50 images) were included in 2750 comparisons using the Yandex Toloka platform. Our team is highlighted in bold.

(a) No denoising (b) RGB denoising (c) Weighted d. (Ours)

Figure 4. Analysis of the denoising operation. Applying denoising to RGB channels leads to a heavier loss of details (Figure 4b). The adopted solution applies stronger denoising to chroma channels than to the luminance channel (Figure 4c).

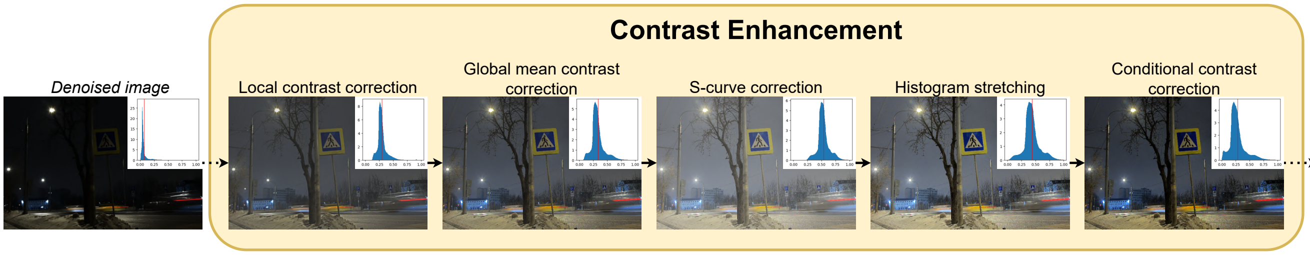
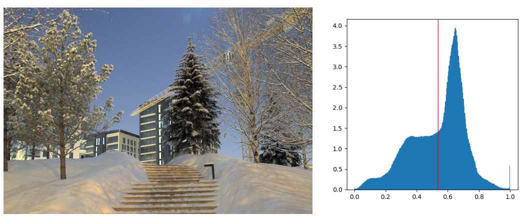
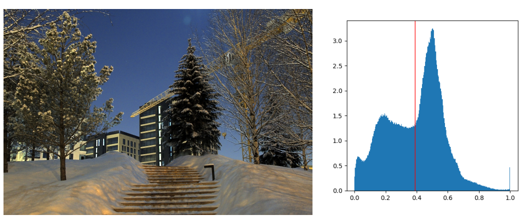


Figure 5. Analysis of the results obtained after each operation within the contrast enhancement step of our pipeline. Image histograms show how global contrast changes after each step.

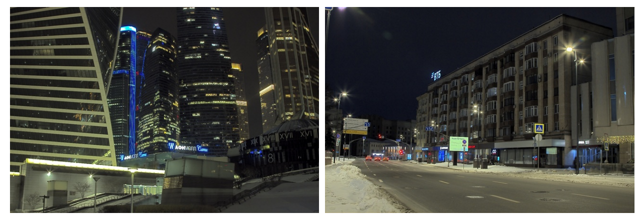


(a) Fixed contrast correction



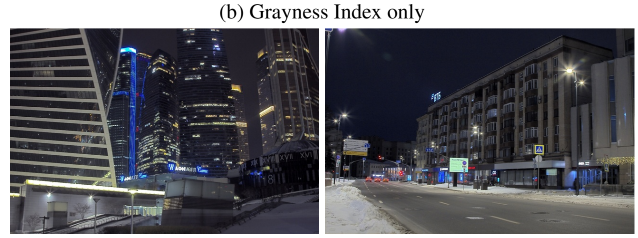
(b) Conditional contrast correction (Ours)

Figure 6. Analysis of the conditional contrast correction operation. If not used, images may have an unnatural illumination typical of daytime scenes (Figure 6a). Instead, the conditional contrast correction operation (Figure 6b) better preserves the nighttime mood.



(a) Gray World only

(b) Grayness Index only



(c) Combination of Gray World and Grayness Index (Ours)

Figure 7. Analysis of the white balancing operations. Rendered results using Gray Word only (Figure 7a), Grayness Index only (Figure 7b) and both the algorithms (Figure 7c). The yellow color cast is better removed when both the algorithms are used, with the scene appearing more natural.

tion fixing operations. The global mean contrast operation stretches the histogram around its mean value, however, the image does not appear contrasted enough because its histogram distribution does not cover the entire dynamic range. The application of an S-curve is needed to move the image histogram towards the center value of the dynamic range. At this point, histogram stretching is applied, with the resulting histogram having a small positive skewness while covering the entire dynamic range. As the resulting image appears too bright, the conditional contrast correction operation restores the typical mood of a nighttime scene.

The conditional contrast correction step is another important operation in our pipeline. We select three different sets of parameters in relation to the mean luminance of the images after the previous step. Specifically, we foresee three possible scenarios: a brightening operation is needed; a darkening operation is required; no further corrections are necessary. The first case occurs when images are very dark because spotlights are not enough to illuminate the entire scene. The second case occurs when images are too bright due to the strong illumination. The third case covers the other scenarios. Figure 6 shows the impact of the conditional contrast correction operation, which leads to a final illumination that keeps the night mood of the scene (Figure 6b). If this operation is not applied in this case, the result is an unnatural illumination similar to a daylight scene (Figure 6a).

Our pipeline involves two white balancing operations. The first one uses Gray World [3] in the RAW domain, while the second one applies Grayness Index [31] to RGB images. Here we show why these two operations are necessary to properly remove the undesired yellow cast typical of night photography. Figure 7 shows some results obtained using Gray World only (Figure 7a), Grayness Index only (Figure 7b) and both the algorithms (Figure 7c). We can see that using only one of these two algorithms is not sufficient to properly remove the color cast. Instead, applying both the algorithms considerably improves the final results, making the scenes appear more natural.

5. Conclusion

In this paper, we presented a traditional ISP pipeline for rendering visually pleasing photographs of night scenes. Our pipeline contains several algorithms, including denoising, color and contrast enhancement, sharpening and white balancing, to address the challenges presented by images captured at night. It is characterized by a shallow structure and a low parameter count, and it does not require training data, which is a significant aspect to address the problem of the lack of nighttime image datasets. Experiments show that our pipeline can produce better results than existing deep learning-based ISP methods, as also confirmed by the ranking of our solution in the NTIRE 2023 Night Photography Rendering Challenge.

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